Urban Dibao program: Targeting and its Effect

Lu Yang[1]

Institute of Population and Labor Economics, Chinese Academy of Social Sciences (CASS),

Beijing, China, 100732

Abstract: We adopt the data of *China's Urban Employment and Social Protection Survey 2010* (CULS3) and evaluate the *dibao* program in China by RD method and matching method. According to our analysis, we got some conclusions: firstly, *dibao* program has limited effects on alleviating poverty based on our data. It may due to *dibao* program's mistargeting. Secondly, healthy condition and living condition of a household are the factors affecting *dibao* program's targeting. Thirdly, the *dibao* program may change the expenditure behavior of a household, however, *dibao* subsidy may reduce food expenditure rate of a poor household. Therefore, Chinese government ought to provide food coupon not merely cash transfer to the poorest household to avoid food shortage.

Keywords: Urban dibao program; Targeting efficient; Poor household; Food Expenditure

JEL classification: H55; C21;

I Introduction

The "Minimum Livelihood Guarantee Scheme"—popularly known as Dibao (DB) — has been the Government of China's main response to the challenges of social protection in its rapidly changing economy. This paper describes the current urban poverty situation of six cities in China, examines the factors affecting the probability of a household being in poverty and investigates how the *dibao* program helps poor people to get out of poverty. The targeting efficiency of the urban *dibao* program is discussed and we also analysis the affecting factors on *dibao* targeting. The data used in this study from China's Urban Employment and Social Protection Survey 2010. The cities include Shanghai, Wuhan, Shenyang, Fuzhou, Xian and Guangzhou.

In 1999, the dibao program was established in China. According to the regulations of this program, people whose per capita household income falls below a locally determined minimum living standard can enjoy this assistance whether or not he or she receives a basic living subsidy, unemployment insurance or any other insurance. Local governments determine their own minimum living standard by reference to the basic living costs. Every urban resident whose per capita household income falls below the local minimum living standard can apply for this assistance. The assistance that a household receives equals household size times the gap between per capital household income and minimum living standard (Wang, 2007).

We are very interested in the following issues: Does the urban dibao program really help the urban poor to escape from poverty? How efficient is the targeting of the urban dibao program?

[1] Corresponding author
E-mail address: lusanmao2002@yahoo.com.cn (Lu Yang).

What the factors influence on the efficient of dibao targeting? And the effect of dibao program on poor household expenditure? The rest of the paper is organized as follows. In Section II, poverty rates of households are estimated before and after the *diba*o program in six cities, so we can analysis the role of the urban *dibao* program in alleviating poverty; Section III shows the targeting outcomes of *dibao* program. In Section IV, we analysis the *dibao* targeting efficient, and the factors affects the targeting efficient. In Section V, we evaluate the effects of *dibao* cash transfer on poor household consumption. In section VI, we evaluate the effects of *dibao* program on food expenditure of poor household. In section VII, the conclusion and some policy suggestions are outlined.

II The effect of Urban dibao program on urban poverty

In this section, we first calculated the poverty rates by household level and individual level. We use the data from China's Urban Employment and Social Protection Survey 2010. The survey included 4273 households of six cities. Household was defined as individuals who live together and share the same budget, whether or not their household registration (*hukou*) is in the same dwelling. The stratified random sampling method was adopted in this survey. In every city, communities are sampled first, and then households within communities.

In our sample, the number of *dibao* household in each city is different. We find that the *dibao* coverage rate in our sample is different between each city (Table 1). The highest coverage rate is Wuhan, whereas Fuzhou has the lowest coverage rate. We also give the *dibao* standards in our survey date in table 1. Xian's *dibao* standard is only 260 yuan RMB, while Shanghai's *dibao* standard is the highest in the six cities. In 2010, shanghai's *dibao* standard is 450 yuan RMB. Such situation is reflecting the different economic development and inflation rate in the six cities.

Table 1 Characteristics of *Dibao* in Six Cities

Index / City	Household Number	*Dibao* Number	Coverage Rate in Sample (%)	*Dibao* Standards in Survey Date
Total	4273	126	2.95	—
Shanghai	700	19	2.71	450
Wuhan	700	47	6.71	360
Shenyang	716	12	1.68	340
Fuzhou	728	4	0.55	290
Xi'an	729	35	4.80	260
Guangzhou	700	9	1.29	398

Information on households mainly included the housing situation, expenditure, transfer income and social protection received. The manner in which to estimate poverty rates has long been discussed by scholars and policy-makers. Households whose per capita household income is below the poverty line are deemed poor households, and all household members in poor households are deemed to belong to a poor individual. Because the present study is concerned with the role of the urban *dibao* program in China in helping poor people to move out of poverty, the *dibao* line of each city is used as the poverty line. Table 2 gives the poverty rates of households in 6 cities using the *dibao* lines (the first column) and the poverty rates of households in 6 cities after adding the dibao subsidy.

In table 2, we calculated the poverty rates by household level first. We find that the poverty rate before *dibao* program is 5.38% if we use the dibao line as the poverty line. The highest rate of poverty rate in Fuzhou and Shenyang of which 9.60% and 8.26% respectively. The lowest rate of poverty rate in our sample is 3.57% in Shanghai. In order to analysis the effects of *dibao* program on alleviating poverty in six cities, we calculated the poverty rate after *dibao* program by using *dibao* line as the poverty line. The results tell us that *dibao* program has same effects on alleviating poverty. In table 2, Shenyang, Fuzhou, and Guangzhou has no significant changes after adding *dibao* subsidy, whereas only Wuhan's *dibao* program has more effects on alleviating poor households to get out of poverty. The poverty rate is 5.38% in six cities before adding dibao subsidy, while its go down to 4.71% if the poor household getting *dibao* cash transfer.

Because poor households might have different household sizes from non-poor households, poverty rates by individual level are also provided (see Table 2) which results have no significant changes if we use the individual sample. As for poverty rates by individual level, the poverty rate of Fuzhou is still the highest of all 6 cities, just the same as poverty rates by household level. And for the total sample, the poverty rate by individual level is changing from 5.17% to 4.51% when we add dibao subsidy.

Table2. Poverty Rate before and after dibao program (%)

City	Poverty Rate Before *dibao* Program		Poverty Rate After *dibao* Program	
	Household	Individual	Household	Individual
Shanghai	3.57	3.59	2.96	3.03
Wuhan	5.41	5.40	3.68	3.46
Shenyang	8.26	8.40	8.14	8.32
Fuzhou	9.60	8.54	9.26	8.33
Xi'an	4.58	4.29	3.71	3.54
Guangzhou	5.75	4.81	5.46	4.58
Total	5.38	5.17	4.71	4.51

In ideal, if we reference *dibao* line as the poverty line, the poverty rate will be zero after *dibao* cash transfer. However, we found the poverty rate does not change too much when we keep *dibao* income as one source of income. Therefore, we will analysis *dibao*'s targeting in part III.

III Targeting Outcomes of Dibao Program

In practice, program officials do not have perfect information about who is poor, because collecting such information is time consuming and costly. Government faces serious identification problems in *dibao* program. And because program is based on imperfect information, so targeting rules they use may mistakenly identify non-poor peoples as poor, and therefore admit them to the program (so-called error of inclusion), or do the opposite, that is, mistakenly identify poor people as non-poor, and thus deny them access to the program (so-called error of exclusion).

We can see the matrix in Table 3. The survey included 4273 households, 265 are classified as poor (eligible) based on the poverty line (eligible threshold). Because the 265 households are selected according to imperfect targeting criteria, so 56 households successful targeting which are poor household (incomes below the *dibao* line), however, 209 households are non-poor household (incomes above the *dibao* line). Both the 56 poor households included in the program and the 3938 non-poor households excluded are successful targeting. We can calculate the successful rate of the program is 93.47%. The 209 poor households excluded are errors of exclusion, while the 70 non-poor households are errors of inclusion. The error rate is 6.53%.

The numbers in Table 3 can also be used to calculate two other measures: under-coverage and leakage. Under-coverage is the proportion of people who actually need assistance but who are not covered by the assistance program; leakage is the proportion of people who actually don't need assistance but are covered by the assistance program. According to the data in Table 3, the under-coverage is 209/265*100=78.87%, whereas the leakage is 70/126*100=55.56%.

Another way to assess the efficiency of an assistance program is by calculating the program coverage among the targeted and non-targeted populations. Table 3 shows that, 21.13 percent (56/265*100=21.13%) of all poor households receive the assistance of the *dibao* program, and 1.75 percent (70/4008*100=1.75%) of non-poor households receive the assistance of the *dibao* program.

Table 3 Targeting Outcomes of Dibao Program

Households / Type	Poor Households	Non-poor households	Total
Have dibao	Success 56	Inclusion error (Error 2) 70	126
Have no dibao	Exclusion error (Error 1) 209	Success 3938	4147
Total	265	4008	4273

Source: Calculated from China's Urban Employment and Social Protection Survey 2009.

From the above analysis, the targeting efficiency of the *dibao* program is very low (only 21.13 percent poor households received *dibao* subsidy), and more than one half of *dibao* receiver are non-poor. According to our above definition, the targeting efficiency of this program is still very low. The most urgent problem for the *dibao* program is the improvement of the efficiency of targeting.

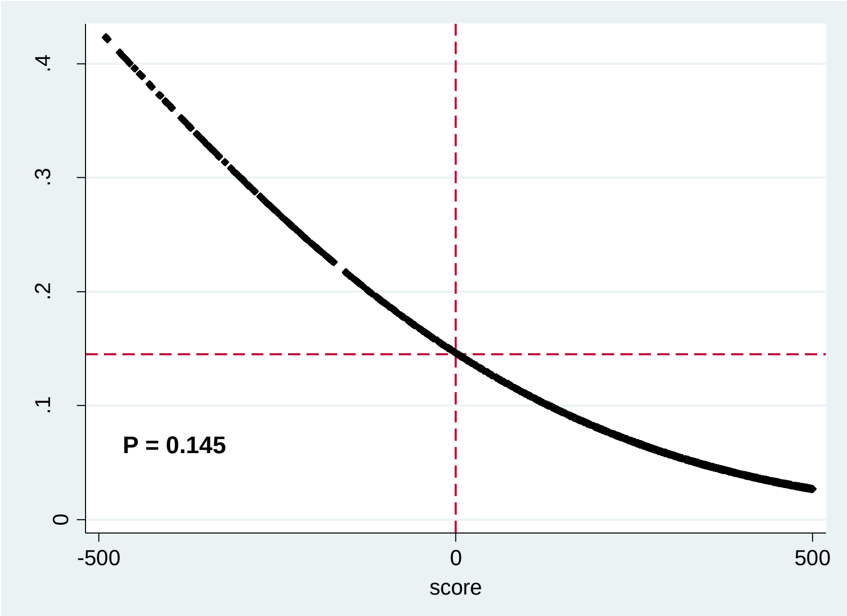

Fig1. Income and the possibility of assess to *dibao*

Fig1 shows the probability of a household assesses to *dibao* protection with the increase of its income. Near the *dibao* line the mistargeting rate is 0.145. However, even though a household per income has a lowest score (poor household), the probability of acquire *dibao* protection is no more than 50%.

However, unemployed workers, low human capital, low skills workers, and old age individuals are very likely to fall into poverty. So there are many factors affecting the probability of a household being in poverty. It is clear that the *dibao* program is putting heavier weight on certain characteristics of a household. The factors affecting the probability of mistargeting are then examined in the next section.

IV Factors Influence on the Efficiency of Dibao Targeting

To analyze the relationship between affecting factors and mistargeting of *dibao* households, the multinomial logit model (MLM) is estimated to examine the determinants of mistargeting. There are many factors affecting the probability of a household acquired *dibao* program besides the incomes level of a household. Such as, age, education, household size, composition of household members and proposition of unemployed household members etc. In the MLM model, variables are incorporated that represent these factors and the model can be written as follows:

$$L_1 = X'b + e$$

$$L_2 = X'b + e$$

$L_{1,2} = 1$ *if targeting is not correct, include error1 and error2;*
$L_{1,2} = 0$ *if targeting is correct*

From which X is a vector of variables which may influence the targeting outcomes, b is a parameter vector, and e is an error term, with zero mean and variance δ. The dependent variable of the model is whether or not the targeting for *dibao* program is correct. The dependent variable is equal to 0 if a household being in correct targeting; otherwise, L_1 equal to 1 if poor households not covered into *dibao* program, and L_2 equal to 1 if mistargeted non-poor households as poor.[2]

Definition of Type1: per capita income of household < Dibao line and not obtain Dibao

Definition of Type2: per capita income of household ⩾ Dibao line and have obtain Dibao

In our above analysis, per capita income of a household is equals to the average income of all family members' income which includes wage, pension, insurance income, transfer income and property income. However, there is more than one way to measure income. Program administrators may have good reason for putting higher weight on certain observables than is implicit in current incomes. Because current income may differs from long-term income. For example, a young well-educated family may have low current income but be on a rising trajectory with good future prospects which not eligible for *dibao* program. Or a family may have a temporarily low income (due to unemployment) but still not be deemed sufficiently poor in terms of their standard of living, as indicated by their consumer durables and housing, to warrant public action. Another source of error is in the weighting of household size and demographic composition in forming the metric of economic welfare (Ravallion, 2008).

So, except of the observed current household income, the independent variables may include a vector of other relevant variables in theory. In our empirical analysis, MLM model includes some basic human capital characteristics of the household head and his/her partner, such as educational level. It also includes the employment situation of household members, such as the proportion of employed and unemployed household members. Household size, proportion of household members aged 0 – 15 years, proportion of female household members aged 55 and above and proportion of male household members aged 60 and above are incorporated in the model. And we also added house conditions dummy variables in our analysis. City dummy variables and an error term are also included in the model. Affecting factors are classified into 6 categories, Including "Per Capita Income", "Basic Human Capital Characteristics", "Employment Status", "Demographic Compositions", "Healthy condition", and "Living Standards". The reason why we add such variable is as follows.

Some variables are included that reflect the basic human capital characteristics of the household head and his/her partner in the model. Human capital endowments are important indicators reflecting a person's income earning ability, especially in the long run. Because the gender of the household head in China is quite random, so it is hard to judge the sign of the effect of female on poverty. So we did not add gender variable in our model.

Educational years of the household head and his/her partner are represented in the form of a continuous variable. Given that educational attainment represents a major part of workers' human capital and workers with higher human capital usually earn more income, a strong and

[2] In our survey sample, information on individuals mainly included basic human capital characteristics, such as age, gender, educational level and marital status, working situation, such as working experience, sector, occupation, income and wage arrears, lay-off status, unemployment and retirement status, social security, such as pension, medical insurance and unemployment insurance, expenditure on education, training and medical treatment and social networks.

negative relationship between educational attainments and mistargeted of *dibao* program is expected.

Variables representing the employment status of household members are included in the model. They are the proportion of employed and unemployed members. These two variables can reflect a household's income earning ability. The higher the proportion of unemployed members, the lower is a household's income earning ability, the household then has a higher probability of covered the non-poor households into the *dibao* program. We expect a positive sign between type 1 mistargeting and proportion of unemployed.

In addition, variables denoting family support or dependence in the models are incorporated. They are household size and demographic compositions, e.g. proportion of household members aged 0 – 15 years, proportion of female household members aged 55 years and above and proportion of male household members aged 60 years and above. City dummy variables are in the model.

Table 4 Miss Targeting: Based on MLM Analysis

Dependent Variable	Type1		Type2	
Variable	Coef.	Std. Err.	Coef.	Std. Err.
Constant	1.932*	1.058	-1.361**	0.615
Original per Income	-0.008***	0.001	-0.001***	0.000
Household size	0.066	0.115	0.123	0.122
Household head educational years	0.007	0.028	0.013	0.027
Partner's educational years	-0.024	0.033	-0.002	0.018
Proportion of employed	0.097	0.443	-0.138	0.319
Proportion of unemployed	0.615	0.628	-1.506	0.993
Proportion of age 0-15	-0.258	0.699	-0.308	0.462
Proportion of women 55+	-0.313	0.670	-1.093**	0.554
Proportion of men 60+	0.991	0.725	1.739***	0.545
Healthy	0.221**	0.095	-0.181**	0.075
Household head's brothers and sisters	0.087	0.066	-0.051	0.043
Partner's brothers and sisters	0.026	0.070	0.038	0.051
Per living area	0.008***	0.003	-0.029***	0.011
Toilet (1=Yes; 0=Not)	0.762	0.475	-0.229	0.220
Gas tubing (1=Yes; 0=Not)	0.062	0.231	0.009	0.150
House property right (1=Yes; 0=Not)	-0.545**	0.220	-0.222	0.169
Durable commodity (1=Yes; 0=Not)	-0.090	0.349	-0.194	0.377
Fit up house (1=Yes; 0=Not)	-0.347	0.382	-4.839***	0.151
City dummy	yes		yes	
Observations	3315			
Probability>chi^2	0.0045			

The results of the MLM models of *dibao* targeting are shown in Table 4. Most estimation results are consistent with our assumption. According to the estimation, before adding *dibao* subsidy, the original per income of a household has a significant negative effect on two types of mistargeting. But it's hard to give a theoretical explanation for type1 mistargeting, in which the lower per household income the higher rate of getting *dibao* subsidy and the lower possibility induce mistargeting. This result is not coincided with our intuition and theory. But we found the higher a household income, the lower possibility for a household gain *dibao* subsidy, and the lower probability induce mistargeting. Therefore *dibao* targeting will be correct.

We did not find there is a strong and positive relationship between household head educational attainment and error 1 of mistargeting, the same as household head's partner. We also find that the proportion of employed and unemployed in a household is not an obvious variable influence *dibao* targeting efficiency.

The variable of proportion of members aged 0－15 years is not significant in the model. However, the proportion of women aged 55+ and proportion of men aged 60+ are very significant in type 2 mistargeting. The higher proportion of elder man in a household may induce program officers make targeting mistakes by including such household into *dibao* household.

We also find that the healthier a household head, the lower probability of his/her family gain *dibao* assistant if they are non-poor, while the higher probability of his/her family not covered by *dibao* assistant if they are poor. Also, the standard of living has influenced the *dibao* targeting. For example, per living area and whether fit up house in the last year also has influenced a household getting *dibao*, because such household condition can warrant public action, and then become a hidden reference index of which influence government decision on dibao targeting. So such variables may be second important criteria in identifying *dibao* household. If a non-poor household has fit up house in the last year may help administers avoid making mistakes of type2 mistargeting.

V Effect of Dibao Cash Transfer on Poor Household Consumption by RD method

We will use two different methods to evaluate the effect of *dibao* program on poor household expenditure rate. The first method we use is regression discontinuity (RD). Because we known, RD method can induce an unbiased estimate of treatment effect at the discontinuity. On the issue of *dibao* problem, there is a narrow band near to the *dibao* line, for example, if *dibao* line is 500 yuan, and the narrow band maybe 490 to 510 yuan in ideal. The *dibao* line (cut-off line) can divide the sample into two subsamples by random if we pick up the narrow sample. Because when the per capita income of a household is very near to the *dibao* line, although this household are not eligible to get *dibao* subsidy because its income is higher than *dibao* line, but in fact it is also a poor family. This can induce two groups---control group in which per capita income is higher than *dibao* line and not eligible to assess to *dibao* program; and treatment group in which per capita income is lower than *dibao* line and eligible to assess to *dibao* subsidy. So we can evaluate the effect of *dibao* program on poor household expenditure rate by using RD method first. This method also has a disadvantage that is *dibao* household has different cash transfer although we choose a very narrow band near to the cut-off line.

Table 5 Effects of dibao program on poor household expenditure with band score of 200

Variable	*Before dibao protection*			*After dibao protection*		
	Coef.	*Std. Err.*	*P>| t |*	*Coef.*	*Std. Err.*	*P>| t |*
c	1.422	0.0752	0.000	1.748	0.123	0.000
score	- 0.00086	0.00060	0.152	-0.00332	0.00094	0.001
Dibao	—	—	—	-0.83704	0.25191	0.001
(1= have dibao)						
N	231			231		
R^2	0.0089			0.0547		

Because different city has very different *dibao* line, at fist we must standardize the income level by each city. According to the target of analysis, I use *dibao* line as an instrument to normalize the household income in each city. If the per capita household income is equals to the *dibao* line, the score of this family is equals to zero. So the new variable "score" is equals to each household per capita income cut the *dibao* line of each city. So households with a score below 0 are poor; households with a score above 0 are non-poor. From this part we will focus on the effect of *dibao* program on household consumption rate before and after cash transfer, comparing households just above and below the cut-off line.

According to RD method, we chose the score of 200 which near the cut-off line as the bandwidth in RD analysis. Table 5 shows the *dibao* effects on household expenditure rate based on bandwidth 200. There's no significant relationship between a household income and its expenditure rate before we add *dibao* variable. However, the variable of per capita household income and *dibao* are all significant in the model after we add dummy variable of *dibao*. In theory, the expenditure will increase as the increasing of a household income. The expenditure rate in our model is equals to the household expenditure divided the household income before adding *dibao* subsidy. So *dibao* program will increase the expenditure rate of a household in theory. However, we found the opposite result in our analysis.

Table 6 effect of dibao program on poor household expenditure with band score of 100

Variable	*Before dibao protection*			*After dibao protection*		
	Coef.	*Std. Err.*	*P>| t |*	*Coef.*	*Std. Err.*	*P>| t |*
c	1.498	0.1205	0.000	1.829	0.2119	0.000
score	0.00057	0.00206	0.781	-0.00519	0.00367	0.161
Dibao	—	—	—	-0.90812	0.48133	0.062
(1= have dibao)						
N	91			91		
R^2	0.0009			0.0397		

When we chose a narrow band of score 100 by which the control group and the treatment group are more homogeneous than before. The results are shown in table 6. We found that the income variable is also not significant after adding *dibao* subsidy. This result demonstrates that the different consumption behavior between the two poor groups is not induced by income but because of whether access to *dibao* program. Because the score of 100 is not very narrow to the cut-off line, so the income must be not significant in our model and by which can identify the *dibao* effects on poor household consumption. Table 6 shows that the effects of *dibao* program on a poor household' expenditure rate is negative. If a household getting dibao protection, the household per month expenditure rate will decrease 0.908.

Fig2 shows the relationship between household per income and the expenditure rate in total sample when we chose the score 100 as the bandwidth. We found poor household and non-poor household have a similar consumption behavior in the cut-off line when we ignore *dibao* effects on households' consumption. But when we add *dibao* variable, the treatment effect of *dibao* program on consumption rate is very significant and move down from the baseline. The negative movement distance is the dibao program's treatment effect on poor household expenditure rate.

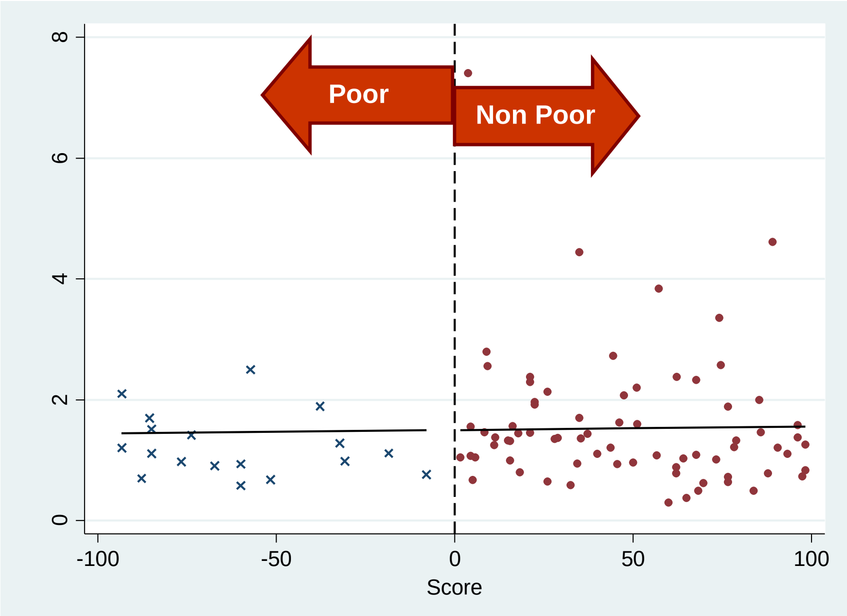

Fig2. Relationship between income and expenditure rate of income in baseline

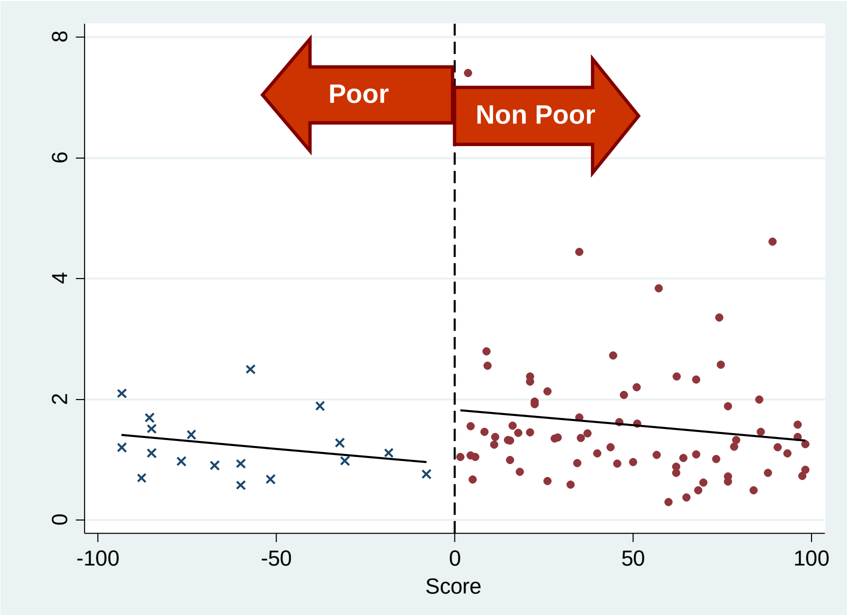

Fig3. The effect of *dibao* program on poor household expenditure rate of income

Fig3 shows the *dibao* program's effect on poor's consumption. Around the cut-off line, the poor household consumption behavior has changed. The poor household expenditure rate is lower than the control groups'. This result may confuse us that the expenditure of *dibao* household is lower than before. But we know the expenditure may increase after a household got an extra income. The jump part is *dibao* program's treatment effect on consumption.

We know that the proportion of food expenditure in total household income of poor families is very large. Does the food expenditure rate in poor household changes significant after they get *dibao* protection? If dibao protection has a significant effect on food expenditure rate of poor family, the *dibao* program has providing a basic living standard for the poor family and helping the poor keep healthy. So we use the same RD method to estimate the treatment effect of *dibao* subsidy on the food expenditure rate of poor.

Table 7 effect of dibao program on food expenditure rate of poor income by band 200

Variable	*Before dibao protection*			*After dibao protection*		
	Coef.	*Std. Err.*	*P>| t |*	*Coef.*	*Std. Err.*	*P>| t |*
c	0.865	0.0360	0.000	1.030	0.0577	0.000
score	-0.00084	0.00029	0.004	-0.00208	0.00044	0.000
Dibao (1= have dibao)	—	—	—	-0.42487	0.11824	0.000
N	230			230		
R^2	0.0362			0.0880		

In table 7, per capita income of a household is significant in the model. The result demonstrates that the two poor groups which near to the *dibao* line influenced by income, and we can not identify the treatment effect by *dibao* protection. When we chose a narrow band we found that the *dibao* program has influenced on the consumption behavior (Table 8). The treatment effect is -0.491. This result is hard to explain by economic theory because the food expenditure is lower than pre-transfer situation.

Table 8 effect of dibao program on food expenditure rate of poor income by band 100

Variable	*Before dibao protection*			*After dibao protection*		
	Coef.	*Std. Err.*	*P>| t |*	*Coef.*	*Std. Err.*	*P>| t |*
c	0.889	0.05479	0.000	1.068	0.09553	0.000
score	-0.00029	0.00094	0.761	-0.00341	0.00165	0.042
Dibao (1= have dibao)	—	—	—	-0.49139	0.21696	0.026
N	91			91		
R^2	0.0010			0.0561		

Fig4 shows the relationship between household per income and the food expenditure rate in total sample when we chose the score 100 as the bandwidth. We found poor household and non-poor household have a similar consumption behavior in the cut-off line, however the treatment effect of *dibao* program on food consumption rate is very significant and move down from the baseline after we add *dibao* variable. The negative movement distance is the *dibao* program's treatment effect on poor household food expenditure rate (see Fig5).

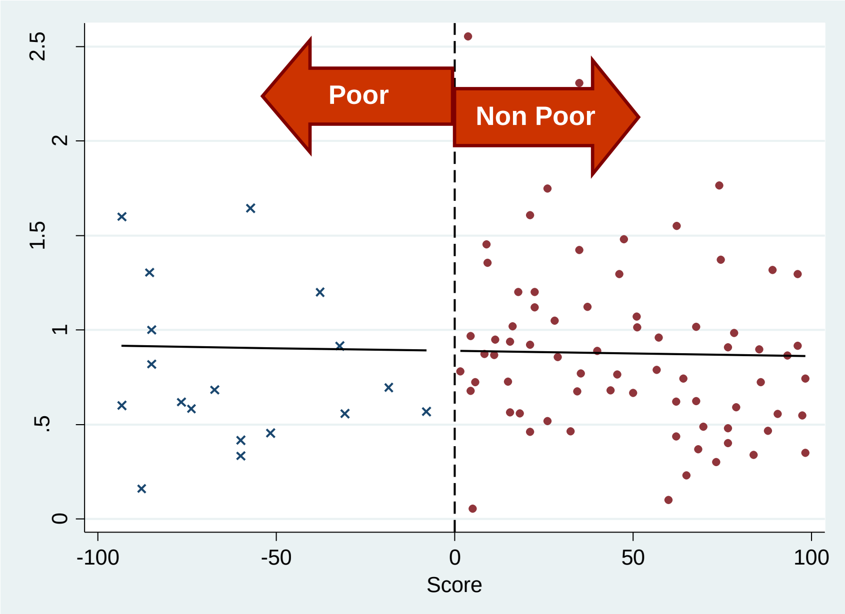

Fig4. Relationship between income and food expenditure rate of income in baseline

There is a problem when we using RD method to evaluate *dibao* effects on poor households. It's still a wide bandwidth by 100 score to divide who eligible to assess to *dibao* protection. The per capita income of households has influenced on the randomization when we use RD method. The two families-----100 yuan below the *dibao* line and 100 yuan above *dibao* line, are not homogeneous in consumption behaviors. So in the next part, a new method will be induced to evaluate the effect of diao program on expenditure.

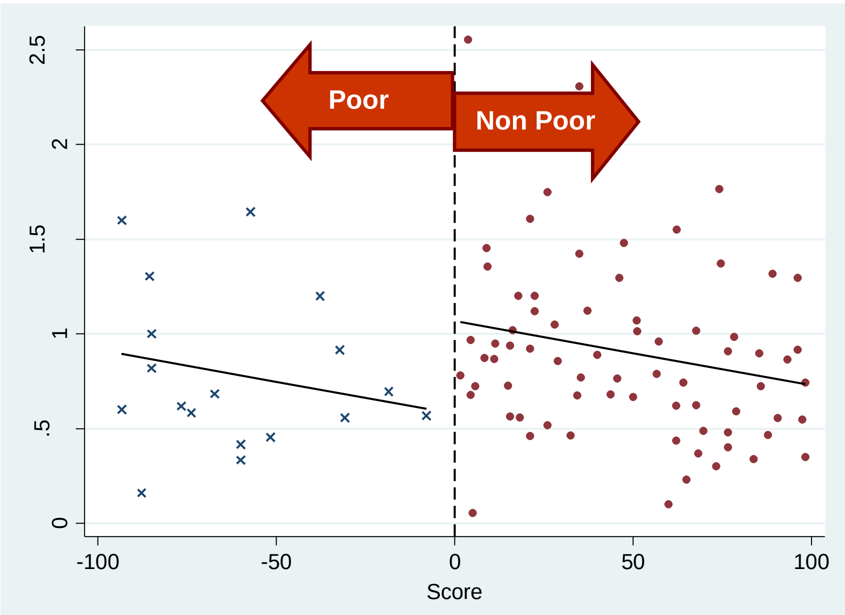

Fig5. The effect of *dibao* program on poor household food expenditure rate of income

The rapid growth of food costs will hurt the poor households than the non-poor households, because there is a high proposition of food expenditure in total expenditure in the poor households or there is a greater proportion of food expenditure in poor household income. Those consumers whose living statuses close to the minimum limit of living will suffer severely affected by lacking food nutritional. So in this part we will analysis the effects of *dibao* program on the proposition of food expenditure in the total expenditure of poor household. Table 9 shows the *dibao* effects on household food expenditure of total expenditure based on bandwidth 200. We find that there is no significant relationship between a household income and the food proportion rate of expenditure. However, *dibao* program also not has significant effect on the food proportion rate of poor household expenditure in RD model. We got the same conclusion when we use score 100 as the bandwidth (see table 10). According to the estimation results, *dibao* program does not significantly increase poor household food expenditure in their expenditure basket.

Table 9 effect of dibao program on food expenditure rate of poor expenditure by band 200

Variable	*Before dibao protection*			*After dibao protection*		
	Coef.	*Std. Err.*	*P>| t |*	*Coef.*	*Std. Err.*	*P>| t |*
c	1.870	0.04737	0.000	1.840	0.05367	0.000
score	0.00042	0.00040	0.295	0.00050	0.00040	0.214
Dibao (1= have dibao)	—	—	—	0.13226	0.11275	0.242
N	352			352		
R^2	0.0031			0.0071		

Table 10 effect of dibao on food expenditure rate of poor expenditure by band 100

Variable	*Before dibao protection*			*After dibao protection*		
	Coef.	*Std. Err.*	*P>| t |*	*Coef.*	*Std. Err.*	*P>| t |*
c	2.020	0.08929	0.000	1.908	0.15951	0.000
score	-0.00110	0.00153	0.475	0.00085	0.00276	0.758
Dibao (1= have dibao)	—	—	—	0.30705	0.36228	0.399
N	91			91		
R^2	0.0058			0.0138		

VI The Effects of Dibao Program on Food Expenditure for Poor Household

In part V, we use RD method to evaluate the effects of *dibao* program on poor household expenditure. However, the strict assumption by which targeting group is random divided by cut-off line. But according to the income criterion, mistargeting can not be avoided. It’s hard to produce an unbiased estimate when we only include correct targeted group and ignore the mistargeting one although the bandwidth is narrow. So in this part, we use another method to evaluate the effect of *dibao* program on poor household’s consumption. In this part, I focus on the poor household which is classified by the *dibao* line (cut-off line). That is the household should be kept in our sample if its score below 0. And there are two sub-samples in total poor household sample----poor and targeted vs. poor but not targeted (mistargeting). In this case, we don't care about whether the two sub-samples are cut-off by random. We will analysis the two consumption curves which formed by the two sub-groups whether could be overlapped, because the expenditure behavior may changes in the targeted group after they got the dibao cash transfer.

Fig6. Consumption discrepancy between *dibao* and non-dibao poor households

Fig6 and Fig7 show the two different consumption curves between poor targeted group and poor non-targeted group. And the expenditure volume and expenditure rate of income in mistargeting group are all higher than targeted group. And Fig8 and Fig9 show the two different food consumption curves between poor targeted group and poor non-targeted group. And the food expenditure volume and food expenditure rate of income in mistargeting group are all higher than targeted group. This phenomenon may demonstrate that the so-called mistargeting group based on our definition may not eligible to got *dibao* subsidy in initial by comparing their higher expenditure with mistargeted group. Mistargeting rate of *dibao* program may smaller than our estimation base on this consideration.

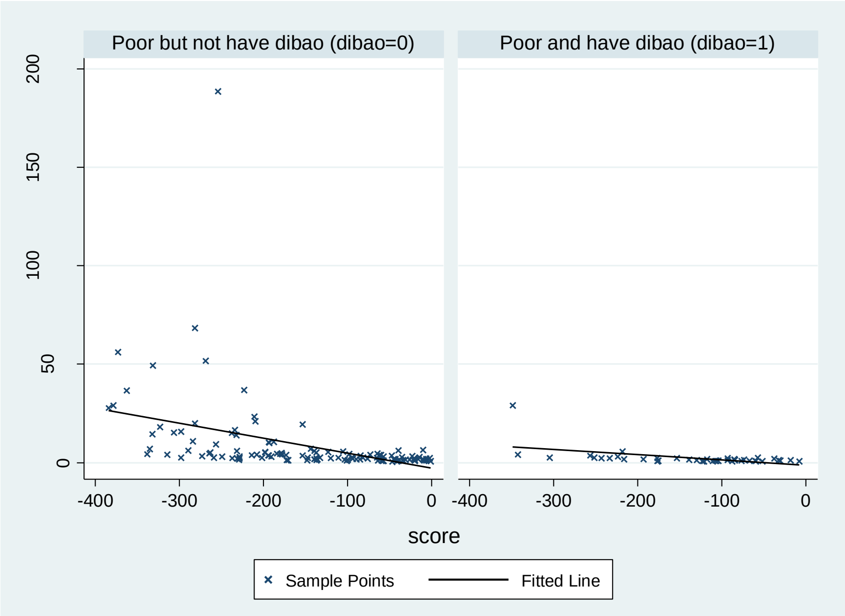

Fig7. Consumption rate discrepancy between *dibao* and non-*dibao* poor households

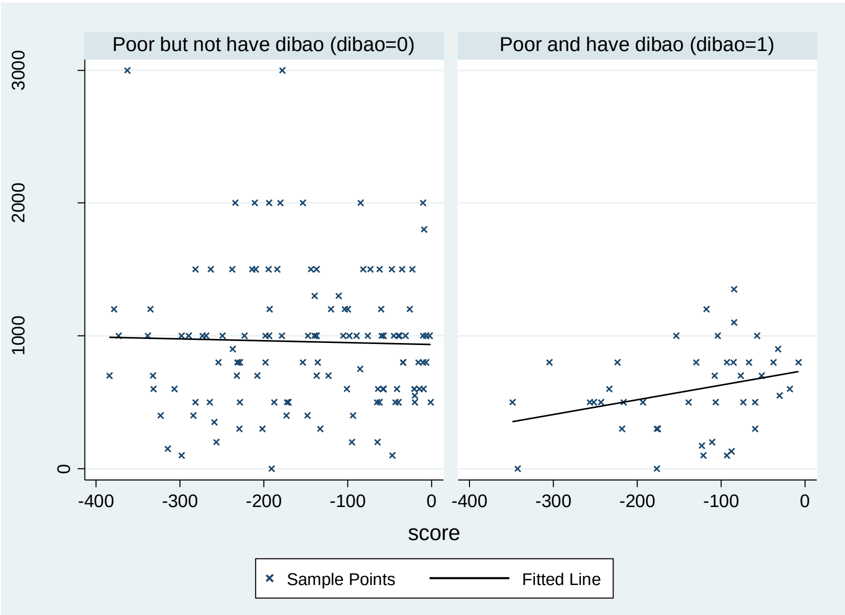

Fig8. Food consumption discrepancy between *dibao* and non-*dibao* poor households

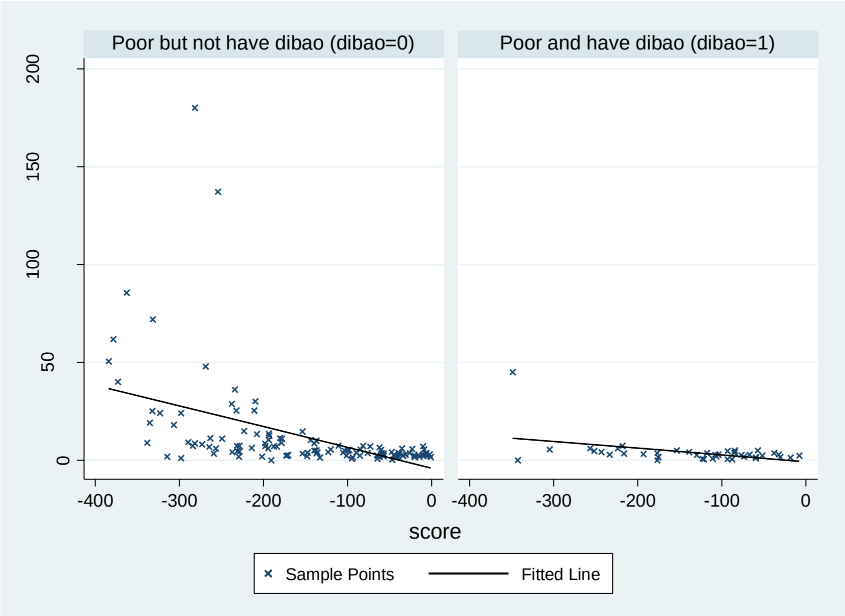

Fig9. Food consumption rate discrepancy between dibao and non-dibao poor households

We can calculate the average gain from treatment on poor household expenditure by using matching method. The average treatment effect on treated (ATT) can be estimated for non-randomized observational studies. Rosenbaum and Rubin (1983) proposed propensity score matching an average treatment effect on treated (ATT) to reduce the bias in the estimation of treatment effects with observational data sets. Propensity score matching is a way to "correct" the estimation of treatment effects controlling for the existence of outcomes is performed using treated and control subjects who are as similar as possible. The bias is eliminated only if the exposure to treatment can be considered to be purely random among individuals who have the same value of the propensity score (Becker and Ichino, 2002). Rosenbaum and Rubin (1983) defined the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(X) \equiv \Pr\{D=1 \mid X\} = E\{D \mid X\} \qquad (1)$$

Where $D=\{0,1\}$ is the indicator of exposure to treatment, and *X* is the multidimensional vector of pre-treatment characteristics. Rosenbaum and Rubin (1983) state that if the exposure to treatment is random within cells defined by *X*, it is also random within cells defined by the values of the mono-dimensional variable *p*(*X*). Base on matching method, we choose per income of household, healthy of household head, and per living area of a household as the pre-treatment characteristics to define the cell. According to the estimation of matching method, control group is poor but not targeted, and treatment group is poor and targeted, each small cell homogeneously in the pre-treatment characteristics. The ATT of *dibao* program on food expenditure rate (the proportion of food expenditure in total expenditure of a household) will decrease 9.2% on average. This conclusion state that food expenditure in the expenditure basket could decrease and the proposition of other terms of expenditure will increase if a household got *dibao* cash transfer. The effect is so limited from which *dibao* program helping poor household acquire more food. Basic food allowance (eg. give more food or food coupon to the poor household) maybe better in helping poorest household avoid food shortage.

VII Conclusions

We adopt the data of *China's Urban Employment and Social Protection Survey 2010* (CULS3) and evaluate the *dibao* program in China. According to our analysis, we got some conclusions: firstly, *dibao* program has limited effects on alleviating poverty based on our data. It may due to *dibao* program's mistargeting. The targeting efficiency of the *dibao* program is very low, only 21.13% poor households received *dibao* subsidy, and more than one half of *dibao* receiver are non-poor.

Secondly, healthy condition and living condition of a household are the factors affecting *dibao* program's targeting. In fact, the healthier a household head, the lower probability of his/her family gain *dibao* assistant if they are non-poor, while the higher probability of his/her family not covered by *dibao* assistant if they are poor. If a non-poor household has fit up house in the last year may help administers avoid making mistakes of type2 mistargeting.

Thirdly, the *dibao* program may change the expenditure behavior of a household, however, *dibao* subsidy may reduce food expenditure rate of a poor household. Therefore, basic food allowance, such as, provide government's food coupon to the poor household, maybe better in helping poorest household avoid food shortage. In some instance, government' food coupon may also avoid the phenomenon of targeting mistake in China.

Reference

Becker, S.O., Ichino, A., "Estimation of average treatment effects based on propensity scores", *The Stata Journal*, 2002, 2(11), pp.358-377.

Rosenbaum, P.R., and Rubin, D.B., "The Central Role of the Propensity Score in Observational Studies for Causal Effects", *Biometrika*, 1983, 70(1), pp.41-55.

Wang, M., "Emerging Urban Poverty and Effects of the Dibao Program on Alleviating Poverty in China", *China and World Economy*, 2007, 15(2), pp.74-88.

Ravallion, M., "Miss-targeted or miss-measured?", *Economics Letters*, 2008, 100, pp.9-12.