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Rural minimum living standard guarantee (rural Dibao) program boosts children's education outcomes in rural China

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Abstract

Purpose – To combat poverty in China's rural areas, Chinese government has established an unconditional cash transfer program known as the Rural Minimum Living Standard Guarantee (Rural Dibao) Program. Interestingly, despite the importance of education in breaking cycles of poverty, little is known about Rural Dibao's impact on rural children's education. This study investigates Rural Dibao's impact on rural children's learning outcomes by first examining targeting issues within the program, exploring a causal relationship between Rural Dibao and learning outcomes, and then exploring potential mechanisms and heterogeneous effects.

Design/methodology/approach – Fixed effects model and propensity score weighting method and data from China Family Panel Studies (CFPS) from the years 2010 and 2014 were used.

Findings – The results suggest that the Rural Dibao program suffers from high levels of targeting error, yet is still effective (i.e., program transfers generally still go to people in need). The fixed effects and propensity score weighting models find that program participation raises rural children's standardized test scores in CFPS Chinese-language and math tests. In investigating mechanisms, increased education expenditure seems to connect Rural Dibao participation to increased learning results. The heterogeneity analysis shows that poorer, non-eastern, not left behind, younger or male children benefit from the program (while others have no effect).

Originality/value – These findings suggest that Rural Dibao participation boosts rural children's learning, which could indicate a long-term anti-poverty effect, and that if the program can resolve targeting problems, this effect could be even greater.

Keywords Education, Low income subsidy, Impact evaluation, Rural China

Paper type Research paper

1. Introduction

Despite four decades of rapid economic growth and development, China continues to struggle with issues of rural poverty. Rural development is seen by the government as a short leg in pursuing the moderately prosperous society (Chen, 2019a). And winning the battle against

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poverty is one of the key missions of that (Han, 2019). A boost of rural residents' income is also needed in Chinese government's rural revitalization strategy (Chen, 2019b). To combat poverty in rural areas, the Chinese government has established the Rural Minimum Living Standard Guarantee (hereafter, Rural Dibao) program. The policy aims to provide approved poor families with monthly unconditional monetary cash transfers that cover their living needs, such as food, clothing, and housing (Han *et al.*, 2016). Rural households with family per capita income lower than local Rural Dibao thresholds can apply for the program. By the end of 2018, more than 100 billion Renminbi (RMB; over US$14 billion) were transferred to 35 million people in 19 million different rural households by the Rural Dibao program (Ministry of Civil Affairs, 2019).

Although many studies have examined Rural Dibao's effect on poor families, these studies have yet to reach consensus on Rural Dibao's effect on household welfare. As Rural Dibao is designed as a direct cash transfer to participants, Rural Dibao participation has been shown to raise the income of the enrolled families (Golan *et al.*, 2017; Kakwani *et al.*, 2019; Li and Sicular, 2014; Westmore, 2018). Beyond the current income effect, however, researchers disagree on how the program affects household welfare more broadly. Gao *et al.* (2015) claim that Rural Dibao has a negative impact on household welfare by showing that Rural Dibao participation leads to less time spent on work, leisure, and social activities and more time spent on being idle, resulting in reduced household welfare. Han *et al.* (2016) support this argument by showing that participation leads to less expenditure on social activities. Nevertheless, Han *et al.* (2016) as well as Zhao *et al.* (2017) and Wang *et al.* (2019a, b) find some positive impacts of Rural Dibao on rural household welfare (e.g., participation is related to increased health expenditure).

Despite the findings of earlier research on Rural Dibao's effect on households as similar in some respects, the findings are mixed. For example, Zhao *et al.* (2017) showed that housing expenditure, and thus household welfare, is increased by Rural Dibao participation. In contrast, Han *et al.* (2016) and Wang *et al.* (2019a, b) found that housing expenditure does not increase. The contradictions that exist among these studies make it difficult to describe Rural Dibao's ultimate effect on household welfare.

Although there may be a number of reasons for why different studies arrive at different conclusions, studies that examine Rural Dibao diverge for two main reasons. The first reason, targeting error, reflects issues in the way that the Rural Dibao program identifies who receives transfer payments versus who does not qualify. According to authors (e.g., Golan *et al.*, 2017 and Kakwani *et al.*, 2019), there is a great deal of targeting error; a large number of households are actually poor but do not qualify, while a large number of non-poor households receive payments. There may be many reasons for this poor targeting (from corruption to just being a difficult process to identify actual household income). However, if targeting error is not considered in analyzing Rural Dibao's anti-poverty impacts, because poverty is no longer the only determinant for program participation, the evaluation may be biased.

The second reason for mixed findings is the absence of researchers to adequately identify the causal relationship between the program and household welfare. Almost all of the previous studies produce empirical findings that are based on correlations and do not produce estimates of the true causal relationship between Rural Dibao participation and household welfare. For example, many previous studies (e.g., Gao *et al.*, 2015; Han *et al.*, 2016; Kakwani *et al.*, 2019; Li and Sicular, 2014; Wang *et al.*, 2019a, b; Zhao *et al.*, 2017) have used only a single set of cross-sectional data in their analyses. In other studies, for example, Golan *et al.* (2017) and Westmore (2018), the authors have panel data but do not exploit the over-time characteristics of their samples to identify causality. The only three papers that claim to address the endogeneity problems that exist in studying the program's impacts on welfare all rely on propensity score matching with their cross-sectional data (Gao *et al.*, 2015; Han *et al.*, 2016; Wang *et al.*, 2019a, b).

Propensity score matching, however, has become increasingly known to be a weak approach to identification when using only cross-sectional data, as the basic assumption needed for propensity score matching – a lack of confoundedness – has been shown to be rarely proven in that case (King and Nielson, 2019).

In addition to the mixed findings on Rural Dibao's effect, the program also receives criticism for offering only short-term poverty relief. Anti-poverty programs are often criticized for providing only short-term aid, which may hinder long-term anti-poverty efforts by generating welfare dependency (Blank, 2003). Rural Dibao also is subject to this criticism. As noted, Gao *et al.* (2015) show that Rural Dibao participants may reduce their work time and time spent on leisure or social activities, resulting in more time in being idle, indicating that, although the program provides short-term relief, this relief might not translate into long-term welfare gains. Research, however, has looked mainly at short-term measures of welfare gains, such as working time and expenditures. Therefore, there is a need for studies to examine the long-term welfare effects of Rural Dibao.

Education is one way to examine long-term welfare gains. Improving educational outcomes is seen as an effective long-term anti-poverty effort (Luccisano, 2004), and financial investments in education are associated with breaking the intergenerational cycle of poverty (Barham *et al.*, 1995). Even though improving children's education affects long-term welfare, only three papers have explicitly investigated Rural Dibao's effects on rural children's education, and these papers have mixed results. Han *et al.* (2016) and Wang *et al.* (2019a, b) both find that Rural Dibao has no significant impact on education expenditure. Zhao *et al.* (2017), however, found that household participation in Rural Dibao increases household expenditure on education by 19%. Although these studies offer a valuable contribution to the literature, unfortunately, like other studies that examine Rural Dibao, they fail to address identification in their analyses. Finally, these studies all focus exclusively on education expenditure, which, although important, does not describe actual changes in student achievement. Therefore, by focusing exclusively on education expenditure, these papers also fail to show whether Rural Dibao participation leads to increased academic achievement (or real increases in learning).

This paper aims to examine the effect of Rural Dibao on rural children's education. To accomplish this goal, we have four specific objectives. First, we describe the distribution of Rural Dibao participants and show the existence of targeting error within our data. Second, we reveal the causal relationships between Rural Dibao participation and children's learning outcomes. Third, we investigate the potential mechanisms that connect Rural Dibao to children's learning results. Fourth, we discuss the program's impact on different groups of children.

To meet these objectives, we used data from the 2010 and 2014 China Family Panel Studies (CFPS). The CFPS is a biennial survey that includes approximately 14,000 Chinese households per survey wave in 25 Chinese mainland provinces (including municipalities and autonomous regions). This nationally representative survey gathers information about the Chinese population's well-being and economic activities. Relevant to our study, the CFPS specifically collects data on Rural Dibao participation and children's education outcomes (expenditure and learning results), as well as other data used to analyze potential mechanisms and controls.

We first describe our sample with descriptive statistics to show the existence of targeting problems within the program. We then use fixed effects model as well as propensity score weighting method to reveal causal relationships between program participation and standardized test scores. We also investigate the mechanisms between Rural Dibao participation and individual learning results. Finally, we divide the children into different groups according to their family per capita income, province, left behind status, age and gender to determine how the program affects these different subgroups.

We find that participation in Rural Dibao leads to better learning outcomes for rural children. We first show that the problem of targeting exists in the program but ultimately find that targeting error does not fully undermine the program's effect. We then use fixed effects model and propensity score weighting method as our identification strategy and find that Rural Dibao participation raises Chinese-language test scores by about 0.3 standard deviations and math test scores by about 0.2 standard deviations. In examining potential mechanisms, we show that Rural Dibao participation leads to higher education expenditure, which leads to better test scores. Finally, from our heterogeneous effects analysis, we find that the program has a significant impact only on poorer, non-eastern, younger, male or not left behind children.

Our study contributes to the broader literature in three ways. First, this is the first paper to elucidate a causal relation between Rural Dibao and rural children's learning, which indicates the long-term impact of the Rural Dibao program. Second, by investigating the mechanisms that connect Rural Dibao to learning outcomes, we further deepen our understanding of Rural Dibao's effect on education. Third, by exploring the program's heterogeneous effect on different groups, we not only clarify the effect of Rural Dibao but also can make suggestions on how best to target the program.

Our paper is organized as follows. First, we present our data and our identification strategy. In addition to providing descriptive statistics, we also show the existence of targeting error in our data and resolve the issues related to it. Second, we present the results of our empirical analysis, showing not only Rural Dibao's effect on learning but also the potential mechanisms that connect Rural Dibao participation and education outcomes. Third, we show the heterogeneous effects of the program on different groups of children. We conclude by discussing the implications of our study and providing policy recommendations.

2. Policy background

Rural Dibao has been implemented nationwide since 2007. Rural households can apply for the program if family per capita income is lower than the local Dibao threshold. If approved by the local government, the family gets monetary transfers from both the central and local governments to lift their family per capita income to the level of the policy-set threshold (The State Council, 2014). The threshold is locally determined according to basic living needs as well as fiscal constraints (Golan *et al.*, 2017).

Rural Dibao has grown rapidly. While the national average threshold was only 840 RMB/year/person (approximately US$120) in 2007, the amount increased to 4,388 RMB/year/person (approximately US$630) in 2018. The number of beneficiaries increased from 35 million in 2007 to 53 million in 2013, but gradually fell back to 35 million until 2018 due to changes in the way the policy was implemented. The total money transferred increased from 10 billion RMB (over US$1.4 billion) in 2007 to over 100 billion RMB (over US$14 billion) in 2018 (Ministry of Civil Affairs, 2008, 2014, 2019).

Compared to international anti-poverty policies, Rural Dibao is unique in many ways. Although Rural Dibao is a type of unconditional cash transfer program, it also takes the form of a guaranteed income program. Guaranteed income programs are often seen in developed countries, while developing countries prefer social assistance programs like public works, conditional cash transfers or distribution of in-kind goods (Golan *et al.*, 2017). On the other hand, unconditional cash transfer programs are part of a class of programs that transfer a regular and specific amount of money to the beneficiary (Handa *et al.*, 2018). At least in theory, Rural Dibao determines its transfers according to the gap between the locally-set threshold and the per capita income of each rural household.

So does Rural Dibao help reduce poverty? In the introduction, the paper summarized how previous research has shown that the program increases the income of rural households.

However, a closer look at the literature finds that there are mixed results for the specific welfare gains of households as well as other outcomes, such as the educational outcomes of children in poor areas.

Although Rural Dibao is not specifically designed for helping rural children, the human capital of children has been shown to be an important way to reduce the long-term negative effects of poverty. It is well known, for example, if poverty of the family is not addressed, it will be likely to be harmful for human capital (Ceroni, 2001). Indeed, the literature has demonstrated that poverty is one of the major determinants of why rural students drop out of school in rural China (Liu and Rozelle, 2020). Internationally, cash transfer programs directed at children often have been shown to have positive effects (Bastagli *et al.*, 2019). Therefore, a salient question is: Can an anti-poverty program aimed at households also help improve the schooling outcomes of children?

In fact, income increases from such programs do possess the potential to enhance the human capital of children. For example, Dahl and Lochner (2012) show that the US Earned Income Tax Credit program enhanced the academic achievements of children by increasing family income. An additional US$1,000 given to households improved reading and math test scores by 6%. Research by Duncan *et al.* (2011) combined different US and Canadian anti-poverty programs and showed similar results – an additional US$1,000 led to an approximately 5% increase in the academic achievement of children. Therefore, it is reasonable to assume that Rural Dibao also might have positive effects on children learning even though, as noted in the introduction, academic achievements have not been studied yet.

3. Data and methodology

3.1 Data

3.1.1 Data source. We use data from the 2010 and 2014 CFPS, which is a nationwide longitudinal survey that has been conducted biennially by the Institute of Social Science Survey of Peking University since 2010. The CFPS focuses on gathering information about the Chinese population's well-being and economic activities, such as education outcomes, spending patterns, Rural Dibao participation, family dynamics, and so on. It collects these data on three levels: individual, family or household, and community. We exclude the 2012 data because the 2012 data does not have the learning outcomes the same as 2010 and 2014.

The CFPS covers 25 out of 31 Chinese mainland provinces (including municipalities and autonomous regions, but excluding Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan). The provinces that are part of the sample contain approximately 95% of the Chinese population. To create a nationally and provincially representative data set, the CFPS uses a multistage, implicit stratification and probability proportional to size sampling approach to collect individual-, family-, and community-level data (Xie and Hu, 2014). All CFPS samples are randomly acquired through three stages. First, county-level units (rural counties or urban districts) are randomly selected from the 25 sampled provinces. Second, from these county-level samples, village-level samples (rural villages or urban communities) are randomly selected. Finally, from these village-level samples, individual households are selected. All family members present during the household survey were interviewed. Around 14,000 Chinese households, including over 30,000 adults and 8,000 children, were surveyed in each wave.

3.1.2 Sample of children. To build a panel data set that we will use, in part, to identify the causal impacts of Rural Dibao on education outcomes, we combine 2010 and 2014 CFPS data to generate one panel data set that spans two waves. We take three steps to arrive at this final dataset. First, we match each child with his or her parents and family characteristics. Second, we drop children with urban *hukou* to generate panel data for children with rural *hukou*. Third, we trim education outcome data by excluding children who go to college or have dropped out of school in 2014. The CFPS children survey, the CFPS section that collects children's data including educational outcomes, targets children younger than 15 years old. Some children were under 15 in 2010 but became too old to participate in the CFPS children survey in later waves. Despite their ages, they still completed the CFPS learning tests. To track long-term changes in educational outcomes, we keep their data only if they are still at school and have not gone to college yet. After doing this, we created a panel data set with a total of 3,228 rural children followed across both waves. Of this overall sample, 786 of the individuals are students over 10 years old and completed Chinese-language and math tests in both 2010 and 2014.

We further divide these children into subgroups to analyze the heterogeneous impact of Rural Dibao on education. We first divide the children into different groups, according to their family per capita income or their home geographic districts. In both ways, the children are divided by using indicator variables to split the sample into two subgroups. Family per capita income subgroups are determined when a family's income is below or above the average Rural Dibao threshold. District subgroups indicate whether a respondent lives in China's wealthier, more developed Eastern provinces. We group China's provinces into two geographical districts: Eastern and non-Eastern China. Eastern China includes the following provinces: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong and Guangdong. Non-eastern China includes all other surveyed provinces. We also divide the sample according to children's gender, age and status of left-behind (whether at least one parent is migrant worker).

3.1.3 Key variables. There are four key variables in the CFPS that are particularly relevant to our study. First, the CFPS contains information about Rural Dibao participation in the two survey years: 2010 and 2014. CFPS enumerators asked each respondent whether the surveyed family participated in Rural Dibao that year. If the answer was yes, the survey labeled all of the members of the family as participants.

Second, the CFPS contains children's learning results, as measured by two CFPS-administered scales. Specifically, the CFPS contains a section that asks children 10 years or older to complete both a Chinese-language test and a math test in 2010 and 2014. The Chinese-language test asks respondents to identify and pronounce (aloud) one Chinese character for each question. The math test is a paper examination that asks respondents to answer increasingly difficult math questions. Both tests are scaled appropriately to the respondent's grade. In each test, the test score is the question number of the most difficult question that the respondent can answer correctly. Each test stops when the respondent incorrectly answers three consecutive questions. We standardize the scores for each wave to capture a student's relative score change compared to others. We use these standardized test scores to indicate childhood learning results. The CFPS switches between two versions of tests biennially, meaning that only the 2010 and 2014 test questions are exactly the same. And the 2012 tests are memory test and reasoning test, but not math test and Chinese-language test. Therefore, to effectively compare test results over time, we do not use 2012 data in this study.

The third variable that we use to measure the impact of Rural Dibao on education investment is the amount of annual education expenditure on each individual in the family. The CFPS items ask about children's education expenditures in detail, including annual spending on tuition, books, school room and board, transportation, and so on. The CFPS also asks for total education expenditure for each individual. In this paper, we use the total sum of annual expenditure in our analyses. Unlike test scores, education expenditure does not measure learning directly. Nevertheless, the variable does tell us how much the families invest in their children's education, which may be connected to learning results (we test this assumption later in our analysis). In this paper, we examine whether increased education expenditure could be the mechanism that connects Rural Dibao participation to increased learning.

The final key variable that we extract from the CFPS data is one that measures food expenditure. Previous studies suggest that nutrition, which may be associated with higher food expenditure, can affect an individual's rate of learning (Li *et al.*, 2018). For example, poor nutrition may lead to anemia, which may limit a child's academic performance. Food expenditure is, therefore, an alternative mechanism whereby Rural Dibao participation can affect a child's level of learning. The CFPS items ask about food expenditure for an entire household. We divide family food expenditure by family size to get annual family per capita food expenditure.

3.1.4 Additional control variables. The CFPS data also has rich information about family and individual demographics which may influence children's academic achievements. In terms of family information, the survey items ask about family annual income, family size, ethnicity and province of residence, allowing us to control for all of these. We divide family annual income by family size to obtain family annual per capita income. We exclude transfers here to represent income before program participation. For ethnicity, we divide our sample based on whether each respondent is ethnically Han.

There are also several additional variables that measure individual characteristics. Specifically, the survey items ask each family member his or her age and the gender of each child is enumerated. The survey asks whether the child is studying in a key school and whether the child is boarding at school. We use the key school information to measure the teaching quality in school, which is highly correlated with children's learning outcomes. And boarding students dieting at school may not be influenced by family food expenditure, so we will control for the boarding information when we analyze food expenditure. The CFPS items also ask about parental education in terms of the highest level of education achieved by a child's mother and father. We use such information to control for parental education by separating parents based on their completion of junior high school.

In addition to above variables closely correlated with children's learning outcomes, there are also numerous household's and household head's characteristics which may influence a family's participation in Rural Dibao. For household's situation, we include information about number of children, number of elderlies, number of members with chronical diseases and number of employed members. For household head's situation, we include information about household head's age, gender, employment status and political status (if a member of the Communist Party of China). Table 1 contains the definitions of all the variables used in our analysis.

3.2 Theoretical analysis

In this paper our theoretical approach to understanding how cash transfers towards the poor may influence family investment in their children's schooling is analyzed based on the theoretical frameworks of Becker and Tomes (1986) and Acemoglu and Pischke (2001). Using their framework, we assume that there are only two periods of the economy. In the first period, the parent has income y and saving s and decides whether to invest in the schooling of their child. The parent dies at the end of this period and s becomes a bequest to the child, who lives for both periods. The parent's utility is based on the parent's consumption and the child's future consumption:

$$U = u_1(C) + \delta u_2(C') \quad (1)$$

where C is the consumption of the parent and C' is the consumption of child. The two quantities of consumption do not include education investment. In the model δ reflects how the parent values the child's future consumption. For simplicity, we assume no discounting

Variable	Definition
Year	CFPS surveyed year (2010 or 2014)
Participation (dummy)	1 = family participated that year; 0 = family did not participate that year
Family per capita income	Family annual income per capita for previous year (pre-transferred; adjusted for inflation using CPI)
Standardized Chinese-language score	Standardized score for CFPS Chinese-language test
Standardized math score	Standardized score for CFPS math test
Individual education expenditure	The individual child's total annual education expenditure for last year (adjusted for inflation using CPI)
Family per capita food expenditure	The child's family per capita food expenditure for last year (adjusted for inflation using CPI)
Ethnicity (dummy)	1 = Han; 0 = other
Father's education (dummy)	1 = completed junior high; 0 = education less than completion of junior high
Mather's education (dummy)	1 = completed junior high; 0 = education less than completion of junior high
Gender (dummy)	Individual child's gender (1 = male; 0 = female)
Age	Individual child's age in years
Eastern China (dummy)	1 = Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, or Guangdong; 0 = all other surveyed Chinese provinces
Key school (dummy)	1 = the child learns in a key school; 0 = other
School boarding	1 = the child boards at school; 0 = other
Age of household head	Household head's age in years
Gender of household head	Household head's gender (1 = male; 0 = female)
Employment status of household head	1 = employed; 0 = unemployed
Political status of household head	1 = member of Communist Party of China; 0 = other
Number of children	Number of children in the household
Number of elderlies	Number of elderlies in the household
Number of members with chronical diseases	Number of family members with chronical diseases
Number of employed members	Number of family members employed

Table 1.
Definition of variables

and $u(C) = \ln(C)$. Under this assumption,

$$U = \ln(C) + \ln(C') \tag{2}$$

Based on these theoretical assumptions, we then suppose a well-educated worker earns a wage w_e and a less educated worker receives a wage w_l. Let E denotes the ability acquired from education and $\exp(E)$ denotes the value of the investment into the child's education. When trying to understand overall educational investment, we can show that the parent will invest in the child's education if utility gains from the child's ability to earn a higher wage surpasses the utility loss from the education investment:

$$\ln(w_e - w_l) \geq E \tag{3}$$

If we let $e = 1$ denotes that the parent decides to invest in a high level of schooling for the child and if $e = 0$ means there is less investment into quality education, the problem of the parent can be shown to maximize (2) subject to:

$$C + \exp(E)e + s = y \tag{4}$$

$$C' = w_l + (w_e - w_l)e + s$$

$$s \geq 0$$

Importantly, if a household is wealthy enough, s is always positive. If s is positive, then the parent will always invest in the child's education and this suggests $e = 1$ no matter how large $\exp(E)$ is.

In contrast, poor families have another outcome. In the case of poor families, the problem is more complicated. For the case of poor families, we suppose that $s = 0$ and e varies between zero and one. If the parent decides not to let the child become well-educated, the utility becomes $U(e = 0) = \ln y + \ln w_l$, while the utility to let the child become well-educated is $U(e = 1) = \ln(y - \exp(E)) + \ln w_e$. Let $U(e = 0) = U(e = 1)$. We will get the equilibrium for E:

$$E^* = \ln\left[\frac{y(w_e - w_l)}{w_e}\right] \tag{5}$$

From this analysis, then, poor families will only consider investing in their children's education when $\exp(E) \leq \exp(E^*)$. Furthermore, for poor families, the equilibrium amount of investment in their children's education is $\exp(E^*) = \frac{y(w_e - w_l)}{w_e}$, which is increasing in the family's income. Therefore, to the extent that this theoretical framework is accurate, an anti-poverty program, like Rural Dibao, that focuses on increasing income for poverty stricken families, has the potential to enhance the investment into education of the children of poor families, which in turn will, on average, result in higher learning outcomes.

3.3 Empirical strategy

We first use a basic ordinary least squares (OLS) model to explore the correlation between Rural Dibao and childhood learning:

$$\text{Learning}_{it} = \beta_0 + \beta_1' \text{Dibao}_{it} + \gamma' X_{it} + \varepsilon_{it} \tag{6}$$

Here, Learning_{it} is child i's education outcome in year t. We use standardized test scores (both as Chinese-language test scores or math test scores) to represent learning results. Dibao_{it}, our main independent variable of interest, is a dummy variable that indicates whether child i's family participated in Rural Dibao in year t. X_{it} contains control variables closely related with children's learning outcomes, including family per capita income, ethnicity, father's education, mother's education, gender, age, school (learning in a key school or not) and district (Eastern China or not). ε_{it} is our error term.

Although the results from Eqn (6) are of interest, this basic model does not address endogeneity from unobserved characteristics that are correlated with both the independent variable of interest and the dependent variable. A fixed effects model can address part of this endogeneity problem. By controlling for individual fixed effects, we are able to eliminate differences that stem from individual, unobserved, non-time varying characteristics. The fixed effects model that we use for the rest of our analyses can be written as follows:

$$\text{Learning}_{it} = \beta_0 + \beta_1' \text{Dibao}_{it} + \beta_2' \text{Income}_{it} + \beta_3' \text{School}_{it} + \mu_i + \varepsilon_{it} \tag{7}$$

The variable Learning_{it} and Dibao_{it} are the same in Model (7) as in Model (6). Income_{it} denotes child i's family per capita income in year t, School_{it} denotes if child i learns in a key school in year t, and μ_i captures child i's individual fixed effects. All observed and unobserved non-time varying individual and family characteristics are controlled for by μ_i. Except for income and school information (which vary over time), other control variables in X_{it} (which are all non-time varying) from Model (6) are controlled for by μ_i in Model (7).

To further control for endogeneity stemming from targeting problems, we use a propensity score weighting method based on Model (7) to estimate the following model:

$$\text{Learning}_{it} = \beta_0 + \beta_1^{'}\,\text{Dibao}_{it} + \beta_2^{'}\,\text{School}_{it} + \mu_i + \varepsilon_{it} \tag{8}$$

Income_{it} is not here because it will be used to calculate propensity score.

To implement this model, we first use a Logit model to estimate the probability of joining the program: $P(Z_{it}) = \Pr(\text{Dibao}_{it} = 1|Z_{it})$. Here, Z_{it} contains variables we use to calculate the propensity score. We include most of the variables that are in X_{it} of Model (6) in Z_{it}, only excluding children's gender, age and school information, which are not closely correlated with a household's participation in the Rural Dibao program. We also include more household characteristics, as well as characteristics of the household head, which are shown in the literature to be closely related to program participation (Gao *et al.*, 2015; Han *et al.*, 2016; Wang *et al.*, 2019a, b). The additional household characteristics include the number of children, the number of elderlies, the number of household members with chronic diseases and the number of employed household members. The household head's characteristics that are added, include age, gender, employment status and political status (if the household head is a party member). The added variables allow us to more precisely estimate the process of participating in Rural Dibao, reducing concerns from targeting.

Second, we use the calculated propensity scores to estimate weighted regression of Model (8). The propensity score weighting method has the benefit to balance the characteristics of treatment and control groups without sacrificing observations. If the predicted probability of joining Rural Dibao is e, the efficient estimator can be attained through a weighted regression with a weight of 1 for participants and a weight of $e/(1-e)$ for non-participants (Hirano *et al.*, 2003; Chen *et al.*, 2009; DuGoff *et al.*, 2014; Kvande *et al.*, 2019). The results of weighting also can help verify the robustness of the fixed effects model in Model (7). Moreover, according to the literature, control variables used to calculate propensity scores will not be used again in Model (8) since the weights already contain the information. We also tried to add control variables again in regressions related to Model (8), but found the results were similar with the same significance and a small change in magnitude (within 0.05). Therefore, in the results section below, we follow the literature and exclude the controls in the weighted regressions.

4. Results

In this section, we present the results of our empirical analyses. First, we demonstrate targeting problems with Rural Dibao and provide the summary statistics of our sample. Second, we present our main regression results and then investigate possible mechanism between participation and learning results. Finally, we investigate the program's heterogeneous effect on different groups of children.

4.1 Targeting error and descriptive statistics

Our data suggest that two types of targeting error exist in the Rural Dibao program. On the one hand, there are wealthy families who should not qualify but are participating. On the other hand, there are poor families who should be qualified but do not participate. Despite these errors, our results suggest that the overall targeting of the program is still relatively good, as the program generally targets those who are poor, have fallen upon hard times, or have fairly poor educational outcomes.

The existence of targeting error in the Rural Dibao program is shown in Table 2, which shows children's participation across five different family per capita income quantiles. As it is a poverty-relief program, Rural Dibao should exclusively assist poor families. According to the Ministry of Civil Affairs (2011, 2015), the average annual Rural Dibao threshold was 1,404

Year	Family per capita income quantile	Family per capita income range (RMB)	Respondents in each quantile	Rural Dibao children in each quantile (*n*)	Rural Dibao children in each quantile (%)
2010	Poorest	Lower than 1,737	646	171	26
	Poor	1,737–3,000	648	53	8
	Middle	3,001–4,427	643	33	5
	Wealthy	4,428–6,990	646	30	5
	Wealthiest	Higher than 6,990	645	18	3
2014	Poorest	Lower than 2,111	646	224	35
	Poor	2,111–5,000	647	78	12
	Middle	5,001–7,840	645	60	9
	Wealthy	7,841–12,016	645	57	9
	Wealthiest	Higher than 12,016	645	20	3

Table 2.
Participation across five income quantiles

RMB in 2010 and 2,777 RMB in 2014. These amounts are within the first two quantiles in each wave. Ideally, we would expect Rural Dibao participants to be almost exclusively in the first two income quantiles. However, as seen in Table 2, this is not the case. The table shows the existence of two kinds of targeting errors in the implementation process of the program. The first error is that many poor are not in the program. For example, in 2010, only 26% of the poorest quantile are part of the program. The second error is that some wealthy families who should not qualify are in the program. In each year, children from every quantile, including those above Dibao thresholds, participate. In 2014, 3% of the wealthiest income quantile participated in Rural Dibao. In addition, these trends change slowly over time. Wealthier families continue to participate in each year. Participation rates for those in the lower income quantiles also remain consistently low. In each year, only around 30% of the poorest quantile join the program, meaning that around 70% of the poorest quantile, those who may benefit the most from joining Rural Dibao, continually do not join the program.

Although the targeting error suggests that program leakages exist, our data also demonstrate that such leakages do not completely undermine the Rural Dibao program, as Rural Dibao transfers, on average, still go to families in need. Table 3 shows the summary statistics of our sample, including income levels, levels of academic achievement and expenditures, as well as other controls. Column 1 presents the results for children who were over 10 years old in 2010 and who did the same math and Chinese-language tests in 2010 and 2014, with 786 total observations. Column 2, a subgroup of Column 1, contains the results for children who participated in Rural Dibao for each wave and who completed math and Chinese tests in 2010 and 2014, with only 43 observations.

The results presented in Table 3 show that these Rural Dibao children (Column 2) are still worse off in terms of income and food expenditure than are other children (Column 1). For example, in 2010, the average annual family per capita income of these Rural Dibao children was 1,678 RMB (approximately US$240), compared to an average income of 4,968 RMB (approximately US$715) among all of the children 10 years or older. As noted, this suggests that, although targeting error exists, Rural Dibao transfers still go to those in need.

It is also worth noting that Rural Dibao tends to go to families with lower levels of human capital. Table 3 shows that Rural Dibao children have lower test scores and education expenditure. For example, in 2010, the average standardized Chinese-language test score for Rural Dibao children was −0.154 standard deviations, compared to an average of −0.025

Table 3.
Summary statistics

Variable	Year	(1) Children over 10 years old in 2010 Mean (SD)	(2) Children over 10 years old in 2010 (always participated in Dibao) Mean (SD)
Family per capita income	2010	4,968 (211.1)	1,678 (497.8)
(RMB)	2014	7,771 (281.1)	3,129 (907.6)
Standardized Chinese-	2010	−0.025 (0.035)	−0.154 (0.169)
language score	2014	0.550 (0.029)	0.463 (0.118)
Standardized math score	2010	−0.102 (0.034)	−0.408 (0.135)
	2014	0.506 (0.036)	0.433 (0.117)
Individual education	2010	780.6 (45.10)	371.9 (79.00)
expenditure (RMB)	2014	4,679 (161.7)	2,798 (389.4)
Family per capita food	2010	1,248 (61.20)	633.5 (88.30)
expenditure (RMB)	2014	2,487 (121.1)	1,546 (265.3)
Ethnicity (1 = Han)		0.906 (0.010)	0.837 (0.033)
Gender (1 = male)		0.477 (0.018)	0.457 (0.044)
Age (in 2010)		11.971 (0.058)	11.651 (0.264)
Father's education (1 = completed junior high)		0.536 (0.019)	0.355 (0.046)
Mother's education (1 = completed junior high)		0.328 (0.018)	0.139 (0.035)
Number of observations		786	43

standard deviations for all of the children 10 years or older, a difference of over 0.1 SDs. In addition, Table 3 shows that the human capital of Rural Dibao parents is low. Only 35.5% of Rural Dibao fathers whose children are at least 10 years old completed junior high school, compared to 53.6% of all fathers whose children are at least 10 years in the sample. The situation for Rural Dibao mothers is even worse. Only 13.9% of Rural Dibao mothers whose children are at least 10 years old completed junior high school, which is less than half the average rate of all mothers whose children are at least 10 years in the sample (32.8%). Thus, although the program has targeting errors, Rural Dibao participants are generally worse off than are their non-Dibao counterparts.

It is clear that targeting errors exist in Rural Dibao program implementation. It is important to note, however, that our data show that this targeting error does not completely undermine the program. The program, at least in general, appears to be targeting families with lower income and human capital. However, the targeting problem still needs to be dealt with in the regressions to get causal relations. In the next section, we address the second objective of the paper and present the results of the analysis of the impact of the program on educational outcomes.

4.2 Children's learning outcomes

Table 4 shows the results of Model (6), our basic OLS regression, that help us to analyze the effect of Rural Dibao program participation on children's learning results. Each column represents one dependent variable (standardized Chinese-language test scores or standardized math test scores). Columns 1 and 2 show the OLS results with family per capita income as our only control variable. Columns 3 and 4 contain other control variables, including location, age, gender, ethnicity, school information and parental education.

The results of our OLS model show no statistically significant relationships between Rural Dibao participation and children's standardized test scores, while the directions are all negative. This is true regardless of whether the analysis uses control variables. According to these simple OLS regressions, the program appears to be failing to raise the learning

Table 4. OLS correlations between participation and children's learning outcomes

Variable	(1) Standardized Chinese-language score	(2) Standardized math score	(3) Standardized Chinese-language score	(4) Standardized math score
Participation (1 = participated)	−0.0144 (0.0715)	−0.0272 (0.0778)	−0.0567 (0.0622)	−0.0993 (0.0630)
Family per capita income (1,000 RMB)	0.0209*** (0.00337)	0.0175*** (0.00367)	0.0117*** (0.00299)	0.00688** (0.00303)
Ethnicity (1 = Han)	–	–	0.397*** (0.0696)	0.249*** (0.0705)
Father's education (1 = completed junior high)	–	–	0.0320 (0.0428)	0.0547 (0.0433)
Mother's education (1 = completed junior high)	–	–	0.114** (0.0455)	0.134*** (0.0461)
Gender (1 = male)	–	–	−0.180*** (0.0404)	−0.00812 (0.0409)
Eastern China (1 = coming from eastern provinces)	–	–	0.0669 (0.0484)	0.0530 (0.0490)
Age	–	–	0.221*** (0.0125)	0.322*** (0.0127)
Key school (1 = learning in key school)			0.123** (0.0589)	0.169*** (0.0597)
Year	–	–	−0.0983*** (0.0164)	−0.191*** (0.0166)
Constant	0.131*** (0.0342)	0.0940** (0.0372)	194.6*** (32.84)	380.3*** (33.25)
Observations	1,572	1,572	1,572	1,572
R^2	0.025	0.015	0.296	0.385

Note(s): Standard errors in parentheses
$*p < 0.10$, $**p < 0.05$, $***p < 0.01$

outcomes of children whose families receive Rural Dibao. This model, however, cannot express a causal relationship. Because the program is giving money to the households, it is not reasonable to believe Rural Dibao leads to lower score. As noted in the summary statistics, the Rural Dibao children are in generally worse-off situation. It may be that situation which leads to a worse environment for the scores to increase, but not participation itself.

To better address this endogeneity, we use a fixed effects model. Table 5 shows results of the fixed effects regression analysis of the program's effect on learning results, as stated by Model (7). We see that, once we control for individual fixed effects, the relationship between Rural Dibao participation and learning outcomes becomes positive and statistically significant, indicating that participation in Rural Dibao benefits children's learning. Specifically, we see in Column 1 that a child's Chinese-language test score will rise, on average, by 0.286 ($p < 0.01$) standard deviations if the child's family participates in Rural Dibao. Column 2 shows that a child's math test score will increase, on average, by 0.205 ($p < 0.10$) standard deviations if the child's family joins Rural Dibao. Thus, program participation is shown to causally benefit a child's learning. The changes of the coefficients

Table 5. Impact of participation on Children's learning outcomes from fixed effects model

Variable	(1) Standardized Chinese-language score	(2) Standardized math score
Participation (1 = participated)	0.286*** (0.108)	0.205* (0.112)
Family per capita income (1,000 RMB)	0.0271*** (0.00506)	0.0259*** (0.00527)
Key school (1 = learning in key school)	0.366*** (0.0717)	0.380*** (0.0746)
Constant	−0.00646 (0.0407)	−0.0510 (0.0424)
Observations	1,572	1,572
R^2	0.086	0.076

Note(s): Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 6. Logit regression of household participation in rural Dibao

Variable	Participation
Family per capita income (1,000 RMB)	−0.0759*** (0.0191)
Ethnicity (1 = Han)	−0.677*** (0.224)
Father's education (1 = completed junior high)	−0.109 (0.177)
Mother's education (1 = completed junior high)	−0.0533 (0.188)
Eastern China (1 = coming from eastern provinces)	−0.932*** (0.248)
Year	0.0674 (0.0695)
Age of household head	−0.00009 (0.00918)
Gender of household head (1 = male)	−0.0228 (0.209)
Employment status of household head (1 = employed)	−0.554** (0.236)
Political status of household head (1 = CCP member)	0.433 (0.305)
Number of children	0.0986 (0.0833)
Number of elderlies	0.173 (0.110)
Number of members with chronical diseases	0.0910 (0.122)
Number of employed members	−0.0934 (0.0809)
Constant	−136.3 (139.7)
Observations	1,572
Pseudo R^2	0.091

Note(s): Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

between OLS and fixed effects model reflect that the endogeneity problem is better relieved now.

In this section of the results, we now turn to propensity score weighting to further control for targeting problems. Table 6 shows the result of the Logit regression for program participation. From the significant coefficients, we see that the Rural Dibao participants tend to have lower family per capita income, come from minority areas and poorer districts, and have unemployed household heads. From the less significant coefficients, we can further infer that the family members of the participating households tend to have lower education levels as adults, are more vulnerable (that is, they have more children to raise and more elderly family members to take care of and more family members with chronical diseases to care for), and have lower employment rates. These statistics also suggest that the program is primarily targeting households that are indeed poor, which is consistent with the program's anti-poverty goals. We test the balance of covariates between participants and non-participants in the Appendix, and the analysis shows no significant difference between the covariates of the two groups after weighting.

Table 7 shows the result of the weighted regression as estimated by Model (8). According to the findings, program participation enhances children's standardized Chinese-language scores by 0.316 ($p < 0.01$) standard deviations and standardized math scores by 0.167 ($p < 0.1$) standard deviations. Interestingly, since it shows the robustness of the findings, the coefficients of participation on the two standardized scores are similar to the results of the fixed effects in Model (7). The two model have similar levels of significance and there is little change (below 0.05) in magnitude. Again, this suggests that our findings in the analysis are relatively robust.

Another interesting point in the results of this table is that the magnitude of and significance for the regression looking at impacts on language are both greater than when compared to those for math. Parents that are more well-off spend more time reading with their children (Child Trends and Center for Child Health Research, 2004). In addition, academic achievement of reading is more likely to be affected by parenting in family with lower income (Hill, 2001). Therefore, supplementing the income for poor households through a program such as Rural Dibao can lead to rises in the Chinese-language test performance of children from those households.

4.3 Mechanism for the relationship between participation and test scores

In this part of the analysis that we are looking for the mechanisms that are connecting Rural Dibao to the educational outcomes of children, we assume that both education and food expenditures play intermediate roles in connecting Rural Dibao to learning results. Education expenditure has a direct impact on academic achievements, as higher expenditure implies that more resources are invested into a child's learning process, facilitating greater academic

Variable	(1) Standardized Chinese-language score	(2) Standardized math score
Participation (1 = participated)	0.316*** (0.0930)	0.167* (0.0925)
Key school (1 = learning in key school)	0.444*** (0.0763)	0.479*** (0.0759)
Constant	−0.212 (2.176)	0.745 (2.166)
Observations	1,572	1,572
R^2	0.432	0.489

Note(s): Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table 7. Impact of participation on Children's learning outcomes using propensity score weighting

achievement. Similarly, more food expenditure may lead to improved nutrition, which may then improve learning results. Therefore, we hypothesize that Rural Dibao's participation boosts education and food expenditures, which results in higher test scores.

To examine the mediating effect, we use the traditional three-step procedure proposed by Baron and Kenny (1986). First, we check if participation has a significant effect on the two types of expenditures as well as on standardized scores. As the results for scores are already present in Tables 5 and 7, we do not present the results again. Second, we check if the expenditures have significant effects on the standardized scores. To examine this question we also use both the fixed effects approach from Model (7) and the propensity score weighting approach from Model (8) with only a minor change. In the first step, the expenditures are dependent variables and participation is the key independent variable. In the second step, the expenditures are key independent variables and the standardized scores are the dependent variables. Participation is not included in the second step. Considering that a child will not be influenced by family food expenditure if in boarding school, we add boarding information as a new control in the regressions about food expenditure. Finally, we turn back to Models (7) and (8) and include the expenditure, which is significant in both of the former steps, as a new control. If one of the expenditures is positively significant in the first and second steps, and the coefficient of participation becomes lower or even insignificant in the third step than the coefficients in Tables 5 and 7, this expenditure can be seen as a mechanism.

There is one potential problem with the above analysis. It may be that since we have included both income and expenditure in the same regression, we may have multicollinearity that makes it appear that the results are insignificant when they really are. To assess this, we calculated variance inflation factors (VIF) for regressions that included both income and expenditure variables. As it turns out, the VIFs are all under 2. Since VIF coefficients below 10 are commonly thought to be a sign that multicollinearity is not severe, our analysis can proceed without the concern for multicollinearity.

Table 8 shows results of all the three steps of the modeling. Only education expenditure is significant in both the first and the second steps, so we only include education expenditure in the third step. According to the first and second step findings, participation leads to an increase of around 600–800 RMB (around US$100) in the educational expenditures on the family's children. A thousand RMB increase (approximately US$145) in educational expenditures leads to an increase of around 0.03–0.06 standard deviations in standardized Chinese-language scores and an increase of around 0.05–0.07 standard deviations in standardized math scores.

In the third step, the coefficients of participation from the fixed effects model, as well as from the propensity score weighting models, although still significant, are both smaller compared to those that are reported in Tables 5 and 7. The results allow us to conclude that Rural Dibao's participation enhances children's education expenditure, which leads to better learning results.

As shown above, the results demonstrate that the effects of participation are significant in the third step and the size of the coefficients are relatively small. These findings also suggest that there may be other mechanisms connecting Rural Dibao with learning outcomes. Ma *et al.* (2014) show that test scores can be boosted by 0.11 standard deviations after they provide eyeglasses to children with myopia in rural China. Therefore, Rural Dibao transfers could be used flexibly to address specific challenges which may not belong to a typical expense category that either the family or child faces, such as allowing parents to buy glasses for their children as another way to improve learning results. Because the CFPS dataset does not include information about many other large expense categories, we are not able to investigate all spending possibilities or possible mechanisms. Future research may want to address these other channels.

Table 8. The mediation effect of food and education expenditures using fixed effects model and propensity score weighting (n = 1,572)

Variable	Step 1		Step 2		Step 3	
	Family per capita food expenditure (RMB)	Individual education expenditure (RMB)	Standardized Chinese-language score	Standardized math score	Standardized Chinese-language score	Standardized math score
Fixed effects estimates						
Participation (1 = participated)	199.11 (355.69)	799.50* (436.63)	–	–	0.219** (0.105)	0.182* (0.109)
Individual education expenditure (1,000 RMB)	–	–	0.0305*** (0.00735)	0.05*** (0.00750)	0.0146* (0.00780)	0.0496*** (0.00439)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Propensity score weighting estimates						
Participation (1 = participated)	116.02 (253.01)	634.63* (389.64)	–	–	0.289*** (0.105)	0.164* (0.0891)
Individual education expenditure (1,000 RMB)	–	–	0.0577*** (0.00933)	0.0719*** (0.00911)	0.0312*** (0.0101)	0.0719*** (0.00909)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Note(s): Standard errors in parentheses
*p < 0.10, **p < 0.05, ***p < 0.01

4.4 Heterogeneity analysis

In this section, we present the heterogeneous effects for children with different circumstances such as their family per capita income, location of the families in different geographical areas of China, parental presence, age and gender. As a poverty alleviation program, we expect Rural Dibao to focus on helping people with lower income or from poorer districts. To do so, we first look at children with different family per capita income levels. As noted in relation to Table 2, the average national Rural Dibao thresholds are within the first two income quantiles in each wave. We use this information to divide the children into two groups. Group one's children are from the first two family per capita income quantiles for each wave; they represent children from families with per capita income below Rural Dibao thresholds. Group two's children are from those families that are relatively well-off who also received Rural Dibao (likely due to targeting errors) and are from the other three quantiles.

Beyond household wealth, we also investigate other heterogeneous effects. The analysis also examines the effects of location. Eastern provinces in China tend to be wealthier than other provinces (Table 1 for the provinces). Therefore, in this section we examine the program's impact on learning for children from Eastern and non-Eastern (or Central and Western) provinces separately. The analysis also includes sections that looks at the heterogeneous effects of Rural Dibao when children are left-behind or when they are living with their parents; and by gender of the children (Wang *et al.*, 2019a, b). Finally, it is possible that cash transfers may have different impacts on children from different age groups (Behrman *et al.*, 2009). To examine this, we divide the children based on their initial age in 2010. Children who are 10–12 years old are in the younger group; while children who are 13–15 years old belong to the older group.

Table 9 presents the results of the heterogenous effects of participation. According to the findings, significant heterogeneous effects of Rural Dibao on the scores of children are found in the cases of children from family's with lower per capita income; children from families that are living in Central and Western China; children that are living with their parents (that is, there are no effects on left behind children); children that are younger; and on male children. The effects estimated from the fixed effects and propensity score weighting models are both quite similar. The results for children from poorer families and children from Central and Western China are in line with the theoretical expectations that these children should benefit more. Hence, according to the findings, if the program could more effectively target the poorer families in poorer parts of China, the anti-poverty effects of Rural Dibao could be increased. One possible reason why left behind children do not benefit is that it may be that they lack the guidance and support of their parents on a regular basis, which may be reducing the impact on learning that is being enjoyed by children that area living with their parents. The other results (on younger, male children) may also point to ways to better target the program. The findings suggest that maybe a cash transfer program placing higher weight on younger, female children, conditional on parents being at home could be a way to increase the impact of Rural Dibao.

5. Discussion and conclusion

Although education is an important long-term impact of anti-poverty programs, only three papers have investigated Rural Dibao's effect on rural children's education (Han *et al.*, 2016; Wang *et al.*, 2019a, b; Zhao *et al.*, 2017). These three papers diverge on whether the program increased participating children's education outcomes. In this paper, we argue that these studies almost certainly diverge because they fail to address targeting error, and the authors did not use methods that consider issues of identification. In response to these shortcomings, we extensively analyzed Rural Dibao's targeting issues and sought to identify the causal relationship of Rural Dibao and several key outcome variables by using fixed effects models as well as propensity score weighting method and utilizing panel data

Table 9. Impact of participation on different groups of children's learning outcomes using fixed effects model and propensity score weighting

Groups		n	Fixed effects estimates Standardized Chinese-language score	Fixed effects estimates Standardized math score	Propensity score weighting estimates Standardized Chinese-language score	Propensity score weighting estimates Standardized math score
Income Quantile	Lower	638	0.430** (0.183)	0.325* (0.184)	0.418** (0.174)	0.340* (0.180)
	Higher	934	−0.0662 (0.195)	−0.0954 (0.201)	0.0368 (0.154)	−0.152 (0.140)
Eastern China	No	1,202	0.343*** (0.117)	0.194* (0.118)	0.386*** (0.103)	0.197** (0.102)
	Yes	370	−0.0964 (0.302)	0.388 (0.327)	−0.176 (0.234)	0.169 (0.231)
Left Behind	No	1,314	0.248** (0.115)	0.209* (0.121)	0.331*** (0.0994)	0.196* (0.0996)
	Yes	258	0.255 (0.299)	0.164 (0.305)	0.236 (0.258)	0.211 (0.243)
Age	Younger	1,014	0.424*** (0.154)	0.317** (0.153)	0.445*** (0.134)	0.261** (0.127)
	Elder	558	0.0528 (0.128)	0.0289 (0.154)	0.129 (0.0980)	0.0251 (0.124)
Gender	Male	750	0.492*** (0.160)	0.301* (0.174)	0.560*** (0.132)	0.273** (0.133)
	Female	822	0.0231 (0.143)	0.161 (0.154)	0.0326 (0.130)	0.0420 (0.130)

Note(s): Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

from the CFPS from the years 2010 and 2014. In addition, the earlier research focused only on education expenditures and did not examine learning. In the education literature, it is well known that, when studying the impact of a program on learning outcomes, using outcome measures from a standardized scale is generally a better metric than are educational expenditures. Our study examines the impact on both educational expenditures and learning, thus allowing us to better analyze the effects of Rural Dibao on long-term human capital outcomes.

Using our approach, we show and address targeting problems within the Rural Dibao program. The analysis demonstrates that there are two types of targeting error. First, many poor households that can participate do not. Second, many wealthy households that should not be participating still receive Rural Dibao money. Based on the data, this pattern does not appear to change much over time. Although the analysis indicates that targeting is not perfect, it should be emphasized that the descriptive statistics show that, at the time that they are chosen to receive Rural Dibao, these recipients are generally worse off in terms of income and education than are those families who do not receive Rural Dibao. In other words, there is empirical evidence that the program does not completely fail at targeting people in need. We conclude that, even though targeting error exists, China's Rural Dibao program from 2010 to 2014 are still, in general, targeting families in need.

Once we address the issue of causal identification, we find that Rural Dibao improves children's learning outcomes. When we use a fixed effects model, which helps to control for endogeneity by accounting for all non-time varying unobserved heterogeneity, we find positive and significant results. Then we turn to propensity score weighting method to furtherly control for targeting problem and get very close results. Specifically, the models find that program participation increases Chinese-language test scores by around 0.3 SDs and standardized math test scores by 0.2 SDs. When reviewing the impacts of different education interventions, Hill *et al.* (2008) found that middle school student's tests scores, over the course of a normal academic school year, improve by about 0.2–0.3 SDs. Hence, it seems that the Rural Dibao program can be thought of as a relatively effective means of increasing a child's learning. These results also are important, as, according to our descriptive statistics, Rural Dibao participants tend to underperform academically. As a consequence, the boost from Rural Dibao may be allowing these children to (at least partially) catch up.

In trying to identify the mechanism that links Rural Dibao and improved learning, we find through analysis that Rural Dibao participation boosts education expenditures. The analysis also shows that higher education expenditure leads to higher scores. Although the magnitude of the increase in education expenditure is modest, it is still significant in the context of rural China, as this increase may be allowing poorer, rural Chinese families to better cover a number of incidental education expenditures that, in turn, lead to better learning.

We also conduct a heterogeneity analysis to investigate the program's impact on different groups of children. We find that the program has stronger positive impacts on the learning outcomes of those from poorer families and poorer districts. Specifically, the program increases scores only for those people with a family per capita income below Rural Dibao threshold. This implies that, if the program can target well and reduce program leakages, the positive impacts will be even larger. We also find that the program has a positive impact on the learning of only younger, male or not left behind children.

Thus, our results appear to strongly suggest that at least part of the financial transfers from Rural Dibao that are received by poorer families spills over into the education and increases learning of the children in the family. This means, of course, that there almost certainly will be a positive, long-term impact of the program. This finding is consistent with previous studies that analyze anti-poverty programs in other countries. As noted, Dahl and Lochner (2012) and Duncan *et al.* (2011) show that in developed countries' anti-poverty programs, an additional US$1,000 leads to about 6% increase in children's academic achievement. Our study shows that this trend continues in China's rural areas, which may contribute to the literature streams on developing Asian countries.

Our findings have implications for policy. First, like other papers (e.g., Golan *et al.*, 2017; Kakwani *et al.*, 2019; Westmore, 2018), we show the existence of targeting error in the program. Our heterogeneous effects analysis shows that, if the program can target well, the effect on rural children's education will be even larger. The Rural Dibao program should, therefore, be reformed to address targeting error and reduce program leakages. An example reform could be a proxy means test developed by Kakwani *et al.* (2019), which they suggest could enhance Rural Dibao's targeting and, thus, performance.

Second, our results suggest that an effective way to improve children's education may be to improve the general household situation. Our results show that, when households have more resources (in this case, more income from Rural Dibao), these resources naturally spill over into their children's education. By raising a household's level of income, policymakers can enable a certain desired behavior. Thus, if policymakers have a specific goal or behavior that they wish to encourage, they should first consider whether solving a more general issue may help to achieve their specific goal.

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Appendix

Table A1. Balance test for covariates after propensity score weighting (n = 1,572)

	Coefficient	t-ratio
Family per capita income (1,000 RMB)	0.0459	0.22
Ethnicity (1 = Han)	0.00348	0.18
Father's education (1 = completed junior high)	0.000576	0.02
Mother's education (1 = completed junior high)	−0.00458	−0.13
Gender (1 = male)	0.0428	1.08
Eastern China (1 = coming from eastern provinces)	0.00219	0.14
Age	0.167	1.30
Year	−0.0257	−0.26
Key school (1 = learning in key school)	−0.0206	−1.07
School boarding (1 = boarding at school)	0.00001	0.00
Age of household head	−0.191	−0.26
Gender of household head (1 = male)	0.00181	0.07
Employment status of household head (1 = employed)	0.0136	0.46
Political status of household head (1 = CCP member)	0.0156	0.61
Number of children	−0.00268	−0.05
Number of elderlies	−0.0228	−0.53
Number of members with chronical diseases	−0.00919	−0.27
Number of employed members	−0.00790	−0.11

Note(s): *p < 0.10, **p < 0.05, ***p < 0.01

To test balance of the covariates, we run propensity score weighted OLS regression of each covariate on program participation. If the coefficients are all insignificant, there will be no statistically significant difference between Dibao and non-Dibao children in terms of covariates after weighting. Table A1 shows the results of the balance test. We see that the coefficients of participation are all insignificant, which means the covariates are well balanced after weighting. Moreover, variables like key school information, though not considered in score calculating, are also well balanced, meaning the weighting process has good balance quality for other controls.

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