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How do poverty alleviation coordinators help the impoverished in rural China? -- Evidence from the Chinese poor population tracking dataset

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ABSTRACT

The loss of targeting efficiency due to information asymmetry is a longstanding problem in aid programs. China's Targeted Poverty Alleviation (TPA) program addresses this problem by assigning local government officials to individual impoverished households. These officials, referred to as poverty alleviation coordinators (PACs), are required to pay frequent home visits to the assigned households and to deploy policy resources for poverty reduction. The program is costly in terms of human resources because the officials also have regular duties in a variety of departments. We investigate the effects of the PAC system on poverty alleviation and explore the mechanisms of the effects. Based on the Chinese Poor Population Tracking Dataset and econometric analysis, we find that the households with a larger income increase are those whose PACs work in a department that has the type of resources needed by the household. This indicates that a good match between the resource and the need could enhance the effect of the TPA program. In addition, PACs at a higher position in the governance structure show a larger income increase in their assigned households, which is expected, because a higher position could have more resources to deploy. These findings shed light on role of institutional arrangements in alleviating information asymmetry in poverty reduction programs.

1. Introduction

Eliminating poverty by 2030 is the top goal among the 17 Sustainable Development Goals set by the United Nations in 2015. How to reach the poor, especially those at the very bottom of the economic ladder, and how to lift them out of poverty and into sustainable livelihoods are now topics of wide concern by both developed and developing countries. Foreign aid is one of the prominent policy tools to help poor countries reduce poverty (Sachs, 2005).[1] However, aid programs are often criticized for inaccurate targeting and ineffectiveness due to the absence of feedback and accountability, incentive problems, corruption, poor institutional development, etc. (Banerjee, 1997; Easterly, 2003, Easterly, 2006a, 2006b, Easterly, 2009; Martens, 2005; Moyo, 2009; Olken, 2006; Qian, 2015; Reinikka & Svensson, 2004). In order to make aid work, some scholars act as "searchers" for information and use randomized

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[1] In *The End of Poverty*, Sachs (2005) argues that poverty could have been entirely eliminated if the rich world committed 195 billons dollars in foreign aid per year between 2005 and 2025.

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controlled trials to target aid to the right kind of projects (Banerjee, 2007; Banerjee and Duflo, 2011). Yet, these studies tell little about broader implementation – for instance, how to combine "small but sure" interventions into scaled up programs (Ravallion, 2012). Is it possible to target the poor through well-informed and well-thought-out public aid programs over a limited period, or is a "big push" doomed to fail? In particular, is it possible for officials to be information "searchers," undertaking simultaneous actions in a wide range of districts, and to deliver the assistance that is truly needed? In this paper, we answer these questions by exploring the Poverty Alleviation Coordinator (PAC) system in the Targeted Poverty Alleviation (TPA) program in China and investigating the effects of the PAC system on poverty alleviation.

The PAC system is an institutional arrangement for the TPA program in China, which was initiated in 2013, with the aim of eliminating extreme poverty by 2020 with no one left behind. At the beginning of the TPA program, poor households were identified and a list of identified poor households (IPHs) was formed. The PAC system was then established to better reach the IPHs. The PACs are local government officials who – in addition to their regular duties in various departments – are assigned to specific impoverished households. They are required to pay regular home visits to the households. Through the home visits, the coordinator can verify and keep updated about the household's economic status, figure out the household's needs, and coordinate related policy resources accordingly. Given these roles of the PAC system in the TPA program, this paper is in line with literature on targeting efficiency and tools of poverty-reduction and growth-boosting aid programs.

Previous literature shows that general poverty-reduction aid programs rarely reached the poor because of the problems of asymmetric information and corruption (Briggs, 2017 ; Collier & Dollar, 2002; Qian, 2015; World Bank, 2013). For example, World Bank (2013) documented that foreign aid had only a small effect on poverty reduction and approximately half of Africans still lived below a $1.25 a day poverty line even with huge foreign aid; Qian (2015) showed that only about 1.69–5.25% of foreign aid was given to the poorest 20% of counties in any given year. Golan, Sicular, and Umapathi (2017) and Kakwani, Li, Wang, and Zhu (2019) showed that China's rural minimum living standard guarantee program (Dibao) reached nearly 75 million poor recipients during 2007–2009 but had large inclusion and exclusion errors. To address the targeting problem, a large literature has explored potential optimal targeting rules, including government and NGO implementation (Banerjee, Duflo, Chattopadhyay, & Shapiro, 2009), proxy means testing (Alatas, Banerjee, Hanna, Olken, & Tobias, 2012; Niehaus, Atanassova, Bertrand, & Mullainathan, 2013), community-based methods (Alatas et al., 2012), self-targeting and top-down screening and enrolment (Alatas et al., 2016), etc. Through identifying and excluding ineligibles from the list, the PAC system reduces the inclusion error and therefore improves the targeting efficiency of the TPA program. Therefore, by studying the PAC system, our paper contributes an alternative targeting tool.

Besides targeting impoverished households, targeting their needs is also difficult, but is critical for the effectiveness of aid programs. Some international antipoverty programs have adopted the approach of home visits in targeting needs and delivering the needed assistance. For example, program staff in BRAC's Ultra-poor Graduation program (Banerjee et al., 2015; Hashemi & De Montesquiou, 2011) do weekly home visits to participating households. During the visits, they offer guidance to participants on running a business, mastering skills, engaging in remunerative jobs, obtaining social support, developing healthy habits, forming positive attitudes, etc. Academic studies investigating the effects of home visits have focused on the message, money and coaching involved. Roelen and Devereux (2019) studied the role of home visits in the Graduation program in Burundi (also known as *Terintambwe*) and found that training and coaching are imperative for achieving change, because they deliver both money and message to the participants. Roelen, Kim, Barnett, and Chanchani (2019) studied the impacts of the Chemen Lavi Miyò (CLM) program in Haiti and concluded that home visits were ranked as medium importance in the package of support, because home visits allow the participants to gain new knowledge related to nurturing care, particularly in relation to health, sanitation, and nutrition, which is important knowledge for human capital accumulation.

The PAC system in China also utilizes a home visit approach as the channel for poverty alleviation, but it is distinguished from previous programs studied in the literature by its unprecedented scale and its institutional arrangements. This study will shed light on the success of poverty reduction interventions on a national scale. In addition, previous programs that have adopted home visits paid little attention to the households' specific needs and the relationship between the staff and the participants, which is at the heart of the success of home visits (Wasik, 1993). Therefore, our paper also contributes to the literature by addressing the role of the quality of matching between the coordinators' resources and the households' needs.

Our work draws on two features of the PAC system in China. First, the comprehensive dataset allows us to link the PACs' characteristics with the causes of households' poverty. The PACs differ in departments, positions, government levels, etc., so they have different information and resources. The impoverished households differ in poverty level and cause, so they have different needs. The two-sided heterogeneity allows us to construct a matching quality index to gauge the delivery of needed assistance. Second, the PACs in a particular department are randomly assigned to poor households. This provides the researchers a unique opportunity to examine the causal effect of a good match between PACs and impoverished households on poverty alleviation, which is understudied in the literature.

Utilizing econometric models, we find that households whose PACs are a good match to their needs and those whose PACs are at a higher position have a larger income increase after the program. Through analyzing households' different income sources, we investigate the potential channels of the increased income; we find that home visits work mainly through increasing labor supply incentives in the impoverished households.

The remainder of the paper proceeds as follows. Section II introduces the Poverty Alleviation Coordinator system in the TPA program of China. Section III describes the Chinese Poor Population Tracking Dataset and relevant variables used in this paper. Section IV presents the analytical framework and empirical results. Section V explores the mechanisms. Section VII concludes.

2. The PAC system in China's TPA program

The Targeted Poverty Alleviation program in China was initiated in 2013, following a decline in the marginal efficiency of regional poverty alleviation (Liu, Liu, & Zhou, 2017). The TPA program includes a series of policies: industrial projects, housing support and relocation, employment support, education support, social security programs, financial support, health support, and infrastructure investment (i.e., safe drinking water programs for rural residents, paved road construction, etc.). As for the institutional arrangement, the central government acts as the headquarters, provincial governments take overall responsibility, and city and county governments oversee the implementation of the TPA policies. The TPA program covers all the households on the IPHs list, which were identified at the beginning of the program.

The PAC system is set up with the role of reaching the IPHs, identifying their needs, delivering policy information, and deploying resources according to their needs. The PACs are not full-time social workers or aid workers; rather, they are officials in various departments of county and lower-level governments, and are assigned PAC duties in addition to other duties in their departments. Each PAC is assigned by the county government to several IPHs and is required to pay frequent home visits to the households. The following subsections describe the PAC system in detail.

2.1. Assignment of the PACs to IPHs

Assigning PACs to the identified poor households is the first task of the PAC system. The assignment procedure is as follows. First, the county government assigns subordinate departments to villages, forming department-village pairs. The assignment rule is based on the size of the departments and the number of IPHs in a village. It tends to assign the departments with more officials to villages with more impoverished households. Second, the departments assign their officials to the impoverished households in the villages, and these officials are then referred to as PACs. The assignment at this level is basically random, although we notice that a few departments are inclined to first assign subordinate officials with higher positions (who are only a small proportion of department staff) to the more impoverished households in their paired-up village, and then randomly pair up the rest of the households and the officials.

2.2. Home visits by the PACs

The PACs are required to visit the households regularly. During the home visits, the PACs check whether the IPHs are truly poor based on the following three screening criteria: (1) survival standards (whether the households have difficulty in obtaining food, clothing, children's compulsory education, basic medical care, and housing), (2) proxy means tests (whether the households have few assets, elderly members, children dropping out of school, children currently in college, or members suffering from severe or chronic diseases), and (3) income test (whether the household annual income is less than the local absolute poverty line). During home visits, the PACs also figure out the main causes of the household's poverty, which could include disease, disability, children's education (a burdensome expense), lack of skill, lack of labor, lack of motivation, etc.

Based on the information collected during home visits, the PACs explain the TPA policies to the households, and coordinate relevant resources to help them. In practice, the PACs adjust the method of assistance according to household characteristics, such as endowment, education background, and cognitive abilities. For example, if the household's education is too low to complete the application forms, PACs provide in-person help, such as filling in the application form and collecting documentation.

The home visit frequency is strictly monitored. PACs need to sign their name and put a thumbprint on the record book at the beginning of each home visit, and record the assistance they offer and the current condition of the paired household at the end of the home visit. These record books are regularly checked by a supervision team and archived by the county government. If PACs are absent from home visits or make no effort to assist households, and are caught by the supervision team, they will be criticized; if no improvement is made, their career development could be hindered.

3. Data

The data used for the empirical analysis are from Xin County of Henan Province in the period 2014–2018. Xin County is one of the 832 identified national poor counties in China (see Fig. 1), which are the target counties of the TPA program. Xin County is comparable in numerous dimensions to the median of all counties in China, as shown in Fig. A1 in the appendix, indicating that a typical household in Xin County would be representative of households in other regions of China.

3.1. IPHs information

The main data are from the Chinese Poor Population Tracking Dataset of Xin County. It is part of the national system built by the central government in 2013 for the purpose of tracking the dynamics of the IPHs and the effects of the TPA program. It covers the

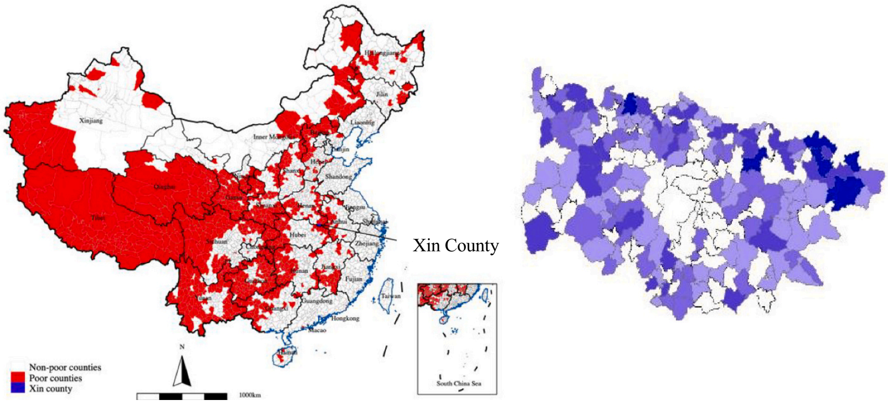

Fig. 1. National poor counties in China.
Notes: The left shows the distribution of China's 832 national poor counties, red color indicating the poor counties, blue color indicating the location of Xin County. The right is the map of Xin County and the distribution of poor households in 2014, deeper color indicating more households in the area.

population of the IPHs and collects household-level information. The IPHs are not removed from the registration system even if they succeed in getting out of poverty; instead, they are marked as "out of poverty" but continue being tracked in the system and enjoying the TPA policies until the end of the TPA program in 2020.[2]

At the beginning of 2014, Xin County completed the first round of identification of poor households. A total of 12,121 households from 206 villages were identified and registered. The distribution of the IPHs is illustrated on the lower right of Fig. 1. It shows that most IPHs live far from the central area of the county, mostly in the peripheral villages.

The information recorded by the system includes household's income from various sources, assets, labor supply, cause of poverty, demographics of household members such as age, education, health status, etc., place of residence, and condition of the road connected to the place of residence. As shown by Fig. A2 in the appendix, between 2014 and 2018, the average income of households in the poverty registry increased from about 7000 yuan (3.1 dollar a day, calculated by the exchange rate in 2014)[3] to 32,000 yuan (13.3 dollar a day, calculated by the exchange rate in 2018). The summary statistics of the household information are summarized in Panel A of Table 1.

3.2. PACs information

With the authorization of the head of the local county and the support of the Poverty Alleviation Office in Xin County, we obtained the names of all the PACs and their work information and demographics, such as department, position classification, government level, whether a Communist Party of China (CPC) member, gender, age, education, etc. The information is summarized in Table 1, Panel B.

In Xin County, there are 3476 PACs, who continuously visited the designated households three times a week[4] during 2014–2018. They are from city-level, county-level, town-level, and village-level governments. More than 60% of them are affiliated with the county-level government. Their positions from low to high are clerk, deputy section chief, section chief, deputy division director, division director, and bureau director. Clerks account for more than 70% of the sample.

The working departments are grouped into ten categories, based on characteristics and similarity of departments' functions. They are social aid, agriculture and assets, infrastructure, comprehensive departments (which have overall policy responsibilities), supervision departments (which have personnel assignment responsibilities), finance, labor and market, health, education, and information. The details about the grouping and the functions of the departments are presented in Table A1 in the appendix. In Xin County, most of the PACs come from the governments' comprehensive department at different levels, accounting for 28% of the sample, followed by the departments of agriculture and assets (14%). Only 3% of PACs are from the department of social aid.

The PACs with education of "college and above" account for 89% of the sample, those with high school education account for 10%, and the remaining 1% have middle school education. PACs' individual characteristics – such as gender, age, education and political status – can influence their ability to assist households. However, the data on age has a lot of missing values; we therefore excluded this

[2] The policy document "*Guidance of Effective Connection between Rural Minimum Living Security System (Dibao) and Targeted Poverty Alleviation Program*" was issued by the Ministry of Civil Affairs of the People's Republic of China. In line 16 of the document, it stipulates that the IPHs who shake off poverty should continue enjoy supporting policies such as medical care, education and housing assistance until 2020. http://www.mca.gov.cn/article/gk/wj/201811/20181100012656.shtml

[3] According to the World Bank, the poverty line for low - and middle-income countries is less than $3.2 a day.

[4] According to Xin County's poverty alleviation policy document "Notice on strengthening the working mechanism of poverty alleviation in 'wartime'" issued by the headquarter of the poverty alleviation office in Xin County, the frequency of PACs' home visits is three times a week.

Table 1
Summary Statistics.

	Obs	Mean	Std.Dev.	Min	Max
Matching quality	32,955	0.537	0.499	0	1
Panel A: IPHs' Data, 2014–2018					
Income	32,953	21,221	16,323	2250	82,895
Income per capita	32,953	6182	5011	−4123	234,651
Change of Income	25,408	5161.736	4795.386	−784	12,326
Change of Income per capita	25,408	1540.059	1393.677	−284	3590
Change of wage	25,307	5067.098	6210.091	−1000	17,800
Change of operation income	25,408	1540.059	1393.677	−284	3590
Change of property income	24,851	339.036	695.242	0	3800
Change of transfer	25,410	697.252	1095.574	−400	3643
Poverty cause(dummy)					
Disease	32,955	0.276	0.447	0	1
Disability	32,955	0.150	0.357	0	1
Children's education	32,955	0.107	0.309	0	1
Lack of skill	32,955	0.243	0.429	0	1
Lack of labor	32,955	0.072	0.258	0	1
Lack of motivation	32,955	0.049	0.280	0	1
Other	32,955	0.103	0.019	0	1
Characteristics at village level					
Gini coefficient (within IPHs)	371	0.279	0.06	0.171	0.376
Ratio of IPHs with a good match to all IPHs	291	0.071	0.085	0	0.56
IPHs' income per capita	371	0.082	0.029	0.023	0.155
Labor force participation Rate of IPHs	371	0.594	0.087	0.219	0.848
Mean education level of IPHs	371	2.495	0.215	1.837	3.002
Panel B: PACs' Data, 2014–2018					
Helping intensity	3476	2.104	1.180	1	14
Departments					
Information	3476	0.0567	0.231	0	1
Agriculture and assets	3476	0.124	0.329	0	1
Education	3476	0.065	0.247	0	1
Finance	3476	0.096	0.295	0	1
Comprehensive	3476	0.231	0.421	0	1
supervision department	3476	0.107	0.309	0	1
Health	3476	0.057	0.231	0	1
Infrastructure	3476	0.185	0.388	0	1
Labor and market	3476	0.072	0.258	0	1
Social aid	3476	0.211	0.408	0	1
Position class					
Clerk-level	3476	0.297	0.457	0	1
Section-head level and above	3476	0.703	0.457	0	1
Government level					
County-level and below	3457	0.346	0.477	0	1
County-level	3457	0.654	0.480	0	1
Other characteristics of PACs					
Education level	2333	15.544	1.335	1	3
CPC member	3476	0.904	0.295	0	1
Male	3356	0.748	0.434	0	1
Age	1123	45.839	8.657	24	80
Panel C:Policy Data, 2014–2018					
Poverty alleviation industrial projects	32,955	0.788	0.409	0	1
Housing support and relocation policy	32,955	0.103	0.303	0	1
Education support	32,955	0.326	0.469	0	1
Financial support	32,955	0.325	0.468	0	1
Infrastructure investment	32,955	0.874	0.463	0	1

Notes: In the summary statistics for households' characteristics, the unit of all income variables is Chinese Yuan. The statistics of the IPHs' characteristics at village level are based on our analysis of 371 villages where the number of IPHs is greater than or equal to 50. Gini coefficient denotes the income inequality within the IPHs in the village. Village income per capita is the average of all households' (including non-poor households) income in the village; the unit is 10 thousand yuan. Labor force participation rate per village is the average of labor force participation rate per IPHs in the village. The mean education level per village is the average schooling year per IPHs (excluding the children receiving education) in the village, because we have no data of all villagers' education level.

variable in the following analysis.

3.3. Policy information

The poverty registry system also records information on the support received by the impoverished households. TPA is a policy package that includes a series of projects and support. (1) Poverty alleviation industrial projects are selected based on the village's resource endowment, mainly labor-intensive industries like clothing factories, electronics factories, vegetables and fruit greenhouses, etc. Nearly 79% of poor households participate in this type of projects, either as workers to earn wages, or by transferring their land to professional companies or large agricultural households to obtain rent and dividends. (2) Housing support and relocation policies have moved 10% of poor households located in barren mountain areas to newly constructed communities that are near to the town and job opportunities. (3) Education support includes establishing boarding schools for poor left-behind children (children whose parents have moved away), providing free nutritious food in rural schools, and offering subsidies to poor college students. (4) Financial support provides interest-free microfinance (no more than 50,000 yuan per household). About 33% of the poor households have obtained loans to run businesses and increase income. (5) Infrastructure investment targets all rural residents in the poor villages via programs of safe drinking water, sanitary facilities, roads, electricity grids, cultural and sports facilities, clinics, schools, etc. The summary statistics of the policy support are summarized in Table 1, Panel C. Fig. A3 in the appendix shows that the total number of households receiving relevant policy support has risen significantly from 2014 to 2018.

4. Empirical analysis

Based on the data described above, we empirically estimate the effect of the matching quality of the PACs on poverty alleviation. The hypotheses are that (1) a good match between resources and needs leads to a better effect on poverty alleviation, and (2) a PAC from a higher level of government can deploy more resources to help the poor and therefore can achieve a better poverty alleviation outcome.

4.1. Definition of matching quality

To measure the quality of a match, we construct a matching quality index by pairing the PACs' department with the cause of the household's poverty. We set the matching quality index equal to 1 if the PAC's department has resources that could address the cause of the household's poverty; otherwise it is 0. We say this household has a good match when the matching quality index equals 1. The data show that 53.7% of the households in the sample have a good match. More measurement methods are explored in subsection E. The effect analysis results remain robust to alternative measurements of matching quality.

In Fig. 2, we show how we decide whether the department has the resources needed by the household. First, we divide these departments into two groups: integrated and function-oriented groups. The integrated group includes departments of information, agriculture and assets, comprehensive government, and supervision. The former two have the resources (information, training, assets, etc.) that most households need,[5] and the latter two engage in many policy programs and have a wider network in the overall government system.[6] Apart from households whose poverty is caused by lack of motivation, PACs from the departments in the integrated group can potentially deploy the needed resources; thus, the matching quality index equals 1 for these matches.

The function-oriented group refers to the departments specializing in a certain type of public service, including departments of education, health, finance, labor and market, social aid, and infrastructure. The matching quality index is set to 1 only when the type of public service is the same as the cause of poverty. Specifically, the matching quality index equals 1 only when (1) PACs from education departments are paired with households whose poverty cause is either the financial burden of children's education or lack of motivation; (2) PACs from financial departments are paired with households who are trapped in poverty by disease, disability and the cost of children's education; (3) PACs from health departments and social-aid departments are paired with households with members suffering from disease or disability and those lacking labor (elderly); (4) PACs from departments of labor and market are paired with households with member suffering disabilities, children receiving education, and lack of skill; (5) PACs from infrastructure departments are paired with households with members suffering from disabilities and those with children receiving education.

Our matching rules are based on the policy implementation description in the "Notice on strengthening the working mechanism of poverty alleviation in 'wartime'" document cited above, the PACs' work records, and related news reports. These materials show that the PACs' working departments and households' poverty causes indeed determine the matching quality. Those households whose needs match the endowment advantages of the PACs' working departments are more likely to get the type of assistance that is identified during the home visits. For instance, the PACs who work in the education departments can deploy education subsidies for households with school-age children, but they have difficulty in coordinating the social aid allowance for households with members suffering disease or disabilities (see Fig. A4 in Appendix).

[5] PACs from information departments know the TPA policies well and are good at spreading information to households. They can encourage potentially eligible households to apply for relevant programs. PACs from departments of agriculture and assets can deliver assets, such as fertilizer, seeds, machines, or livestock, to promote production, and can provide agricultural training for those who lack skills, thus increasing their engagement in agricultural activities.

[6] In China, comprehensive departments (county level and below) are responsible for implementing and promoting overall programs. They connect officials in other departments and have the power to call those who work in subordinate departments (or departments at the same level) to coordinate relevant resources. Similarly, supervision departments are responsible for arranging staff positions, monitoring staff, proposing policies, etc., which helps them construct a close relationship with other departments; thus, they also can easily coordinate with other departments.

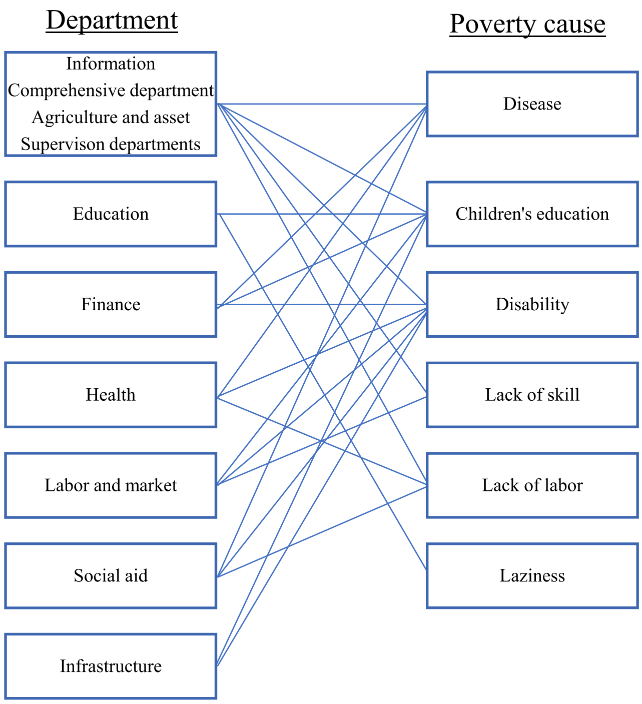

Fig. 2. The assignment of matching quality index.
Notes: Based on the analysis of the function and responsibility of different departments, this figure shows the assignment of matching quality index by relating households' poverty cause and PACs' department. The line between two blocks shows that the PAC from this department and the household with this poverty cause are a good match.

4.2. Regression

We estimate the effect of good match on poor households' income using the regression as follows:

$$\Delta \mathrm{y}_{\mathrm{ijt}} = \beta_0 + \beta_1 \mathrm{M}_{\mathrm{ij}} + \beta_2 \mathrm{O}_{\mathrm{ij}} + \beta_3 \mathrm{H}_{\mathrm{it}} + \beta_4 \mathrm{P}_{\mathrm{it}} + \mathrm{v}_{\mathrm{t}} + \epsilon_{\mathrm{it}} \tag{1}$$

where Δy_{ijt} is the change of household i's income from year $t-1$ to year t and the household's PAC is denoted as j; M_{ij} is the matching quality index between household i and PAC j, which is measured as described in section (IV)A. Given that the coordinators are assigned before the home visits start and do not usually change, the corresponding matching quality index remains constant over the studied period. O_{ij} is a vector of the characteristics of the PAC j, including work department, position classification, government level, helping intensity (the number of households assigned to them), political status, and gender. These are all dummy variables, defined as follows: the comprehensive departments of government, a position below section level, and village-level government are treated as the base groups. H_{it} are characteristics of household i, including the main poverty cause, number of kids less than five years old, the dependency ratio in the family, whether there are members suffering from disability or disease, average education level of working age members, and the distance of the residence to the main road. P_{it} are policy dummies, indicating whether household i at year t benefits from policies regarding education support, housing relocation, financial support, industrial development program, and infrastructure program. v_t is year fixed effects and ϵ_{it} is the error term.

β_1 is the estimated coefficient of M_{ij}. To interpret β_1 as the causal effect of a good match, we need to assume that households with good and bad matches are comparable, conditional on PACs' and households' characteristics and on the services received, i.e., that the assignment of the matching quality index is as good as random, conditional on the control variables, which is referred as the "unconfoundedness assumption". Given that the unconfoundedness assumption cannot be tested directly, we use the following procedures to assess the plausibility of this assumption.

First, we compare a series of observable characteristics of the households with a good match to those with a bad match. The comparison results are summarized in Table 2 . Columns 1–2 report the mean values and Column 3 reports the differences between the two groups and the t-statistics. It shows that all the differences are small and not statistically significant. It indicates that on the dimensions of these observables, the two groups are comparable. We also depict in Fig. 3 the income distributions of the two groups in the initial year and find that the income distributions have no statistically significant difference.

Second, we control characteristics of departments and households and year fixed effects, in order to minimize the omitted variable bias. After controlling these variables and time fixed effects, only individual-level time-variant unobservables could cause an omitted variable bias problem. Considering that the assignment of PACs is on the village level (i.e., all PACs from the same department of the

Table 2
Balance test.

Variables	Mean		Difference	
	Good match	Bad match		
	(1)	(2)	(3)	
Initial income (yuan)	10,347	10,197	150	[0.69]
Head's gender(male = 1)	0.921	0.915	0.006	[0.66]
Head's education level	7.155	7.076	0.079	[−0.59]
Number of HH's member	3.568	3.527	0.041	[1.01]
HHs with kids less than 5 years old (=1)	0.224	0.227	−0.003	[−0.15]
HHs with member suffering disability (=1)	0.208	0.21	−0.002	[−0.13]
HHs with member suffering disease (=1)	0.468	0.468	0	[−0.02]
Dependency ratio	0.522	0.535	−0.013	[−0.67]
Mean education of HH's member	2.538	2.535	0.003	[0.16]
Irrigation area (mu)	1.704	1.672	0.032	[0.82]
House area (square meters)	98.772	99.067	−0.295	[−0.27]

Notes: This table compares various characteristics between households with a good match and those without a good match. T-value in brackets. No difference is statistically significant. It indicates that the two groups are comparable in terms of these characteristics.

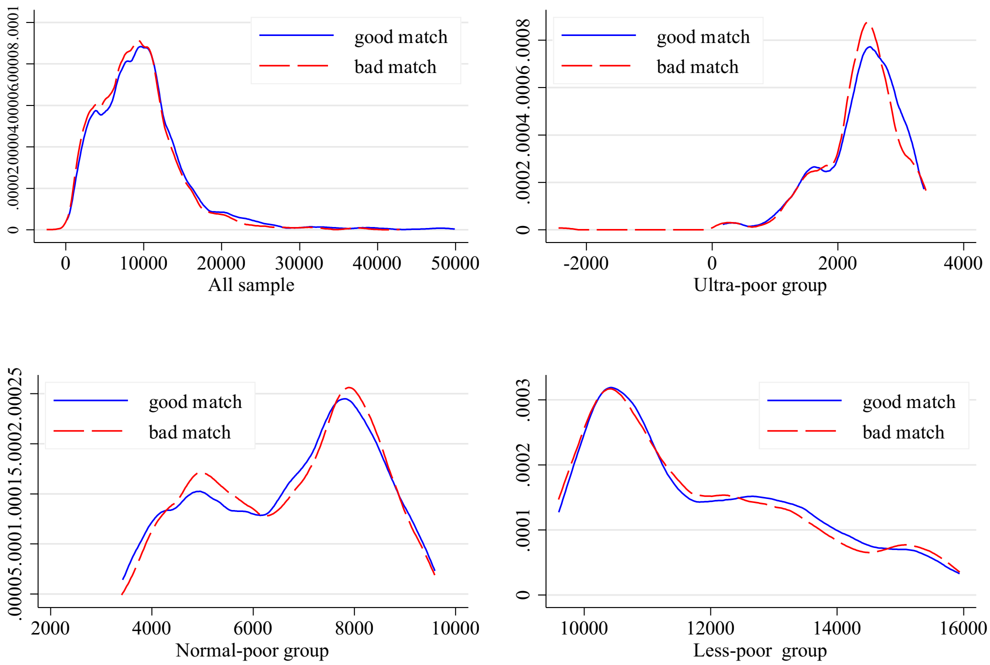

Fig. 3. Distribution of initial income of households by poverty level.
Notes: The figure shows the curves of kernel density estimates of the initial income (in 2014, the beginning year of TPA Strategy) of households with a good match and those with a bad match in the full sample and three subsamples (Ultra-poor group, Normal-poor group and Less-poor group). It shows that the income distribution curves of households with a good match and those with a bad match are nearly overlapping.

same level are assigned to the same village), we do not control for village fixed effects and department fixed effects, because these fixed effects could absorb the effects of factors that are time-invariant and specific to village and department.

In addition, given that PACs can observe households' income before the assignment, they might choose relatively richer or poorer households to form pairs based on individual capability or political goals. Thus, using absolute income as the explained variable might bring reverse causality and cause biased estimation. To address this concern, we instead use as the explained variable the income change, which is not known in advance.

4.3. Income effect of a good match

Table 3 reports the estimated results of matching quality on the change of household income and the change of per capita income. Columns (1) and (3) report the impacts of household- and PAC-specific characteristics without adding the matching quality index. Columns (2) and (4) add in the matching quality index. This shows that adding in the matching quality index does not change the

Table 3
The effect of matching quality on the change of IPH's income.

	Δincome	Δincome per capita		
Variables	(1)	(2)	(3)	(4)
Matching quality		133.4*		42.98*
		(78.45)		(22.69)
Helping intensity	−123.3***	−124.7***	−30.63***	−32.91***
	(23.42)	(23.41)	(6.752)	(6.935)
PACs' department dummy				
Supervision	937.7***	916.0***	247.7***	226.6***
	(111.0)	(111.6)	(30.99)	(31.91)
Health	639.2***	676.1***	210.3***	231.6***
	(176.0)	(178.3)	(53.88)	(55.40)
Finance	513.8***	513.9***	167.8***	189.9***
	(115.9)	(116.0)	(34.29)	(34.64)
Infrastructure	430.3***	478.1***	118.3***	145.6***
	(106.6)	(109.7)	(29.64)	(30.97)
Social aid	317.3***	296.0***	86.94***	78.90**
	(108.9)	(110.1)	(31.84)	(32.87)
Agriculture and asset	368.2***	385.0***	119.0***	100.2***
	(109.7)	(110.8)	(32.08)	(33.17)
Information	331.7***	370.5***	61.74*	75.06**
	(121.9)	(124.3)	(32.87)	(33.86)
Labor and market	390.8	386.3	92.21	84.98
	(256.5)	(257.5)	(69.42)	(70.69)
Education	119.6	197.4	20.16	73.04*
	(140.9)	(148.6)	(40.03)	(42.47)
PACs' position dummy				
Section head level and above	236.4***	233.8***	92.97***	94.55***
	(72.54)	(72.54)	(20.69)	(21.03)
Government level dummy				
County level	−410.6***	−388.3***	−104.2***	−105.4***
	(85.05)	(85.56)	(25.42)	(25.92)
Other PACs' characteristics				
Education level	176.7*	175.7*	35.27	34.18
	(98.34)	(98.45)	(28.79)	(29.18)
CPC member	−158.0	−154.6	−55.45*	−49.47
	(108.4)	(108.7)	(31.55)	(32.11)
Male	−41.67	−42.77	−0.463	3.575
	(77.67)	(77.69)	(21.76)	(22.05)
Household's control	Yes	Yes	Yes	Yes
Policy control	Yes	Yes	Yes	Yes
Year-effect	Yes	Yes	Yes	Yes
Observations	13,644	13,644	13,371	13,371
R-squared	0.126	0.126	0.115	0.109

Notes: The table estimates the impact of matching quality on the change of household's income and income per capita. Columns (1) and (3) estimates the impact of household- and PAC-specific characteristics without matching quality index. Columns (2) and (4) add in the variable of matching quality index, investigating the impact of a good match on the change of income. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

estimated coefficients of other variables, reinforcing the plausibility of the unconfoundedness assumption. The estimated coefficients of the matching variables are positive, indicating that a good match between PACs and households leads to a larger increase in household income: column (2) shows that the increase of household income with a good match is 133.4 yuan higher than those with a bad match. In column (4), the income effects are also significant when per capita income is used as the dependent variable.

Fig. 4 visualizes the coefficients of the matching quality index, helping intensity, department dummies, position class dummies, government level dummies, and PACs' individual characteristics (education level, political status, and gender). It shows that helping intensity exerts a significantly negative effect on the increase in households' income, on average 123 yuan (nearly 20 dollars) from helping one more poor household. This indicates that assigning too many households to the PACs might disperse their time and energy, thus reducing the attention paid to a single household and decreasing the efficiency of poverty alleviation. For department dummies, the coefficients of the departments of supervision, finance, infrastructure, agriculture and assets, and information are statistically significant and positive. The magnitudes of the coefficients indicate that households with PACs from the department of supervision experienced the highest growth in household income and per capita income. One possible explanation is that PACs from supervision departments have more power, so they can direct related departments to deliver targeted policies to households. The PACs who have the second largest positive effect on income increase come from finance departments, infrastructure departments, information departments, and the departments of agriculture and assets. PACs from these departments may be able to transfer money in the form of a grant or loan, improve infrastructure to promote households' productivity, spread policy information and positive attitudes or values, and provide agricultural production training, technology, and capital, including seeds, livestock, etc. In these ways, they help increase the income of their households.

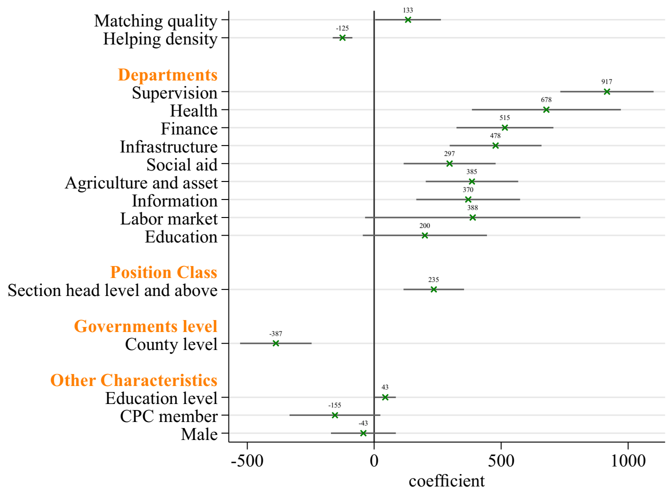

Fig. 4. Coefficients of PACs' characteristic on the change of household's income.

Notes: This figure shows the coefficients of PACs' characteristics based on the results presented in column (2) of Table 4. Helping intensity is the number of households assigned to each PAC, denoting the potential work intensity of home visits. The PACs' work departments are divided into 10 groups: comprehensive departments (the base group), social aid departments, agriculture and asset departments, infrastructure departments, supervision departments, finance departments, labor and market departments, health departments, education departments, and information departments. The PACs' positions are divided into two groups: (1) clerk level refers to those who are clerks; (2) section-head level and above are those who are section deputy section chief, section chief, deputy division director, division director or Bureau-Director. PACs' affiliated government levels are also divided into two groups: village- and town-level governments, and county-level governments. The PACs' education level is the average schooling years calculated by the following formula: schooling years = primary education or below*6 + middle school education *9+ high school education*12+ university education *16+ master graduate education *18+ doctoral graduate education*22.

For position class dummies, the coefficients of section-head level and above are significantly positive, indicating that the more power PACs have, the more able they are to assist households in achieving an income increase. This is expected, because more power means access to more resources to deploy for helping the impoverished.

For government level dummies, households with PACs who are affiliated with a higher level of government show a lower increase. This suggests that negative effects such as the distance between PACs (located in central areas) and poor households (farther from the county center), or their own busy work schedules, dominate the positive effect of the ability to deploy more resources.

In addition, we find that PACs with a higher level of education can help households achieve a higher income increase. This could suggest that a high level of education is necessary to improve the efficiency of targeted poverty alleviation, as it empowers individuals with knowledge and capabilities(He and Wang, 2017). Yet, we find no significant effect of PACs' political status and gender. The possible reason could be the lack of variation in the two variables, in that CPC members and males account for 90% and 75% of the sample respectively.

Taken together, the PACs who made a significant contribution to households' income increases are those in a higher position, working in departments affiliated with a lower level of government but having a close relationship with other departments, and having resources of money, information, and agricultural production.

4.4. Inequality effect of a good match

Considering that the effect on income is likely to be heterogeneous across different households by poverty level, we estimate the effect of matching quality on the change of household income in (i) the ultra-poor group, whose income is lower than the local poverty line (3400 yuan); (ii) the normal-poor group, whose income is above the poverty line but below the mean of our sample; and (iii) the less-poor group, whose income is higher than the mean of the sample but below the mean of the 20% top income group. Table 4 shows that the coefficients of the three groups are all positive, consistent with the results of all samples. Particularly, compared to the mean of initial income or income per capita, we observe that the households with a good match in the ultra-poor group achieved higher income growth than that achieved by households in the normal-poor and less-poor group.

The above finding suggests that matching quality could affect policy resource allocation among the poor. A good match benefits the households at the very bottom of the economic ladder to the largest degree. Hence, at the macro-level, we infer that better matching quality could reduce income inequality among the poor. Therefore, we calculate the Gini coefficients among the poor and the ratio of households with a good match in the village, and plot the relationship of the two variables in Fig. 5. It shows a negative correlation as expected. We then quantify the relationship using a regression as follows:

$$gini_{vt} = \rho_0 + \rho_1 ratio\_matching_{vt} + \rho_2 control_{vt} + \lambda_t + \rho_v + \zeta_{vt} \quad (2)$$

Table 4
The effects of matching quality on the change of IPH's income by poverty level.

Variables	Full Sample	Ultra-poor	Normal-poor	Less-poor
	(1)	(2)	(3)	(4)
Panel A: Change of income				
Matching quality	133.4*	272.4*	189.9**	177.4*
	(78.45)	(148.2)	(75.86)	(94.69)
X	Yes	Yes	Yes	Yes
Average income	9747.2	2405.7	6660.1	11,896.2
Observations	13,644	1822	7804	5256
R-squared	0.126	0.166	0.092	0.042
Panel B: Change of per capita income				
Matching quality	42.98*	317.2*	115.7**	88.23**
	(22.69)	(175.9)	(48.23)	(37.60)
X	Yes	Yes	Yes	Yes
Average income	2895.5	1943.9	2496.8	2863.3
Observations	13,371	1822	7804	5256
R-squared	0.109	0.069	0.047	0.063

Notes: The table estimates the effect of matching quality on the change of IPH's income by poverty level. We probe the robustness of the estimates' accuracy by dividing the sample into three subsamples, i.e., Ultra-poor group (initial income less than the poverty line), Normal-poor group (initial income less than the average income of all IPHs) and Less-poor group. In model (2)–(4), we winsorize the samples to avoid the impacts of extreme values on small sample estimation and set the upper bound of income to be 35,000 yuan. Average income is the average value of initial income of the full ample and the three subsamples. Control variables (*X*) include the characteristics of households and PACs, and policy dummies. All regressions include year effects. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

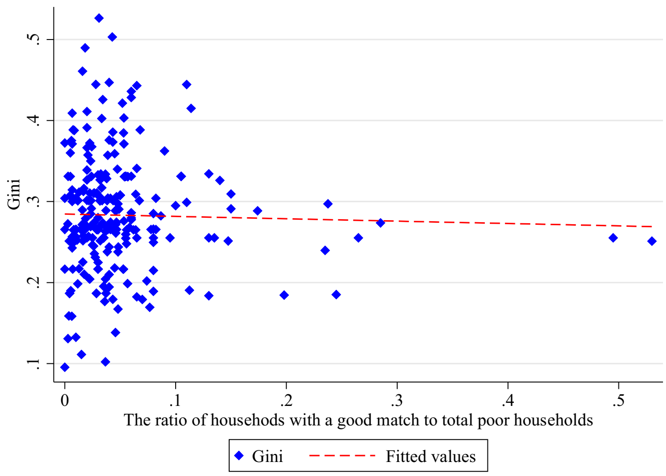

Fig. 5. Relationship between Gini coefficient and ratio of households with a good match.
Notes: The figure shows the relationship between the Gini coefficients among the poor and the ratio of households with a good match in the village.

where $gini_{vt}$ is the Gini coefficient within the IPHs in village v at year t, $ratio\_matching_{vt}$ is the ratio of IPHs with a good match to total IPHs, $control_{vt}$ is a vector of characteristics of the IPHs in village v at year t, including the village income per capita and its square (which in theory is based on Kuznets's inverted U-curve hypothesis), labor force participation rate per households, and mean of the education level of the poor.[7] λ_t is year fixed effects, ρ_v is village fix effects, and ζ_{vt} is the error term. The summary statistics of these variables are summarized in Table 1, Panel A. The average Gini coefficient among the poor is 0.28.

Table 5 summarizes the regression results. Columns 1–3 present results of the full sample. They show that a good match has a significant negative effect on the Gini coefficient, indicating that a good match could help the households at the very bottom obtain needed assistance, and thus reduce income inequality among the poor.

Because the county-wide implementation of some TPA policies, including housing relocation and industrial poverty alleviation, did not start until 2015, we exclude the year 2014 and present the results in columns 4–6. The results show a larger effect as expected, as more policies available mean more resources to be deployed to help the poor.

[7] Greenwood, Guner, Kocharkov, and Santos (2014) and Eika, Mogstad, and Zafar (2019) have explored household income inequality by focusing on women's labor force participation and education level of couples.

Table 5
The effect of matching on income inequality.

	2014–2018			2015–2018		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Ratio of IPHs with a good match to all IPHs	−0.052	−0.077**	−0.054*	−0.054	−0.084**	−0.058*
	(0.033)	(0.033)	(0.029)	(0.036)	(0.036)	(0.031)
Village income per capita		2.083***	2.914***		2.422***	3.013***
		(0.602)	(0.527)		(0.630)	(0.555)
Square of village income per capita (all HHs)		−9.239***	−10.518***		−11.022***	−11.227***
		(3.421)	(2.953)		(3.543)	(3.093)
Labor force participation rate per village			−0.152***			−0.149***
			(0.038)			(0.039)
Mean education level of IPHs per village			−0.097***			−0.089***
			(0.014)			(0.014)
Year-effect	Yes	Yes	Yes	Yes	Yes	Yes
Village-effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	329	329	329	291	291	291
R-squared	0.075	0.120	0.351	0.053	0.113	0.332

Notes: The table shows the results based on village-level data. The dependent variable is the Gini coefficient of all IPHs within a village. Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5. Different measures of matching quality

To further justify our assignment rule, in this subsection we construct three alternative matching quality indexes to re-estimate the effect of matching quality. Following Mendes, Van Den Berg, and Lindeboom (2010) and Hagedorn, Law, and Manovskii (2017),[8] we first divide the sample into households with different poverty causes. In each subsample, we then regress households' income change on the department dummies as follows:

$$\Delta y_{itr} = \alpha_{0r} + \alpha_{1r} \sum depart_{ij} + \alpha_{2r} X_{itr} + \delta_{rt} + \epsilon_{itr} \tag{3}$$

where the subscript r represents the poverty cause of a particular household, $depart_{ij}$ represents the department of household i's PAC j, and X_{itr} are control variables including other characteristics of PACs and households as discussed above.

For each poverty cause r, a larger α_{1r} indicates a larger contribution of the department. So, we use α_{1r} as the alternative matching quality index (Alternative #1). We then replace the matching quality index in the main regression with this alternative and run the otherwise identical regression. The results remain stable, as shown in Table 6, Panel A. We also use the rank of α_{1r} as the alternative matching quality index (Alternative #2). The results remain stable as well, as shown in Table 6, Panel B.

In addition, we conduct a placebo test by generating a random dummy variable as a proxy for the matching quality between PACs and households (Alternative #3), and re-estimate the main regression using the random dummy variable as the matching quality index. The results are summarized in Table 6, Panel C. The coefficient of the random dummy variable is estimated to be small and not statistically significant, as expected.

5. Mechanism

In this section, we explore the mechanism through which a good match increases household income by a larger degree. The potential mechanism is that the poor households with a good match are more likely to receive needed assistance. To construct a measure of whether needed assistance is received needs very detailed information, such as each PAC's home visit records and the corresponding feedback from the visited households. We do not have such data, yet. As a feasible alternative, we distinguish income sources and compare across income levels and poverty causes to indirectly gauge the potential assistance obtained by the households. While not perfect, this exploration could shed light on the mechanism.

[8] Mendes et al. (2010) use three different measures, including correlation coefficient, rank correlation coefficient and regression coefficient, to measure the association between firm-specific productivity and the skills of workers in the firm, based on Portuguese matched employer-employee data; they find evidence of positive assortative matching, that is, good workers are teamed up with good firms. Hagedorn et al. (2017) develop strategies for ranking workers and firms in terms of adjusted wage and job vacancy, respectively, and calculate the rank correlation between workers and firms to denotes the direction and strength of sorting. We are aware that there are two differences between our case and these two studies. One is that the formation of the official-villager match in our case is not a two-way selection. The assignment is randomly assigned by the chief administrators of each department; households have no right to choose the PACs they prefer. The other is that the characteristics of households and PACs are complex and multi-dimensional, and cannot be ranked simply by one-dimensional and available continuous variables. Therefore, we combine and modify the strategies used in the work of Mendes et al. (2010) and Hagedorn et al. (2017).

Table 6
Regression results of the alternative of matching quality index.

Variables	All Sample	Ultra-poor	Normal-poor	Less-poor
	(1)	(2)	(3)	(4)
Panel A: matching quality index, Alternative #1				
Matching quality	0.473***	0.636***	0.421***	0.330***
	(0.0578)	(0.244)	(0.0963)	(0.104)
X	Yes	Yes	Yes	Yes
Observations	13,644	1822	7804	5256
R-squared	0.126	0.166	0.092	0.042
Panel B: matching quality index, Alternative #2				
Matching quality	18.53***	19.20***	15.66***	11.60*
	(3.726)	(3.730)	(5.737)	(6.570)
X	Yes	Yes	Yes	Yes
Observations	13,644	1822	7804	5256
R-squared	0.107	0.166	0.092	0.042
Panel C: Placebo test, Alternative #3				
Matching quality	23.94	423.8	98.47	44.23
	(83.16)	(501.0)	(119.6)	(155.5)
X	Yes	Yes	Yes	Yes
Observations	12,251	1136	5546	3140
R-squared	0.104	0.141	0.129	0.042

Notes: The table estimates the effects of three alternative matching quality indexes on the change of IPHs' income. Panel A and Panel B use the regression coefficient (α_{1r}) and the rank of regression coefficient in eq. (3) as the first two alternative matching quality indexes. Panel C uses the random dummy as the third matching quality index. In model (2)–(4), we winsorize the samples to avoid the impacts of extreme values on small sample estimation and set the upper bound of income to be 35,000 yuan. Control variables (*X*) include the characteristics of households and PACs, and policy dummies. All regressions include year effects. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.1. Heterogeneous effects on income of various sources in income level

We estimate the effect of matching on different sources of income and present the results in Table 7. In panels A through C, we estimate the effects on various sources of income of ultra-poor, normal-poor, and less-poor households, respectively.

Panel A shows that, for the households in the ultra-poor group, the effect of matching quality is mainly from the increase in operational income (e.g., income from farming and small family business). Because most of the households in this group already have been covered by transfer policies (like Dibao), the marginal improvement that the PACs could offer is by providing health services or safety guidance in agricultural production to promote productivity and obtain more operational income.

Panel B shows that the households in the normal-poor group with a good match have a higher increase in both operational income

Table 7
Effects of matching on different sources of income by poverty level.

Variables	Δwage	Δoperational income	Δproperty income	Δtransfer
	(1)	(2)	(3)	(4)
Panel A: Households in Ultra-poor group				
Matching quality	76.78	191.4***	205.7	−22.86
	(189.3)	(63.62)	(217.3)	(48.11)
X	Yes	Yes	Yes	Yes
Observations	1805	1802	1782	1822
R-squared	0.149	0.024	0.024	0.131
Panel B: Households in Normal-poor group				
Matching quality	137.0	77.56**	7.169	48.75**
	(92.58)	(36.29)	(22.28)	(20.77)
X	Yes	Yes	Yes	Yes
Observations	7772	7721	7597	7804
R-squared	0.119	0.022	0.030	0.189
Panel C: Households in Less-poor group				
Matching quality	187.2*	61.23	12.06	12.55
	(112.2)	(80.77)	(15.24)	(21.46)
X	Yes	Yes	Yes	Yes
Observations	5242	5002	5035	5256
R-squared	0.070	0.021	0.102	0.169

Notes: The table estimates the effects of matching quality on the change of IPHs' difference income sources (i.e., wage, operational income, property income and transfer). Control variables (*X)* include the characteristics of households and PACs, and policy dummies. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

and transfer income. This suggests that, for this group, there are multiple channels to achieve an income increase with the help of PACs. First, this group is usually able to work. So the PACs could provide them with work opportunities (e.g. work information from downtown, other counties, and other provinces), incentivize them to migrate to urban areas for work (e.g. providing subsidies for the poor who work outside the province), and help women find a nearby and flexible job. Second, PACs could help improve labor productivity by offering agricultural and internet technology training, helping households apply for interest-free loans to raise livestock or plant cash crops, and so on. Besides, households in this group are always on the brink of the ultra-poor group but are less covered by transfer policies. PACs could encourage or help those households apply for transfer income.

Panel C shows that the households with a good match in the less-poor group show a large increase in wage income, while the other three sources of income are not significantly different from those in the same income group but without a good match. Households in this group have a relatively higher education level and are relatively competitive in the labor market. Hence, the PACs could help them by eliminating the potential barriers of labor markets and incentivizing them to earn more.

Together, these findings suggest that the assistance that the PACs provided not only solved the basic needs of the poorest households but also helped poor households with available labor to participate in agricultural production or labor markets, and increased their productivity through various measures, leading them on the path toward sustainable livelihoods.

5.2. Heterogeneous effects on income of various causes of poverty

To investigate whether the assistance provided by the PACs meet households' needs, we divide the sample into different poverty causes and explore the effects on income of various sources for the households with different poverty causes. Each panel in Table 8 summarizes the results for one poverty cause.

Panels A shows that the poor households with disease as the cause of poverty have a significantly higher increase of wage, property income (e.g., rents from land, collective income dividends, and other property appreciation gains), and transfer income in the good match group. This result suggests that PACs may deliver employment opportunities or transportation subsidies to those household members without disease. They may also provide loans for the households to overcome the difficulties in medical expenditure, help those members with disease apply for medical reimbursement and transfer policies to relieve the burden of disease, etc.

Panels B shows that, for households with members suffering from disabilities, a good match leads to a higher increase in wage, operational income, and transfer income. Column 1 suggests that PACs may help households participate in the labor market. This result is consistent with the findings of field surveys in Xin County: with PACs' assistance, some people with disabilities get a public welfare job, while some obtain free assistive devices like a wheelchair, crutches, or a hearing aid, and thus have an improvement of self-care ability, which allows other household members to go to work. Column 2 suggests these households get assistance related to agricultural production. Column 4 indicates that, with the help of PACs, more disabled people are able to get access to disability policies and receive disability allowance.

Panel C shows that a good match leads to a higher increase of transfer income and wages for the households whose poverty is caused by children's education expenditure. The PACs may help the children apply for education subsidies or loans and may also provide job opportunities to their parents to become able to afford education expenditures.

Panel D indicates that, with the help of the PACs, households who lack skills may receive training related to practical agricultural technology and skill training that increases their labor productivity. From a sustainability perspective, the PACs offer labor-incentive oriented assistance rather than direct transfer, which enhances the ability of households to sustain a livelihood.

Panel E confirms the finding in panel A in Table 8 that elderly households have a higher increase of agricultural income in the good match group. It suggests that some of them are still able to work, implying that there is still a potential labor dividend in rural areas.

In panel F, rather interestingly, we find that the households who lack motivation have a higher increase in wages and agriculture income in the good match group. It suggests that PACs succeed in shifting their attitude about working to be positive, probably through life coaching and encouragement. We are encouraged to find no increase in transfer income, which would further decrease the incentive to work.

6. Conclusion

Targeting assistance to the truly poor is one of the most pressing issues in international development, especially in developing countries. The predominant practice of international poverty reduction, including the UN's Millennium Village Project (MVP) and many “small but true” experiments, mainly focuses on economic growth or the efficacy of a specific approach. Little attention has been paid to the implementation issues in targeting assistance to the truly poor, which is critical to the success of anti-poverty programs. In this paper, we introduce the Poverty Alleviation Coordinator (PAC) system adopted in China's TPA program and evaluate the role of the quality of the match between PACs and poor households.

Applying regression analysis to China's Poor Population Tracking Dataset in Xin County, we find that households with a large income increase after the program are those whose assigned PACs work in government departments that have the resources needed by the households – in particular, the PACs in higher positions, in departments related to agricultural resources, and those who have advantages in deploying money, and information. Further analysis points out that PACs indeed provide needed assistance for paired households. These types of assistance are incentive-oriented and aim to promote labor supply. These findings provide evidence that matching between PACs' resources and the causes of a household's poverty could play a central role in accurately targeting the truly poor and effectively targeting interventions to poor households.

Due to the lack of specific information about what PACs have done during the home visits, we can only infer their efforts in terms of

Table 8
Effects of matching on different sources of income by poverty cause.

Variables	Δwage	Δoperational income	Δproperty income	Δtransfer
	(1)	(2)	(3)	(4)
Panel A. Households impoverished by disease				
Matching quality	320.4**	55.14	63.78***	46.22*
	(127.3)	(44.42)	(17.76)	(28.04)
X	Yes	Yes	Yes	Yes
Observations	4353	4312	4265	4361
R-squared	0.125	0.026	0.113	0.164
Panel B. Households impoverished by disability				
Matching quality	290.2*	460.8***	35.85	249.2*
	(146.0)	(174.4)	(24.42)	(132.6)
X	Yes	Yes	Yes	Yes
Observations	2077	2036	2022	2001
R-squared	0.135	0.024	0.162	0.114
Panel C. Households impoverished by children's receiving education				
Matching quality	1056**	219.6	264.5	1137***
	(462.7)	(172.5)	(172.91)	(327.9)
X	Yes	Yes	Yes	Yes
Observations	1448	1441	1408	1558
R-squared	0.092	0.036	0.141	0.443
Panel D. Households impoverished by lack of skill				
Matching quality	522.1***	216.4**	99.87	15.58
	(163.5)	(88.34)	(88.75)	(53.65)
X	Yes	Yes	Yes	Yes
Observations	4901	4414	4247	4457
R-squared	0.109	0.028	0.200	0.117
Panel E. Households impoverished by lack of labor (the elderly)				
Matching quality	141.1	378.8**	54.48	28.62
	(238.1)	(161.4)	(46.16)	(78.28)
X	Yes	Yes	Yes	Yes
Observations	769	766	762	770
R-squared	0.153	0.025	0.141	0.148
Panel F. Households impoverished by lack of motivation				
Matching quality	552.2**	276.1**	43.94	−7.156
	(272.8)	(109.4)	(36.65)	(54.96)
X	Yes	Yes	Yes	Yes
Observations	1197	1382	2168	2202
R-squared	0.111	0.062	0.202	0.121

Notes: The table estimates the effect of matching quality on the change of IPHs' difference income sources (i.e., wage, operational income, property income and transfer). Control variables (*X)* include the characteristics of households and PACs, and policy dummies. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

changes in households' income from different sources. Further investigation is needed on the mechanisms, such as which activities during home visits could help with information collection and communication. What kind of specific assistance can most help different types of households? Further, given that the process of home visits can provide information, money, training, and social capital/networks, it is worth investigating the specific contributions of these elements and whether better communication technologies or holding meetings can replace home visits. Answering these questions could help us better understand the mechanisms of matching quality and home visits and therefore improve the targeting efficiency of aid programs.

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Appendix

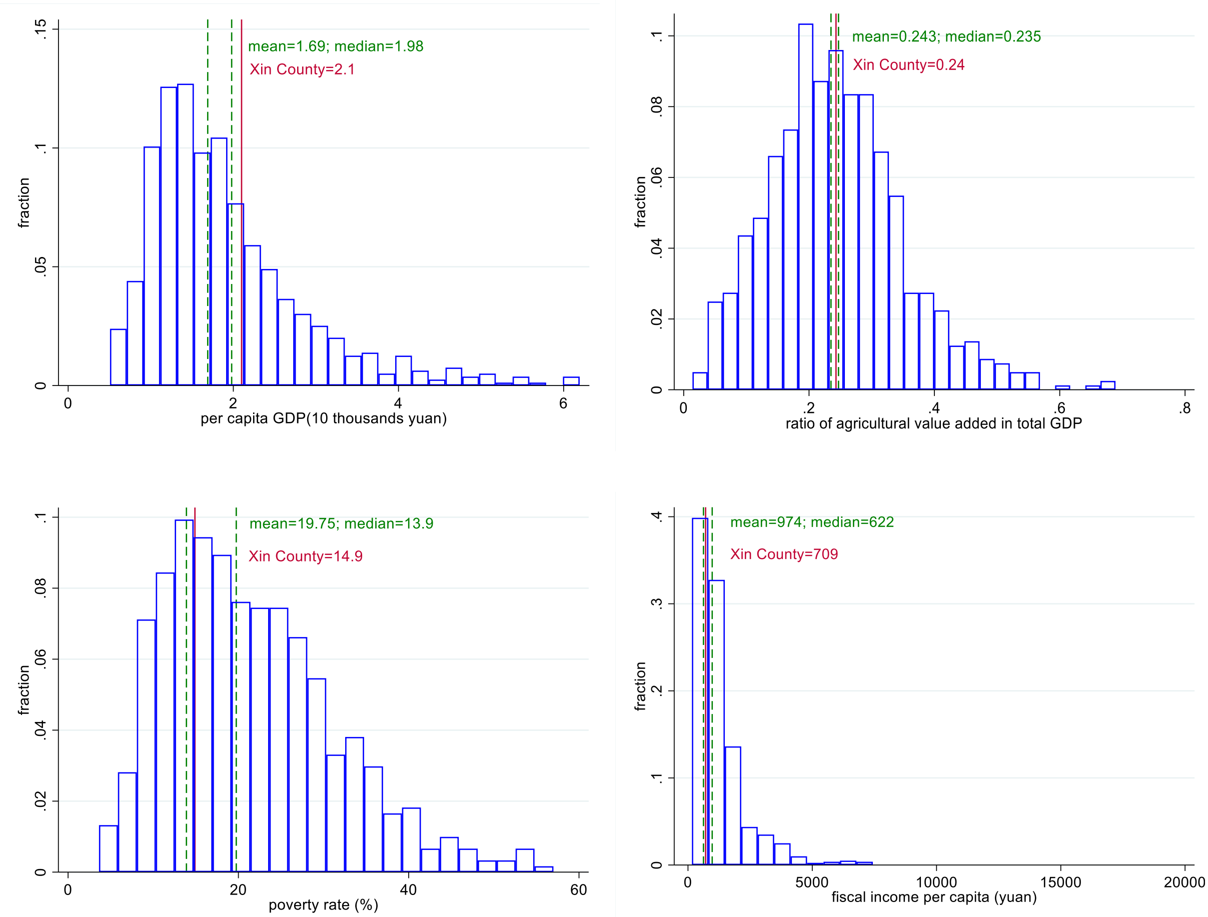

Fig. A1. Distributions of Socioeconomic Variables.

Notes: Fig. A2 shows that the poverty level and the economic characteristics of Xin County are similar to the median of the poverty-stricken counties, including poverty rate, economic development level (per capita GDP), industrial structure (ratio of agricultural value-added in total GDP), and fiscal income per capita in 2014. Data are from the China Statistical Yearbook (county-level).

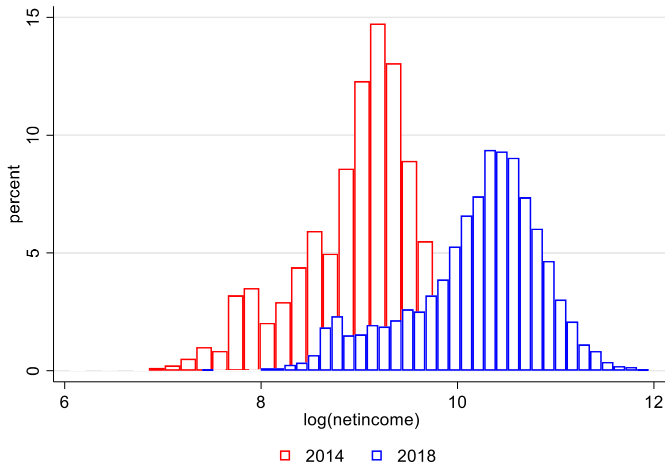

Fig. A2. The distribution of households' net-income in 2014 and 2018.

*Notes:*This figure shows the distribution of households' net-income (logarithm) in the IPHs system in 2014 (red-color bar) and 2018(blue-color bar). To avoid the risk of recurrence of poverty, households that succeed in getting out of poverty are not cleared from the poverty registry system, and local governments are expected to track their information until 2020. Thus, we can observe a higher level of income distribution in 2018.

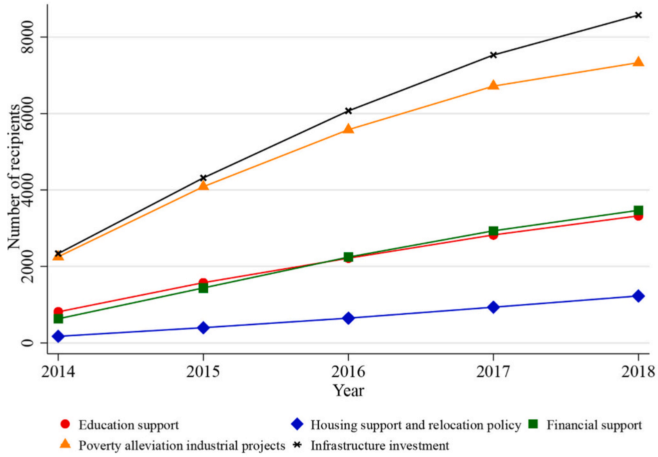

Fig. A3. The accumulated number of recipients of different policies in 2014–2018.
Notes: This figure shows the accumulated number of households that receive policy support (education support and financial support) or covered by policy programs (Housing support and relocation policy, poverty alleviation industrial projects and infrastructure investment) has increased from 2014 to 2018.

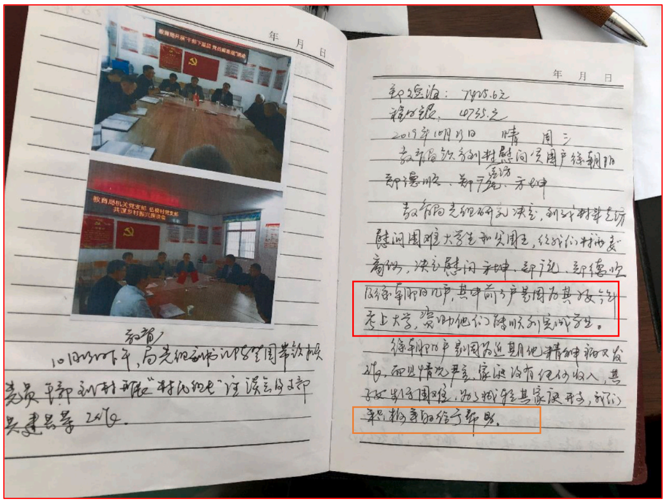

Fig. A4. The work records of a PAC from the department of education.
It records that in October, 23th, 2019, this PAC and his colleagues in the department of education visited poor households in the designated villages. During the home visits, they provided education funds for the three households whose poverty cause is children's education expenditure. Yet, for one household that has a member suffering from disability and lack of support from children, the PAC could only promise to strive for available assistance rather than directly provide the assistance.

Table A1
Categories of departments.

Departments	Sectors	Function/ resources
Comprehensive departments	government at the county, township and village level, development and reform commission, the Chinese People's Political Consultative Conference, and National People's Congress.	making plans and effective intervention according to the guideline of TPA strategy
Agriculture and asset	Department of grain, tobacco, tea, food, livestock, agriculture, forest and land	developing industrial poverty alleviation projects, providing agricultural production materials (like seeds, fertilizer, livestock etc.).
Infrastructure	electricity department, electric company, electric communication company, water conservancy department, road and transport department, petroleum and petrochemical company, postal and logistics enterprises	Improving accessibility of infrastructure to the poor
supervision departments	organization department, state commission office, bureau of government offices administration, united front work department, judicial office, procuratorates, discipline inspection commissions	Managing the operation of government, assigning staff positions, monitoring, proposing policy, etc.
Finance	Public finance department, bank, credit institution, guarantee company	Financial support

(continued on next page)

Table A1 (*continued*)

Departments	Sectors	Function/ resources
Labor and market	Labor department, Human Resources and Social Security Bureau, commerce bureau, investment promotion bureau, commerce and industry bureau	Employment support
Health	County health and family planning commission, hospital, village health service centers	health services
Education	school, education department	Education support
Information	publicity department, complaints bureau, statistics bureau, culture and broadcasting bureau	Spreading policy information
Social aid	civil administration, women's federation, disabled persons' federation, the Red Cross	Social assistance (money or in-kind transfer)

Notes: The table shows the sectors covered by departments by function.

References

Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., & Tobias, J. (2012). Targeting the poor: Evidence from a field experiment in Indonesia. *American Economic Review, 102*, 1206–1240.

Alatas, V., Purnamasari, R., Wai-Poi, M., Banerjee, A., Olken, B. A., & Hanna, R. (2016). Self-targeting: Evidence from a field experiment in Indonesia. *Journal of Political Economy, 124*(2), 371–427.

Banerjee, A.. (1997). A theory of misgovernance. *Quarterly Journal of Economics, 112*(4), 1289–1332.

Banerjee, A., Duflo, E., Chattopadhyay, R., & Shapiro, J. (2009). *Targeting efficiency: How well can we identify the poorest of the poor?*. Unpublished.

Banerjee, A., & Duflo, E.. (2011). *Poor economics: A radical rethinking of the way to fight global poverty*. Public Affairs.

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Parienté, W., & Udry, C. (2015). A multifaceted program causes lasting Progress for the very poor: Evidence from six countries. *Science, 348*, 1260799.

Banerjee, A. V. (2007). *Making aid work*. MIT Press.

Briggs, R. C. (2017). Does foreign aid target the poorest? *International Organization, 71*(1), 187–206.

Collier, P., & Dollar, D. (2002). Aid allocation and poverty reduction. *European Economic Review, 46*(8), 1475–1500.

Easterly, W. (2003). Can foreign aid buy growth? *Journal of Economic Perspectives, 17*(3), 23–48.

Easterly, W. (2006a). Planners Vs. Searchers in Foreign Aid. *Asian Development Review, 23*(2), 1–35.

Easterly, W. (2006b). The big push Déjà vu: A review of Jeffrey Sachs's the end of poverty: Economic possibilities for our time. *Journal of Economic Literature, 44*(1), 96–105.

Easterly, W. (2009). Can the west save Africa? *Journal of Economic Literature, 47*(2), 373–447.

Eika, L., Mogstad, M., & Zafar, B. (2019). Educational Assortative mating and household income inequality. *Journal of Political Economy, 127*, 2795–2835.

Golan, J., Sicular, T., & Umapathi, N. (2017). Unconditional cash transfers in China: Who benefits from the rural minimum living standard guarantee (Dibao) program? *World Development, 93*, 316–336.

Greenwood, J., Guner, N., Kocharkov, G., & Santos, C. (2014). Marry your like: Assortative mating and income inequality. *American Economic Review, 104*, 348–353.

Hagedorn, M., Law, T. H., & Manovskii, I. (2017). Identifying equilibrium models of labor market sorting. *Econometrica, 85*, 29–65.

Hashemi, S. M., & De Montesquiou, A. (2011). Reaching the poorest: Lessons from the graduation model. *Focus Note, 69*, 1–15.

He, G., & Wang, S. (2017). Do College graduates serving as village officials help rural China? *American Economic Journal: Applied Economics, 9*, 186–215.

Kakwani, N., Li, S., Wang, X., & Zhu, M. (2019). Evaluating the effectiveness of the rural minimum living standard guarantee (Dibao) program in China. *China Economic Review, 53*, 1–14.

Liu, Y., Liu, J., & Zhou, Y. (2017). Spatial-temporal patterns of rural poverty in China and targeted poverty alleviation strategies. *Journal of Rural Studies, 52*, 66–75.

Martens, B. (2005). Why do aid agencies exist? *Development Policy Review, 23*(6), 643–663.

Mendes, R., Van Den Berg, G. J., & Lindeboom, M. (2010). An empirical assessment of Assortative matching in the labor market. *Labour Economics, 17*, 919–929.

Moyo, D. (2009). *Dead aid: Why aid is not working and how there is a better way for Africa*. Macmillan.

Niehaus, P., Atanassova, A., Bertrand, M., & Mullainathan, S. (2013). Targeting with agents. *American Economic Journal: Economic Policy, 5*(1), 206–238.

Olken, B. A. (2006). Corruption and the costs of redistribution: Micro evidence from Indonesia. *Journal of Public Economics, 90*(4–5), 853–870.

Qian, N. (2015). Making Progress on foreign aid. *Annual Review of Economics., 7*(1), 277–308.

Ravallion, M. (2012). Fighting poverty one experiment at a time: Poor economics: A radical rethinking of the way to fight global poverty: Review essay. *Journal of Economic Literature, 50*(1), 103–114.

Reinikka, R., & Svensson, J. (2004). Local capture: Evidence from a central government transfer program in Uganda. *The Quarterly Journal of Economics, 119*(2), 679–705.

Roelen, K., & Devereux, S. (2019). Money and the message: The role of training and coaching in graduation programming. *The Journal of Development Studies, 55*, 1121–1139.

Roelen, K., Kim, S. K., Barnett, I., & Chanchani, D. (2019). *Pathways to stronger futures in Haiti: The role of graduation programming in promoting early childhood development*. Brighton: Institute of Development Studies.

Sachs, J. D. (2005). *Investing in development: A practical plan to achieve the millennium development goals*. New York: United Nations Millennium Project.

The World Bank. (2013). *Africa's pulse* (Vol. 7). The World Bank.

Wasik, B. H. (1993). Staffing issues for home visits programs. *The Future of Children, 3*, 140–157.