Differential Impact of a Poverty Alleviation Program Targeting the Ultrapoor in the Philippines

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ABSTRACT

Poverty alleviation programs typically target households below a certain threshold and provide the same intervention. International Care Ministries is a non-governmental organization in the Philippines that provides an educational training program called Transform targeting the ultrapoor. Using data collected from pre- and post-Transform, we estimated a multivariable logistic regression to analyze the differential impact of Transform on the income of the participants. The program appeared to be successful in increasing the income of the poorest thereby helping alleviate persisting inequalities. The analyses showed that baseline income, highest educational attainment of the participant, and geographically type of residence affect the outcome of the intervention. The results demonstrated that thresholds are important in identifying a target population, but programs can be more successful when interventions are designed for a certain profile of people living below these thresholds.

Keywords: Poverty alleviation, Ultrapoor, Inequality, Philippines

1. Background

The Philippines has experienced significant economic growth in recent years. In contrast with this growth, poverty reduction efforts have not followed suit. In 2006, The World Bank estimated that 26.6% of the country lived in poverty, representing 23 million people. According to estimates by Philippine Statistics Authority in 2015, almost a decade later, 26.3% of Filipinos remain in poverty, reflecting virtually no change in the proportion of poor, and an increase in the absolute number living in poverty. From 1991 to 2012, the Gini coefficient in the Philippines reported by The World Bank stayed between 42 to 46, showing that inequality remained unaffected by the country's economic development.

In the same period, significant efforts were made to alleviate poverty. For example, the Department of Social Welfare and Development (DSWD) of the Philippine government implemented a conditional cash transfer program called Pantawid Pamilyang Pilipino Program (4Ps) to the 'poorest of the poor' across all regions of the country. This program provides cash grants of up to 15,000 Philippine Pesos (PHP) per year to families with 3 or more children. According to the Philippine government's website, 27.15 Billion PHP has been paid to beneficiaries in August 2015, and the budget in 2017 has increased to 49.4 Billion PHP (Ager, 2016). Non-governmental organizations (NGOs) have concurrently implemented programs that target families living at a comparable socio-economic position (SEP). This study will focus on data from a poverty-alleviation program run by International Care Ministries (ICM).

ICM's program is called 'Transform', a 16-week curriculum covering health, values and livelihood topics for households that are classified as 'ultrapoor'. Households are targeted using a poverty score card, loosely based on the Progress out of Poverty Index (PPI) developed for the Philippines (Innovations for Poverty Action, 2014). Prioritized are households estimated to be ultrapoor by income ($\leq$ 22 PHP per person per day) versus those in extreme poor (>22 PHP & $\leq$55 PHP per person per day) or entrepreneurial poor (>55 PHP & $\leq$110 PHP per person per day) categories. During Transform, participants are also screened for health issues, provided treatment if necessary, given gardening kits, encouraged to engage in group savings and receive micro-loans to experience entrepreneurship via small business kits. Unpublished internal longitudinal household surveys on participants and randomized controlled trial analyses have found that on average, households will experience statistically significant income growth over the course of the program.

In previous rounds of the program, a proportion of Transform households were found to be actively part of the 4Ps program, which targets the poorest families of an area using a survey called NHTS-PR. This study will examine how households in Transform compare to households which are in both Transform and 4Ps, in addition to the role of other factors such as family size, baseline income level, and geographical type. As a key outcome of program success is the increase of household income or consumption, the following analysis will explore whether certain Transform households are more or less likely to experience positive income change and if there are differential effects due to baseline characteristics.

2. Data and Methods

We used data collected from baseline and endline household surveys of Transform participants who joined from October 2016-January 2017. Participants were screened using a poverty score card for qualification as a participant. The analyses reported here focus on the 3726 households who were surveyed at baseline and endline and classified as either ultrapoor, extreme poor, and entrepreneurial poor at baseline. There were 102 households who earned more than 110 PHP per person per day and were dropped from the analyses. Approximately 90% of the households were ultrapoor and extreme poor.

To better understand the possible differential impact of a poverty alleviation program like Transform on people living in different levels or intensities of poverty, we investigated the factors that affect a participating household's income change. In the regression model, we defined the experience of an income increase after Transform as the dependent variable and participation in government programs, socio-economic characteristics and geographical types of residence as explanatory variables. Our final specification is

$$\begin{aligned} IncomeChange_i &= \beta_1 PovertyCat_i + \beta_2 Pantawid_i + \beta_3 PhilHealth_i + \beta_4 Educ_i \\ &+ \beta_5 Geotype_i + \varepsilon \end{aligned}$$

where $IncomeChange_i$is a binary variable denoting when a Transform participant experiences an increase in income. $PovertyCat_i$ is a categorical variable that classifies the Transform participant's level of poverty at baseline. $Pantawid_i$ is a binary variable that identifies whether a Transform participant is a participant of the government's 4P's program. $PhilHealth_i$ is a binary variable that identifies registration with the government health insurance program. $Educ_i$ is a categorical variable that identifies the participant's highest educational attainment. $Geotype_i$ is a categorical variable that identifies whether the participant lives in a rural mountain, rural coastal, rural plain, rural slum, urban mountain, urban coastal, urban plain, or urban slum area.

We initially considered change in income as a continuous main outcome variable. After performing a Shapiro-Wilk Normality test, we reject the null hypothesis that the variable is normally distributed with test statistic of 0.9231 with a p-value of $2.2e{-16}$. The result suggested that a linear regression model would not be appropriate. So we estimate our model using a multivariable logistic regression model on a binary outcome. To account for other demographic variables that may affect program experience, we accounted for civil status, ownership of birth certificate, and gender. However, these coefficients were dropped from the analysis because they were statistically insignificant and no improvements in AIC were observed. The set of covariates was selected by minimizing the Akaike Information Score (AIC) and therefore selected according to parsimony. The outcome coefficients of the regression model were transformed into predicted probabilities for clearer interpretation of findings. All analyses were conducted in R version 3.3.0.

3. Results

Descriptive summary of households living in different levels of poverty

In our dataset, 1866 households (50.08%) were ultrapoor, 1477 households (39.64%) were extreme poor, and 372 households (9.98%) were entrepreneurial poor at baseline. These households were located across 10 different provinces of the Philippines and lived in coastal (7.83%), rural mountain (33.31%), rural plain (36.77%), urban mountain (2.98%), and urban slum (18.81%) geographical types.

TABLE 1: Summary statistics of data, stratified by poverty status

Variable		Ultrapoor	Extreme Poor	Entrepreneurial
Total	3726	1866 (50.08%)	1477 (39.64%)	372 (9.98%)
Outcome variable				
Change in Income	*average*	19.59 PHP	3.62 PHP	-18.40 PHP
	s.d.	27.41 PHP	29.73 PHP	42.89 PHP
Dependent variables				
Household Size	*average*	5.05	4.62	3.86
	s.d.	1.99	1.90	1.77
Pantawid		712 (38.15%)	534 (36.15%)	99 (26.61%)
PhilHealth		1197 (64.15%)	960 (64.99%)	237 (63.71%)
No education		64 (3.43%)	31(2.09%)	9 (2.42%)
Prep		1 (0.05%)	0 (0%)	2 (0.54%)
Some		581 (31.14%)	367 (24.85%)	86 (23.12%)
Graduated elementary		291 (15.59%)	220 (14.90%)	46 (12.37%)
Some high school		410 (21.92%)	355 (24.04%)	74 (19.89%)
Graduated high school		378 (20.26%)	351 (23.76%)	97 (26.08%)
College or		120 (6.4%)	141 (9.55%)	53 (14.25%)

Table 1 provides the summary statistics of the variables we used in our analysis, stratified by poverty category. At baseline, ultrapoor households earned on average 11.95 PHP per person per day, while the extreme poor and entrepreneurial poor households earned on average 34.77 PHP and 72 PHP, respectively. After Transform, the ultrapoor earned on average 31.54 PHP per person per day. The average income after Transform was 38.40 PHP for the extreme poor households and 53.60 PHP for the entrepreneurial poor households. The ultrapoor households showed the highest increase in income after Transform, while the entrepreneurial poor households experienced on average a reduction in income. The household size of the ultrapoor was on average 5.02 members, while there were on average 4.62 members for the extreme poor households and 3.86 members for the entrepreneurial poor households. Only 38.15% of the ultrapoor households reported they are recipients of 4Ps and 64.15% are members of Philhealth. The numbers are similar for the extreme poor and entrepreneurial poor households. Most Transform participants, regardless of poverty category, attained some level of schooling. Participants in the entrepreneurial poor category were able to attain a higher level of education compared to the extreme poor and ultrapoor.

Regression Results

The results of the mutivariable logistic regression are presented in Table 2. We found that the intensity of poverty at baseline significantly affected the probability of experiencing an increase in income after Transform. Specifically, being extreme poor and entrepreneurial poor rather than being ultrapoor changed the log odds of experiencing an increase in income after Transform by -1.43 and -2.56, respectively. Being a recipient of 4Ps and PhilHealth did not appear to affect the dependent variable. Graduating from high school or attending some college significantly increased the log odds of experiencing a positive change in income after Transform by 0.57 and 0.72, respectively. Living in an urban slum rather than coastal area decreased the log odds of experiencing an increase in income by 0.49.

TABLE 2: Multivariable logistic regression

Variable	Coefficient	Standard
Intercept	1.244 ***	0.261
Ultrapoor	-	-
Extreme poor	-1.437 ***	0.079
Entrepreneurial	-2.560 ***	0.143
Pantawid	-0.024	0.083
PhilHealth	-0.054	0.084
No education	-	-
Prep	0.507	1.770
Some elementary	0.169	0.230
Graduated	0.245	0.239
Some high school	0.297	0.233
Graduated high	0.574 *	0.224
College or higher	0.718 **	0.257
Coastal	-	-
Rural mountain	-0.295	0.151
Rural plain	-0.230	0.150
Urban slum	-0.494 **	0.162
Urban mountain	-0.337	0.252

Note: *** Significant at the 0.1 percent level. ** Significant at the 1 percent level. * Significant at the 5 percent level.

We then calculate predicted probabilities of experiencing an increase in income after Transform based on different characteristics of a Transform participant. We stratified our results based on poverty intensities at baseline, whether the participant is a member of both 4Ps and PhilHealth or not, geographical type of residence, and highest educational attainment of the Transform participant. The results are presented in Table 3.

TABLE 3: Predicted probabilities of experiencing income increase after Transform

		Ultrapoor		Extreme poor		Entrepreneurial poor	
		Non-recipient of 4Ps and PhilHealth	Recipient of 4Ps and PhilHealth	Non-recipient of 4Ps and PhilHealth	Recipient of 4Ps and PhilHealth	Non-recipient of 4Ps and PhilHealth	Recipient of 4Ps and PhilHealth
Coastal	No	0.776	0.762	0.452	0.432	0.211	0.199
	Prep	0.851	0.842	0.578	0.558	0.308	0.292
	Some	0.804	0.791	0.494	0.474	0.241	0.227
	Graduated	0.816	0.804	0.513	0.493	0.255	0.241
	Some high	0.824	0.812	0.525	0.506	0.266	0.250
	Graduated	0.860	0.851	0.594	0.575	0.323	0.306
	College or	0.877	0.868	0.628	0.610	0.354	0.337
Rural Mountain	No	0.721	0.705	0.380	0.362	0.166	0.156
	Prep	0.811	0.798	0.504	0.485	0.249	0.234
	Some	0.753	0.739	0.421	0.402	0.191	0.179
	Graduated	0.767	0.753	0.440	0.420	0.203	0.191
	Some high	0.777	0.763	0.452	0.433	0.212	0.199
	Graduated	0.821	0.809	0.521	0.502	0.262	0.247
	College or	0.841	0.830	0.557	0.538	0.290	0.275
Rural Plain	No	0.733	0.718	0.395	0.377	0.176	0.164
	Prep	0.820	0.809	0.521	0.501	0.261	0.246
	Some	0.765	0.751	0.436	0.417	0.201	0.189
	Graduated	0.779	0.765	0.456	0.436	0.214	0.201
	Some high	0.788	0.774	0.468	0.449	0.223	0.209
	Graduated	0.830	0.819	0.537	0.518	0.274	0.259
	College or	0.849	0.839	0.573	0.554	0.304	0.288
Urban Mountain	No	0.712	0.696	0.370	0.352	0.161	0.150
	Prep	0.804	0.792	0.494	0.474	0.241	0.227
	Some	0.746	0.731	0.410	0.392	0.185	0.173
	Graduated	0.760	0.745	0.430	0.410	0.197	0.185
	Some high	0.769	0.755	0.442	0.422	0.205	0.192
	Graduated	0.815	0.802	0.511	0.491	0.254	0.239
	College or	0.835	0.824	0.547	0.527	0.282	0.266
Urban Slum	No	0.679	0.662	0.335	0.317	0.141	0.131
	Prep	0.778	0.764	0.455	0.435	0.214	0.201
	Some	0.715	0.698	0.373	0.355	0.162	0.152
	Graduated	0.730	0.714	0.391	0.373	0.173	0.162
	Some high	0.740	0.725	0.404	0.385	0.180	0.169
	Graduated	0.790	0.776	0.472	0.452	0.225	0.212
	College or	0.813	0.800	0.507	0.488	0.251	0.237

The calculations demonstrated that that regardless of geographical type of residence, recipients of government programs, and highest educational attainment, ultrapoor households had the highest predicted probability of experiencing an increase in income after Transform compared to extreme poor and entrepreneurial poor households. We also found that across different baseline poverty intensities, participants with higher educational attainment were more likely to benefit from Transform in terms of increased income. The relationship did not appear to be linear, with those attended prep having similar predicted probabilities with those that graduated high school or attended college or higher. Households that lived in urban slum areas appeared to have the lowest predicted probabilities of experiencing a positive income change. Interestingly, while the predicted probabilities of experiencing an increase in income after Transform is similar to those who are recipients of both 4Ps and PhilHealth and those who are not, the predicted probabilities are slightly lower if one was a recipient of both government programs.

4. Discussion

In sum, our findings show that different levels of poverty intensities, even within this narrow stratum of income poverty (i.e. households with income between 0 and 110 PHP per person per day), play a significant role in affecting program outcomes and effectiveness. Households falling into a single broad category, such as having incomes below a rough poverty line, do not imply that the same poverty alleviation program will be effective. It is therefore important to design and implement programs that are effective for a specific level of poverty then target those households precisely with uniquely designed programs.

Government and non-government organizations such as ICM and BRAC have recognized these differential impacts, designing programs specifically targeting the poorest of the poor. The analyses performed above show that ICM's Transform program appears to be effective in reducing inequalities among those living below the poverty line rather than aggravating it by improving the incomes of those who had the lowest baseline income. Interestingly, studies of BRAC's Targeting the Ultrapoor Program showed that income increased in every quantile of income distribution after the program, but the impact is smallest among the people in the lowest quantile (Emran, Robano and Smith, 2009; Gobin, Santos, and Toth, 2016).

The significant coefficients on poverty levels show how people living in different categories of poverty respond differently to a poverty reduction intervention like Transform. This result is important because most poverty reduction interventions like the Philippine government's 4Ps and ICM's Transform target a population below a certain threshold and offer the same program. While this general cutoff may be useful to identify a target population, it can be ineffective for program targeting and design. Specifically, when people living in different poverty intensities respond differently to a program, treating everyone the same way can be less effective. Karlan and Thuysbaert (2016) also argue that the benefits of a program are likely not maximized when a program designed for the ultrapoor are offered to those who may just be above the cutoff. However, most poverty reduction efforts do not consider this differential impact, and it may be one reason why inequality persists in the Philippines and other countries.

The statistical significance of graduating from high school or attending college suggests the important role of education in helping alleviate poverty. This finding is likely because those who have attained a higher level of education have acquired more skills and knowledge to more effectively apply the lessons taught during Transform. Because we observe a differential impact of a program based on educational attainment, it is important for those who design poverty alleviation programs to keep in mind the educational attainment of a typical participant and ensure lessons are understandable and applicable at their level. For example, ICM's impact may improve among the ultrapoor if they are able to revise their curriculum or program delivery that is fit for participants with lower levels of education, as only approximately 30% of the ultrapoor and extreme poor participants that have graduated from high school and/or attended college.

The finding that households living in urban areas are predicted to less likely experience an increase in income provides an example of a poverty alleviation program that works better in certain contexts, such as rural or coastal areas, than in others. For example, it is possible that the livelihood lessons taught during Transform are less likely to be successful in urban areas due to increased competition. Governments and organizations such as ICM with a scale strategy of offering the same poverty reduction program regardless of geographical context may find it beneficial to some lessons of their curriculum to allow their participants to apply lessons based on their contexts.

Further research has to be done in order to understand the determinants of the differential responses of the people living in different intensities of poverty and how programs can be designed that are more effective in increasing incomes for a specific segment of poverty and other interacting characteristics such as education and geographical type of residence.

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