CONDITIONAL CASH TRANSFERS AND SHOCKS: EVIDENCE FROM THE PHILIPPINES

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ABSTRACT

We evaluate the impact of the Pantawid Pamilyang Pilipino Program, a conditional cash transfer (CCT) program in the Philippines, on household welfare in the presence of various shocks to household members such as death, illness, loss of employment, business failure, and natural or man-made disasters. Using a regression discontinuity design (RDD), we estimate whether the CCT program induces its beneficiary households to adjust their spending patterns differently from nonbeneficiaries when exposed to shocks. Our estimates show that on average, CCT beneficiary households may allot anywhere from 1.2 to 2 percentage points smaller share of their household income on alcohol and tobacco, relative to non-CCT beneficiary households when exposed to shocks. We find no evidence that CCT beneficiary households adjust their spending on education when exposed to shocks.

1. Introduction

The implementation of conditional cash transfer (CCT) programs has been increasing steadily in various countries (Das, Do, & Özler, 2005), with the Prospera program in Mexico and the Bolsa Família program in Brazil among the largest in scale. The use of CCTs as a form of social assistance gained popularity in Latin America in the late 1990s and early 2000s, and by the mid-2000s, CCTs were undergoing pilot-testing in Asian countries such as the Philippines. Several studies have estimated the impact of the local CCT program, Pantawid Pamilyang Pilipino Program, on household welfare in the Philippines. These studies generally find that CCT beneficiary households have improved health and education outcomes.

However, one dimension that has yet to be fully studied in the literature is the impact of CCT programs on household welfare in the presence of various shocks to members of the household such as death, illness, loss of employment, business failure, natural or man-made disasters. Using evidence from the CCT program in the Philippines via a regression discontinuity design (RDD), we estimate the impact of the program on expenditures on alcohol and tobacco, and education when households are exposed to shocks. Does the CCT program induce its beneficiary households to adjust their spending patterns differently from nonbeneficiaries when exposed to shocks? This question is interesting because it is possible that CCT beneficiary households are more insulated from shocks relative to nonbeneficiary households, due to the CCT program.

In this paper, we confirm the results of previous impact evaluation studies of the CCT program in the Philippines (Abdon et al., 2014) that first, CCT beneficiary households are more likely to receive healthcare coverage, relative to non-beneficiary households. In addition, we also verify the authors' result that CCT beneficiary households are more likely to attend family development sessions (parenting classes that educate participants on reproductive health), relative to non-beneficiary households. Although we find no evidence that CCT beneficiary households normally spend a smaller proportion of their household income on adult goods such as alcohol and tobacco, our estimates show that when exposed to shocks, CCT beneficiary households on average may allot anywhere from 1.2 to 2 percentage points smaller share of their household income on alcohol and tobacco, as compared to nonbeneficiaries. Our estimates show no significant relationship between receiving CCT benefits and adjusting household expenditures for education. Moreover, we find no evidence that CCT beneficiary households adjust their spending on education when exposed to shocks.

Section 2 provides a review of related literature, while Section 3 gives a more detailed background on the CCT program in the Philippines. The data used in our analysis is described in more detail in Section 4, while Section 5 provides the empirical strategy and identification assumptions. The estimation equations are described in Section 6, and the results are discussed in Section 7, while Section 8 concludes.

2. Literature review

Conditional cash transfers (CCTs) have been one of the most widely-used social assistance programs to reduce poverty, decrease inequality, and expand social inclusion in recent years. CCTs have a two-fold agenda as a tool for poverty alleviation. Beyond supplementing the short-term consumption needs of poor households by providing additional household income, CCTs also support long-term investment in human capital through education, nutrition, and health (de la Brière & Rawlings, 2006). Poor families that satisfy the program requirements receive cash transfers, conditional on increased school attendance or regular visits to health centers (Rawlings & Rubio, 2005). Implementation in various countries in Latin America, Sub-Saharan Africa, and Asia has steadily increased over the last two decades.

The general consensus in empirical studies that assess the impact of cash transfer programs commonly agree that CCTs have significant and positive impacts on various welfare indicators of poor households in developing countries (de Brauw & Hoddinott, 2011). In a systematic review done by Baird, Ferreira, Özler, and Woolcock (2014), they find that cash transfer programs generally improve school outcomes in low- and middle- income countries.[1] The authors use data from 75 reports which covered 35 different studies and find that cash transfers, regardless of being conditional or unconditional, improve the likelihood of school enrollment and attendance.

Some studies evaluate the impact of cash transfers on outcomes while accounting for the exposure of poor households to various shocks. These shocks could arise from unexpected changes in factors such as income, weather, policy or when an accident or natural disaster occurs. In the case of the PROGRESA program, de Janvry, Finan, Sadoulet, and Vakis (2006) find that cash transfers conditional on school attendance significantly affect a poor household's school and labor choices.[2] To estimate the impact of CCTs on school enrollment and employment status of children in the presence of shocks, the authors construct "a simple dynamic model of a household's school enrollment and child work decision" (de Janvry et al., 2006, p. 353) given school re-entry costs, availability of conditional cash transfers, and vulnerability to shocks. They confirm their model predictions using panel data from four rounds of the household census conducted from November 1998 to May 2000 in 506 rural localities.[3] In their empirical analysis, the authors estimate the impact of idiosyncratic income, illness and climatic shocks (e.g. unemployment of household head, illness of household head, illness of younger siblings, drought, and natural disaster) on school and labor decisions of poor households receiving cash transfers. de Janvry et al. (2006) find that conditional cash transfers from PROGRESA help mitigate the negative effects of unemployment and illness of the household head and natural disaster shocks.[4] On the other hand, shocks such as drought and illness of younger siblings have no

[1] Studies included in the systematic review were restricted to those published after 1997 (when PROGRESA was implemented) and only those which used experimental (randomized controlled trials) and quasi-experimental designs with a controlled comparison group. A detailed list of databases and search terms used can be found in Baird, Ferreira, Özler, and Woolcock (2014).

[2] The Programa de Educación, Salud y Alimentación (PROGRESA), also referred to as Oportunidades, is a conditional cash transfer program implemented in Mexico in 1997. Poor mothers in rural communities received cash transfers under the condition that their children regularly use the available health facilities and attend school.

[3] The authors restrict the sample to only include children who belong to poor, eligible households.

[4] The authors also examine the heterogenous effects of these shocks on different children sub-groups, conditional on CCT receipt. For instance, they learn that unemployment of the household head affects the schooling outcomes of boys more than girls; while severe natural disasters affect girls more than boys.

significant effect on schooling outcomes, conditional on receiving CCT benefits. These results strongly suggest that the PROGRESA CCT program serves as a valuable safety net for poor households that are exposed to shocks.

Adhvaryu, Nyshadham, Molina, and Tamayo (2018) also investigate the interaction of conditional cash transfers from PROGRESA and household shocks. In particular, they examine the impact of early childhood shocks on the schooling outcomes of children from CCT and non-CCT beneficiary households using a difference-in-difference model. Since most villages in the PROGRESA program are in rural areas, the authors use local rainfall data at the time of a child's birth to represent early-life endowment shocks. [5] They find that children born during heavy rainfall periods have unfavorable school and employment outcomes, relative to children born in periods of normal rainfall. Moreover, their estimates indicate that an additional year of exposure to the program during childhood decreased approximately 20 percent of early life disadvantage. This indicates that beneficiary households of the PROGRESA program that experience early-life shocks are able to recover from the negative impact of poor early life circumstance on education and employment outcomes through conditional cash transfers.

Related similar results have also been found in Asia, particularly in the case of Bangladesh (Alvi & Dendir, 2011). The authors examine the impact of economic factors, such as access to credit, on a household's child labor decision after the Great Floods in 1998. Using data from a unique survey conducted after the floods, the authors use the ratio of assets lost after the floods as a proxy for the exogenous weather shock. Their estimates present a positive relationship between monthly child labor and the number of assets lost, but only if households received no credit.[6] On the other hand, the effect of weather shocks on child labor was not statistically significant for households that received credit. These findings imply the importance of households' economic status – access to credit in the case of the Bangladesh study and receipt of cash transfers in the case of Mexico, in potentially decreasing child labor when shocks occur.

A study by Gitter and Barham (2009) also looks into the impact of cash transfers on school enrollment outcomes of children from poor households exposed to shocks in Nicaragua. The authors account for differences in household wealth, employment opportunities and exposure to negative shocks in estimating the effect of transfers on school versus child labor decisions among poor households. [7] They consider two types of negative shocks, namely occurrence of droughts and major declines in coffee price. Their main findings show that during a price hike, CCTs increase the likelihood of school enrollment in poorer households and also improve enrollment in coffee-cultivating villages.

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[5] Adhvaryu, Nyshadham, Molina, and Tamayo (2018) use the variation in rainfall data to "identify changes in early-life circumstances not correlated with the initial conditions of the parents" (p. 10). They also show that adverse rainfall decreases agricultural wage and significantly affects physical health and cognitive ability. Due to missing rainfall data and after restricting the sample to those from poor households, only the children from 420 out of 506 localities were included.

[6] Alvi and Dendir (2011) use a Tobit difference-in-difference model to estimate the likelihood a child will work. Controlling for child and household characteristics, the regressors used were main asset loss ratio, a dummy variable for credit receiving households, and an interaction term.

[7] The authors point out that coffee-cultivating communities in Nicaragua, holding other factors constant, have better labor market opportunities for children

Although education and labor are the common outcomes focused on in cash transfer studies, some literature also examines the relationship between cash transfers and household consumption in the presence of shocks. Unconditional cash transfers in Zambia were found to be an important factor in the climate change coping mechanism of poor households that experience agricultural production and price shocks (Lawlor, Handa, Seidenfeld, & the Zambia cash transfer evaluation team, 2019).[8] In particular, these transfers considerably help households smooth food consumption and increase food security. Lawlor et al. (2019) also emphasize the importance of timing in the distribution of cash transfers. They find that when transfers are received by households before exposure to shocks, the positive impact on food security is stronger than when it is received *ex-post*.

A systematic review by (Evans & Popova, 2017) studies the impact of cash transfers on spending on temptation goods[9] such as alcohol or tobacco.[10] Using meta-analysis to summarize quantitative evidence from a survey of 42 studies, the authors find that cash transfers, whether conditional or unconditional, for the most part, have either no significant impact, or a significant negative impact on temptation goods (Evans and Popova, 2017). The scope of literature surveyed by the authors include studies on cash transfers from countries in Latin America, Africa, and Asia.

3. Background

The conditional cash transfer (CCT) program in the Philippines, known locally as Pantawid Pamilyang Pilipino Program, is a social protection program implemented by the Department of Social Welfare and Development (DSWD) that is central to the government's poverty reduction and social protection strategy (Fernandez & Olfindo, 2011) . Pantawid Pamilya provides social assistance to poor households in exchange for their participation in education and health programs. In addition to providing monetary assistance to alleviate the financial burden faced by poor households, the CCT program is intended to promote human capital development by improving health and education outcomes.

The Pantawid Pamilya program design is modelled after earlier CCT programs in Latin America such as Bolsa Familia in Brazil and Oportunidades in Mexico. Cash incentives are given to poor households in exchange for fulfilling program conditions such as investing in the education of school-aged children, as well as the health and nutrition of both children and adults in the household. Households classified as poor and have children aged 0 to 14 and / or pregnant women during the assessment period are eligible for the program, as long as they comply with the conditions of the program.

Eligibility for the CCT program is determined through a Proxy Means Test (PMT) that predicts the income of households, based on socioeconomic and demographic indicators such as ownership of assets, characteristics of the dwelling, access to water, sanitation and electricity, and education of household head (Fernandez, 2012). Details of the PMT are discussed in (Fernandez, 2012). Predicting household income based on a set of uniform and observable characteristics as opposed to surveying declared household income

[8] The Zambian unconditional cash transfer program, also known as the Zambian child grant program, gives monthly cash grants to households with the aim of lessening "extreme poverty and intergenerational transmission of poverty to children" (Lawlor et. al., 2019, p. 211). Households that have a child aged less than five are eligible to be in the program.

[9] We refer to alcohol and tobacco in this paper as "adult commodities".

[10] The review includes studies from 1997 to early 2014 that analyze conditional and unconditional cash transfer programs in low and middle-income countries.

may avoid biases in under or overreporting household income. Households with predicted annual per-capita income in Philippine Pesos below their respective provincial poverty line are considered poor.

Utilizing a PMT to estimate household income and determine poor households that are eligible for the CCT program hinders households from manipulating their location with respect to the poverty threshold, which is also the cut-off in the regression discontinuity design (RDD), while the predicted household per capita income is used as the running variable.

4. Data

For our empirical analysis, we use the 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set. This cross-section data set is based on a survey of 5,041 households in 26 provinces. The survey covers 30 municipalities, with 10 municipalities in each of the three major islands of the Philippines.

Table 1: Program implementation among households

	Poverty status		
CCT	Non-poor	Poor	Total
Non-beneficiaries	2,238	308	2,546
Beneficiaries	144	2,351	2,495
Total	2,382	2,659	5,041

The PMT produced estimates of per-capita income within each household. A household is classified as poor if the estimated income based on the PMT is below the regional poverty threshold. The program design designates poor households to receive CCT benefits. On the other hand, if the estimated income is equal to or above the regional poverty threshold, the household is classified as non-poor, and is therefore ineligible to receive CCT benefits. However, **Table 1** shows the actual program implementation in the sample, where 308 out of the 2,659 poor households did not receive CCT benefits, while 144 out of 2,382 non-poor households received CCT benefits.

Table 2 shows the extent to which the PMT predicts CCT participation using a linear probability model:

$$yCCT_i = a + bPoor_i + u_i \quad (1)$$

where CCT = 1 if household *i* is a CCT beneficiary, 0 otherwise; and Poor = 1 if household *i* is considered poor and should ideally receive benefits; 0 otherwise.

Table 2: Poverty status and CCT benefits

	(1)
VARIABLES	CCT beneficiary
Poor	0.824***
	(0.00790)
Constant	0.0605***
	(0.00488)
Observations	5,041
R-squared	0.677

Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

For households whose predicted incomes are near their respective regional poverty threshold (cut-off), being classified as a poor household based on the PMT is estimated to increase the probability of receiving CCT benefits by 82.4 percentage points, relative to households classified as non-poor based on the PMT.

Table 3 below shows the distribution of poor and non-poor households by province. The provincial poverty line is used as the cut-off. Households with an estimated annual per-capita income in Philippine Pesos (based on the PMT) less than the provincial poverty line are considered poor. Except for Zamboanga Sibugay and Agusan del Sur, most provinces in the sample have a similar proportion of sampled households on both sides of the cut-off. For our analysis, we use re-centered income (*Rinc*) which is the deviation of the annual per-capita household income, predicted using the PMT, from the corresponding poverty line in the province a household belongs to. A household is considered poor if the re-centered income is less than zero.

Table 3: Distribution of poor households by province

Province	Cutoff	Households	% poor	% non-poor
Bukidnon	12,186	180	50	50
Zamboanga Sibugay	12,188	154	63	37
Catanduanes	13,654	145	51	49
Sarangani	13,746	180	48	52
Samar (Western Samar)	13,869	341	54	46
Leyte	13,919	291	53	47
Zamboanga del Norte	13,947	166	56	44
Cebu	13,960	322	51	49
Negros Occidental	13,975	180	50	50
Masbate	14,248	172	53	47
Agusan del Sur	14,544	152	73	27
Misamis Oriental	14,787	165	55	45
Iloilo	14,810	168	52	48
Guimaras	14,811	145	52	48
Camarines Norte	14,854	176	52	48
Aklan	15,150	180	50	50
Surigao Del Sur	15,264	166	54	46
South Cotabato	15,431	210	50	50
South Cotabato	15,431	180	52	48
Pangasinan	15,656	180	50	50
Quezon	16,125	150	51	49
Albay	16,128	175	53	47
La Union	16,372	150	50	50
Lanao Del Sur	16,567	180	50	50
Zambales	16,685	150	50	50
Oriental Mindoro	16,723	203	54	46
NCR First District	20,868	180	52	48

Cut-offs are in Philippine Pesos, annual.

5. Empirical strategy and identification assumptions

To evaluate the impact of the CCT program on households, we use a Regression Discontinuity Design (RDD) to compare the outcomes of households below and above the cut-off. Although **Table 1** shows imperfect program implementation, we present estimates using both fuzzy RDD and a reduced-form sharp design where we directly compare the outcomes of poor vs. non-poor households.

Since each province has its own poverty line, each province in our sample has its own cut-off. Thus, we use re-centered per capita income, which is the difference between household per capita income and the provincial poverty line the household belongs to. We also use three bandwidths in our analysis to vary the evaluation sample.

Using a uniform bandwidth for all provinces that is not based on income percentiles that are province-specific may result in biased estimates. For instance, if one province has many observations above and only a few observations below the cut-off, then the results may be driven by differences in the proportion of households above and below the cut-off in this province relative to others. Thus, balancing the weights of different provinces on both sides of the cut-off requires a different bandwidth per province based on local income percentiles.

To this end, we use bandwidths that compare the same re-centered income percentile range on both sides of the cut-off for each province. These bandwidths are shown in **Table 4**. In our sample, the province with the most disproportionate distribution in the sample is Agusan del Sur where 73% of households are below the cut-off **(Table 3).** Thus, to include all provinces in the analysis, the bandwidth should include at most 27% of the sample on either side of the cut-off.

The narrowest bandwidth, BW1, has an evaluation sample of households with re-centered income up to 10 percentiles below, and 10 percentiles above each corresponding provincial cut-off. BW1 has a sample size of 1,016 households. BW2, which has an evaluation sample of households with re-centered income up to 15 percentiles below, and 15 percentiles above each provincial cut-off has a sample size of 1,502 households. The widest bandwidth, BW3, has an evaluation sample of households with re-centered income up to 20 percentiles below, and 20 percentiles above each corresponding provincial cut-off. The sample size of BW3 is 2,010 households. Being the narrowest among the three, BW1is likely to yield the least bias but also the largest standard errors, given the smaller sample size. On the other hand, BW3, which has the highest number of observations among the three bandwidths, may give the most precise estimates, but it may also result in the largest bias among the three.

Table 4: Bandwidths by Province

Province	BW1: 10 percentiles			BW2: 15 percentiles			BW3: 20 percentiles		
	Below	Above	Range	Below	Above	Range	Below	Above	Range
Lanao del Sur	-1451	1447	2898	-1882	2134	4016	-3357	2844	6201
Cebu	-1643	1281	2924	-2519	2073	4592	-3780	3030	6809
South Cotabato	-1824	1202	3026	-2798	2127	4925	-3649	3265	6915
Aklan	-1510	1649	3160	-2400	2536	4937	-3831	4259	8090
Leyte	-1925	1236	3162	-3336	1963	5300	-4083	2818	6901
NCR First District	-1399	1919	3318	-2327	3013	5340	-3080	3907	6987
Zambales	-1936	1458	3394	-2295	2763	5058	-3059	3875	6934

Western Samar	-2012	1443	3455	-2887	2067	4954	-3525	2621	6146
Misamis Oriental	-2338	1167	3505	-3361	2014	5375	-4265	2552	6817
Masbate	-2688	830	3518	-3500	2260	5760	-4085	2927	7011
Pangasinan	-2227	1296	3522	-3036	1871	4907	-4321	3089	7410
Catanduanes	-2310	1302	3612	-3051	1818	4869	-3870	3152	7022
Bukidnon	-2190	1454	3644	-2842	1953	4795	-3723	3123	6847
La Union	-2464	1243	3707	-3548	2215	5763	-4704	3287	7991
Saranggani	-1916	1847	3763	-3359	2408	5767	-4427	3454	7881
Zamboanga del Norte	-2367	1429	3795	-3454	1899	5353	-4222	3247	7469
Zamboanga Sibugay	-2151	1695	3846	-3161	2747	5908	-3940	4457	8398
Zamboanga Sibugay	-2151	1695	3846	-3161	2747	5908	-3940	4457	8398
Camarines Norte	-2510	1336	3846	-3380	2220	5599	-4308	3533	7841
Negros Occidental	-2001	2048	4049	-2979	3128	6108	-3978	4106	8084
Oriental Mindoro	-2593	1512	4105	-3454	2040	5494	-4756	3411	8167
Iloilo	-2097	2529	4626	-3438	3626	7064	-4651	4318	8969
Quezon	-2102	2564	4666	-2655	3435	6090	-3540	3917	7457
Surigao del Sur	-2840	1918	4758	-3524	3207	6731	-4486	4128	8614
Guimaras	-2624	2240	4863	-3468	2869	6337	-4269	3604	7873
Albay	-2063	3227	5291	-2497	3589	6086	-3297	4700	7997
Agusan del Sur	-3131	2919	6050	-3881	4994	8875	-4753	7713	12465

We rely on two main identification assumptions to establish the validity of our estimates. The first condition is that the population should not be able to manipulate their status with respect to the cut-off. Since the PMT used to classify a household as poor or non-poor is based on a set of measurable household characteristics and not the declared household income (Fernandez, 2012), it would be very difficult for households to manipulate their status with respect to the cut-off.

The other condition is that households on both sides of the cut-off should be comparable in that there should be no statistically significant differences in socioeconomic and demographic characteristics measured pre-intervention between households on either side of the cut-off. To this end, we perform validation tests using three different bandwidths and present the results in **Appendix 1**. The results of the validation tests show that overall, there is no statistically significant difference among socioeconomic and demographic indicators between poor and non-poor households. Among the 13 covariates (measured pre-intervention) tested, only the indicator for house ownership showed discontinuity at the cut-off for the narrowest bandwidth, but reassuringly, the indicator for renting a house did not show discontinuity for any of the three bandwidths. It is not unusual to have one out of the 13 covariates statistically significant for one bandwidth. Thus, the validation tests verify the comparability of poor and non-poor households by establishing the socioeconomic and demographic similarity of households on either side of the cut-off.

6. Estimation equations

We estimate both sharp and fuzzy RDD in our analysis. Sharp RDD refers to a reduced-form analysis where we directly compare the outcomes of poor vs. non-poor households as discussed below.

Equation 2 gives the specification for the sharp RDD estimate for each sampling bandwidth $\boldsymbol{h}$

$$Y_i = \alpha + \delta Poor_i + \beta Rinc_i + \gamma(Rinc_i * Poor_i) + u_i \quad (2)$$

where
y_i = outcome
$Poor_i$ = 1 if $Rinc_i < 0$
$Rinc_i$ = income – provincial poverty line
$-\boldsymbol{h} < Rinc_i < \boldsymbol{h}$

The dummy variable $Poor$ indicates whether household i lies below or above the poverty line. A household is considered poor if $Rinc$ is less than zero. $Rinc$ is the re-centered per-capita income for household i, and is computed as the difference of annual household per capita income in pesos from the corresponding provincial poverty line. The coefficient δ captures the effect of the intervention at the threshold, while the interaction term γ allows for different slopes at either side of the cut-off. Although **Table 1** above shows imperfect program implementation, where some poor households do not receive CCTs and some non-poor households receive CCTs, we still estimate using sharp RDD and use it as baseline.

For our analysis, the estimates generated using fuzzy RDD are the coefficients of primary interest. **Table 2** shows that the probability of receiving CCTs increases significantly if a household's estimated per capita income lies below the corresponding provincial poverty line. However, being below the poverty line is not a guarantee of receiving CCTs. For the fuzzy RDD estimate, we use instrumental variables two-stage least squares (IV-2SLS), with $Poor$ as an instrument for CCT. **Table 2** indicates that a household's status as poor or non-poor is a reliable predictor of whether or not that household would receive CCTs, establishing the significance of $Poor$ as a relevant instrument for the endogenous variable CCT.

The two first stage equations of the 2SLS are given by equations (3.1) and (3.2)

$$\overline{CCT_i} = \alpha_1 + \phi_1 Poor_i + \beta_1 Rinc_i + \gamma_1(Rinc_i * Poor_i) + \varepsilon_{1i} \quad (3.1)$$

$$(Rinc_i * \overline{CCT_i}) = \alpha_2 + \phi_2 Poor_i + \beta_2 Rinc_i + \gamma_2(Rinc_i * Poor_i) + \varepsilon_{2i} \quad (3.2)$$

where $\overline{CCT_i}$ is the endogenous dummy variable equal to one if any member of household i is a recipient of CCTs during the survey period, and zero otherwise.

The 2SLS second stage captures the causal relationship of interest, and is given by equation (4).

$$Y_i = \alpha_3 + \lambda \widehat{CCT_i} + \beta_3 Rinc_i + \gamma_3\left(\widehat{Rinc_i * CCT_i}\right) + \varepsilon_{3i} \quad (4)$$

The second stage captures the impact of receiving CCTs on our outcomes of interest. The parameter λ is the causal effect of CCTs on various outcomes, while $\widehat{CCT_i}$ is the first-stage fitted value obtained from estimating equation (3.1), and $\widehat{Rinc_i * CCT_i}$ is the fitted value obtained from estimating equation (3.2).

7. Results and discussion

Using both sharp and fuzzy[11] RD, we present the effect of receiving CCTs on health care coverage in **Table 5**. Extending health care coverage to the most impoverished households is one of the cornerstones of poverty alleviation and social assistance. The Philippines has taken steps towards establishing a universal health care system by passing the Universal Health Care (UHC) law in 2019, although full implementation could take at least a few years.

Until the Universal Health Care (UHC) law in the Philippines gets fully implemented, the CCT program acts as a safety net for poor households by providing health care coverage to the most impoverished households. **Table 5** indicates that on average, CCT program beneficiaries are more likely to receive health care coverage through the PhilHealth and PhilHealth Indigent programs, relative to non-beneficiaries. Estimates using sharp RD (columns 1 to 3) indicate that being a CCT beneficiary household increases the probability that the household receives health care coverage through PhilHealth by about 38 percentage points. Fuzzy RD yields higher coefficient estimates. For all three bandwidths (columns 4 to 6) in the fuzzy RD, being a recipient household of CCTs is estimated to increase the probability of receiving health care coverage through PhilHealth by around 48 percentage points, relative to households that do not receive CCTs.

Table 5: Health Care Coverage

	Sharp RDD			Fuzzy RDD		
PhilHealth	(1)	(2)	(3)	(4)	(5)	(6)
	BW1	BW2	BW3	BW1	BW2	BW3
Poor (OLS)	0.385***	0.384***	0.374***	0.481***	0.473***	0.481***
CCT (IV)	(0.0595)	(0.0502)	(0.0407)	(0.0734)	(0.0638)	(0.0525)
Rinc	-1.02e-06	1.16e-05	1.79e-05	-2.25e-05	-4.36e-07	1.74e-05
	(4.17e-05)	(2.33e-05)	(1.35e-05)	(5.04e-05)	(2.69e-05)	(1.38e-05)
Rinc x Poor (OLS)	1.83e-05	1.36e-06	-1.08e-05	4.53e-05	6.01e-06	-1.50e-05
Rinc x CCT (IV)	(5.01e-05)	(2.49e-05)	(1.61e-05)	(7.18e-05)	(3.91e-05)	(2.14e-05)
Constant	0.538***	0.530***	0.529***	0.517***	0.507***	0.497***
	(0.0550)	(0.0463)	(0.0395)	(0.0591)	(0.0482)	(0.0410)
Observations	1,016	1,502	2,010	1,016	1,502	2,010
R-squared	0.161	0.149	0.136	0.090	0.083	0.088

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

The CCT program also promotes family development and educates poor households on reproductive health. **Table 6** shows that on average, households that receive CCTs are over 60 percentage points more likely to participate in family development programs such as parenting sessions, relative to households that do not receive CCTs.

[11] The two first stage regressions have very high F-statistics and hereafter, we do not include the F-statistics in the tables.

Table 6: Attend family development sessions

	Sharp RDD			Fuzzy RDD		
Attend family development sessions	(1) BW1	(2) BW2	(3) BW3	(4) BW1	(5) BW2	(6) BW3
Poor (OLS)	0.500***	0.525***	0.530***	0.628***	0.643***	0.680***
CCT (IV)	(0.0563)	(0.0478)	(0.0454)	(0.0733)	(0.0591)	(0.0560)
Rinc	4.99e-06	3.21e-05*	2.23e-05*	-1.43e-05	2.34e-05	2.24e-05*
	(3.53e-05)	(1.71e-05)	(1.13e-05)	(3.84e-05)	(2.03e-05)	(1.33e-05)
Rinc x Poor (OLS)	-2.60e-05	-4.31e-05*	-2.55e-05	-1.08e-05	-5.86e-05*	-3.48e-05*
Rinc x CCT (IV)	(3.95e-05)	(2.47e-05)	(1.56e-05)	(4.87e-05)	(3.12e-05)	(2.07e-05)
Constant	0.201***	0.182***	0.185***	0.171***	0.149***	0.139***
	(0.0292)	(0.0242)	(0.0232)	(0.0303)	(0.0250)	(0.0239)
Observations	1,015	1,501	2,008	1,015	1,501	2,008
R-squared	0.273	0.258	0.253	0.362	0.351	0.344

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

There is some argument that cash transfers to poor households may induce dependency, where households spend their cash transfer benefits on adult commodities such as alcohol and tobacco (Moore, 2009) instead of health and education. In **Table 7**, we find no evidence that the CCT program in the Philippines encourages its beneficiary households to spend more on adult commodities that are detrimental to overall health, such as alcohol and tobacco.

On the other hand, **Table 8** shows no significant relationship between receiving CCT benefits and adjusting household expenditures for education. The sharp RD estimate in columns 1 to 3 shows no indication that CCT beneficiary households allocate a higher proportion of their household expenses for education, relative to nonbeneficiary households. The fuzzy RD estimate at the widest bandwidth in column 6 shows some weak evidence that CCT beneficiary households may allot a 0.8 percentage point larger share of their household income on education expenses, relative to non-beneficiary households but this result does not hold for other bandwidths. Although the impact evaluation study by Abdon et al., (2014)[12] find much stronger positive results, our estimates in this study show no significant relationship between receiving CCT benefits and allocating a higher proportion of household expenditures for education.

[12] The authors conduct an RDD using a sample and bandwidths somewhat different from what we use in this study

Table 7: Share of alcohol and tobacco to total expenditures

	Sharp RDD			Fuzzy RDD		
Share of alcohol and tobacco to total expenditures	(1) BW1	(2) BW2	(3) BW3	(4) BW1	(5) BW2	(6) BW3
Poor (OLS)	-0.00224	0.000691	0.000530	-0.00310	0.000982	0.000753
CCT (IV)	(0.00436)	(0.00406)	(0.00341)	(0.00541)	(0.00495)	(0.00427)
Rinc	-6.07e-06*	-2.23e-06	-1.47e-06	-6.86e-06**	-2.65e-06	-1.56e-06
	(2.98e-06)	(1.46e-06)	(9.96e-07)	(3.43e-06)	(1.77e-06)	(1.04e-06)
Rinc x Poor (OLS)	5.17e-06	2.28e-06	1.18e-06	7.12e-06	3.39e-06	1.53e-06
Rinc x CCT (IV)	(3.68e-06)	(2.71e-06)	(1.38e-06)	(5.34e-06)	(3.91e-06)	(1.75e-06)
Constant	0.0298***	0.0277***	0.0276***	0.0301***	0.0278***	0.0275***
	(0.00279)	(0.00256)	(0.00243)	(0.00294)	(0.00268)	(0.00259)
Observations	1,016	1,502	2,010	1,016	1,502	2,010
R-squared	0.007	0.003	0.003	0.005	0.007	0.005

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Share of education to total expenditures

	Sharp RDD			Fuzzy RDD		
Share of education to total expenditures	(1) BW1	(2) BW2	(3) BW3	(4) BW1	(5) BW2	(6) BW3
Poor (OLS)	0.000278	0.00184	0.00658	0.000312	0.00219	0.00838*
CCT (IV)	(0.00733)	(0.00527)	(0.00404)	(0.00901)	(0.00632)	(0.00507)
Rinc	-1.41e-06	3.22e-07	2.35e-06	-1.53e-06	4.81e-07	2.42e-06
	(3.65e-06)	(2.22e-06)	(1.53e-06)	(3.75e-06)	(2.40e-06)	(1.60e-06)
Rinc x Poor (OLS)	6.49e-07	-1.26e-06	-1.26e-06	9.23e-07	-1.85e-06	-1.66e-06
Rinc x CCT (IV)	(3.88e-06)	(2.48e-06)	(1.63e-06)	(5.33e-06)	(3.59e-06)	(2.10e-06)
Constant	0.0254***	0.0234***	0.0210***	0.0255***	0.0233***	0.0205***
	(0.00495)	(0.00405)	(0.00329)	(0.00526)	(0.00425)	(0.00345)
Observations	1,016	1,502	2,009	1,016	1,502	2,009
R-squared	0.001	0.001	0.002	0.002		

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

The main research question of this paper is whether CCTs affect households' responses to shocks. Shocks, such as grave illness or natural disasters, can be devastating for impoverished households. The 2016 World Risk Report finds that the Philippines has the third highest risk for disasters among a sample of 171 countries (Garschagen et. al, 2016). Households in the Philippines are regularly exposed to disaster shocks.

In **Table 9**, we first estimate whether CCT beneficiary households are more likely to experience shocks compared to non-CCT beneficiary households. For purposes of our analysis, a household is defined to be exposed to shocks if it experiences any of the following in the past 12 months: death or grave illness in the household; loss of employment or business failure; fire or earthquake; natural or man-made disasters. In **Table 9**, we show that CCT beneficiary households are not significantly more likely affected by shocks, relative to non-CCT beneficiary households. This result implies that for all three bandwidths, shocks affect the two groups of households in our sample randomly.

To account for the impact of shocks on households in our analysis, we run specifications that estimate the impact of the CCT program on adult commodities expenditures (**Table 10**) and education expenditures (**Table 11**) for households that were exposed to shocks relative to those who were not. In these two specifications, the coefficient of interest is an interaction term of the CCT indicator (or the dummy for being below the cutoff for poverty) and shocks. This coefficient gives an estimate of how the CCT program induces households to differently adjust their expenditures on adult commodities (**Table 10**) and education (**Table 11**) when exposed to various shocks.

Table 9: Shocks

	Sharp RDD			Fuzzy RDD		
	(1)	(2)	(3)	(4)	(5)	(6)
Shocks	BW1	BW2	BW3	BW1	BW2	BW3
Poor (OLS)	-0.0621	-0.0175	-0.00897	-0.0835	-0.0214	-0.00541
CCT (IV)	(0.0505)	(0.0494)	(0.0397)	(0.0629)	(0.0603)	(0.0518)
Rinc	-7.71e-05**	2.30e-06	2.57e-05	-9.20e-05***	2.52e-06	1.86e-05*
	(2.92e-05)	(1.78e-05)	(1.61e-05)	(3.41e-05)	(1.92e-05)	(1.11e-05)
Rinc x Poor (OLS)	0.000103**	1.79e-06	-3.13e-05	0.000141**	2.48e-06	-1.85e-05
Rinc x CCT (IV)	(4.11e-05)	(2.23e-05)	(2.23e-05)	(5.67e-05)	(3.28e-05)	(1.33e-05)
Constant	0.408***	0.351***	0.327***	0.416***	0.352***	0.341***
	(0.0328)	(0.0281)	(0.0296)	(0.0350)	(0.0297)	(0.0233)
Observations	1,016	1,502	2,010	1,016	1,502	2,010
R-squared	0.007	0.001	0.004		0.002	0.004

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

Table 10 shows that for two out of the three bandwidths estimated using sharp RD, we find some evidence that CCT recipient households that are exposed to shocks may relatively decrease their proportion of household expenditures allotted for adult commodities such as alcohol and tobacco by about 1.2 percentage points. For all three bandwidths, fuzzy RD estimates indicate that on average, CCT beneficiary households

may allot anywhere from 1.6 to 2 percentage points smaller share of their household income on alcohol and tobacco, relative to non-CCT beneficiary households when exposed to shocks. This result serves as suggestive evidence that the CCT program discourages its beneficiary households from spending on adult commodities when exposed to shocks.

Although **Table 7** shows that the CCT program per se does not discourage its beneficiary households from spending less on adult commodities, **Table 10** indicates that when exposed to shocks, which are rather prevalent in the Philippines, CCT beneficiary households allocate a smaller proportion of their household income on adult alcohol and tobacco as compared to nonbeneficiaries.

Table 10: Shocks and adult commodities

	Sharp RDD			Fuzzy RDD		
Share of alcohol and tobacco to total expenditures	(1) BW1	(2) BW2	(3) BW3	(4) BW1	(5) BW2	(6) BW3
Poor (OLS)	0.00258	0.00501	0.00479	0.00307	0.00607	0.00603
CCT (IV)	(0.00578)	(0.00512)	(0.00407)	(0.00678)	(0.00600)	(0.00496)
Rinc	-5.35e-06*	-1.03e-06	-6.73e-07	-6.20e-06**	-1.44e-06	-8.33e-07
	(2.77e-06)	(1.98e-06)	(1.31e-06)	(2.95e-06)	(2.29e-06)	(1.38e-06)
Shocks	0.00234	0.00304	0.00173	0.00342	0.00394	0.00281
	(0.00514)	(0.00370)	(0.00281)	(0.00578)	(0.00382)	(0.00288)
Rinc x Poor (OLS)	5.55e-06	1.55e-06	1.14e-06	7.56e-06	2.28e-06	1.48e-06
Rinc x CCT (IV)	(3.59e-06)	(3.49e-06)	(1.78e-06)	(4.82e-06)	(4.97e-06)	(2.31e-06)
Rinc x Shocks	-2.46e-06	-3.04e-06	-1.69e-06	-1.95e-06	-2.98e-06	-1.58e-06
	(5.87e-06)	(2.58e-06)	(1.21e-06)	(7.14e-06)	(3.01e-06)	(1.25e-06)
Poor x Shocks (OLS)	-0.0141	-0.0123*	-0.0120**	-0.0196*	-0.0157*	-0.0159**
CCT x Shocks (IV)	(0.00881)	(0.00639)	(0.00469)	(0.0114)	(0.00806)	(0.00635)
Rinc x Poor x Shocks (OLS)	-1.81e-07	1.68e-06	-5.93e-07	-1.38e-06	2.33e-06	-9.19e-07
Rinc x CCT x Shocks (IV)	(7.40e-06)	(4.28e-06)	(2.28e-06)	(1.10e-05)	(6.33e-06)	(3.00e-06)
Constant	0.0290***	0.0265***	0.0267***	0.0290***	0.0263***	0.0263***
	(0.00300)	(0.00309)	(0.00287)	(0.00309)	(0.00316)	(0.00302)
Observations	1,016	1,502	2,010	1,016	1,502	2,010
R-squared	0.013	0.007	0.006	0.011	0.009	0.005

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

We attempt to extend our findings in **Table 8** that CCT beneficiary households allot a higher proportion of their household income for education relative to nonbeneficiaries, by incorporating shocks to the analysis. Our estimation results are presented in **Table 11.** The interaction term for CCT and shocks shows that there is no statistically significant relationship between CCT beneficiary households that are exposed to shocks and the share of education to total expenditures. This indicates that the CCT program has no statistically significant impact on the share of education to total expenses of beneficiary households after being exposed

to various shocks. One possible explanation is that CCT beneficiary households earmark their expenditures for education, and do not take away from the funds they allot for education, even when they experience various shocks.

Table 11: Shocks and education expenditures

	Sharp RDD			Fuzzy RDD		
Share of education to total expenditures	(1) BW1	(2) BW2	(3) BW3	(4) BW1	(5) BW2	(6) BW3
Poor (OLS)	-0.000981	0.00414	0.00740	-0.00116	0.00482	0.00900
CCT (IV)	(0.00944)	(0.00685)	(0.00561)	(0.0111)	(0.00784)	(0.00670)
Rinc	-5.65e-08	1.36e-06	3.43e-06	2.93e-07	1.43e-06	3.59e-06
	(4.62e-06)	(3.39e-06)	(2.67e-06)	(4.78e-06)	(3.71e-06)	(2.82e-06)
Shocks	0.00347	0.00389	0.00304	0.00421	0.00419	0.00299
	-0.000981	(0.00898)	(0.00769)	(0.0128)	(0.00946)	(0.00802)
Rinc x Poor (OLS)	-2.31e-06	-1.20e-06	-2.37e-06	-3.15e-06	-1.78e-06	-3.22e-06
Rinc x CCT (IV)	(5.44e-06)	(3.77e-06)	(2.90e-06)	(7.34e-06)	(5.47e-06)	(3.83e-06)
Rinc x Shocks	-4.95e-06	-2.63e-06	-2.33e-06	-7.61e-06	-2.29e-06	-2.47e-06
	(1.06e-05)	(5.16e-06)	(3.46e-06)	(1.22e-05)	(5.68e-06)	(3.70e-06)
Poor x Shocks (OLS)	0.00328	-0.00626	-0.00121	0.00282	-0.00764	-0.000515
CCT x Shocks (IV)	(0.0145)	(0.0116)	(0.00919)	(0.0189)	(0.0142)	(0.0118)
Rinc x Poor x Shocks (OLS)	9.74e-06	-6.95e-07	2.42e-06	1.48e-05	-1.17e-06	3.40e-06
Rinc x CCT x Shocks (IV)	(1.37e-05)	(6.96e-06)	(4.52e-06)	(1.86e-05)	(1.01e-05)	(5.79e-06)
Constant	0.0244***	0.0219***	0.0196***	0.0244***	0.0217***	0.0191***
	(0.00608)	(0.00551)	(0.00499)	(0.00645)	(0.00577)	(0.00518)
Observations	1,016	1,502	2,009	1,016	1,502	2,009
R-squared	0.002	0.003	0.003			

Robust standard errors in parentheses. Standard errors are clustered by province.
*** p<0.01, ** p<0.05, * p<0.1

8. Conclusion

In this paper, we assess the impact of the Philippines' conditional cash transfer (CCT) program on households' behaviour in response to shocks. Using sharp and fuzzy RDD, we first reinforce previous estimates of impact evaluation studies (Abdon et al., 2014) on healthcare coverage and family development program participation. We next incorporate shocks into the analysis. We first test whether CCT beneficiary households are more likely to be exposed to various shocks such as grave illness, death in the household, loss of employment, business failure, natural or man-made disasters relative to non-beneficiary households. We then estimate the impact of the CCT program on changes in household expenditures on adult commodities and education of CCT beneficiary households when exposed to various shocks.

Using bandwidths that allow comparability of households on both sides of the cut-off, we confirm the results of previous studies that CCT beneficiary households are more likely to receive healthcare coverage, relative to non-beneficiary households. Moreover, we also verify the result that CCT beneficiary households

are more likely to attend family development sessions, relative to non-beneficiary households. Although we find no evidence that CCT beneficiary households normally spend a smaller proportion of their household income on adult goods such as alcohol and tobacco, our estimates show some suggestive evidence that when exposed to shocks, CCT beneficiary households allot a relatively smaller proportion of their household income on alcohol and tobacco. Our estimates show no significant relationship between receiving CCT benefits and adjusting household expenditures for education. Furthermore, we find no evidence that CCT beneficiary households adjust their spending on education when exposed to shocks.

The CCT program in the Philippines is a valuable social safety net for impoverished households. The impact of the CCT program on health and education outcomes of its beneficiary households has been well documented in many studies, including this one. However, the literature on the impact of CCTs in the presence of shocks is currently rather sparse. In this study, we briefly examine the relationship between CCTs, shocks, and household welfare by looking at household expenditure outcomes. Given that the Philippines has the third highest risk for disasters among a sample of 171 countries (Garschagen et. al, 2016) in the 2016 World Risk Report and that households in the Philippines are regularly exposed to disaster shocks, it seems reasonable to incorporate shocks more often in the analysis of social welfare programs in the Philippines in further research.

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Appendix 1: Validation tests for discontinuity at the threshold

Log family size

Log family size	(1) BW1	(1) BW2	(1) BW3
Rinc	-3.71e-05	-7.55e-06	-2.21e-05**
	(2.78e-05)	(1.53e-05)	(8.59e-06)
Poor	0.0334	0.0462	0.0321
	(0.0393)	(0.0321)	(0.0276)
Rinc x Poor	4.28e-05	-5.64e-06	4.03e-06
	(3.62e-05)	(1.99e-05)	(1.23e-05)
Constant	1.731***	1.706***	1.716***
	(0.0260)	(0.0212)	(0.0175)
Observations	1,017	1,503	2,011
R-squared	0.009	0.014	0.030

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Children below 5 years old

Children below 5 years old	(1) BW1	(1) BW2	(1) BW3
Rinc	-6.42e-05	-2.56e-05	-6.53e-05***
	(6.62e-05)	(3.88e-05)	(2.15e-05)
Poor	-0.00315	0.0296	-0.0549
	(0.111)	(0.0919)	(0.0797)
Rinc x Poor	5.39e-05	3.07e-05	2.86e-05
	(9.33e-05)	(5.37e-05)	(3.46e-05)
Constant	0.780***	0.759***	0.797***
	(0.0694)	(0.0579)	(0.0479)
Observations	1,017	1,503	2,011
R-squared	0.002	0.001	0.009

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If roof is made of strong materials

If roof is made of strong materials	(1) BW1	(1) BW2	(1) BW3

Rinc	-1.18e-05	-9.80e-06	6.08e-06
	(3.70e-05)	(2.13e-05)	(1.33e-05)
Poor	0.00548	-0.0299	-0.0222
	(0.0581)	(0.0489)	(0.0425)
Rinc x Poor	8.33e-05*	2.97e-05	1.69e-05
	(5.05e-05)	(2.94e-05)	(1.91e-05)
Constant	0.540***	0.534***	0.530***
	(0.0360)	(0.0306)	(0.0265)
Observations	1,016	1,502	2,010
R-squared	0.009	0.003	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If walls are made of strong materials

If walls are made of strong materials	(1) BW1	(1) BW2	(1) BW3
Rinc	4.83e-05	3.44e-05*	3.19e-05**
	(3.56e-05)	(2.01e-05)	(1.26e-05)
Poor	0.0379	0.0199	0.0315
	(0.0527)	(0.0441)	(0.0382)
Rinc x Poor	-2.82e-05	-2.06e-05	-5.48e-06
	(4.66e-05)	(2.69e-05)	(1.72e-05)
Constant	0.256***	0.268***	0.273***
	(0.0335)	(0.0282)	(0.0244)
Observations	1,016	1,502	2,010
R-squared	0.003	0.005	0.013

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If roof is made of light materials

VARIABLES	(1) BW1	(1) BW2	(1) BW3
Rinc	1.37e-05	1.80e-05	-2.22e-06
	(3.44e-05)	(1.89e-05)	(1.12e-05)
Poor	0.0224	0.0512	0.0315
	(0.0517)	(0.0429)	(0.0374)
Rinc x Poor	-5.42e-05	-2.04e-05	-2.03e-06
	(4.63e-05)	(2.60e-05)	(1.67e-05)
Constant	0.232***	0.232***	0.250***
	(0.0324)	(0.0266)	(0.0226)

Observations	1,016	1,502	2,010
R-squared	0.006	0.002	0.003

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If walls are made of light materials

VARIABLES	(1) BW1	(1) BW2	(1) BW3
Rinc	-3.12e-05	-1.31e-05	-2.63e-05**
	(3.53e-05)	(2.05e-05)	(1.23e-05)
Poor	-0.0321	0.000659	-0.0422
	(0.0572)	(0.0480)	(0.0416)
Rinc x Poor	-1.34e-05	-3.47e-06	-7.39e-06
	(4.92e-05)	(2.88e-05)	(1.84e-05)
Constant	0.420***	0.407***	0.421***
	(0.0351)	(0.0299)	(0.0255)
Observations	1,016	1,502	2,010
R-squared	0.004	0.003	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household has no toilet

If household has no toilet	(1) BW1	(1) BW2	(1) BW3
Rinc	-1.90e-05	-1.56e-05	-1.93e-05**
	(2.92e-05)	(1.57e-05)	(9.21e-06)
Poor	0.0274	0.0348	0.0322
	(0.0457)	(0.0383)	(0.0335)
Rinc x Poor	3.86e-05	3.45e-05	3.65e-05***
	(3.87e-05)	(2.19e-05)	(1.41e-05)
Constant	0.201***	0.201***	0.202***
	(0.0289)	(0.0236)	(0.0200)
Observations	1,016	1,502	2,010
R-squared	0.002	0.002	0.004

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household water source is shared tubed / piped well

VARIABLES	(1) BW1	(1) BW2	(1) BW3
Rinc	6.20e-05*	2.19e-05	-1.04e-05
	(3.44e-05)	(1.86e-05)	(1.05e-05)
Poor	0.0118	-0.0144	-0.0277
	(0.0489)	(0.0400)	(0.0345)
Rinc x Poor	-6.78e-05	-3.59e-05	7.54e-06
	(4.48e-05)	(2.50e-05)	(1.53e-05)
Constant	0.185***	0.206***	0.229***
	(0.0314)	(0.0258)	(0.0217)
Observations	1,016	1,502	2,010
R-squared	0.005	0.002	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household has electricity

If household has electricity	(1) BW1	(1) BW2	(1) BW3
Rinc	1.13e-06	-1.19e-06	1.02e-05
	(2.31e-05)	(1.36e-05)	(7.98e-06)
Poor	-0.0159	0.000580	0.0132
	(0.0426)	(0.0352)	(0.0305)
Rinc x Poor	1.72e-05	3.40e-05	2.62e-05*
	(3.65e-05)	(2.14e-05)	(1.38e-05)
Constant	0.876***	0.873***	0.864***
	(0.0230)	(0.0198)	(0.0171)
Observations	1,016	1,502	2,010
R-squared	0.004	0.008	0.019

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household has a refrigerator

If household has a refrigerator	(1) BW1	(1) BW2	(1) BW3

Rinc	2.90e-05	2.12e-05	4.07e-05***
	(3.11e-05)	(1.84e-05)	(1.20e-05)
Poor	0.00427	-0.00116	0.00791
	(0.0452)	(0.0385)	(0.0334)
Rinc x Poor	5.53e-07	5.77e-06	-2.58e-05*
	(3.97e-05)	(2.36e-05)	(1.57e-05)
Constant	0.191***	0.187***	0.163***
	(0.0292)	(0.0254)	(0.0223)
Observations	1,016	1,502	2,010
R-squared	0.007	0.011	0.022

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household has a washing machine

If household has a washing machine	(1) BW1	(1) BW2	(1) BW3
Rinc	2.33e-05	1.01e-05	1.06e-05
	(2.09e-05)	(1.35e-05)	(9.07e-06)
Poor	0.00291	-0.000661	-0.0124
	(0.0326)	(0.0280)	(0.0253)
Rinc x Poor	1.29e-06	9.89e-06	-1.93e-06
	(2.74e-05)	(1.66e-05)	(1.17e-05)
Constant	0.0994***	0.105***	0.105***
	(0.0200)	(0.0189)	(0.0171)
Observations	1,016	1,502	2,010
R-squared	0.008	0.008	0.008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household owns the house

If household owns the house	(1) BW1	(1) BW2	(1) BW3
Rinc	-4.60e-05	-2.28e-05	1.03e-05
	(3.55e-05)	(2.10e-05)	(1.33e-05)
Poor	-0.179***	-0.127***	-0.0781*
	(0.0559)	(0.0472)	(0.0412)
Rinc x Poor	-2.50e-05	-5.29e-06	-2.13e-05
	(4.88e-05)	(2.87e-05)	(1.87e-05)
Constant	0.468***	0.450***	0.422***

	(0.0355)	(0.0304)	(0.0264)
Observations	1,016	1,502	2,010
R-squared	0.010	0.005	0.006

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

If household rents the house

	(1)	(1)	(1)
If household rents the house	BW1	BW2	BW3
Rinc	6.52e-06	-2.87e-06	1.87e-06
	(1.04e-05)	(4.32e-06)	(3.94e-06)
Poor	0.0103	0.00632	0.00855
	(0.0160)	(0.0130)	(0.0117)
Rinc x Poor	2.45e-06	1.19e-05*	2.97e-06
	(1.33e-05)	(6.15e-06)	(5.08e-06)
Constant	0.0170*	0.0224***	0.0172**
	(0.00935)	(0.00759)	(0.00735)
Observations	1,016	1,502	2,010
R-squared	0.002	0.003	0.001

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1