Southeast Asian Journal of Economics 9(2), August 2021: 1-38
Received: 15 January 2021
Accepted: 7 May 2021

Cash Transfers, Shocks, and Temptation Goods: 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 alcohol and tobacco (temptation goods) expenditures 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 allocate 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. This result serves as suggestive evidence against the notion of cash transfer misuse towards temptation goods when beneficiary households are exposed to various shocks.

Keywords: transfer payments, provision, and effects of welfare programs, redistributive effects

JEL Codes: I38, H23

1. Introduction

The implementation of conditional cash transfer (CCT) programs has increased 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 (Calvo, 2011). By the mid-2000s, CCTs were undergoing pilot-testing in Asian countries such as the Philippines, which was the first Southeast Asian country to implement a CCT program in 2007 (Kim & Yoo, 2015). Several studies have estimated the impact of the local CCT program, Pantawid Pamilyang Pilipino Program, on household welfare in the Philippines. These studies (Orbeta et al., 2014; Tutor, 2014) generally find that CCT beneficiary households have improved health and education outcomes.

However, one dimension that has yet to be thoroughly 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, and natural or man-made disasters. As one of the world's most vulnerable countries for disaster risks, the Philippines is susceptible to various shocks, perennially ranking among the worst-performing countries in the World Risk Index. From 2012 to 2018, the Philippines ranked third lowest among a sample of 171 countries (Bündnis Entwicklung Hilft, 2017, 2018). A country's susceptibility to and capacity to cope with shocks such as disasters and other risks severely affects its citizens' social welfare. Thus, it is important to consider risks when evaluating social welfare programs, especially in countries that are disproportionately vulnerable to various shocks, such as the Philippines.

Policymakers have also raised concerns that cash transfer recipients may use cash benefits for temptation goods such as alcohol and tobacco (Evans & Popova, 2017). Several senior government officials, particularly in Nicaragua (Moore, 2009) and Kenya (Ikiara, 2009), as well as aid agencies (Harvey, 2007), held strong beliefs that cash transfers received by poor households would be misused towards temptations goods and other non-essential items. Concerns of cash transfer misuse support the argument for in-kind transfers instead of cash despite evidence of cash transfers' efficiency over in-kind transfers (Case & Deaton, 1998; Evans & Popova, 2017).

Using evidence from the Philippines' CCT program via a regression discontinuity design (RDD), we estimate the program's impact on expenditures on alcohol and tobacco when households are exposed to shocks. Does the CCT program induce its beneficiary households to adjust their spending patterns on temptation goods differently from nonbeneficiaries when exposed to shocks? Our estimates show that when exposed to shocks, CCT beneficiary households, on average, may allocate anywhere from 1.2 to 2 percentage points smaller share of their household income on alcohol and tobacco, as compared to nonbeneficiaries that experienced shocks. Our results are consistent with Evans and Popova's (2017) findings across 50 estimates in 19 studies that cash transfer programs generally have no significant impact or a significant negative impact on alcohol and tobacco expenditures. Our study's key contribution to the literature is that we account for various shocks, which households in the Philippines are particularly susceptible to.

Section 2 provides a literature review, while Section 3 gives a more detailed background on the Philippines' CCT program. The data and empirical strategy used in our analysis are described in more detail in Section 4. Section 5 discusses the results, while Section 6 gives policy implications and Section 7 concludes.

2. Literature Review

Conditional cash transfers (CCTs) have been among the most widely used social assistance programs to reduce poverty, decrease inequality, and expand social inclusion in recent years. CCTs have a twofold agenda as a tool for poverty alleviation. Beyond supplementing poor households' short-term consumption needs 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 consensus in empirical studies that assess the impact of cash transfer programs commonly agrees that CCTs have significant and positive effects 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 found that cash transfer programs generally improved 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.

Adhvaryu, Nyshadham, Molina, and Tamayo (2018) investigated the interaction of conditional cash transfers from PROGRESA and household shocks. The authors examined the impact of early childhood shocks on children's schooling outcomes 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 used local rainfall data at the time of a child's birth to represent early-life endowment shocks.[2] They found that children

[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 et al. (2014).

[2] Adhvaryu et al., (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 wages 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.

born during heavy rainfall periods had unfavorable school and employment outcomes relative to children born in regular rainfall periods. Moreover, their estimates indicated that an additional year of exposure to the program during childhood decreased approximately 20% of early life disadvantage. This suggests that beneficiary households of the PROGRESA program that experience early-life shocks can recover from the negative impact of poor early life circumstances on education and employment outcomes through conditional cash transfers.

Gitter and Barham (2009) also investigated the impact of cash transfers on children's school enrollment outcomes from poor households exposed to shocks in Nicaragua. The authors accounted for differences in household wealth, employment opportunities, and exposure to adverse shocks in estimating the effect of transfers on school versus child labor decisions among poor households.[3] They considered two types of adverse shocks, namely the occurrence of droughts and significant declines in coffee price. Their main findings showed that CCTs increased the likelihood of school enrollment in poorer households during a price hike and improved enrollment in coffee-cultivating villages.

Despite the literature on the positive impacts of CCT programs on household welfare, some policymakers have raised concerns about the misuse of cash transfers, particularly to buy "temptation goods" such as alcohol and tobacco, instead of its intended use for health and education expenditures. In this paper, we refer to alcohol and tobacco as "temptation goods." A systematic review by Evans and Popova (2017) examined the impact of cash transfers on spending on temptation goods. Using meta-analysis to summarize quantitative evidence from a survey of 42 studies, the authors found that cash transfers, whether conditional or unconditional, for the most part, had either no significant impact or a significant negative impact on temptation goods, leading the authors to conclude that concerns about the misuse of cash transfers in favor of temptation goods are unsubstantiated by empirical evidence (Evans & Popova,

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

2017).[4] The scope of literature surveyed by the authors includes studies on cash transfers from countries in Latin America, Africa, and Asia.

Although the role of CCT programs in improving the development and overall well-being of its recipients in various countries has been well documented in the literature, the impact of CCT programs in light of various income shocks has not been as thoroughly studied. In this paper, we intend to contribute to the literature on CCTs by accounting for various income shocks and examining spending behavior during shocks using data from the Philippines, a country that is perennially vulnerable to shocks and disasters.

3. Background

The conditional cash transfer (CCT) program in the Philippines, known locally as Pantawid Pamilyang Pilipino Program, is modeled 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 and 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 program's conditions. While strict conditionality is desired, program implementation is imperfect, with some poor households unable to receive cash transfers, while some non-poor households are given transfers.

Eligibility for the CCT program is determined through a Proxy Means Test (PMT) that predicts the income of households, based on socio-economic and demographic indicators such as ownership of assets, characteristics of the dwelling, access to water, sanitation and electricity, and education of household head, all of which are highly correlated with household income (Fernandez, 2012). Moreover, respondents cannot easily manipulate these variables since

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

most of these variables are observable and verifiable by the enumerators during the interview (Fernandez, 2012). There are 22 variables included in the PMT model to predict household income and determine program eligibility. The PMT is extensively considered one of the most reliable ways to measure poverty in countries with a large informal sector, and incomes are difficult to verify (Fernandez & Olfindo, 2011). Further details of the PMT are discussed in Fernandez (2012).

4. Methodology

4.1 Data

For our empirical analysis, we use the 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set. This cross-sectional data set is based on a survey of 5,041 households in 26 provinces. The survey covers 30 municipalities, with ten municipalities in each of the Philippines' three major islands. Information for the Wave 2 data set – the second round of household evaluation in the program – was collected from October to December 2013. Beneficiary households in the sample areas of the Wave 2 data set have been exposed to the CCT program for about two to four years at the time of data collection (Orbeta et al., 2014). 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; or natural or man-made disasters.

Table 1 shows the distribution of poor and non-poor households by province, the mean household income, and the corresponding provincial poverty lines used as the cut-off for each province. Households with an estimated annual per capita income in Philippine Pesos (PHP) (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 1. Mean Household Income and Cut-off by Province

Province	Mean household income	Cut-off provincial poverty line	House-holds	% poor	% non-poor
Bukidnon	12,963	12,186	180	50	50
Zamboanga Sibugay	10,943	12,188	154	63	37
Catanduanes	14,393	13,654	145	51	49
Sarangani	14,987	13,746	180	48	52
Samar (Western Samar)	13,807	13,869	341	54	46
Leyte	14,018	13,919	291	53	47
Zamboanga del Norte	13,611	13,947	166	56	44
Cebu	14,946	13,960	322	51	49
Negros Occidental	15,537	13,975	180	50	50
Masbate	13,970	14,248	172	53	47
Agusan del Sur	11,755	14,544	152	73	27
Misamis Oriental	13,800	14,787	165	55	45
Iloilo	16,165	14,810	168	52	48
Guimaras	15,004	14,811	145	52	48
Camarines Norte	15,343	14,854	176	52	48
Aklan	16,434	15,150	180	50	50
Surigao Del Sur	15,374	15,264	166	54	46
South Cotabato	16,336	15,431	180	52	48
General Santos City	16,851	15,431	210	50	50
Pangasinan	17,573	15,656	180	50	50
Quezon	17,460	16,125	150	51	49
Albay	16,497	16,128	175	53	47
La Union	16,776	16,372	150	50	50

Lanao Del Sur	17,903	16,567	180	50	50
Zambales	17,506	16,685	150	50	50
Oriental Mindoro	17,418	16,723	203	54	46
NCR First District	22,515	20,868	180	52	48

Note: Cut-offs are in annual PHP.

Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

Table 2 presents the average incidence of shocks to households in the sample by province. The incidence per type of shock varies considerably by province. While sample households from Lanao del Sur are notably more exposed to grave illness or death in the household, the incidence of employment loss/business failure or natural or man-made disasters is low. On the other hand, sample households in Zambales are noticeably more exposed to natural or man-made disasters relative to households in other provinces. To increase sample size and the statistical power of our estimates in Section 5, we analyzed the exposure of households to any of the shocks described in Table 2.

Province	Grave illness or death in the household	Loss of employment of business failure	Natural or man-made disaster	Total
Lanao del Sur	44.26	0.06	1.00	45.32
Misamis Oriental	29.22	0.05	7.04	36.32
Zambales	16.23	0.10	19.02	35.36
Bukidnon	28.29	0.06	2.01	30.36
Masbate	29.26	0.06	1.01	30.32
Sarangani	25.25	0.09	4.02	29.36
Agusan del Sur	26.21	0.01	3.00	29.22
Surigao del Sur	19.23	0.04	9.01	28.28
Cebu	23.69	0.07	4.51	28.27
Zamboanga Sibugay	22.21	0.03	6.03	28.27
Catanduanes	20.28	0.08	7.03	27.39
Negros Occidental	23.30	0.06	3.03	26.38
Albay	26.21	0.08	0.02	26.31

South Cotabato	25.18	0.01	1.00	26.20
Camarines Norte	23.28	0.12	0.05	23.45
Samar	19.69	0.04	3.04	22.77
Oriental Mindoro	16.22	0.05	6.04	22.32
Aklan	19.19	0.08	2.01	21.28
Guimaras	20.38	0.08	0.01	20.47
Leyte	13.23	0.09	7.06	20.37
La Union	17.25	0.07	3.03	20.34
Panay	18.20	0.03	2.03	20.26
NCR First District	17.19	0.11	2.02	19.33
Zamboanga del Norte	15.23	0.04	1.01	16.28
South Cotabato	14.18	0.02	1.00	15.19
Quezon	12.21	0.04	1.02	13.27
Pangasinan	12.19	0.02	0.01	12.22

Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

Table 3. 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

Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

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 3 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 4 shows the extent to which the PMT predicts CCT participation using a linear probability model:

$$CCT_i = a + bPoor_i + u_i \tag{1}$$

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 4. Poverty Status and CCT Benefits

VARIABLES	(1) CCT beneficiary
Poor	0.824***
	(0.0079)
Constant	0.0605***
	(0.00488)
Observations	5,041
R-squared	0.677

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

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. The provincial poverty line is used as the cut-off. Households with an estimated annual per capita income in PHP (based on the PMT) less than the provincial poverty line are considered poor.

4.2 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 3 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. RDD is a quasi-experimental measure that is typically used in impact evaluation. It aims to estimate causal effects of interventions (Imbens & Lemieux, 2008) where treatment is determined by whether a running variable exceeds a cut-off point (Lee & Lemieux, 2010). Although the use of RDD was introduced by Thistlewaite and Campbell (1960) in psychology, several notable papers in economics including Van Der Klaauw (2002), Angrist and Lavy (1999), Lee (2008), Chay and Greenstone (2005), among many others (Imbens & Lemieux, 2008) use RDD, which is particularly advantageous when randomization is not possible. The average treatment effect is estimated by comparing observations within a bandwidth close to either side of the cut-off point. However, given the quasi-experimental nature of RDD, establishing true causal inference from its use may not be attainable. Moreover, bandwidth selection is subject to the trade-off between bias and the precision of estimates. Still, RDD is one of the most useful methods for impact evaluation when randomization is not possible.

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 two 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.

Since bandwidth selection is subject to the trade-off between bias and efficiency, we use two different bandwidths in our estimates. The narrower 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. The wider bandwidth, BW2, has an evaluation sample of households with re-centered income up to 15 percentiles below and 15 percentiles above each provincial cut-off, resulting in a sample size of 1,502 households. Being the narrower among the two, BW1 is likely to yield the least bias, but also the largest standard errors, given the smaller sample size. On the other hand, BW2, which has a higher number of observations, may give more precise estimates, but it may also result in a slightly larger bias than BW1. Additionally, while having a 5-percentile bandwidth would have been interesting, the sample size would be reduced drastically, and the precision of estimates may be compromised.

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 measurable household characteristics and not the declared household income, it would be tough for households to manipulate their status with respect to the cut-off (Fernandez, 2012).

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 socio-economic and demographic characteristics measured pre-intervention between households on either side of the cut-off. To this end, we performed validation tests using different bandwidths and present them in the Appendix. The validation tests results show that overall, there is no statistically significant difference in socio-economic and demographic indicators between poor and non-poor households. Among the 13 covariates tested (measured pre-intervention), 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 socio-economic and demographic similarity of households on either side of the cut-off.

4.3 Estimation Equations

Ideally, households classified as poor should receive CCTs while non-poor households should not receive CCTs. However, due to imperfect program implementation as shown in Table 3, there are poor households who do not receive CCTs while there are non-poor households that receive CCTs. Because of imperfect program implementation, you cannot rely entirely on beneficiary status to determine if a household should actually receive CCTs or not. To address this, we used poverty status and determined whether a household is above or below the poverty threshold for their respective province (which is the cut-off) and used it as an instrument for beneficiary status, which is an endogenous variable.

Poverty status is the instrument (IV) used for the endogenous variable, beneficiary status. Cut-off rules are common in social programs. For instance, beneficiaries and non-beneficiaries are systematically different but for households within a bandwidth near the poverty threshold, there are only slight differences, and these households should be comparable. Sharp RDD is used when treatment is assigned based on a discrete cut-off point where all eligible households receive the treatment, and all ineligible households do not receive the treatment. In this case, sharp RDD is appropriate if all poor households receive CCTs and all non-poor households do not receive CCTs. However, due to imperfect program implementation as shown in Table 3, fuzzy RDD is more appropriate to estimate the effect of the treatment. However, we still show the results of sharp RDD estimates as a baseline and as a robustness check for the fuzzy RDD estimates.

Fuzzy RDD is used when some poor households eligible to receive CCTs do not receive CCTs, while some non-poor households ineligible to receive CCTs end up receiving CCTs due to imperfect program implementation. Fuzzy RDD is estimated through an IV-2SLS approach, in which case we use poverty status as an IV for the endogenous variable, beneficiary status. 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.

Given the nature of the variables we intend to estimate, there is no need to use higher-order polynomials. Thus, we used a linear local regression discontinuity (RD) estimator. Moreover, attempting to control for higher-order polynomials in RDD may lead to three major issues: poor coverage of confidence intervals, noisy estimates, and sensitivity to the degree of the polynomial (Gelman & Imbens, 2018). Equation 2 gives the specification for the sharp RDD estimate for each sampling bandwidth h,

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

where Y_i = outcome; $Poor_i = 1$ if $Rinc_i < 0$; $Rinc_i$ = income – provincial poverty line (in PHP); and $-h < Rinc_i < h$.

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 between annual household per capita income in PHP from the corresponding provincial poverty line. The coefficient δ captures the intervention's effect at the threshold, while the interaction term γ allows for different slopes at either side of the cut-off.

For our analysis, the estimates generated using fuzzy RDD are the coefficients of primary interest. Table 4 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 4 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)

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

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

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).

5. Results and Discussion

We present the summary statistics of the outcome variables and covariates for CCT recipients and non-recipients within the 15-percentile in Table 5. *Household expenditures on alcohol and tobacco* is expressed both as a share of total household expenditures and as a value in PHP. Since we are interested in potential misuse of cash transfers in the context of overall household expenditures, and to account for the different costs of living and poverty lines across the Philippines, we use the share of alcohol and tobacco to total expenditures, and not the raw PHP values in the analysis. *Poor* is a dummy variable taking on the value of one if a household's income falls below their respective provincial poverty line. Although program implementation is imperfect, falling under the provincial poverty line is a reliable predictor of whether a household will receive cash transfers. *Estimated re-centered income* is the deviation of a household's income, estimated using PMT, from their respective provincial poverty line. In our 15-percentile bandwidth sample, the average household income of CCT recipients is on average PHP 1,333 (about 25 USD) lower than their respective provincial poverty line, while the average household income of non-recipients is about PHP 749 (about 15 USD) higher than their respective poverty line.

On average, about 32% of CCT recipient households have been exposed to a shock (death or grave illness in the family, loss of employment or business failure, or natural/man-made disaster), while 36% of non-recipient households have been exposed to a shock. Our analysis does not distinguish between what type of shock a household was exposed to because we are not interested in the effects of specific types of shocks on households' spending patterns. Although disaggregating the effects of exposure to different types of shocks would potentially add depth to the analysis, the sample size would be reduced drastically for each type of shock households are exposed to per province and the precision of estimates will be compromised. Thus, clustering all shocks together in the analysis also makes sense from a practical standpoint, considering the number of observations per province. If a household experienced death or grave illness in the family, loss of employment or business failure, typhoons or other extreme weather disturbances, earthquake, fire, or other natural or man-made disasters in the past 12 months, then the household is coded as having been exposed to a shock.

Table 5. Summary Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max
CCT recipients					
Share of alcohol and tobacco to household expenditures	655	2.70	3.57	0	22.89
Expenditures on alcohol and tobacco (PHP)	655	3,541	4,874	0	32,850
Poor	655	0.91	0.29	0	1
Estimated re-centered income	655	-1,333	1,260	-3,781	3,214
Exposure to shocks	655	0.32	0.47	0	1

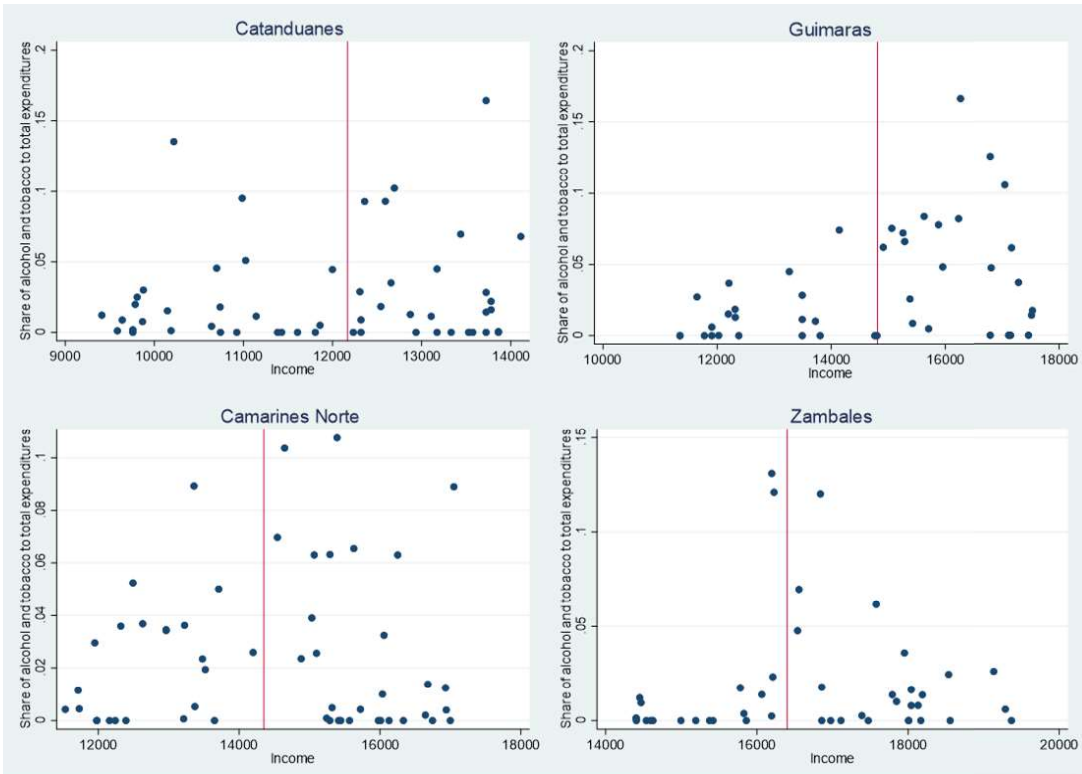
CCT Non-recipients					
Share of alcohol and tobacco to household expenditures	847	2.64	3.94	0	21.58
Expenditures on alcohol and tobacco (PHP)	847	3,204	4,920	0	29,710
Poor	847	0.14	0.35	0	1
Estimated re-centered income	847	749	1,314	-3,564	4,808
Exposure to shocks	847	0.36	0.48	0	1

Note: Sample includes households within a 15-percentile bandwidth on both sides of the cut-off.

Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

RD plots for the 15-percentile bandwidth are presented in Figure 1. The vertical axis shows the share of alcohol and tobacco to total household expenditures, while the horizontal axis shows household income and the provincial poverty line. Each province has its own cut-off, the respective provincial poverty line. We show RD plots for several provinces that represent various poverty lines, average exposure of households to shocks, populations, and geographic locations for brevity. Although the relationship between expenditure on alcohol and tobacco and income may vary from one province to another, the RD plots show that generally, expenditures on alcohol and tobacco are slightly lower for households below the cut-off. Being below the provincial poverty line or cut-off is the primary criteria for receiving cash transfers. Households below the cut-off, of which most are cash transfer recipients, generally spend a smaller share of their household income on alcohol and tobacco.

Figure 1. RD Plot



Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

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 (Bündnis Entwicklung Hilft, 2017). Households in the Philippines are regularly exposed to disaster shocks. In Table 6, we first estimate whether CCT beneficiary households are more likely to experience shocks compared to non-CCT beneficiary households. For the purposes of our analysis, a household is defined to be exposed to shocks if it experienced 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; or natural or man-made disasters.

Table 6 shows that CCT beneficiary households are not significantly more likely affected by shocks relative to non-CCT beneficiary households. This results implie that shocks affect the two groups of households in our sample randomly for both bandwidths, 10-percentile and 15-percentile.

Table 6. Determinants of Shocks

	Sharp RDD		Fuzzy RDD	
	(1)	(2)	(3)	(4)
Shocks	BW1	BW2	BW1	BW2
	10-percentile	15-percentile	10-percentile	15-percentile
Poor (OLS)/CCT (IV)	-0.0621	-0.0175	-0.0835	-0.0214
	(0.0505)	(0.0494)	(0.0629)	(0.0603)
Rinc	-7.71e-05**	2.30e-06	-9.20e-05***	2.52e-06
	(2.92e-05)	(1.78e-05)	(3.41e-05)	(1.92e-05)
Rinc x Poor (OLS)/Rinc x CCT (IV)	0.000103**	1.79e-06	0.000141**	2.48e-06
	(4.11e-05)	(2.23e-05)	(5.67e-05)	(3.28e-05)
Constant	0.408***	0.351***	0.416***	0.352***
	(0.0328)	(0.0281)	(0.0350)	(0.0297)
Observations	1,016	1,502	1,016	1,502
R-squared	0.007	0.001		0.002

Note: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; standard errors are clustered by province.

To account for the impact of shocks on households in our analysis, we run specifications that estimate the impact of the CCT program on temptation goods (alcohol and tobacco) spending as a share of total expenditures (Table 7) for households exposed to shocks relative to those who were not. In Table 7, the coefficient of interest is an interaction term of the CCT indicator (or the dummy for being below the cut-off for poverty) and shocks. This coefficient estimates how the CCT program induces households to adjust their expenditures on temptation goods (alcohol and tobacco) when exposed to various shocks.

Table 7 shows that for the 15-percentile bandwidth estimated using sharp RD, we find some suggestive evidence that CCT recipient households exposed to shocks may relatively decrease their proportion of household expenditures allocated for alcohol and tobacco by about 1.2 percentage points. For both bandwidths, fuzzy RD estimates indicate that on average, CCT beneficiary households may allocate 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. Table 5 above indicates that on average, alcohol and tobacco account for about 2.6% to 2.7% of household expenditures. Thus, a decrease of 1.2 to 2 percentage points share of household expenditures for alcohol and tobacco among CCT recipient households when exposed to shocks is substantial. This result also serves as suggestive evidence against the notion of cash transfer misuse towards temptation goods when beneficiary households are exposed to various shocks.

Table 7. Shocks and Temptation Goods (Alcohol and Tobacco)

	Sharp RDD		Fuzzy RDD	
	(1)	(2)	(3)	(4)
Share of alcohol and tobacco	BW1	BW2	BW1	BW2
to total expenditures	10-percentile	15-percentile	10-percentile	15-percentile
Poor (OLS)/CCT (IV)	0.00258	0.00501	0.00307	0.00607
	(0.00578)	(0.00512)	(0.00678)	(0.00600)
Rinc	-5.35e-06*	-1.03e-06	-6.20e-06**	-1.44e-06
	(2.77e-06)	(1.98e-06)	(2.95e-06)	(2.29e-06)
Shocks	0.00234	0.00304	0.00342	0.00394
	(0.00514)	(0.00370)	(0.00578)	(0.00382)
Rinc x Poor (OLS)/ Rinc x CCT (IV)	5.55e-06	1.55e-06	7.56e-06	2.28e-06
	(3.59e-06)	(3.49e-06)	(4.82e-06)	(4.97e-06)
Rinc x Shocks	-2.46e-06	-3.04e-06	-1.95e-06	-2.98e-06
	(5.87e-06)	(2.58e-06)	(7.14e-06)	(3.01e-06)
Poor x Shocks (OLS)/ CCT x Shocks (IV)	-0.0141	-0.0123*	-0.0196*	-0.0157*
	(0.00881)	(0.00639)	(0.0114)	(0.00806)

Rinc x Poor x Shocks (OLS)/	-1.81e-07	1.68e-06	-1.38e-06	2.33e-06
Rinc x CCT x Shocks (IV)	(7.40e-06)	(4.28e-06)	(1.10e-05)	(6.33e-06)
Constant	0.0290***	0.0265***	0.0290***	0.0263***
	(0.00300)	(0.00309)	(0.00309)	(0.00316)
Observations	1,016	1,502	1,016	1,502
R-squared	0.013	0.007	0.011	0.009

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; standard errors are clustered by province.

Since we are interested in testing whether there is cash transfer misuse towards temptation goods (alcohol and tobacco) and its overall impact on household expenditures when shocks occur, we present our estimates as a proportion of household expenditures instead of raw spending. This also allows us to account for the different costs of living and poverty lines across the Philippines. Due to various costs of living and poverty lines in different provinces, expressing alcohol and tobacco expenditures as a share of total household expenditure standardizes the unit of measurement and makes the estimates more comparable across provinces.

To verify the robustness of our main results in Table 7, we estimate the treatment effect only on households that experienced shocks in Table 8. The results in Table 8 for households that were exposed to shocks are consistent with our main results in Table 7 (Poor x Shocks (OLS) and CCT x Shocks (IV)). Table 8 shows that when limiting the sample only to households exposed to shocks, we find CCT recipient households allocate about 1.2 (Sharp RD estimate) to a 1.7 (Fuzzy RD estimate) percentage points smaller share of their income on alcohol and tobacco. The results in Table 8, which only include households exposed to shocks, confirm that, on average, CCT recipient households decrease their expenditures on temptation goods when exposed to shocks.

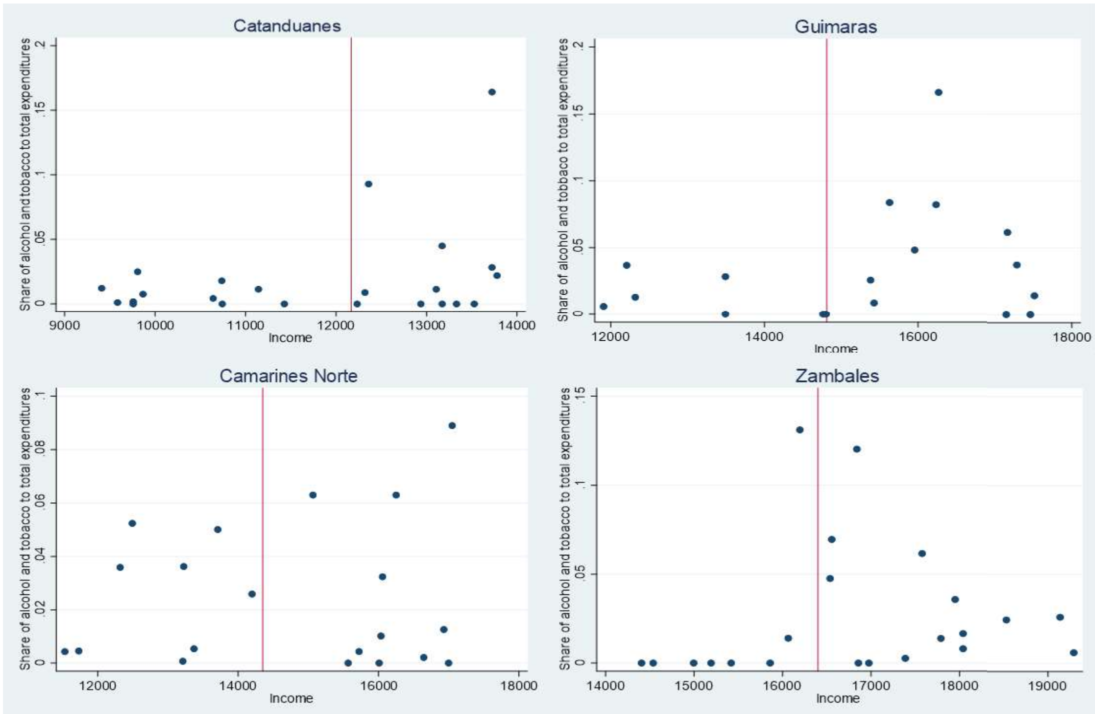
Table 8. Alcohol and Tobacco Expenditures for Households Exposed to Shocks

	Sharp RDD		Fuzzy RDD	
	(1)	(2)	(3)	(4)
VARIABLES	BW1	BW2	BW1	BW2
	10-percentile	15-percentile	10-percentile	15-percentile
Poor (OLS)/CCT (IV)	-0.0116*	-0.00730	-0.0165*	-0.00961
	(0.00670)	(0.00519)	(0.00913)	(0.00685)
Rinc	-7.81e-06	-4.06e-06**	6.19e-06	4.60e-06
	(6.09e-06)	(1.81e-06)	(1.13e-05)	(4.58e-06)
Rinc x Poor (OLS)/ Rinc x CCT (IV)	5.37e-06	3.23e-06	-8.14e-06	-4.42e-06**
	(7.40e-06)	(3.10e-06)	(7.55e-06)	(2.18e-06)
Constant	0.0313***	0.0295***	0.0324***	0.0302***
	(0.00493)	(0.00323)	(0.00549)	(0.00341)
Observations	338	512	338	512
R-squared	0.010	0.006	0.015	0.011

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses; standard errors are clustered by province.

Figure 2 shows the RD plot that includes only households exposed to shocks within the 15-percentile bandwidth. Although spending on alcohol and tobacco may vary across provinces, especially due to different prices of goods and costs of living, on average, households below the cut-off (CCT recipients), spend a smaller share of their household income on temptation goods when exposed to shocks. On the other hand, households above the cut-off or poverty line (non-CCT recipients) spend a larger proportion of their household income on temptation goods when exposed to shocks, on average.

Figure 2. RD Plots for Households Exposed to Shocks



Source: Author's calculations based on 2014 Pantawid Pamilya Impact Evaluation Wave 2 data set.

6. Policy Implications

We first established that households on either side of the cut-off (poverty line) are comparable in terms of socio-economic characteristics. The results of the validation tests are presented in the Appendix. We then verified that shocks affect households randomly in Table 6. This result means that being below or above the poverty line has no implications on a household's exposure to shocks. Establishing that shocks affect households randomly is important before incorporating shocks into the succeeding estimation equations. Table 7 shows that, on average, CCT beneficiary households may allocate 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 confirm these estimates in Table 8, which limited the sample to only households that experienced shocks and show that CCT recipient households allocate about 1.2 to 1.7 percentage points smaller share of their income on alcohol and tobacco. The RD plots in Figure 1, which include the full sample, and Figure 2, which uses a sample limited to households that were exposed to shocks, confirm our findings that, on average, CCT recipient households spend a smaller share of their income on alcohol and tobacco when exposed to shocks.

The results of our study confirm that CCT recipient households in the Philippines do not increase their spending on temptation goods when experiencing shocks. This provides evidence against the notion of cash transfer misuse, especially when shocks occur. However, one limitation of this study is the sample size, which did not allow us to distinguish between the impacts of different types of shocks on household spending patterns. Another limitation is that household incomes were estimated using PMT. Although the use of PMT is intended to minimize bias compared to asking households for their declared income, PMT is still an imperfect measure, and the estimates may be subject to measurement error. Finally, imperfect program implementation is another limitation of this study. Not all households below their respective provincial poverty lines received cash transfers. Likewise, some households above the cut-off were able to receive transfers. To address this, we used IV-2SLS and estimated fuzzy RD, in addition to sharp RD.

The results of our estimates show that at least in the Philippines, there is no evidence of cash transfer misuse towards temptation goods such as alcohol and tobacco when households are exposed to shocks. This finding is important in evaluating the program's impact on recipients' overall welfare and dampening some policymakers' concerns of misallocation of transfers towards temptations goods. Social welfare programs such as CCTs can advance the vulnerable population's protection from various disasters and shocks (World Bank, 2018). By supplementing household income during times of disasters, the CCT program can provide immediate relief and make poor households more resilient to shocks (World Bank, 2018). The effectiveness of the CCT program in the Philippines in producing positive outcomes for its recipients provides a greater incentive to improve targeting to ensure that benefits are allocated to the most impoverished households.

7. Conclusion

In this paper, we assess the impact of the Philippines' conditional cash transfer (CCT) program on households' behavior in response to shocks using sharp and fuzzy RDD. 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, and natural or man-made disasters, relative to non-beneficiary households. We then estimate the CCT program's impact on changes in household expenditures on temptation goods of CCT beneficiary households when exposed to various shocks.

Our estimates show that CCT beneficiary households allocate a relatively smaller proportion of their household income on temptation goods, such as alcohol and tobacco, when exposed to shocks. The CCT program in the Philippines is a valuable social safety net for impoverished households. By providing evidence that CCT beneficiary households do not increase spending on alcohol and tobacco when exposed to shocks, we resolve concerns regarding the misuse of cash transfers.

The literature on the impact of CCTs in the presence of shocks is currently relatively sparse. Given that the Philippines has the third-highest risk for disasters among a sample of 171 countries (Bündnis Entwicklung Hilft, 2017) in the 2016 World Risk Report, it seems reasonable to incorporate shocks more often into the analysis of social welfare programs in countries that have a high risk of exposure to shocks such as the Philippines.

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Appendix: Validation Tests for Discontinuity at the Threshold

Note: BW1 includes households within a 10-percentile bandwidth; BW2 includes households within a 15-percentile bandwidth; and BW3 includes households within a 20-percentile bandwidth for all provinces.

Table A1. Log Family Size

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A2. Children Below 5 Years Old

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A3. If Roof is Made of Strong Materials

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A4. If Walls are Made of Strong Materials

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A5. If Roof is Made of Light Materials

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A6. If Walls are Made of Light Materials

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A7. If Household Has No Toilet

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A8. If Household Water Source is Shared Tubed/Piped Well

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A9. If Household Has Electricity

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A10. If Household Has a Refrigerator

	(1)	(2)	(3)
VARIABLES	BW1	BW2	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A11. If Household Has a Washing Machine

VARIABLES	(1) BW1	(2) BW2	(3) 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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table A12. If Household Owns the House

VARIABLES	(1) BW1	(2) BW2	(3) 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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.

Table 21. If Household Rents the House

	(1)	(2)	(3)
VARIABLES	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

Notes: *** p<0.01, ** p<0.05, * p<0.1; robust standard errors in parentheses.