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Conditional Cash Transfers and School Enrollment:

Impact of the Conditional Cash Transfer Program in the Philippines

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Summary

Despite modest economic growth over the past decade, the Philippines has made little progress in reducing poverty. In this regard, the Philippines is an outlier in the region, seemingly unable to translate economic growth into meaningful poverty reduction. This underscores the fact that structural poverty remains a binding constraint to equitable growth. Furthermore, the Philippines remains highly vulnerable to climatic and other adverse shocks, making the task of poverty reduction even more challenging.

To help meet short-term consumption needs while fostering investment in human capital to help break the intergenerational transmission of poverty, the Philippines launched a conditional cash transfer (CCT) program in early 2008. The *Pantawid Pamilyang Pilipino Program* provides cash transfers to poor households conditional upon investments in child education/health, as well as prenatal/postnatal check-ups for pregnant women. The program has expanded and evolved to be one of the major social protection programs in the Philippines, covering 3 million poor households nationwide.

This study represents a first step toward rigorously documenting the causal impact of the CCT program, focusing on school enrollment from a small selective sample survey. Primarily for illustrative purposes, the study concentrated on areas where education outcomes were low before the intervention, to determine the impact on marginalized areas. The study compared school enrollment before and after CCT program implementation, using panel data of about 2,000 CCT and non-CCT children from 900 sample households in three regions of the country. The baseline data was collected in 2008 before program implementation, matched to the follow-up survey which was conducted in 2011. Under the CCT program, households receive cash transfers conditional on school enrollment and regular attendance of children aged 6-14, therefore the analysis used the sample of children aged 6-14 during the baseline (2008), and the same children aged 9-17 at the time of the follow-up survey (2011).

The Philippine Social Protection Note series aims to disseminate experiences, good practices, and key findings from the Philippines on the topics related to social protection. It also aims to broaden the dialogue on social protection and stimulate public engagement in moving forward the policy agenda. The views expressed here are those of the authors and do not necessarily reflect those of the World Bank.

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Using difference-in-difference (DD) and regression discontinuity design (RDD), impact evaluation analysis of children aged 9-17 during follow-up indicates a strong and statistically significant impact of the CCT program on improving school enrollment among the younger cohort of children aged 9-12 as of 2011. The analysis found an almost 9 percent increase in the enrollment among the younger cohort aged 9-12 (as of 2011) who were eligible for grants under the program throughout 2008 and 2011. The program was able to help address the education gap between beneficiary and non-beneficiary households in a short amount of time. However, no statistically significant impact was found for the older cohort of children aged 13-17 (as of 2011), most of whom were no longer eligible for grants due to the age limit (14 years) set by the program. This suggests that additional measures (e.g., raising the age limit, increasing the grant amount for older children, parallel supply-side interventions in the education sector) are required to improve educational outcomes for older children. The study findings also indicated variation in program impact by household composition, which suggests that future studies should focus not only on average impact but also on variation in outcomes by socioeconomic factors.

1. Background of the CCT Program

Structural poverty is a binding constraint to equitable growth in the Philippines. Despite annual economic growth of 4.7 percent in the 2000s, the Philippines has had essentially no reduction in poverty over the past decade. According to the latest official statistics, poverty incidence remains high at 26.5 percent (NSCB 2011). In this respect, the Philippines remains an outlier in the region, seemingly unable to translate economic growth into meaningful poverty reduction. Furthermore, the Philippines remains highly vulnerable to climatic shocks, and millions of Filipino households are faced with a plethora of natural and adverse idiosyncratic shocks. Nearly 10 percent of the population lives just above the poverty line and is therefore vulnerable to falling into poverty as various shocks arise (Velarde and Fernandez, 2011).[2]

The multi-dimensional nature of poverty is manifest in disparities in education and health outcomes. Elementary school completion rates are low, and only one quarter of children 11-13 years old in the lowest income quintile finish elementary school, compared to 55 percent in the highest income quintile (World Bank, 2010 and 2011). According to the 2008 National Demographic and Health Survey, for the lowest wealth quintile, the under-five mortality rate is high at 59 per 1,000 live births, more than triple the rate of the highest wealth quintile (National Statistics Office and IFC Macro, 2009). Access to health care is also more problematic for poor women. For example, 74 percent of women in the lowest wealth quintile face financial constraints to seeking treatment, compared to 38 percent in the highest wealth quintile. The share of women who received antenatal care from a skilled provider[3] is 77 percent in the lowest wealth quintile and 98 percent in the highest wealth quintile.

To address issues of structural poverty and vulnerability, the Government of the Philippines initiated a CCT program, the *Pantawid Pamilyang Pilipino Program (Pantawid Pamilya)*, in 2008. The *Pantawid Pamilya*, implemented by the Department of Social Welfare and Development (DSWD), provides cash transfers to poor households conditional upon investments in education and health. Like many other CCT programs worldwide, the *Pantawid Pamilya* has both short- and long-term objectives for addressing poverty. In the short-term, cash transfers can supplement and smooth household income, helping to meet the immediate consumption needs of poor households and address current poverty. In the longer term, promoting school attendance and utilization of health centers can lead to improved education and nutrition status for poor children, thereby helping to break the intergenerational cycle of poverty.

[2] Calculated as the proportion of the population whose income lies within 20 percent above the official poverty lines.
[3] "Skilled provider" meaning doctor, nurse, or midwife.

The *Pantawid Pamilya* provides health and education grants subject to beneficiary households complying with education and health conditionalities. The education conditionality is that daycare and school-aged children between 3-14 years of age should be enrolled in daycare/school and maintain "regular" attendance.[4] The program has multiple health conditionalities which are more complex, in accordance with the protocols set by the Department of Health. For example, pregnant women are required to attend prenatal/postnatal consultations, children 0-5 years old need to go through regular growth monitoring,[5] and children 6-14 years old are required to take deworming pills twice a year. On a regular basis,[6] schools and health centers verify whether beneficiaries have complied with the conditionalities. After this verification process, as long as eligible household members comply with these program conditionalities,[7] beneficiary households are entitled to receive the cash transfers.[8]

The level of transfer was designed to be sufficient enough to encourage poor households to send children to schools and health centers on a regular basis, yet low enough as not to encourage dependency (e.g., reduction in time worked or withdrawal from the labor market). The health grant is a lump sum of PhP 500 (USD 11.6[9]) per month per household, while the education grant is PhP 300 (USD 7.0) per month per child, up to a maximum of three children per household for ten school months during the year (DSWD, 2011a). The amount of monthly grants ranges from Php 500 (USD 11.6) to PhP 1,400 (USD 32.5) per household, depending on the number of eligible household members. On average, the program transfer accounts for 20 percent[10] of the annual income of beneficiary households (Velarde and Fernandez, 2011).

***Pantawid Pamilya* is a targeted program—geographically targeted to poor areas, with selection of poor beneficiary households from within those priority areas.** Since means testing is not possible due to lack of systematic income data for the overwhelming majority of Filipino households in the informal economy (as in many developing and middle-income countries), a proxy means test (PMT)[11] approach has been adopted to identify poor households. The Government scaled up the CCT program in phases, referred to as "Sets",[12] which specify target areas. Within those areas, poor households are identified using PMT under the National Household Targeting System for Poverty Reduction (NHTS-PR).[13] Under the NHTS-PR, the DSWD conducted nationwide household interviews using a short questionnaire called the Household Assessment Form (HAF) to collect information on household composition and socioeconomic characteristics, which serve as proxies to estimate the per capita income (PMT score) of each household. The NHTS-PR then systematically classifies the poor whose PMT scores are at and below the 2006 poverty thresholds.[14] Only poor households (as identified by PMT) with children aged 0-14 years old and/or pregnant women are eligible for the program.[15]

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[4] In the school system in the Philippines, "regular" attendance is defined as attending 85 percent of the school days on a monthly basis in a school year.

[5] "Regular" growth monitoring is defined as monthly for children 0-23 months old. Children 2-5 years old were/are required to avail of growth monitoring quarterly until 2011 and once every two months starting in 2012.

[6] Until 2010, verification and payments were processed on a quarterly basis. Starting in 2011, they have been processed every two months.

[7] For the monitoring period of November and December 2011, 83 percent of school-aged children (6-14 years old) eligible for the education grant complied with the school attendance conditionality in Set 1 areas (DSWD, 2012). For health, 88 percent of children between 0-5 years old complied with the growth monitoring conditionality in Set 1 areas. Compliance rates varied by Set.

[8] Via cash card, over the counter payments, and payouts through the mobile phone network.

[9] Using the USD-PhP exchange rate of 43 Pesos to 1 USD, (based on the average exchange rate between January to March 2012 (Bangko Sentral ng Pilipinas, 2012).

[10] This is calculated as the amount of transfer (PhP 10,630) over annual household income (PhP 53,976), using the *Pantawid Pamilya* database as of February 2011 (Velarde and Fernandez, 2011).

[11] PMT is a statistical/econometric method in which a set of core variables (which must be relatively easy to verify) correlated with income/consumption is used to predict household level income/consumption. In the Philippines case, PMT is used to predict income, and households are then stratified according to official income poverty lines (which vary by province).

[12] Set 1 areas (covering mainly the poorest 20 provinces starting in 2008) and Set 2 areas (covering municipalities with poverty incidence higher than 61.23 percent starting in 2009) are the CCT program areas currently supported by World Bank financing.

[13] The National Household Targeting Office (NHTO) was officially established in March 2009. Previously, HAF administration was conducted under the *Pantawid Pamilya* office.

[14] The NHTS-PR applies previous 2006 poverty thresholds, while the NSCB revised the computation methodology and released new poverty thresholds in March 2011.

[15] Hence by design, various categories of poor are left out of the CCT program: poor households without children, poor households with children above the age of 14, elderly poor households, poor households with members with disabilities.

2. Objective of the Study

Given the centrality of this program as the pioneer social safety net intervention, it is critical to have rigorous empirical evidence on the causal impacts of this program on key outcomes. The *Pantawid Pamilya* has become the largest and core social assistance program in the Philippines. Since the program's launch in 2008, the number of CCT beneficiary households has increased rapidly to 3 million. The program currently covers almost 60 percent[16] of total poor Filipino households who are identified under the NHTS-PR. Parallel to program expansion, budget support for the program has nearly doubled every year from 2010,[17] and PhP 39 billion (USD 906 million) was allocated to cover 3 million households in 2012. Given the size and importance of the program, it is critical to understand its effectiveness and impact.

Monitoring and evaluation (M&E) is embedded in the fabric of the CCT program. The *Pantawid Pamilya* has a strong monitoring system in order to monitor the process regularly and improve the quality of program implementation. It also designed to facilitate impact evaluation: the program intervention was rolled out in batches, and in some priority areas, intervention was postponed purposefully to serve as *control* areas.[18] This allows for exogenous identification of program impact when comparing *control* and *treatment* areas. Several rounds of surveys are planned for a rigorous impact evaluation (IE) using Randomized Control Trial (RCT) methodology. Furthermore, the fact that poor beneficiaries are selected with PMT scores just at and below the poverty line allows for evaluation with the Regression Discontinuity (RD) methodology, essentially comparing outcomes of poor households who received the program with similar poor households just above the poverty line. The first survey round to inform the detailed and comprehensive IE is currently underway, with the objective of establishing the causal impact of the program on a wide range of outcomes (e.g., household food consumption, child education, and nutritional status).

While the more comprehensive impact evaluation is underway, the objective of this study is to provide a limited yet rigorous snapshot of the impact of the CCT program on one of the program's most important objectives: increasing school participation. With its expansion, the *Pantawid Pamilya* program has been receiving greater attention in the Philippines. However, rigorous impact evaluation that could provide scientific evidence on the causal impact of the program for policy discussions is still lacking to date, and evidence on program impacts has been largely anecdotal. Therefore, responding to a request from the DSWD, the World Bank designed and conducted a small survey of the *Pantawid Pamilya* in limited locations, using Difference-in-Difference (DD) and RD methodology, while the more comprehensive IE effort is being conducted.[19]

This study focuses on impacts on the school enrollment status of children, based on data collected from 900 households. Random sampling was stratified at the village (barangay) level and covered 900 households residing in 9 municipalities in all three island groups in the Philippines. The sample size was split evenly between beneficiary (*treatment*) and non-beneficiary (*control*) households based on program status from the *Pantawid Pamilya* central database.

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[16] Under the NHTS-PR, 5.2 million households are classified as poor based on PMT scores, out of 10.2 million households surveyed.

[17] The program budget increased from PhP 10 billion in 2010 to PhP 21 billion in 2011 and PhP 39 billion in 2012.

[18] During the initial design of the program, a set of 8 poor municipalities was randomly selected to be included in the Impact Evaluation (IE) study. These municipalities are in four provinces that were purposefully selected to represent the country's macro regions. Two municipalities in each of the four provinces were then randomly selected. Consequently, half of the barangays (villages) within each municipality were randomly assigned to participate when the program was launched, and the other half would participate after a delay of approximately two years—resulting in 65 "*treatment*" barangays and 65 "*control*" barangays.

[19] The comprehensive IE was initially scheduled in 2010. The actual data collection took place from October 2011 to March 2012. The overview design of the quantitative impact evaluation is summarized in the Concept Note (Filmer, D. et el, 2010).

3. Methodology

The CCT impact on school enrollment was estimated by comparing the changes that happened to CCT beneficiary children (*treatment* group) and non-CCT children (*control* group), using the Difference-in-Difference (DD, or double difference) methodology. In an ideal impact evaluation setting, the net impact of the program that happened to the same evaluation unit (in this case, children) would be measured by comparing the change in the *presence* of the intervention and in the *absence* of the intervention. In the real world, however, it is not feasible to observe the same child in both states, one state of *becoming* a CCT beneficiary and the other state of *not becoming* a CCT beneficiary. The DD estimator assumes the change of *control* group as the counterfactual indicator, in order to remove changes that could have happened over the reference period even in the *absence* of the CCT program.

Having credible baseline data from before the start of the program intervention in 2008 was critical to this estimation strategy. The small sample household assessment survey was carried out in 2011. Before there was any CCT program, the same households were surveyed in 2008 during the administration of the HAF for PMT scoring purposes (for subsequent selection of program beneficiaries). The education status of children in those households before the program intervention (baseline) comes from the HAF survey under the NHTS-PR, while post-intervention data on education outcomes—among other information—comes from the 2011 assessment survey (follow-up).

3.1 Difference-in-Difference (DD) Approach

The net impact of the CCT program is defined as the enrollment change of CCT children minus that of non-CCT children, before and after the CCT program implementation. First, we define $y_{child,\ time}$ to indicate the enrollment status of the same child from pre- and post-CCT implementation, at two time periods which are before and after the CCT program, where y takes a value of 1 if the child is enrolled in school and 0 if otherwise. Next, the enrollment change of CCT children is given as $(y_{cct,\ after} - y_{cct,\ before})$. Similarly, the enrollment change of non-CCT children is given as $(y_{non\text{-}cct,\ after} - y_{non\text{-}cct,\ before})$. Therefore, the net CCT impact on the change in school enrollment is calculated with the following equations, which yield the difference of enrollment growth for the CCT group (*treatment* group) before and after the CCT program and that for the non-CCT group (*control* group).

$(y_{cct,\ after} - y_{cct,\ before}) - (y_{non\text{-}cct,\ after} - y_{non\text{-}cct,\ before})$, alternatively $\Delta y_{cct} - \Delta y_{non\text{-}cct}$

We then run the following regression to estimate net enrollment growth:

$$\Delta y_{child} = \alpha_0 + \alpha_1 T_{child} + \varepsilon_{child} \qquad \cdots (1)$$

where Δy_{child} denotes the change in enrollment status for the same child, therefore can take a value of 1 if the child was enrolled in school in 2011 but not in 2008; 0 if the child was either enrolled or not enrolled in both 2011 and 2008; and -1 if the child was enrolled in school in 2008 but not in 2011. T is a dummy variable which takes 1 for CCT beneficiary child and 0 for non-CCT beneficiary child. The coefficient α_1 is the average impact estimator of the CCT program, based on the basic DD model. The basic DD estimator allows for differences in initial level (i.e. intercepts) but assumes similar growth trends (i.e. slope) in absence of the intervention.

We also run an estimation in which we include other covariates to help reduce some of the estimation bias inherent in the basic DD model, specification (1). We add additional dummy variables to control for sex and age of children, urban/rural characteristics, and regional characteristics. This model is a basic DD with covariates, as specified in the following equation (2). For the sensitivity analysis, we separately run the regressions (Model 1 and 2) by the number of school-aged children per household.

$$\Delta y_{child} = \alpha_0 + \alpha_1 T_{child} + \alpha_2 Sex_{child} + \alpha_3 Age_{child} + \alpha_4 Urban_{child} + \alpha_5 Region_{child} + \varepsilon_{child} \qquad \cdots (2)$$

3.2 Regression Discontinuity Design (RDD) Approach

Sharp Discontinuity Assumption

One way to deal with possible selection bias is to use a RDD technique that exploits the targeting design itself. One key assumption of the estimation strategy described above is that unobservable factors ("heterogeneity") that shape actual program participation of the household is additively linear in nature and "differenced away" by the DD estimation. The error term, however, could still be contaminated with factors that shape both program participation and outcomes. RDD makes use of discontinuities generated by program eligibility criteria such that program assignment is based on a cut-off point of some assignment variable. The eligibility for becoming beneficiaries of a program is solely determined by whether they are below or above the unique value of a cut-off point. This is a case of sharp RD design[20] (Rosenbaum and Rubin, 1983; Heckman et al., 1997). In other words, the probability of being exposed to treatment changes from 0 to 1 discontinuously as one crosses the cut-off. RDD identifies and estimates the program impact in the neighborhood of the cut-off point for selection into the program. Within a small interval of the cut-off, households on either side of the cut-off have similar income levels and can be thought to have similar enrollment growth in the *absence* of cash transfers or in the *presence* of cash transfers, and therefore form very good comparison groups. This can be translated to the following equation to give the impact estimate, α:

$$a = E(\Delta y_{child} \mid P - h) - E(\Delta y_{child} \mid P + h) \qquad \cdots (3)$$

where T takes 1 for PMT score at and below the poverty lines $(P) \geq PMT$ and T takes 0 for PMT score above the poverty lines $(P) < PMT$, and for some arbitrary small value $h > 0$.

The Philippines CCT Case

In the *Pantawid Pamilya's* case, the strict assumption for the sharp discontinuity, wherein there is only one unique cut-off value (in our case PMT score) to determine the program participation, does not hold due to the multiple cut-off points which vary by province. In the Philippines, poverty thresholds are officially set at the provincial level by the National Statistics and Coordination Boards (NSCB), and provincial poverty thresholds in 2006 ranged from around PhP 12,000 (USD 279) to PhP 21,000 (USD 488) (NSCB, 2008). Thus, the program has multiple cut-off values, and cut-off values in the sample areas are shown in Table 1. Ideally, RD estimations should be done separately for each cut-off, but our sample size is very small.

Table 1. Provincial Poverty Thresholds in 2006 (PhP (USD), Per Capita Income)

Masbate (Region 5)	Negros Oriental (Region 7)	Lanao del Norte (Region 10)
PhP 14,248 (UDS 331)	PhP 12,159 (USD 283)	PhP 15,225 (USD 354)

Source: NSCB (2008)

Furthermore, our sample data does not strongly support choosing RDD analysis along the sharp discontinuity assumption. As shown in Table 2, 5 percent of beneficiary households have higher PMT scores than the program cut-off point, and 19 percent of non-beneficiary households have lower PMT scores than the program cut-off point. While the cut-off discontinuity holds for the overwhelming majority of households (95 percent of beneficiary households have PMT scores below the cut-off point), strictly speaking, the cut-offs were not binding/discontinuous for the entire sample for various reasons, such as program implementation and mobility of household members.[21]

Table 2: Distribution of Sample Households by Poverty Status before CCT Implementation (%)

	Poor (PMT ≤ cut-off)	Non-poor (PMT > cut-off)	Total
CCT	95.1	4.9	100.0
Non-CCT	18.8	81.2	100.0

Source: Poverty status from DSWD (2011b and 2011c), CCT status from TNS (2011)

[20] In the Philippines CCT case, the cut-off is not unique, as poverty thresholds are set at the provincial level.

[21] See Annex 1 for more detailed reasons for discrepancies.

Semi-parametric Specification

In the RD framework, the net impact can be estimated either by parametric or nonparametric methods. The parametric approach estimates the average impact using all observations anywhere from above and below the poverty lines. Nonparametric specification extrapolates the average impacts near the poverty lines by assigning a larger weight to observations closer to the cut-off.

For this study, we use a semi-parametric approach, which combines a parametric polynomial approximation with kernel density nonparametric weights. We use a less restrictive nonparametric approach using local linear regression (LLR) with kernel weights as suggested by Hahn et al. (2001) and Porter (2003) and used the impact evaluation literature such as Chaudhury and Parajuli (2010). Using the kernel weights, this model assigns larger weights to observations with PMT scores closer to the poverty thresholds and smaller weights to observations with PMT scores further from the poverty thresholds. The LLR can be estimated using the following equation:

$$\Delta y_{child} = \phi_0 + \phi_1 T_{child} + \phi_2 (P - PMT)_{child} + \phi_3 T_{child} * (P - PMT)_{child} + \varepsilon_{child} \quad \cdots (4)$$

with kernel[22] weights $w_{child} = \kappa((P\text{-}PMT)_{child} / h)$ using a bandwidth[23] of h

where P is poverty thresholds that are cut-offs for the CCT program. PMT is PMT score, which is per capita income estimated under the NHTS-PR. Therefore $(P\text{-}PMT)$ measures the distance between the poverty threshold and the PMT score of the household to which the child belongs. In this approach, ϕ_1 provides the average impact, with more weight given to households near the poverty threshold. We can also add a similar set of covariates as in the DD specification to control for children's sex, age, urban/rural characteristics, and regional characteristics to Model 4. As described above, *Pantawid Pamilya* does not have one cut-off that determines eligibility; rather, we have multiple provincial-level cut-offs. Ideally, we should do province-wise estimation, but due to data limitations in sample size, we do one estimation with the assumption that ϕ_1 still gives the impact of the CCT program (averaged across provinces and households). Thus, for both types of specifications (DD and RDD), we are interested in examining changes in enrollment patterns for children aged 6-14 in the HAF baseline before program implementation in 2008, and subsequent enrollment by *treatment* and *control* status for the same panel of children (aged 9-17 in the follow-up survey round in 2011).

4. Data

As previously mentioned, the panel data used for the analysis consists of information from pre- and post-CCT intervention. As described above, pre-intervention information comes from the NHTS-PR database, which served as the basis for selecting the poor beneficiary households for the *Pantawid Pamilya* program. Household data was recorded in the HAF, and information from the HAF variables was used to estimate the PMT score for each household before the CCT program was implemented. In the sampled municipalities for this study, the HAF survey was conducted between June to October 2008. After the PMT processing, the program registration of eligible households started from September 2008 and May 2009, subsequently followed by the release of the first grant after registration. In August-September 2011, household interviews were conducted to collect post-CCT information from the selected 900 households.

[22] We use Epanechnikov kernel: $K(Z)=(3/4)(1-Z^2)$ for $|z| \le =1$, 0 otherwise. This kernel is widely thought to be most optimal for LLRs.

[23] The choice of bandwidths is ultimately arbitrary despite a slew of so-called optimal selection criteria suggested in the literature. Ultimately, there is no consensus in the literature on optimal choice of bandwidth. We use 2000, 3000, 4000, and 5000 for sensitivity analysis. Larger bandwidth would increase bias, while smaller bandwidth increases variance. At the high levels of bandwidth that we use for this analysis leading to excessive smoothing, the LLR essentially collapses to a more generalized polynomial regression.

The sample households were selected among those who had at least one child between 6-14 years old, which is the age bracket for education grants, as of 2008 when the program started. The panel data consists of 1,961 children in the defined age bracket[24] from 900 households, residing across 47 barangays, 9 municipalities, 3 provinces, and 3 regions. In each barangay, the same or nearly equal number of household interviews was conducted for beneficiary and non-beneficiary households, respectively. Three provinces were selected, covering all of the three major island groups,[25] from the Set 1 areas (the first roll-out batch of the *Pantawid Pamilya*) to ensure adequate gestation period of the CCT program. Furthermore, we purposefully picked areas from the 40 lowest-performing divisions as ranked by the Department of Education (2011) to focus on whether the program made any difference in places where it was most needed. Table 3 shows the distribution of sample children by CCT status and age group. Detailed descriptive statistics are summarized in Annex 1 to show the socioeconomic characteristics of the sample households.

Table 3. Distribution of Sample Children, by Program Status and Age (Children)

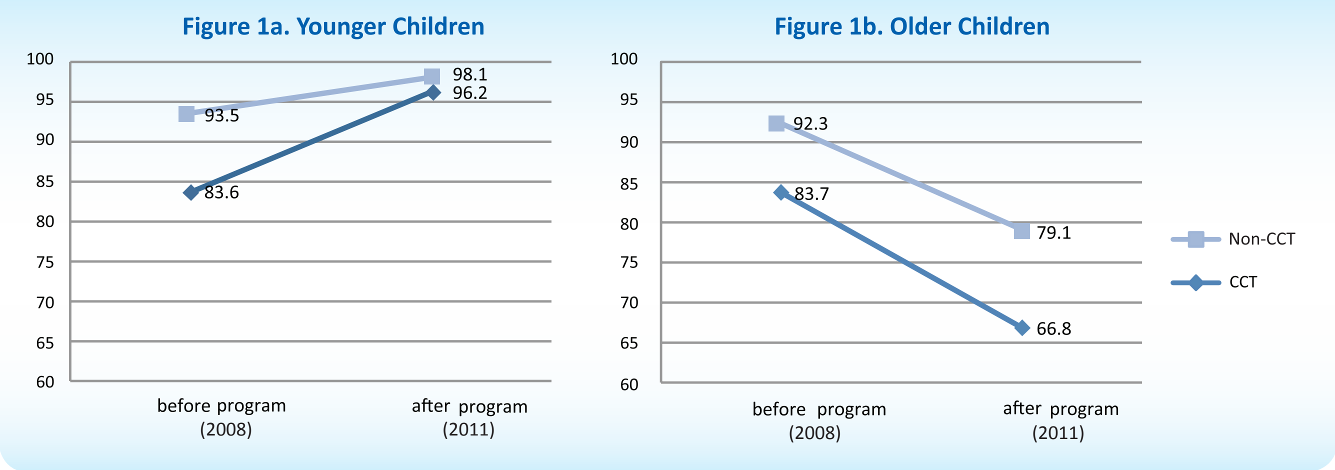
Age as of 2011 Program Status	All 9-17 years old	Younger Children 9-12 years old	Older Children 13-17 years old
In CCT households	1,298	525	773
In non-CCT households	663	232	431
Total	1,961	757	1,204

Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)

Raw data show two striking facts: first, poorer children in the CCT *treatment* group started off at a much lower enrollment rate compared to relatively richer children in the non-beneficiary *control* group. Second, enrollment rates increased significantly for children in the younger cohort regardless of program status, but the increase was most dramatic for children in CCT beneficiary households. Figures 1a and 1b illustrate the changes in enrollment rates of sample children, by *treatment* and *control* group. Before the CCT program, the average enrollment rate for younger children in the *treatment* group was 10 percent lower than for younger children in the *control* group (Figure 1a).

In 2011, three years after the CCT program was initiated, the gap in enrollment rate among younger children narrowed dramatically to 2 percent. In contrast, the enrollment rate among older children drastically decreased over this period for both *control* and *treatment* children. This reflects the reality of dropout patterns in the Philippines: significant gaps persist between the poor and non-poor in accessing education and completing school, as well as in the enrollment rates and elementary completion rates by income quintile (see Annex 3).

Figure 1. Enrollment Rates of Sample Children, by Program Status (%)



Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)

[24] 6-14 years old as of 2008 when the *Pantawid Pamilya* program started, therefore 9-17 years old as of 2011 when the post information was collected.
[25] Masbate from Luzon, Negros Oriental from Visaya, and Lanao del Norte from Mindanao.

5. Impact Estimates of the CCT Program on Change in Enrollment Status

5.1 DD Approach

While the results are not significant for the overall sample of children aged 9-17 years old as of the 2011 follow-up survey, the results from DD analysis show positive impact in school enrollment among children in the younger cohort aged 9-12 as of 2011 (the children who received education grants under the CCT program throughout the period). Table 4 shows the estimation results derived from the basic DD (Model 1) and with covariates (Model 2), by age cohort. The basic DD estimate suggests the CCT program on average increased school enrollment by almost 9 percent (column 4, Table 4) for younger children from beneficiary households. Consistent results are obtained when we add covariates to control for sex, actual age, and geographical characteristics. Controlling for covariates slightly decreases the impact estimate to 6 percent (column 5, Table 4).

The DD analysis indicates that there was no impact of the program on increasing enrollment for the older cohort of children aged 13-17 during the follow-up in 2011. The majority of children (15-17 years old) in this older cohort were not receiving CCT grants as of 2011 since the age limit for coverage is 14 years old. As shown in columns 6 and 7 in Table 4, the coefficients for older children were not significant. Thus, pooling the data (9-17 years old) dilutes the age-specific nuanced impact of the program. Similarly, Shultz (2004) examined similar age-specific impacts in the Mexican CCT program, finding that it was only significant for increasing enrollment for beneficiary children in grade 6.

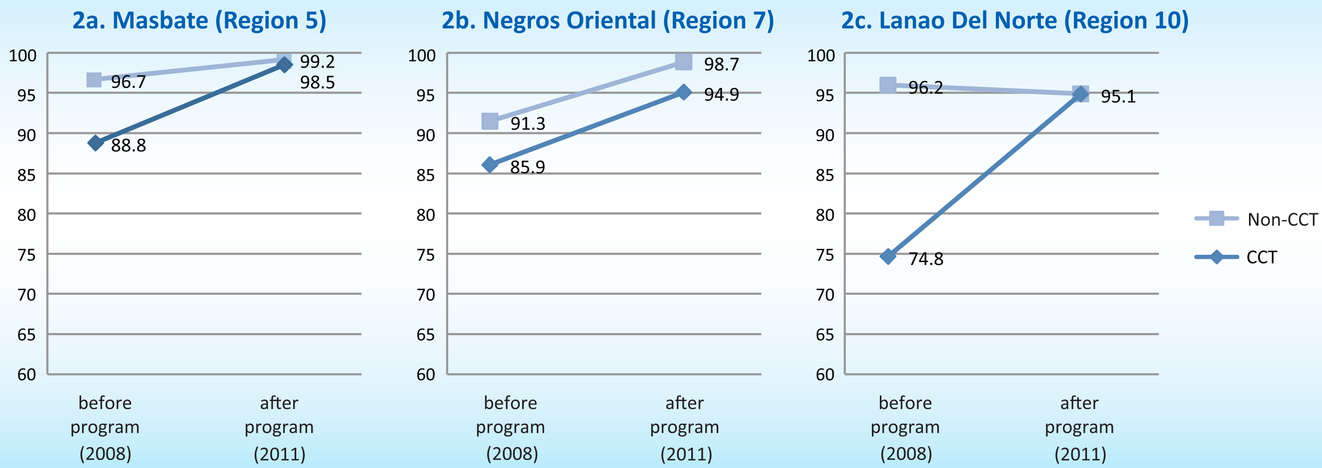
Table 4: Impact Estimates of School Enrollment using DD Approach

Column	(2)	(3)	(4)	(5)	(6)	(7)
Age as of 2011	All 9-17 years old		Younger Children 9-12 years old		Older Children 13-17 years old	
Model	(1)	(2)	(1)	(2)	(1)	(2)
	Basic DD	w/ covariates	Basic DD	w/ covariates	Basic DD	w/ covariates
CCT	0.032	0.010	0.088***	0.061**	-0.023	-0.019
(t-statistic)	(1.45)	(0.48)	(3.12)	(2.17)	(-0.79)	(-0.67)
Girl		0.016		0.025		0.011
Age - 6 years old		0.528***		0.214***		
Age - 7 years old		0.427***		0.115***		
Age - 8 years old		0.363***		0.050		
Age - 9 years old		0.305***				
Age - 10 years old		0.259***				0.257***
Age - 11 years old		0.185***				0.182***
Age - 12 years old		0.129***				0.126***
Age - 13 years old		0.004				0.002
Urban		0.015		0.019		0.014
Masbate, Region 5		-0.071***		-0.069**		-0.070**
Negros Oriental, Region 7		-0.076***		-0.063*		-0.084**
Constant	-0.071***	-0.249***	0.043*	0.015	-0.132***	-0.223***
Observations	1,961	1,961	757	757	1,204	1,204

Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)
*** p<0.01, ** p<0.05, * p<0.1, denoting the statistical significance at 99%, 95%, and 90% levels, respectively.
Notes: Age dummies, referring to children's age as of 2008. The base is the oldest age for the age bracket for each regression. For region, the base is Lanao Del Norte, Region 10.

Aside from our main objective of estimating the overall average CCT impact, the coefficient estimates from the other covariates also provide useful information on how these observable characteristics are associated with the change in school enrollment. Not surprisingly, younger children were more likely to be enrolled in school in 2011 compared to older children, even within the younger age cohort, as illustrated by significant, positive, and larger coefficients for age-specific dummy variables. The coefficient for the urban dummy is insignificant for all age groups, indicating there is no differential impact of the program on schooling between urban and rural areas. Larger sample surveys are needed to estimate the model separately by rural and urban to examine this issue appropriately.[26] The increase in enrollment is most pronounced in the province of Lanao del Norte, as shown by significant and negative coefficients for Negros Oriental and Masbate. These findings suggest the importance of factoring in regional differences across the country. For example, just looking at the simple enrollment rates of young children (Figure 2), the baseline figures and change over the period are substantially different across sample provinces. In Lanao Del Norte, the enrollment rate of CCT (*treatment*) children was the lowest (75 percent) compared to the other two provinces before the program intervention and sharply rose to 95 percent, which is the same level as that of the non-CCT (*control*) group in 2011.

Figure 2. Enrollment Rates of Younger Children, by Program Status (%)



Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)

5.2 Sensitivity Analysis Using DD Approach, by the Number of School-Aged Children in a Household

Younger children who come from households with a relatively smaller number of school-aged children seem to be benefiting more from the program, compared to those who come from larger households. For illustrative purposes (given the limitations of our sample size), we show the impact estimates for the sample of households with one to three school-aged children and for the sample of households with four or more children (Tables 5a and 5b). Among smaller households, the program increased the enrollment rate by 7 percent without covariates (column 4, Table 5a) and 5 percent when controlling for other covariates associated with children's sex and age, urban/rural characteristics, and region (column 4, Table 5b). In contrast, no significant impact was found among children coming from households with more than three school-aged children (column 4, Table 5a). Results were consistent when controlling for children's sex, age, urban/rural characteristics, and regional characteristics (column 4, Table 5b).

[26] More than 80 percent of our sample children for this study resided in rural areas, as the sample barangays consisted of 7 urban barangays and 40 rural barangays.

Table 5a. DD Impact Estimates by the Number of School-Aged Children in Household, without Covariates

Column	(2)	(3)	(4)	(5)	(6)	(7)
Age as of 2011	**All 9-17 years old**		**Younger Children 9-12 years old**		**Older Children 13-17 years old**	
Number of School-Aged Children	coefficient	(t-statistic)	coefficient	(t-statistic)	coefficient	(t-statistic)
1-3 Child(ren)	0.041*	(1.75)	0.071**	(2.46)	0.011	(0.34)
More than 3 Children	-0.011	(-0.18)	0.037	(0.52)	-0.037	(-0.45)

Table 5b. DD Impact Estimates by the Number of School-Aged Children in Household, with Covariates

Column	(2)	(3)	(4)	(5)	(6)	(7)
Age as of 2011	**All 9-17 years old**		**Younger Children 9-12 years old**		**Older Children 13-17 years old**	
Number of School-Aged Children	coefficient	(t-statistic)	coefficient	(t-statistic)	coefficient	(t-statistic)
1-3 Child(ren)	0.026	(1.14)	0.054*	(1.83)	0.012	(0.39)
More than 3 Children	-0.015	(-0.27)	0.026	(0.37)	-0.048	(-0.58)

Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)
*** p<0.01, ** p<0.05, * p<0.1, denoting the statistical significance at 99%, 95%, and 90% levels, respectively.

This sensitivity analysis is only intended to highlight potential variation in impact by an array of complex socioeconomic and institutional factors. Household size is highly correlated with poverty and is a significant factor in the PMT modeling. According to PMT scores, households with more than three school-aged children are poorer on average than households with fewer than four children (Table 6). Given the resource constraints of poor households, *a priori,* it would have been more likely that the CCT grants would have more of an impact on relatively poorer households in increasing enrollment. However, the CCT program only covers a maximum of three children (to discourage higher fertility[27]), and poor households with a large number of children have to spread resources thinly across school-aged children. While public primary schooling is free and "costless" in terms of tuition, there are still expenses associated with "free schooling" (e.g., paying for uniforms). Thus, larger households are poorer to start with, plus potentially face more difficulties sending children to school due to financial constraints as the per head grant amount decreases after the third child. To develop a solid understanding of the impacts of the various socioeconomic and institutional factors at work, a larger sample size and more complex survey are needed.

Table 6. Estimated PMT Score/Per Capita Income of Sample Households (PhP (USD))

Column **Number of School-Aged Children** **Program Status**	**(2)** **1-3 Child(ren)**	**(3)** **More than 3 Children**	**(4)** **Difference** **(2) – (3)**
CCT households	PhP 7,657 (USD 178)	PhP 5,145 (USD 120)	PhP 2,512 (USD 58)
Non-CCT households	PhP 16,412 (USD 381)	PhP 11,982 (USD 278)	PhP 4,430 (USD 103)

Source: Estimated PMT score from DSWD (2011b and 2011c)

5.3 Sensitivity Analysis Using RDD Semi-parametric Specification

Sensitivity analysis was also conducted using the semi-parametric local linear regression in RDD approach, yielding results consistent with those obtained in the DD analysis. While DD suggests positive impacts among younger children only, the program impacts are further estimated using semi-parametric local linear regressions in RDD approach, as specified in the methodology section. The nonparametric RDD specification considers the distance between households' PMT score

[27] Incidentally, no CCT program that has been evaluated has ever found that grants have given incentives for poor households to have more children. If anything, there is evidence that poor households are more likely to invest in the human capital of existing children.

and the poverty lines which are the cut-off for identifying poor versus non-poor. Given that parameter estimates can be dramatically influenced by choice of bandwidth in such estimation, the semi-parametric RDD estimation (as per model specification 4 in the methodology chapter) was done using different bandwidths between 2000 and 5000.[28] Consistent with findings from the DD specification, the estimated CCT impact using the nonparametric RDD specification was also significantly positive for the younger cohort. The average impact was about a 7-14 percent increase in enrollment for the younger cohort of children (column 4, Table 8a). This finding remained significant and consistent across different bandwidths and inclusion of covariates, suggesting strong and positive CCT impacts for the younger cohort. By controlling covariates (sex, age, urban/rural, and regions), the estimated impacts even increased slightly to 7-17 percent (column 4, Table 8b). In contrast, the impact estimations among older children are not stable and extremely sensitive to the choice of bandwidths (column 6, Tables 8a and 8b). Thus, consistent with the findings from DD analysis, we cannot say anything conclusive about the impact of the program for the older cohort of children.

Table 8a. Impact Estimates using Semi-parametric RDD, without Covariates

Column	(2)	(3)	(4)	(5)	(6)	(7)
Age as of 2011	**All 9-17 years old**		**Younger Children 9-12 years old**		**Older Children 13-17 years old**	
Bandwidth	coefficient	(t-statistic)	coefficient	(t-statistic)	coefficient	(t-statistic)
2000	0.011	(0.44)	0.140***	(5.50)	-0.056	(-1.50)
3000	-0.011	(-0.42)	0.123***	(4.77)	-0.074**	(-2.08)
4000	-0.008	(-0.31)	0.102***	(3.95)	-0.053	(-1.45)
5000	-0.016	(-0.63)	0.067**	(2.56)	-0.047	(-1.29)

Table 8b. Impact Estimates using Semi-parametric RDD, with Covariates

Column	(2)	(3)	(4)	(5)	(6)	(7)
Age as of 2011	**All 9-17 years old**		**Younger Children 9-12 years old**		**Older Children 13-17 years old**	
Bandwidth	coefficient	(t-statistic)	coefficient	(t-statistic)	coefficient	(t-statistic)
2000	0.014	(0.55)	0.167***	(6.75)	-0.099***	(-2.71)
3000	-0.000	(-0.00)	0.142***	(5.55)	-0.093***	(-2.67)
4000	0.001	(0.03)	0.115***	(4.42)	-0.064*	(-1.81)
5000	-0.009	(-0.36)	0.073***	(2.77)	-0.054	(-1.52)

Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)
*** p<0.01, ** p<0.05, * p<0.1, denoting the statistical significance at 99%, 95%, and 90% levels, respectively.

6. Conclusion

This limited and focused study covering nine selected municipalities found that *Pantawid Pamilya* has had a strong and robust impact in improving education outcomes among younger children between 9-12 years old who were eligible for CCT education grants throughout 2008 and 2011. The evaluation analysis employed several empirical strategies, using panel data on 2,000 children from 900 households before and after implementation of the CCT program, with well-defined *control* and *treatment* assignment. While the results varied depending on the specification of the econometric model, the positive significant impact of the CCT program among children aged 9-12 (during the follow-up survey in 2011) was found consistently across many specifications.

[28] Out of 1,961 observations, the number of observations with positive kernel weights is, respectively: 369 (bandwidth=2000), 522 (bandwidth=3000), 706 (bandwidth=4000), and 857 (bandwidth=5000).

To start with, the basic Difference-in-Difference (DD) estimate suggests that the average CCT impact in terms of increasing enrollment rates among younger children was about 9 percent, which decreases slightly to 6 percent when controlling for more detailed information on sex, age, and geographic characteristics. Furthermore, the RDD semi-parametric approach gives an average impact estimate between 7-14 percent[29] (depending upon choice of bandwidth) without covariates and 7-17 percent when controlling covariates. Overall, the estimated program effect for younger cohort ranges between 6-17 percent. This strongly suggests that CCT beneficiary households are more likely to send their younger children to school compared to non-CCT households in the Philippines.

The inconsistent results for older children between 13-17 years old (age as of 2011)–the majority of whom are outside the age cut-off for CCT education grant eligibility–as suggested by insignificant coefficients across specifications, could be explained by a number of factors. First, sending older children to school is associated with higher direct and indirect (opportunity) costs. Direct costs may be incurred in the form of school fees, supplies, transportation costs, and so on. For example, since there are less high schools than primary schools, high school children are generally more likely to travel farther away from the homestead to school, requiring households to spend more money on transportation. As children grow older, the opportunity cost also increases as they could earn money from working instead of studying in school. To address this issue, many CCT programs (e.g., in Bangladesh, Brazil, Mexico,[30] Honduras, and Turkey) provide larger cash transfers to older children to compensate for the higher implicit/explicit cost associated with schooling. Another plausible explanation for the program's lack of impact for the older cohort could be the fact that the age bracket for older children was set at 10-14 years old as of 2008 when the CCT program started. Three years later, these children were 13-17 years old during the time of the follow-up survey. Since *Pantawid Pamilya* provides education grants up to 14 years of age (plus 15 years until completion of the school year), 15-17 year old children are no longer eligible for the grants.

Furthermore, the estimated CCT impact varied depending on the number of school children in the household, with positive impacts among young children in small households. As discussed earlier, basic DD suggested a 7 percent increase in school enrollment among the sample of younger children from beneficiary households with three or fewer school-aged children. When controlling for child's sex and age, urban/rural characteristics, and region, the estimated impact slightly decreased to 5 percent. In contrast, no program impact was evident among children from households with more than three school-aged children in the household. As described above, this could be explained by the fact that larger households are usually poorer to start with, therefore the financial burden is more binding compared to smaller households. In addition, the education grant per child decreases after the third child since the program currently sets the maximum number of children who are eligible for education grants at three per household, while households bear non-tuition related expenses such as transportation costs and school supplies for every child.

The comprehensive quantitative impact evaluation currently underway will provide more robust evidence on the impact of the CCT program, based on data collected from a much larger sample size and information collected on a vast range of issues. This study was conducted to serve as a rapid assessment of the *Pantawid Pamilya* focused on school enrollment, while waiting for the comprehensive impact evaluation. For the comprehensive impact evaluation, data has been collected through 8,000 household interviews as well as interviews with teachers, midwives, barangay captains, and mayors to capture different institutional characteristics. The comprehensive impact evaluation will evaluate not only school enrollment and health center attendance but also an extensive range of outcomes including household consumption, child labor, educational attainment, and child nutrition status, applying rigorous analytical methods of Randomized Control Trials (RCT) and Regression Discontinuity Design (RDD).

[29] With the bandwidths of 2000-5000, with which stable impacts are estimated.

[30] Under Mexico's CCT program, the monthly education grant ranges from USD 11.5 up to USD 73.4 (1USD=12.6MXP). Starting from the third year of elementary school, higher transfer are granted for older children until the end of high school. Grants are also set higher for girls after middle school to address gender inequality (Oportunidades, 2011).

Annex 1. Descriptive Statistics of Household Characteristics

Table 9 presents the socioeconomic characteristics of sample households used for this study, by CCT and non-CCT status. Different characteristics are observed between CCT and non-CCT households.[31] For example, CCT households are characterized with a larger number of household members (7.2 members) compared to non-CCT households (5.1 members). Regarding the housing materials, CCT households are worse off compared to non-CCT households as well. For instance, nearly 60 percent of CCT households live in a house with light wall materials, while nearly half of non-CCT households reside in a house made of strong wall material. Over the period, improvement in roof/wall materials has been observed among CCT households, while access to toilet and electricity remain as issues, particularly for CCT households.

Table 9. Socioeconomic Characteristics of Sample Households

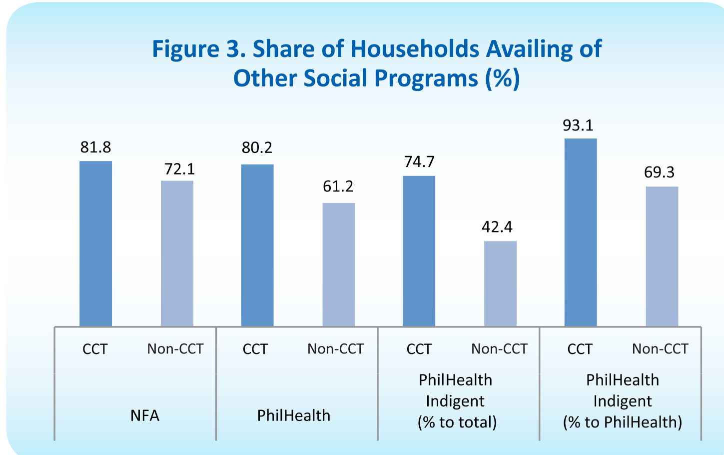
		Before Program (2008)			After Program (2011)			(change=after-before)		
	(unit)	CCT	Non-CCT	Total	CCT	Non-CCT	Total	CCT (a)	Non-CCT (b)	Total (a-b)
Observations	(Households)				506	394	900			
PMT Score (Estimated per capita income)	(PhP)	7,588	16,800	11,621	8,749	17,616	12,631	1,161	816	345
Household Composition										
Household Size	(members)	7.2	5.1	6.3	7.4	5.4	6.5	0.2	0.2	0.0
Number of children 0-5 years old	(members)	1.3	0.4	0.9	1.0	0.4	0.7	-0.3	0.0	-0.3
Number of children 6-14 years old	(members)	2.8	1.7	2.3	2.5	1.4	2.1	-0.3	-0.3	0.0
Number of children 15-18 years old	(members)	0.7	0.5	0.6	1.0	0.7	0.9	0.4	0.2	0.1
Number of HH members 61 years+	(members)	0.1	0.2	0.1	0.1	0.2	0.2	0.0	0.1	-0.1
Number of HH members without any education	(members)	1.5	0.4	1.0	1.2	0.5	0.9	-0.3	0.1	-0.4
Number of elementary graduates HH members	(members)	1.2	0.9	1.1	1.0	0.9	1.0	-0.2	-0.1	-0.1
Number of collage graduates HH members	(members)	0.1	0.4	0.2	0.1	0.4	0.3	0.0	0.0	0.0
Housing Condition										
Share of HHs with light roof material	(%)	56.1	22.6	41.4	47.2	20.6	35.6	-8.9	-2.0	-6.9
Share of HHs with strong wall material	(%)	12.1	49.5	28.4	25.5	53.6	37.8	13.4	4.1	9.4
Share of HHs with light wall material	(%)	57.7	26.4	44.0	49.2	25.9	39.0	-8.5	-0.5	-8.0
Share of HHs without own toilet	(%)	51.2	21.3	38.1	47.6	26.4	38.3	-3.6	5.1	-8.6
Share of HHs using shared tube/piped well	(%)	8.1	9.6	8.8	8.7	6.9	7.9	0.6	-2.8	3.4
Share of HHs using dug well	(%)	39.5	37.1	38.4	40.1	33.3	37.1	0.6	-3.8	4.4
Share of HHs with electricity	(%)	27.7	69.8	46.1	46.1	71.3	57.1	18.4	1.5	16.9
Share of HHs wit washing machine	(%)	0.2	6.6	3.0	2.2	9.1	5.2	2.0	2.5	-0.6
Share of HHs with refrigerator	(%)	3.4	26.1	13.3	4.4	31.0	16.0	1.0	4.8	-3.8
Share of HHs owning house	(%)	29.6	49.8	38.4	31.4	46.2	37.9	1.8	-3.6	5.3
Share of HHs renting house	(%)	1.8	1.0	1.4	0.4	0.8	0.6	-1.4	-0.3	-1.1

Source: Pre-intervention data from DSWD (2011b and 2011c), post-intervention data from TNS (2011)

CCT and non-CCT Status (*Treatment* and *Control* Groups): Despite our sample strategy to split 900 households evenly between the *treatment* and *control* groups, 394 respondents claimed that they were not CCT beneficiaries while 506 claimed that they were CCT beneficiaries during the follow-up interviews in 2011. The analysis used the CCT status as reported during the follow-up interview, considering the mobility of people and the dynamic nature of the program. For instance, households selected as the *control* group were found to have become *Pantawid Pamilya* beneficiaries recently through the expansion of the program. There were also cases in which a new household member was a *Pantawid Pamilya* beneficiary, such as siblings recently transferred to the households that were selected for the *control* group. Figure 3 shows the distribution of households when they received the first CCT grant. Nearly half of the CCT beneficiary households answered that they received the first grant in 2008, 43 percent in 2009, and 6 percent in 2010. There were a small number (1 percent) of new CCT beneficiary households who had newly enrolled in 2011 and had not received the first grant as of the survey in August-September 2011 (TNS, 2011).

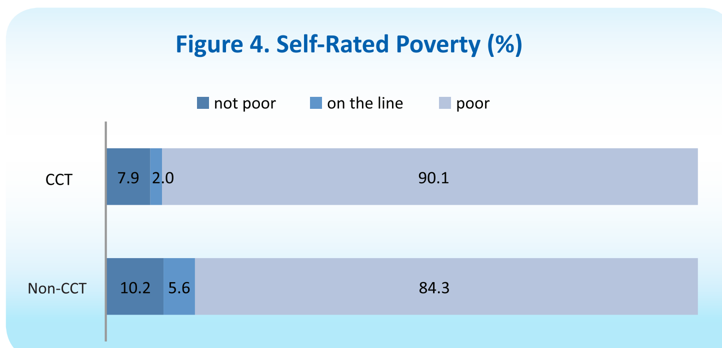
[31] For our sample, *treatment* households were selected among CCT beneficiary from the *Pantawid Pamilya* database, while *control* households were selected among non beneficiary households using the NHTS-PR database. The baseline values of our samples are different between CCT and non-CCT, and this study uses Difference-in Difference (DD) methodology, which controls for the fact that CCT and non-CCT groups start from different levels (in regression setting, allowing for different intercepts), under the assumption that the growth rate (slope) would have been similar without the CCT program intervention. In this regard, please note of the distinction from the Randomized Control Treatment (RCT) sample, which should have the same (or very similar) baseline values of *treatment* and *control* groups, given that evaluation units are randomly assigned to *treatment* or *control* status.

Access to Social Assistance Programs: In the 2011 follow-up survey, households were asked whether they had benefited from two other social assistance programs—the National Food Authority (NFA) rice subsidy program and PhilHealth Program—in the last 12 months. As shown in Figure 3, higher benefit incidences were observed among CCT households compared to non-CCT households, particularly for PhilHealth membership. For NFA, about 30 percent of total Filipino households and nearly half of poor households had access to NFA subsidized rice in 2009, according to official statistics[32] (Velarde, 2011). Compared to these figures, sample households had a higher share of those availing of the NFA program, at 72 percent of non-CCT households and 82 percent of CCT households. For health insurance, 61 percent of non-CCT households and 80 percent of CCT households had a PhilHealth membership, and the coverage was much higher than the national average of 38 percent based on the 2008 National Demographic and Health Survey[33](NSO and IFC Macro, 2009).



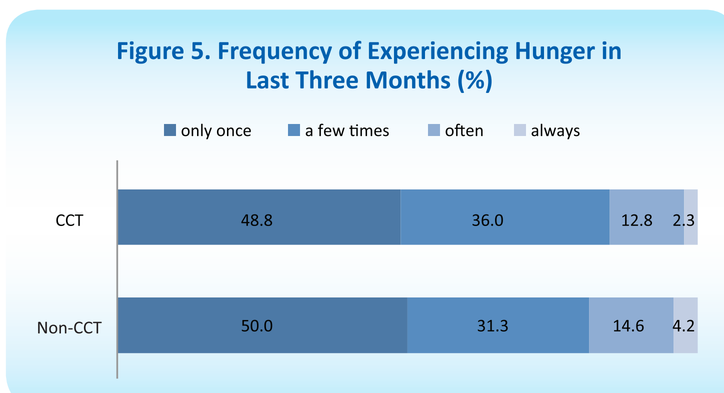
Source: TNS (2011)

Self-Rated Poverty and Hunger: The follow-up survey also included self-rated poverty and hunger questions from the Social Weather Station's self-rated poverty survey. Figure 4 shows the answers on where they would place themselves on the simple card showing poor, non-poor, and the line between them. The majority of our sample respondents considered themselves as poor regardless of CCT status, while the Social Weather Station poverty survey reports 52 percent[34](SWS, 2011). Among CCT beneficiaries, 90 percent of CCT households rated themselves as poor, while the share of "poor" answers was slightly lower by about 6 percent among non-CCT beneficiaries.



Source: TNS (2011)

For hunger, households were asked whether they had experienced hunger even once in the previous three months. Around 17 percent of CCT beneficiary households reported the experience of hunger, while 12 percent of non-CCT households did so. Figure 5 shows the frequency of hunger incidence among those who experienced hunger, showing a similar pattern between beneficiary and non-beneficiary households. The incidence of experiencing hunger happened only once to half of the households, and it happened a few times to another 31-36 percent of households over the previous three months. The proportion of non-CCT households reporting constant hunger was higher at 4.2 percent compared to 2.3 percent among CCT households.



Source: TNS (2011)

[32] Family Income and Expenditure Survey 2009.

[33] According to the 2008 National Demographic and Health Survey (NDHS), the national average PhilHealth coverage rate was 37.7 percent, with a higher coverage rate of 57.0 percent in the lowest wealth quintile group. Out of PhilHealth member households, 78.1 percent are paying while 22.9 percent are indigent (those whose premiums are funded by the government) (NSO and IFC Macro, 2009).

[34] September 2011.

Annex 2. Supplementary Descriptive Statistics on Education

Beside the enrollment status of children, the follow-up survey in 2011 collected other information related to education such as current grade, enrollment age, expectations for children's future, and possession of school supplies. This annex provides the summary findings from the descriptive statistics on these education indicators.

Age-Appropriate Enrollment: Table 10 shows the share of sample children who enrolled in elementary school at the age of 6, indicating that age-appropriate enrollment remarkably improved over the period, particularly among CCT children. The share of CCT children who had enrolled in elementary school at 6 years old was only 22 percent among older children aged 13-17 (as of 2011) and became higher among younger children (29 percent among 9-12 year old children, and 56 percent among 6-8 year old children).

Table 10: Share of Children who Enrolled in Grade 1 at the Age of 6 (%)

Column Age as of 2011	(2) 6-8 years old	(3) 9-12 years old	(4) 13-17 years old
CCT	55.5	29.4	21.7
Non-CCT	57.3	36.0	37.3

Source: TNS (2011)

Age-Appropriate Educational Attainment: Tables 11a and 11b present the current grade at which children were enrolled, and the shaded columns refer to the age-appropriate grade, given the children's age. Within our limited sample size, it appears that CCT children were more likely to be delayed in attaining education compared to non-CCT children. For example, at the age of 11, 14 percent of CCT children reached grade 6 while 26 percent of non-CCT children did so. The attainment gap between CCT and non-CCT children widens as children become older.

Tables 11a. Distribution of Younger Children, by Age and Current Grade (%)

Age as of 2011	kinder or daycare	grade 1	grade 2	grade 3	grade 4	grade 5	grade 6	1st year HS	2nd year HS
CCT Children									
9	0.0	8.3	23.3	51.7	14.2	2.5	0.0	0.0	0.0
10	0.8	6.6	13.1	24.6	30.3	23.8	0.8	0.0	0.0
11	0.0	0.0	15.8	15.1	18.0	36.0	14.4	0.7	0.0
12	0.6	1.9	0.6	4.4	15.7	28.3	31.4	15.7	1.3
Non-CCT Children									
9	0.0	2.4	22.0	34.1	31.7	9.8	0.0	0.0	0.0
10	0.0	8.7	4.3	17.4	37.0	30.4	2.2	0.0	0.0
11	0.0	3.7	1.9	5.6	14.8	40.7	25.9	7.4	0.0
12	0.0	0.0	0.9	3.4	5.2	17.2	37.1	33.6	2.6

Tables 11b. Distribution of Older Children, by Age and Current Grade (%)

Age as of 2011	grade 5 and below	grade 6	1st year HS	2nd year HS	3rd year HS	4th year HS	1st year college	2nd year college	3rd year college
CCT Children									
13	27.9	20.9	35.5	14.5	1.2	0.0	0.0	0.0	0.0
14	19.6	17.0	16.3	26.8	19.0	1.3	0.0	0.0	0.0
15	13.4	8.7	14.2	18.1	26.8	18.9	0.0	0.0	0.0
16	8.0	6.7	13.3	14.7	17.3	36.0	2.7	1.3	0.0
17	6.8	4.5	11.4	11.4	25.0	15.9	13.6	9.1	2.3
Non-CCT Children									
13	11.0	18.0	35.0	33.0	3.0	0.0	0.0	0.0	0.0
14	5.8	5.8	19.2	26.0	39.4	3.8	0.0	0.0	0.0
15	4.1	3.1	5.2	18.6	26.8	40.2	2.1	0.0	0.0
16	2.5	2.5	7.5	15.0	17.5	35.0	20.0	0.0	0.0
17	3.6	3.6	3.6	0.0	21.4	21.4	7.1	28.6	10.7

Source: TNS (2011)

Parents' Expectations for Children: Compared to non-CCT counterparts, CCT parents have similar levels of high expectations for younger children to finish high school but lower their expectations as children get older. Figure 6a shows the percentage of parents who answered that their children would complete high school. Nearly 90 percent of younger children between 9-12 years old are expected by their parents to complete high school, regardless of CCT status. However, CCT parents' expectations decrease sharply down to 75 percent as children become older at the age range of 13-17 years old. In addition, Figure 6b shows the parents' broader expectations for their children's future, when children will become around their parents' ages. About 80 percent of parents anticipate better futures for their children than theirs, with both CCT and non-CCT parents showing a similar pattern.

Figure 6. Parents' Expectations

Figure 6a. Expectation for Children to Finish School (%)

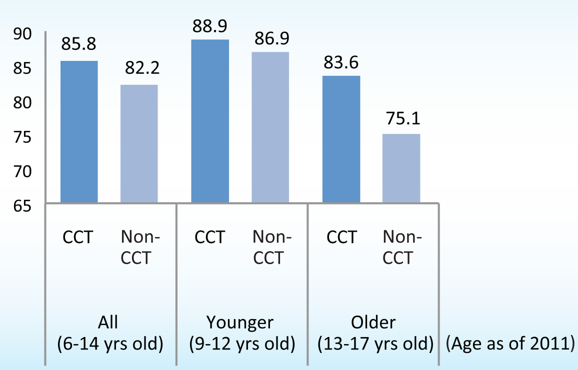
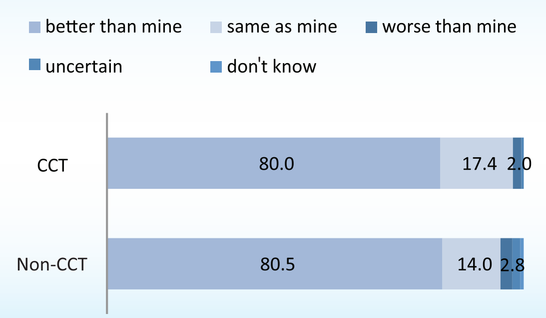


Figure 6b. Expectation for Children's Future (%)



Source: TNS (2011)

Annex 3. School Enrollment and Completion Rates

Figres 7a and 7b show the school enrollment rates and completion rates by income quintile, based on the official household statistics. As shown in Figure 7a, children belonging to the poorest income quintile group have lower enrollment rates throughout school ages between 6 and 17 years old, compared to children in the highest income quintile group. The gap in enrollment rates widens, particularly after 12 years old. By the age of 17, less than 40 percent of poorest children remain in school while more than 70 percent of children in highest income quintile continue their education attainment at school. Completion of elementary school also discriminates poor. Figure 8b shows the share of children between 11-13 years old who completed elementary school (grade 6), by income quintile. Completion rate remain low at around 40 percent even among children in the highest income quintile, however, the completion rates is only at 17 percent among 11-13 year old children belonging to the lowest income quintile.

Figure 7a. School Enrollment Rates by Age and Income Quintile (%)

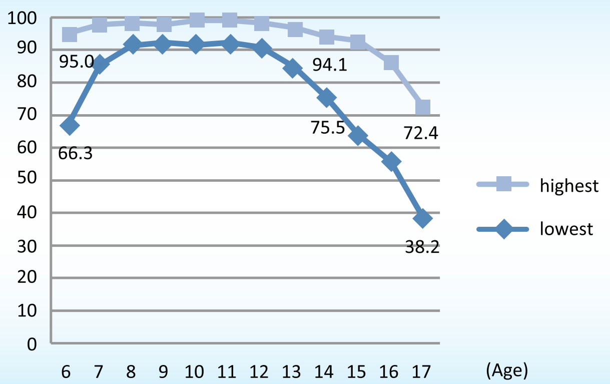
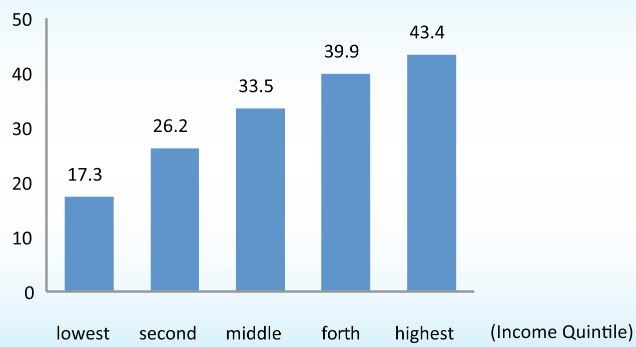


Figure 7b. Elementary Completion Rates by Income Quintile (Children Aged 11-13 years old) (%)



Source: FIES 2009 and LFS January 2010 (National Statistics Office, 2011)

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