UP School of Economics
Discussion Papers

Discussion Paper No. 2014-05 April 2014

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Abstract

Pantawid Pamilyang Pilipino Program provides cash grants to poor households conditional on pre-determined investments in human capital. This study analyzed its impact on consumption using the 2011 Annual Poverty Indicators Survey. Average treatment effect on the treated (ATT) is estimated through propensity score matching methodology. Heterogeneous impacts are examined among the bottom 20% of income distribution.

The study finds that among the total sample, per capita total expenditures is not affected by the program. In per capita monthly terms, only carbohydrates and clothing significantly increased. As expenditure shares, education and clothing registered significant positive impact. No impact is observed on health spending, both in per capita terms and as a share of expenditure. The impact of *Pantawid Pamilya* on consumption is more pronounced among the poorest fifth of households.

Results show that households have responded to program conditionalities but there is very little room to improve consumption of other basic needs. The recent program modification of increasing education grants to older children and covering up to secondary school completion will help households sustain induced behavioral changes over time. Stronger impact on the poorest fifth of households underscores the need to improve the targeting mechanism to address leakage issues.

JEL Classification: I38; D12

Key words: consumption; CCT; impact evaluation; propensity score matching

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An earlier version of this paper was presented at the 51st Philippine Economic Society Meeting held 15 November, 2013 in Makati City, Philippines. I would like to thank Dr. Joseph Capuno and Dr. Aniceto Orbeta for guidance and comments. I would also like to acknowledge the fellowship grant from the UPecon Foundation – Health Policy Development Program.

1 Introduction

Persistent poverty is caused by the inability to acquire and maintain productive asset stocks [Barrett 2003]. Among the poorest households, subsistence living, market failures, and predominance of risks preclude the possibility of investing on development of capital that can improve productivity or income over time [Banerjee and Duflo 2011]. For the past two decades, conditional cash transfer (CCT) programs have gained enormous popularity both as a mechanism for inclusive social protection and as a strategy for breaking the so-called intergenerational cycle of poverty.

CCTs provide cash grants to beneficiary households conditional on compliance to specified investments on human capital, mainly sending children to school and availing of preventive health care services. Cash grants also aim to protect households from persistent hunger and malnourishment that impede productivity and cognition. CCTs are targeted to the poorest section of the population, generally among households that have schooling-age children. Originating in Mexico in 1997, there are now around thirty countries worldwide implementing their version of a conditional cash transfer program [World Bank 2009].

Overall, CCTs appear to be achieving the program's explicit short-term goals.[2] School participation rates have increased among children of CCT households and they are less likely to drop-out from school. The program has also helped address differential access to schooling due to age, gender, or minority group affiliation. Utilization of preventive health services has increased, improving access of children and pregnant women to immunization, nutrient supplements, and regular health monitoring.

The tremendous expansion of CCTs has also highlighted the immense task of improving public infrastructure [Samson, et al. 2010]. CCT experience have increasingly emphasized that the more substantial outcomes – better student learning and improved health status – will not be realized unless governments build more and better facilities and provide accessible essential services.

The Philippines embarked on its own CCT program in 2007. *Pantawid Pamilyang Pilipino Program* (*Pantawid Pamilya* or 4Ps) began with a target of 6,000 households from the 20 poorest provinces of the country. Targeted to families with children 0-14 years old or pregnant women, beneficiaries can receive a maximum of Php1,400 cash grants per month, for a maximum of 5 years. By and large, *Pantawid Pamilya* has become the cornerstone of the government's poverty reduction strategy.

In 2013, the World Bank released the results of its impact evaluation study on *Pantawid Pamilya*. It showed that the program has increased enrollment among 3-11 year

[2] The World Bank (2009) and DFID (2011) have a comprehensive review of CCT outcomes and impacts. For a review of CCT experience in Southern Africa, refer to Vincent and Cull (2009); for Latin America and Carribean, Handa and Davis (2006).

olds (an increase of 10 percentage points for 3-5 year olds and 4.5 percentage points for 6-11 year olds). The significant impact on school participation however vanished among children 12 years old and above. This is unfortunate considering that dropout in this age group is one of the main problems in the education sector. A study by Reyes [2013] also showed that *Pantawid Pamilya* is not affecting enrollment rates beyond the age covered by the program. With regard to health outcomes, the World Bank study [2013] finds that there is a 10 percentage point reduction in severe stunting among 6-36 months old children and there is increased intake of deworming pills among elementary students. There was no impact observed on child immunization rates and facility-based birth deliveries of pregnant women.

Along with the education and health conditionalities, CCTs have also aimed to improve consumption of program beneficiaries. In the Philippines, one of *Pantawid Pamilya's* explicit objectives is “to raise the average consumption rate in food expenditure of poor households” [*Pantawid Pamilya* Operations Manual 2012:7]. In fact, earlier documents show that the program aimed to increase the share of food in household expenditures by 4% and expenditure on nutrient-dense foods by 2% [DSWD 2009].

The impact of CCTs on consumption is largely positive [Kabeer et al. 2012]. In Mexico, beneficiary households are found to have obtained 3.3% more calories compared to non-beneficiaries [Hoddinott and Skoufias 2004]. Attanazio and Mesnard [2005] find a 15% increase in total monthly household consumption among CCT recipients while the share of food in total consumption remained the same (72% at baseline). In Paraguay, CCT households experienced between 9 to 15% increase in per capita consumption [Soares et al. 2008]. The effect is even higher among extremely poor households (between 13 and 21%). In addition to eating more food, beneficiary households also reported eating better sources of energy and nutrients (Hoddinott and Skoufias [2004] for Mexico; Attanazio and Mesnard [2005] for Colombia; Soares et al. [2008] for Paraguay; Vincent and Kull [2009] for Zambia).

The World Bank study [2013] on Philippine CCT found significant increases in per capita spending on education (38%) and medicine (34%) among households in *Pantawid Pamilya* areas. *Pantawid Pamilya* parents were also spending 38% more on high-protein food, such as eggs and fish. However, the study did not find significant increase in overall per capita consumption.

CCTs may not lead to overall increase in household consumption due to several factors. While cash grants initially constitute an increase in income, compliance to conditionalities could have offsetting effects that impact directly on total household income. Moreover, households face different incentives in making choices among goods conditioned-on by the program (such as education) and those that are not. Identifying the impact of *Pantawid Pamilya* on consumption sheds light on fundamental yet lingering questions on whether cash grants can tide over households from hunger and enable them to sustain investments in human capital over time. Answers to these questions have substantial policy implications especially now that the program is at the height of metamorphosis, with the culmination of its first batch of beneficiaries and the approval of program modifications.

To evaluate the impact of *Pantawid Pamilya* on consumption, the study implements propensity score matching (PSM) on a large nationwide survey data collected in 2011. The PSM methodology constructs a comparison group of non-beneficiaries that is statistically similar on average to *Pantawid Pamilya* households on observable characteristics that influence program participation and consumption outcomes.

The study finds that *Pantawid Pamilya* led to increased spending on education and clothing, goods that are required for program compliance. Other than these, only spending for carbohydrate foods registered a positive significant increase. Stronger impact is observed on total household consumption among program beneficiaries that belong to the bottom 20% of income distribution. The results highlight the need to improve *Pantawid Pamilya's* targeting mechanism and examine more closely the distribution of program impact on the target population. These are significant inputs to decisions on expansion and design improvements.

The rest of the study is organized as follows. Section 2 reviews the Philippines' conditional cash transfer program. The framework for understanding the impact of cash transfers on consumption is discussed in Section 3. Section 4 presents the impact evaluation methodology and the data. Section 5 discusses the results and findings, with a section on impact heterogeneity. Section 6 concludes with policy and research implications.

2 *Pantawid Pamilyang Pilipino* Program

Pantawid Pamilya is patterned after the CCT programs implemented in Latin America in the late 1990s and in Africa in early 2000s.[3] Similar to other CCT programs, the objectives of the program are: (1) to improve preventive health care among pregnant women and young children; (2) to increase the enrollment and attendance rate of children in school; (3) to contribute to the reduction of incidence of child labor; and (4) to raise the average consumption rate in food expenditure of poor households (*Pantawid Pamilya* Operations Manual, 2012). Program aspects that are salient to evaluating its impact on consumption are discussed below.

2.1 Targeting

The National Household Targeting System for Poverty Reduction (NHTS-PR) endeavors to institutionalize an objective way to locate and identify poor households that will be targeted for social protection programs. It involves two major stages: (1) selection of

[3] For a brief overview of the historical development of CCT programs, see Lavinas [2013].

geographical areas; and (2) household assessment through Proxy Means Test. In the first stage, provinces, municipalities, and cities are selected based on poverty incidence as estimated by the National Statistical Coordination Board (NSCB). Household assessment collects information on variables that are identified as strong predictors of household's poverty status such as household composition, education, housing conditions and tenure status, access to basic amenities, ownership of assets, and location. The information gathered are used to run the Proxy Means Test (PMT)[4] that computes a predicted income for each household. Households are identified as poor if the predicted income falls below the official provincial poverty threshold.

Pantawid Pamilya is the first program to utilize the NHTS-PR. Implementation was conducted from June 2007 to January 2011, in three phases [Fernandez 2012]. The first phase covers the 20 poorest provinces and the municipalities that have a poverty incidence of 60% and above. This was followed by municipalities that have a poverty incidence between 50 to 59% and cities with 'pockets of poverty' areas. The final phase assessed households in municipalities with a poverty incidence of below 50%.[5] Naturally, the expansion of *Pantawid Pamilya* areas mirrors these phases, as discussed in the succeeding subsections. A total of 10.909 million households were assessed, of which 5.255 million were identified as poor [NHTO 2013]. ARMM has the largest number of identified poor households at 531,526 or 64% of the total assessed households. It is followed by Region V with 461,242 (60%) and Region IV-A with 389,811 (43%) identified poor households.

2.2 Program Eligibility and Grant Packages

Given the primary goal of human capital development and the design of the targeting mechanism, eligible households to the program are those that: (1) reside in areas selected for *Pantawid Pamilya*; (2) are identified as poor by the NHTS-PR; and (3) have children between the age of 0 and 14 years or have a pregnant household member.

There are two cash grants provided to beneficiary households. The education grant is Php300 per month or Php3,000 per year for each school-age children 14 years old and below, for a maximum of 3 beneficiary children per household. The education cash grant is expected to cover expenses for sending children to school. Implicitly, it also serves to compensate the family for possible income loss due to school participation. The health grant is Php500 per

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[4] Proxy Means Test uses multivariate regression techniques to correlate proxy indicators of welfare such as assets, housing conditions, and demographic characteristics, with poverty and income. Due to the inherent difficulties of collecting income data to ascertain poverty status, proxy means testing have enjoyed wide application as a targeting mechanism for government programs.

[5] Enumeration of households in each area is also based on poverty incidence. For municipalities with a poverty incidence of more than 50%, complete enumeration was undertaken. Otherwise, complete enumeration was conducted only among "pockets of poverty" areas. For households that reside in "non-poor" areas, assessment has to be requested through the on-demand application process.

month or Php6,000 per year. All beneficiary households are eligible for this grant, which is expected to help improve food consumption [*Pantawid Pamilya* Operations Manual 2012]. Hence, the maximum grant that households can receive is Php1,400 per month or Php15,000 per year. The share of *Pantawid Pamilya* grants to total income ranges from 13 to 26 percent based on the distribution of beneficiaries by household composition [Fernandez and Olfindo 2011]. The poorest households (21% of total families) however, are those that have children 5 years old and below, which means that they are eligible only for the Php500 monthly health grant [Fernandez and Olfindo 2011].

The actual amount that beneficiary households are entitled to depends on compliance to program conditionalities (Table 1). Teachers and local health workers monitor and verify the compliance of *Pantawid Pamilya* beneficiaries to the conditionalities. DSWD-hired "municipal links" work with local government units in the processing of compliance documents, synchronized with the release of cash pay-outs.

[Insert Table 1 here]

2.3 Program Expansion

The program has become one of the vastly scaled-up government programs in recent history. In less than seven years of implementation, the number of *Pantawid Pamilya* households has increased from 6,000 to 3.935 million. [6] The highest annual increase was in 2011 when 1.212 million[7] households were included in the program, from an average of around 307,599 in 2008-2010. World Bank project documents show that the estimated number of beneficiaries will reach 4.87 million households by 2016 [Chaudhury, 2012]. Consequently, the DSWD has grown in resources and personnel more than ten-fold. From a total budget of Php5.33 billion in 2007, the Department has more than Php78 billion in budget allocations for 2014. Out of this total budget, Php66.4 billion (or 85%) is for *Pantawid Pamilya*.

It is important to highlight the geographical expansion of the program since this study uses data from a nationwide survey conducted in 2011. In 2008, *Pantawid Pamilya* Set 1 areas are comprised of 27 provinces. This increased to 50 provinces in 2009, and by 2010 the

[6] According to DSWD Program Monitoring and Evaluation Unit, the number of beneficiaries by Set is sensitive to the date of data extraction. Beneficiary households from previous Sets can get delisted from *Pantawid* due to non-compliance, migration to non-*Pantawid Pamilya* areas, inclusion error, voluntary refusal, among others. Those that do not have eligible children anymore, or are awaiting the results of investigation on complaints or compliance to conditionalities are temporarily deactivated. Based on the Implementation Status Report of the 2nd Quarter of 2013, 103,768 households have been delisted and 250,322 are deactivated so far.

[7] This figure is as of 31December 2013. Based on the 2011 DSWD Accomplishment Report however, there were 1,299,684 new households enlisted that year. The difference would be the number of delisted/deactivated households from that Set.

program has been initiated in all 79 provinces. However, program implementation was stalled from early to late 2010, in principle to avoid political manipulation in the distribution of cash transfers during election season [Delos Reyes 2011]. At the time of the survey used in this study, many of the 2010 beneficiary households became part of the program only in the last quarter of that year and there are reports that some received a full year's worth of cash grants in one pay-out [Delos Reyes 2011]. This is reflected in the dataset used here, as shown by the wide dispersion of cash grants received (more on this in Section 4). Administrative documents also show that as of June 2011, the distribution of cash grants was still erratic, with only 63% of beneficiary households receiving cash grants on time [Chaudhury 2012]. Given that this study investigates impact on consumption, these unexpected fluctuations in cash flows might have influenced the short-term response of households covered by the survey.

2.4 Recent program modifications

More recent expansion of *Pantawid Pamilya* is influenced by modifications advocated by non-government organizations, interest groups, and the academe. By design, *Pantawid Pamilya* systematically excludes specific types of households such as homeless families, unmarried persons with disabilities, and other poor households without 0-14 year old or pregnant members. With the enormity of the program, pressure has been raised to include other sectors of the poor. The government started a Modified CCT (MCCT) in 2012 [SONA Technical Report 2013]. It has 3 categories, covering a total of 94,247 households as of December 2013. These are: (1) MCCT for Families in Need of Special Protection; (2) MCCT for Homeless and Street Families; and (3) MCCT for Extended Age Coverage. The third category refers to households that are still within the 5-year period of program coverage but have become ineligible because beneficiary children are now older than 14 years old.

In 2013, the administration also approved the extension of education grants to all existing beneficiary children until they finish high school. This is in response to the World Bank [2013] and PIDS [2012, 2013] studies that pointed out the substantial advantage of high school graduates over undergraduates in terms of earning potential. There is also indicative evidence that extending coverage up to 4th year will induce would-be dropouts to finish high school because the most-cited reasons for leaving school are the high cost of education and the need to earn for the family [Reyes et al. 2012]. In recognition of the higher opportunity costs of sending older children to school, the government is also increasing the education grant for all high school level beneficiaries to Php500 per month.

3 Conceptual Framework

Since program eligibility is conditioned on pre-determined variables such as household composition and observable correlates of poverty, cash transfers constitute an exogenous shock in household disposable income, resulting to an outward shift in the budget constraint that allows recipients to reach a higher level of welfare. Das, Do, and Ozler [2005] demonstrate the standard theoretical results of CCT impact on consumption (Figure 1).

[Insert Figure 1 here]

Prior to CCTs, a household's feasible set of consumption is bounded by the budget constraint AB, and the universe of goods it can consume is represented by goods *x* and *y*. Good *x* constitutes conditionality goods, or those that are required for CCT compliance. On the other hand, good *y* constitutes preference goods. Without CCTs, households are free to allocate resources between goods *x* and *y*. With CCTs, the budget constraint potentially becomes the line AEDC. The shape of AEDC illustrates the additional income accessible to households if they participate in a CCT program. If households consume at least x_0, the additional income is represented by segment ED. Any consumption less than x_0 disqualifies the household from the program, hence no additional income is received and the budget constraint remains at line AE. With CCTs, households are no longer absolutely free to choose between goods *x* and *y*. The authors illustrate the theoretical results using three types of households. Type I households continue to consume less than x_0 and stays at the same level of welfare. Type II households shift their consumption of *x* to the required minimum amount and avails of the extra income. Lastly, Type III households are consuming more than x_0 with or without CCTs and they shift consumption up to the point made possible by the extra income.

If the cash grant was unconditional, goods *x* and *y* remain fungible and the budget constraint of all households would be line CF, allowing Type I and Type II households to shift their consumption to match their preferences. It is only for Type III households that the conditional and unconditional cash grant lead to the same result, since its consumption of good *x* is already past x_0 even without imposing a condition. CCTs are targeted to Type I and Type II households because their level of consumption of good *x* is lower than the optimal consumption considered beneficial to them and to the society at large. Note that the shape of the indifference curves in Figure 1 indicates that target households have relatively low rates of substitution between goods *x* and *y*. This means that the program will induce behavioral change only among households that find value in shifting from preference goods to goods conditioned on by CCTs, which favor children and mothers.

For households under CCT the resulting disposable income (line AEDC) is expected to be allocated into: (1) consumption of goods related to fulfillment of conditionalities; and

(2) household preferences. The first one stems from the assumption that households want to perpetuate the benefits they receive. Since compliance is tied to the amount of cash payouts received, households are expected to spend the minimum necessary to avail of the maximum possible grant for the full duration of the program.

In the case of *Pantawid Pamilya*, there are two main conditionalities that need to be fulfilled to ensure continued participation. First is the requirement to send children to school. The expected consumption response is to increase spending on education-related goods. These are mainly payment for school fees, school supplies, clothing, and footwear. Second are the health-related conditionalities. The health conditionalities monitored for compliance are utilization of public health services, as presented in Table 1. Health-related goods availed of during clinic visits such as pills and vaccines are typically provided free. Therefore, there need not be significant changes in households' spending on medicines as these are not necessary to continue to receive *Pantawid Pamilya* grants.

Once expenses on conditionalities are fulfilled, household preferences determine the changes in the composition of household consumption. By design, CCTs are targeted to women because of increasing evidence that women respond differently to changes in household resources. Women have been shown to spend proportionately more on education and child-specific goods [Yoong et al. 2012] and on 'female-oriented durables' such as kitchen appliances, fans, electric irons, and the like [Ashraf, Karlan and Yin 2008]. Moreover, there is evidence to show that desired outcomes from increased use of public services manifest more with access to better information by women, especially among poor households [Jalan and Ravallion 2003]. Thus, another key component of CCTs is the conduct of monthly instructional meetings on responsible parenthood, nutrition, hygiene, sanitation, and other health issues.

In the Philippines, *Pantawid Pamilya* grantees, or direct program recipients, should be the mother [*Pantawid Pamilya* Operations Manual 2012]. It is only in the absence of a mother that a household is allowed to nominate another adult member to be the grantee. Likewise, while both parents are encouraged to attend monthly instructional meetings, only the mother's participation, as grantee, is required for program compliance. In sum, increased control of household resources and access to information of women through CCTs are expected to tip the household's preferences towards better food and other goods that enhance children's and total household welfare.

Using data from the Mexican CCT, Attanasio and Lechene [2011] find that conditional on household income, resources in the control of women lead to a positive relationship between food expenditure and income. Allocation of household budget among different food components is also influenced by women's control of resources. These findings are consistent with the somewhat unorthodox findings of previous studies that looked at the impact of CCTs on consumption. Studies on CCT programs of Mexico, Colombia, and Nicaragua found that expenditures on food do not decrease proportionately as a share of total expenditures, contrary to Engel's Law [Angelucci et al. 2012]. It has also been suggested that households use cash transfers from CCT in a different manner as other cash transfers, as shown by the significantly different expenditure patterns that result from a comparison of CCT and non-CCT households over time [Macours et al. 2008].

Overall, the logic and design of CCT programs can have multiple and interacting effects on household consumption decisions. CCTs make households face different incentives in making consumption choices among goods that are conditioned-on by the program and those that are not.

4 Methodology and Data

4.1 Impact evaluation framework

The fundamental question that any impact evaluation seeks to answer is that of causality. [8] In particular, this study wants to determine changes in household consumption that can be attributed to *Pantawid Pamilya.* Let y denote the outcome of interest, say food consumption. For any individual, there exist two potential values of y, the outcome if the individual is exposed to a program (y_1) and the outcome if the individual is not exposed (y_0). Both y_1 and y_0 are defined for all individuals.

Let p denote the program under study, *Pantawid Pamilya*. It has two values: p=1 for *Pantawid Pamilya* participants and p=0 for non-participants. Now, let Y denote the observed value of the outcome or for instance the observed level of food consumption. For any individual, Y is defined by the following relationship: $Y = py_1 + (1-p)y_0$. Program impact (Δ) is the difference between y_1 and y_0.

For any individual, Δ cannot be determined. At any given point in time, an individual participates to a program, in which case y_1 is observed or does not participate, and y_0 is observed. In the impact evaluation literature, Δ is a missing data problem. For instance, $E[y_0 \mid p=1]$ is the level of food consumption that would be observed if the individual did not participate in *Pantawid Pamilya* (when in fact she did). On the other hand, $E[y_1 \mid p=0]$is the food consumption level of non-*Pantawid Pamilya* households if they did participate. Both cases are called the "counterfactuals" and by their nature, are unobservable. Impact evaluation is essentially an exercise at constructing a valid counterfactual to solve the missing data problem and reliably measure program impact.

The most valid way to construct a counterfactual for any given population of interest is through experiments. In an experiment, the assignment of individuals to program status

[8] This section draws from Holland [1986].

(participants or non-participants) is randomized and within the control of the researcher. Randomization results to a nice property: the distribution of observable and unobservable characteristics among participants and non-participants are on average statistically similar prior to any intervention. Hence, two "identical" groups are created and on one of them, the program is implemented. Given the similarity of characteristics prior to intervention, the researcher can substitute the outcome of non-participants (y_0) to E[y_0 | p=1], and the outcome of participants (y_1) to E[y_1 | p=0] to calculate an average treatment effect. The similarity of the two groups (on average) prior to intervention gives the researcher confidence that the difference measured between them is the "true" program impact.

As discussed in Section 2, program placement of *Pantawid Pamilya* was not random. Targeting was applied in all stages of program implementation. The study utilizes also observational data that was not specifically collected for impact evaluation. Propensity score matching (PSM) is one of the most common non-experimental methods of constructing a counterfactual applied to CCT programs. PSM works well when program participation is determined by observable characteristics that are not easily manipulated by potential participants. In principle, if these observable characteristics are known, it is possible to construct a counterfactual group statistically similar to participants by controlling for these factors. These conditions make PSM a viable methodology in estimating the impact of *Pantawid Pamilya.*

4.1.1 Matching assumptions

Two assumptions are needed in order to establish that matching leads to a valid counterfactual [Imbens and Wooldridge 2009]. First is the conditional independence assumption (CIA), denoted as: $(y_{1,} y_0) \perp p \mid \mathbf{x}$. The vector **x** consists of observable characteristics that are known to influence program participation as well as potential outcomes of individuals. Under CIA, after conditioning on **x**, potential outcomes of individuals are independent of participation status. In other words, upon conditioning on **x**, p is no longer correlated to the potential gain from the program. In order for CIA to convincingly hold, the researcher needs to determine what these **x** characteristics are and have data on **x** for both participants and non-participants.

The second assumption is that of common support: $0 < \Pr[p=1 \mid \mathbf{x}] < 1$. This assumes that for all possible values of **x**, the probability of participating and of not participating in the program are both positive and the distribution of these probabilities for participants and non-participants overlap. This assumption ensures that matches can be found for individuals under study. If there are **x** values for which participation status is always 1 or 0, then matching fails for individuals with those **x** values and program impact cannot estimated for them. Moreover, if for some individuals p=0 or p=1 the probability of participation is lower (higher) than the minimum (maximum) of the other group, then these individuals fall outside of the common support region and they are excluded in the estimation of program impact.

If CIA and the overlap assumptions are satisfied, it is as if an experiment was conducted — individuals with the same characteristics have equal chances of being participants or non-participants and the resulting matched groups are statistically similar on average. However, if the two assumptions are suspect, remaining unobservable differences that influence participation and potential outcomes lead to a biased impact estimate.

4.1.3 Matching on the propensity score

Matching on **x** can be cumbersome. If **x** consists only of binary variables and there are n**x** variables, the resulting combination of characteristics that have to be matched is 2^n. This number compounds when there are continuous variables in **x**, such as age or income. The solution to this dimensionality problem is demonstrated by Rosenbaum and Rubin [1983]. Let $\Pr(x)$ be the propensity score or the conditional probability of being a program participant: $\Pr(x) = \Pr(p=1 \mid \mathbf{x})$. They showed that if potential outcomes are independent of participation status conditional on **x,** then they are also independent of participation conditional on the propensity score $\Pr(x)$. The CIA and common support assumptions then transform to $(y_1, y_0) \perp p \mid \Pr(x)$ and $0 < \Pr[p=1 \mid \Pr(x)] < 1$, respectively. Therefore, instead of matching on the vector **x**, we only need to match on $\Pr(x)$ which is a scalar transformation of the **x** characteristics.

Propensity score estimation should credibly establish that conditional on $\Pr(x)$, participation to *Pantawid Pamilya* is no longer related to initial potential outcomes [Rosenbaum and Rubin 1983]. It also needs to balance this goal with that of achieving overlapping $\Pr(x)$ distributions for $p=0$ and $p=1$. Hence, the choice of variables is crucial. Variables selected must contain information on the program assignment mechanism and on outcomes of interest [Blundell and Costa-Dias 2008]. Variables known to be affected by participation or the anticipation of it are excluded in the propensity score model [Caliendo and Kopeinig 2008]. Moreover, as much as possible, only variables that are time-invariant or deterministic with respect to time are included in the model [Stuart 2010].

Studies that have looked at the performance of PSM estimators show that it works well in estimating causal impact when a rich dataset of variables can be used in estimating the propensity score and the data on participants and non-participants are collected using the same questionnaire (Khandker et al. [2010]; Diaz and Handa [2006]). Both requirements are satisfied in this study. This lends credence that the propensity score estimated can substantially reduce the selection bias present in non-experimental data.

4.1.4 Balance tests

The primary objective of propensity score estimation is to balance the distribution of characteristics between program participants and non-participants [Stuart 2010]. Balance tests are carried out to ascertain whether or not conditional on the estimated propensity score, statistically similar groups of *Pantawid* and non-*Pantawid Pamilya* households have been constructed.

As suggested by Rosenbaum and Rubin [1985], examining standardized bias of each of the covariates is a good way to assess the success of the matching procedure. Standardized bias (SB) is the difference of sample means in the participant and matched non-participant groups as a percentage of the square root of the average sample variance in both groups. The established practice is to look at the reduction in standardized bias and consider remaining standardized bias of 5% and below to be sufficient indication of successful matching [Caliendo and Kopeinig 2008].

Another common approach in assessing matching quality is comparison of means before and after matching. After matching there should be no significant differences in covariate means between the two groups. Pseudo-R^2 and LR-statistic in the propensity score model before and after matching are also compared. Though an imperfect measure, substantial reduction in pseudo-R^2 after matching shows that the **x** characteristics no longer explain the variation in participation status in the sample. The LR-statistic after matching should also show that the null hypothesis cannot be rejected.

4.1.5 Matching techniques

Participants are matched to non-participants based on the "closeness" of their propensity scores. This can be achieved through several ways. Let $v(\mathrm{Pr}_i)$ be the neighborhood for each i in the sample of participants. The "neighbors" of individual i are non-participants $j \in I_0$ whose propensity scores $\mathrm{Pr}(j)$ are "close" to the propensity score $\mathrm{Pr}(i)$ of person I, where I_0 is the set of non-participants.

Matching techniques vary on: (1) how $v(\mathrm{Pr}_i)$ is defined; and (2) how weights are constructed. Weights are given to non-participants to adjust for the frequency with which a particular observation is used as a match or to adjust for the relative distances of the non-participant matches to the participant being matched. Typically, several matching techniques are implemented in any study that uses PSM to check the robustness of estimates to the particular technique utilized. [9]

The following matching techniques are implemented: nearest neighbor, nearest neighbor within caliper, radius, and kernel matching. In nearest-neighbor matching, the non-participant with the closest propensity score is selected as the match: $v(\mathrm{Pr}_i) = \min_j | \mathrm{Pr}(i) - \mathrm{Pr}(j) |, j \in I_0$. Its variant imposes a maximum distance (caliper) between the participant and the closest non-participant match. It is common practice to select more than one closest non-

[9] This means that each matching technique also leads to different balance results. Hence, the balance tests described earlier are carried out for each of the matching technique implemented here.

participant match to reduce the variance of the impact estimates. Nearest neighbor (n=1) and nearest neighbor within caliper (n=2, cal=0.01) are used here.[10]

In radius matching, a tolerance limit is set on the distance between the propensity score of participants and non-participants. Instead of setting the number of neighbors to be selected, all non-participants whose propensity score fall within the tolerance limit are included. The choice of tolerance limit is informed by the relative dispersion of propensity scores between the participant and non-participant groups. If the standard deviation of propensity score among participants is larger than that among non-participants, a smaller caliper is advisable [Stuart 2010]. The tolerance limit here is 0.001.[11] In both nearest neighbor and radius matching, the counterfactual outcome is a weighted average of the outcomes of the selected non-participant matches. The weights are based on the number of times a non-participant observation is used as a match (since matching with replacement is used here).

Lastly, kernel matching is a nonparametric matching estimator that uses a weighted average of all non-participants as the counterfactual. It has the advantage of having lower variance since all (eligible) non-participants are included in the estimation of counterfactual outcome. Non-participants with propensity scores closer to the participant observation being matched are given higher weights than more distant observations. The biweight kernel function is implemented, with a bandwidth of 0.01.[12]

4.1.6 Impact and variance estimation

Since program impact is different for each individual, any impact measure is generally an average over the population of interest. Here, the population of interest is the universe of households that are eligible to participate in *Pantawid Pamilya* and our sample is the set of eligible households that actually participated in the program. The “parameter of interest” is called the average treatment effect on the treated (ATT).[13] ATT is the impact of *Pantawid Pamilya* on eligible households that actually participated:

$$\text{ATT} = \text{E}[y_1 \mid p{=}1] - \text{E}[y_0 \mid p{=}1] \qquad (1)$$

[10] The choice of nearest neighbors is arbitrary and involves a bias-variance trade-off. Increasing the number of neighbors tend to increase the bias and reduce variance. Using Monte Carlo simulations, Austin [2010] shows that selecting 2 untreated matches is optimal in most cases, as it improves precision without a corresponding increase in bias. Indeed, going from 2 to 4 nearest neighbours in this study did not change the inference so the estimates for N=4 are no longer reported.

[11] Here, the standard deviations of Pr(x) are 0.2089 for *Pantawid* and 0.1233 for non-*Pantawid Pamilya* households. Nevertheless, the choice of caliper is also arbitrary.

[12] In kernel matching, it is the choice of bandwidth parameter that involves a bias-variance trade-off. Higher bandwidth leads to lower variance, increased bias. Various types of kernel function can be used, though the more critical decision is the bandwidth parameter.

[13] Until this point the impact estimate described is the average treatment effect (ATE), which is the average impact on the entire population.

Thus, the only missing counterfactual is the outcome of participants if they were not treated E[y_0 | *p*=1]. In estimating ATT the matching assumptions are now:

$$E[y_0 \mid \Pr(x), p=1] = E[y_0 \mid \Pr(x), p=0] \quad (2)$$

$$\Pr[p=1 \mid \mathbf{x}] < 1 \quad (3)$$

The first condition means that we need *p* to be uncorrelated with y_0 conditional on the propensity score Pr(*x*). This means that prior to joining the program eligible households should have the same expectation of what their outcomes would be if they do not join the program and this should not drive their decision to participate. Empirically, this means that all variables related to y_0 and *p* are incorporated in the estimation of the propensity score Pr(*x*) as discussed earlier. Moreover, since we are interested in measuring impact only among *p*=1, we do not need to satisfy 0 < Pr[*p*=1 | **x**]. This assumption is needed to ensure that we can find y_1 matches for *p*=0 in order to estimate program impact for non-participants.

The sample analog of Equation 1 is:

$$\widehat{ATT_M} = \frac{1}{n_1}\sum_{i \in I_1 \cap S_P} \left(y_{1i} - \widehat{\mathrm{E}}[y_{0i} \mid p = 1, \Pr(i)]\right) \text{ where } \widehat{\mathrm{E}}[y_{0i} \mid p = 1, \Pr(i)] = \sum_{j \in I_0} w_{ij} y_{oj}$$

I_1 denotes the set of *Pantawid Pamilya* households and I_0 the set of non-*Pantawid Pamilya* eligible households. S_p is the region of common support or the region where propensity scores of I_1 and I_0 overlap. The variable n_1 is the number of people in the set $I_1 \cap S_p$. w_{ij} are the weights given to each non-*Pantawid Pamilya* eligible household selected as a match.

To make proper inferences about *Pantawid Pamilya* impact, the variances of ATT estimates are likewise estimated. The variance of the impact estimates must take into account the variance resulting from the estimation of the propensity score and the imposition of common support [Caliendo and Kopeinig 2008]. In practice, PSM studies use bootstrapping methods to calculate standard errors. However, bootstrap provides valid inference only when the number of matches increases with sample size, such as in kernel matching [Abadie and Imbens 2008]. Here, bootstrap standard errors are calculated under 100 replications for radius and kernel, while bias-adjusted robust standard errors [from Abadie and Imbens 2006] are reported for nearest neighbor matching.

4.1.7 Sensitivity analysis

The bounding approach developed by Rosenbaum [2002] approximates how strong "hidden bias" or unobserved heterogeneity should be in order to alter inference about program impacts [Caliendo and Kopeinig 2008]. Sensitivity analysis computes upper and lower bound estimates of significance levels, and Hodges-Lehmann point estimates and confidence intervals for ATT, starting from the case where there is no "hidden bias" [DiPrete and Gangl

2004]. The RBOUNDS routine in Stata® [Gangl 2004] is utilized here to test the sensitivity of the impact estimates. The tolerance in the odds ratio of participation is set from 1 to 2.0, where 1 means there is no hidden bias.

Another methodology to get an indication of the sensitivity of the impact estimates is to implement the entire PSM methodology using covariates that are definitely unaffected by CCT. This helps establish the case that even when matching is done after program implementation, impact estimates are not sensitive to the possible effect of CCT on the covariates used for matching. Arguably, some of the covariates included in the full propensity score model maybe affected by program participation (directly or indirectly). For instance, dwelling characteristics, which were used in categorizing eligible and non-eligible beneficiaries, may be influenced by CCT if beneficiary households spend part of their grants on improving their walls or roof.

From the full propensity score model, the variables hypothesized to be affected by *Pantawid Pamilya* participation are: a) family size; b) number of children 0-2 years old; c) dwelling characteristics; d) the household head not having wage income; and e) the household head being self-employed. Propensity score is estimated without these variables and impact is estimated using the same matching techniques utilized in the full model.

4.2 Data Description

The Annual Poverty Indicators Survey (APIS) is a nationally representative survey conducted by the NSO during years when the triennial Family Income and Expenditure Survey (FIES) is not conducted. The 8th round of APIS is utilized here, carried out in July 2011. A total of 42,063 households were interviewed. Data is collected on all family members residing in the household, for a maximum of 3 families per housing unit.

The primary objective of APIS is to generate and monitor non-income indicators related to poverty. It collects information on socio-economic indicators that are strong correlates of poverty such as demographic characteristics, schooling status, housing conditions and tenure, access to water and sanitation facilities and other basic amenities, ownership of assets, income and expenditure. Thus, APIS is the most natural dataset for a non-experimental evaluation of *Pantawid Pamilya* as it contains most of the variables used in identifying program eligibility.

In 2011, a module on social protection programs is added in APIS. *Pantawid Pamilya* is one of the programs included for monitoring. This enables the identification of *Pantawid Pamilya* beneficiaries and non-beneficiaries for the implementation of PSM. It is important to note that program participation in this case is self-reported. If the household claims to be a beneficiary, it is asked the amount of cash grant received in the past 6 months.

Out of the total sample, 3,066 households claimed to be *Pantawid Pamilya* beneficiaries. Eighty nine percent of *Pantawid Pamilya* households belong to the bottom 40%

of the income distribution. Sixty percent have an average of 7 family members, 2 members more than the population average. The average per capita monthly income of *Pantawid Pamilya* households is Php1,544.63, a little over the poverty threshold of Php1,529.28. However, upon examination of the income distribution, 63% of the beneficiary households are below the poverty threshold. These households are in fact subsistence poor because their average per capita monthly income is Php1,062.20, lower than the food poverty line. This indicates targeting issues; some 'non-poor' beneficiaries are driving up the mean income of all beneficiaries.

The average amount of cash grants received in the past month is Php1,162. This represents 15% of total monthly expenditures of *Pantawid Pamilya* households. Receipt of cash grants is irregular as there are 884 and 16 *Pantawid Pamilya* households that did not receive any cash grant in the past month and past 6 months, respectively. On the other hand, there are 74 households that received more than Php15,000 in the past 6 months, more than the maximum annual grant per beneficiary family. The impact estimates need to be appreciated in light of the apparent irregularity of cash grants. Nonetheless, the median amounts of cash grants are well within the feasible range based on program rules (Php1,000 and Php3,400 for the past month and past 6 months, respectively).

Analysis is confined to the sub-sample of *Pantawid Pamilya* beneficiaries and eligible non-beneficiaries. In accordance with program eligibility rules, eligible households are defined as those that have children aged 14 years old below.[14] Eligible non-participants are not restricted to 'poor' households to account for the fact that *Pantawid Pamilya* households are distributed across the entire income distribution. Note that the use of proxy means test to classify poor households entail exclusion (inclusion) errors, where income-poor (non-income poor) households are excluded (included) in the program. Thus, beneficiary households in the dataset are those classified as poor by the PMT and may not necessarily be income-poor per NSCB. There are 28,272 eligible households in the dataset, of which 25,206 are non-*Pantawid Pamilya*. A large pool of non-participants to draw matches from is a good condition for the PSM technique to work well, as it increases confidence that the y_0 outcomes for p=1 can be found from the sample [Khandker et al. 2010].

4.2.1 Covariates

Variables that strongly influence program participation and outcomes, based on knowledge of key program implementation details and existing literature, are used in estimating the propensity score. These are: (1) demographic characteristics of the household; (2) household head and spouse characteristics; (3) dwelling characteristics; (4) ownership of

[14] Unfortunately, we cannot capture households with pregnant women among non-*Pantawid Pamilya* in the dataset. For *Pantawid Pamilya* HHs without children aged 14 years old and below, we assume that they have a pregnant member and we still include them in the estimation sample (N=64 cases).

assets; (5) location; and (6) other household characteristics related to participation and outcomes.

All indicators in the DSWD proxy means test model for identifying *Pantawid Pamilya* beneficiaries that are available in the APIS dataset are used (Items 1 to 4 above). Location is important due to the geographical nature of *Pantawid Pamilya* expansion hence dummy variables are included for each region. In addition, a dummy variable that is equal to 1 if households are located in provinces that belong to Set 1 and Set 2 areas of *Pantawid Pamilya*, or those that were covered in the first two years of implementation is included. A dummy variable for whether households are located in the rural areas is also included. All these location variables serve to account for community-level characteristics that may influence consumption outcomes such as infrastructure and market conditions.

As proxy controls for income and consumption, dummy variables that are equal to 1 if the household has an OFW member, the household has wage income, the household head is self-employed, the household belongs to the bottom 40% of the income distribution, and if they have agricultural land used for agricultural purposes are included in the estimation of the propensity score.

4.2.2 Outcome variables

The APIS collects consumption data on food and non-food items to capture total household well-being. Since APIS rounds are conducted in July, the reckoning of expenditures is January to June of the current year. The actual reference period varies by expenditure item. Average weekly consumption is reckoned for all food items. The food items are recoded into four broad groups: carbohydrates, protein, vegetables, and other food. Other food includes cooking oil, sugar, salt, non-alcoholic beverages, and other seasoning items. Average monthly consumption is asked for non-food items such as fuel, transportation and communication, household operations, personal care, and alcohol and tobacco. Meanwhile, actual consumption for the past six months is asked on clothing, education, recreation, medicines, non-durable and durable furnishing, and other expenses. Among non-food items, alcohol and tobacco, education, medicines, and clothing are retained while the rest are lumped under the category 'other non-food'.

The consumption data for each expenditure item is the sum of cash (or credit) and non-cash expenses. Non-cash expenses pertain to the value of own-home production ("in-kind") and those received as gifts. For non-cash expenses, prevailing local prices are used in the valuation. Due to variability in prices over time and space, all expenditure items are adjusted to 2009 prices using the consumer price index produced by the NSO. Further, following the methodology of Balisacan [2001] a cost-of-living index is computed to account for differential prices across provinces. The index is the ratio of provincial poverty thresholds, with Metro Manila as base.[15] Thus, all expenditure items are 2009 Metro Manila prices.[16] Finally, expenditure items are converted to per capita per month levels and as shares of total expenditure. Table 2 presents a summary of the outcome variables for *Pantawid Pamilya* households.

[Insert Table 2 here]

Poverty is apparent in the consumption pattern of beneficiary households. Total per capita monthly expenditures is Php1,787.83. Almost 70% of this is on spent on food. Carbohydrates, the main source of energy, take up more than a third (32%) of food consumption. Protein-enriched foods such as meat, fish, and dairy constitute 19% of total food expenditures. On a per capita per month basis, this is just Php337.93. There is little room for fruits and vegetables in the food budget (5%), which are important sources of minerals and nutrients. The rest (11%) is spent on cooking oil, sugar, and other seasoning.

Very few commodities constitute the rest of the consumption mix. Education and medicine spending is at Php141.29[17] and Php34.24 per person per month, respectively. These levels represent only 2.7% and 1.5% of total expenditures. Clothing takes up an average of 1.9% of total expenditures, which translates to a Php34.03 per person month spending.[18] On the other hand, the expenditure share of alcohol and tobacco is 2.4% or Php102.25 per month per adult household member. This is a considerable amount, which can be reallocated to better uses should household preferences shift.

The rest of the non-food expenditures is on average less than Php300 per person per month. This amount incorporates spending for housing, fuel, electricity, water, household operations, personal care items, and transportation and communication, recreation, non-durable and durable furnishings, and even savings (if any).

5. Results and Discussion

5.1 Propensity score estimation results

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[15] The rationale for this approach is that poverty thresholds can be viewed as a cost-of-living measure since items included in the computation of these thresholds are valued at provincial prices.

[16] The adjustment across provinces is necessitated by the fact that the matching technique is not restricted to geographical location. Though regional location is controlled for in the estimation of propensity score, it is still possible for a *Pantawid Pamilya* beneficiary to be matched to a non-*Pantawid Pamilya* beneficiary from other provinces or regions.

[17] Note that the expenditure reference period includes April-May, when most of the students are in summer break. While this may be balanced by lump sum expenditures on fees and supplies during the opening of classes in June, it is likely that education expenditures captured in APIS is relatively lower than July-December expenses.

[18] Expenses on school uniforms and clothing for end-of-year ceremonies are recorded under this category. Thus, APIS data on clothing may be artificially high and education-related.

The results of propensity score estimation using logit regression are in Table 3. The dependent variable is a dummy equal to 1 if the household claimed to be a *Pantawid Pamilya* beneficiary and equal to 0 otherwise. The results show that the probability of participating in *Pantawid Pamilya* is consistent with the program's targeting mechanism.

[Insert Table 3 here]

Having children within the age group eligible for *Pantawid Pamilya* is significant in predicting participation. Education levels of the household head and spouse are also significant, with those having lower levels of education being more likely to be in the program. All the proxy indicators of income included are significant in predicting participation. For instance, having an OFW member negatively predicts participation. Meanwhile, not having wage income, being engaged in agriculture, the household head being self-employed, and belonging to the bottom 40% of income distribution all strongly predict participation.

With regard to housing conditions, having light materials for roof and walls positively predicts participation. Having a bigger floor area and owning a TV, refrigerator, washing machine and oven are all significant in predicting non-participation, as shown by the negative signs on these variables. Most of the housing tenure categories are not significant predictors, with only renting lot being slightly significant. This could be due to the concentration of beneficiaries in rural areas, where tenure is not a primary problem. In fact, 83% and 79% of *Pantawid Pamilya* and eligible non-*Pantawid Pamilya* households respectively, either own their house and lot or utilizing the lot rent-free with consent of owner.

In terms of water and sanitation, access to a community water system installed within the dwelling or yard negatively predicts participation. Using pail system for defecation is a significant predictor of participation. These show that households without access to improved water and sanitation facilities are more likely to be included in the program than those that do. Given the geographical nature of program expansion, location matters in participation. Residing in a rural area and in a province included in Set 1 and Set 2 areas of *Pantawid Pamilya* strongly predicts participation, as expected.

Figure 2 shows the distribution of propensity scores among *Pantawid* and non-*Pantawid Pamilya* households. Propensity scores of non-*Pantawid Pamilya* households are concentrated at the lower end of the range as expected. There are participants and non-participants across the distribution, there are no breaks inside the distribution, and there are no observations predicted as $\Pr(x) = 0$ or $\Pr(x) = 1$. These are all good indications of overlap. The common support region is the area where non-participants can be found for each value of the participants' propensity score. Therefore, *Pantawid Pamilya* households whose propensity scores are higher than the maximum propensity score of non-participants are outside this region. Fifteen participants are off the common support region in our sample.[19]

[Insert Figure 2 here]

5.2 Balance tests

Balance tests on the distribution of **x** characteristics among *Pantawid* and non-*Pantawid Pamily*a households conditional on the propensity score are carried out for each of the matching technique implemented. Overall, the matching techniques are very successful in balancing covariate distribution conditional on the propensity score between the two groups. None of the **x** characteristics remained statistically different after matching. The full results of covariate balance tests are in Table 4.

[Insert Table 4 here]

To illustrate, the balance test results for the nearest neighbor (N=1) matching technique are discussed here. Using this matching algorithm, N=3,051 *Pantawid Pamilya* households are matched to N=2,201 non-*Pantawid Pamilya* households. Figure 4 shows the distribution of propensity scores of the matched sample using histograms and kernel density graphs for each of the matching technique.

[Insert Figure 4 here]

The first two panels in Figure 4 show the results for nearest neighbor matching. A cursory examination reveals that the histograms between the two groups are mirror images of each other, indicating that matching was successful in balancing the distribution of propensity scores. Nonetheless, this does not necessarily indicate balance in covariates. As discussed earlier, standardized bias for each covariate post-matching is one way of checking the balance of **x** characteristics between participants and non-participants. In the case of nearest neighbor matching technique (N=1), none of the remaining standardized bias after matching is more than 5% (column 4 of Table 4). Figure 3 illustrates covariate balance pre- and post-matching. The lining-up of the red markers close to the 0 axis means that after matching, standardized difference between the groups are largely negligible.

[19] The maximum Pr(x) is 0.9242 and 0.8573 for p=1 and p=0, respectively. Hence, the 15 cases excluded in the estimations are those with propensity scores higher than 0.8573. Upon examination, these households are relatively poorer beneficiaries and are the ones with the most to gain from the program. Hence, it is likely that the impact calculated is underestimated.

[Insert Figure 3 here]

Column 5 in Table 4 shows that p-values for the comparison of means between matched groups are well below the critical values.[20] Comparing pseudo-R^2 and LR-statistic in the propensity score model before and after matching shows that the **x** variables no longer explain the variation in participation status among observations. Pseudo-R^2 substantially decreased (from 0.2948 to 0.007) and the LR-statistic after matching shows that the null hypothesis cannot be rejected ($p>0.78$).

5. 3 ATT estimates

Table 5 shows the ATT estimates by matching technique. For *Pantawid Pamilya* households, the foremost consumption response relates to goods that are conditioned-on by the program. Monthly education expenditure per schooling member increased by Php2.85 to Php6.69[21] per month, but none of these estimates is significant. Nonetheless, the share of education spending to total expenditures significantly increased, albeit small at 0.3 to 0.4 percentage points. The small magnitudes of impact detected are possibly due to limitations of observational data and/or because the share of education spending among our sample households is small to begin with (2-4% of total expenditures). The expenditure reference period could also account for the weak impact. In any case, the direction of expected impact is as hypothesized and this is robust to all the matching techniques utilized.

[Insert Table 5 here]

The estimates show that per capita monthly spending on clothing went up by Php7.51 to Php8.75 and these are highly significant across all matching techniques. Although a disaggregated data on adult and children clothing is not available, this increase in clothing expenditure is most likely education-related due to the survey reference period. The share of clothing to total expenditures also significantly increased by 0.5 percentage points. In fact, clothing experienced the biggest increase as a share of expenditure. Medicine expenditure, both in per capita levels and as share of total expenditure, is unaffected by *Pantawid Pamilya* participation as hypothesized. Other studies that had similar results on medicine assert that this is probably due to improved health among beneficiaries [Macours et al. 2008].

Estimates show that *Pantawid Pamilya* beneficiaries increased food spending by Php20.50-Php23.65 per person per month, though this is significant in just two of the

[20] There have been criticisms on the use of significance testing in assessing covariate balance due to the influence of sample size, and therefore statistical power in the results [Austin 2009; Stuart 2010].

[21] To reiterate, expenditure levels reported here represent 2009 Metro Manila prices. For brevity we do not repeatedly mention this in the discussion.

matching techniques utilized. This result is driven by the increased spending on carbohydrate foods, such as rice and corn. Expenditure for carbohydrates increased by Php24.81 to 29.08 per person per month (robust to all matching techniques). The share of food to total expenditure is however unaffected by the program, consistent with other studies on the impact of CCT on consumption [Angelucci et al. 2012].

Pantawid Pamilya does not have any impact on alcohol and tobacco spending. This finding is similar to that of the WB experimental study [2013]. Thus, the popular concern among middle income Filipinos that taxpayers' money will be spent on vice is not supported by empirical data so far. Finally, the program has no observed impact on total per capita expenditures. Though the estimates are positive (Php13.45 to Php26.50 for nearest neighbor matching techniques), they are not statistically significant. It is likely that the level of cash grants is not enough to make a substantial dent in total household spending.

5.4 Impact heterogeneity

The nature and design of CCT programs lends itself naturally to impact heterogeneity. For instance, the study on Paraguayan CCT found that while total households experienced between 9 to 15% increase in per capita consumption, the extremely poor ones experienced between 13 and 21% increase [Soares et al. 2008]. The study on Mexican PROGRESA found that poverty status and the marginality index of villages strongly predict the differential impact observed on consumption [Djebbari and Smith 2008]. Higher increase in mean consumption was observed among poorer households, and more so for poorer households in more marginal villages.

This study contributes to this literature by examining the impact of *Pantawid Pamilya* on households that belong to the bottom 20% of the income distribution. Propensity score matching is implemented as discussed and following Schaffland [2012] filter the observations on the subsample of interest. Table 6 presents the ATT estimates by matching technique.[22]

[Insert Table 6 here]

The most notable result is that the impact of *Pantawid Pamilya* on per capita total expenditures is now strongly significant (robust across all matching techniques). Among *Pantawid Pamilya* households in the poorest 20% of the population, per capita expenditures increased by Php42.60 to Php76.03 per month, which represents 3-5% of pre-program expenditure levels. This is substantial given that the average family size of a program beneficiary is six members.

[22] The full results of the balance tests are available upon request. The same propensity score model is used, except that the variable 'bottom40' is removed. Overall, covariate balance is also successfully achieved among this subsample.

The significant increase in per capita total expenditures is driven by spending on food. Expenditures significantly increased by Php28.03 to Php49.18 per person per month. Among food sub-categories, *Pantawid Pamilya* beneficiaries have allocated their increased resources most on carbohydrates (Php 25.82 to Php30.96). Spending on proteins and fruits and vegetables also significantly increased by Php9.88 to Php10.80 and by Php3.06 to Php4.89 per person per month, respectively (significant in two matching techniques utilized).

The consumption response of poorest beneficiary households with regard to education and health is not markedly different from that of the total sample. Education increased as a share of total expenditures (0.3 to 0.4 percentage points), though per capita spending is still unaffected by the program. Clothing remains strongly significant, with per capita levels increasing by Php6.90 to Php7.79 per month and expenditure share by 0.5 percentage points. There is still no observed impact on spending for medicines, whether on a per capita basis or as a share of total expenditures.

Another noteworthy result is that the share of savings to total expenditures is slightly significant in two of the matching techniques used, but the positive increase is due to a reduction in negative savings. From having around negative 5% share of savings to total expenditures prior to the program, *Pantawid* households in the bottom fifth of income distribution have reduced their shortfall by about 1.6 percentage points. Though small in magnitude, this is a welcome indirect impact as it indicates that households are reducing their debts. If sustained over time, households may eventually have some room for gainful investments to improve productivity.

Overall, the differential impact of *Pantawid Pamilya* among the poorest 20% of households is very promising. The stronger and positive impact on outcome variables of interest indicates that those who are expected to gain the most from the program actually do.

5.5 Sensitivity of ATT estimates

Using the RBOUNDS routine in Stata®, the statistically significant outcomes appear to be fairly sensitive to hidden bias. Estimated tolerance bounds in the odds ratio of participation is between 1.05 and 1.50.[23] This means that the estimates are valid only up to the point where the odds that two individuals with similar observable characteristics have different treatment status is less than 1.5. Nonetheless, the results do not indicate that there are in fact unobserved variables that render the impact estimates biased. Moreover, as discussed in the previous chapter, the CIA can be relaxed in estimating ATT. Instead of complete statistical independence, the mean of initial potential outcomes y_0 only need to be uncorrelated to p conditional on the propensity score $\Pr(x)$. This is achieved by including all

[23] Due to space constraints, results are not presented but are available upon request.

the relevant variables determining participation and outcomes in the estimation of the propensity score, as implemented here.

Overall, inference is not altered by removing the covariates that are potentially affected by *Pantawid Pamilya*.[24] Expenditure shares of education and clothing are still statistically significant. In per capita monthly terms, spending for clothing and carbohydrate foods also remain strongly significant across all matching techniques. Stronger impact is again observed among households in the bottom fifth of the income distribution. Though the magnitudes are different, these results indicate that the estimated impact of *Pantawid Pamilya* on consumption is fairly robust and is not sensitive to the propensity score specification.

6. Conclusions and Recommendations

This study analyzed the impact of *Pantawid Pamilya* on consumption by comparing two groups of observationally-similar households, one of which benefitted from the program. Propensity score matching methodology is employed on a large nationwide cross-sectional data collected on *Pantawid* and non-*Pantawid Pamilya* households.

Consumption pattern among beneficiary households revealed their extreme poverty. Two thirds of consumption is spent on food, the rest on a few basic necessities. Education, health, and clothing together constitute a meager 6% of total household consumption. The hypothesized consumption response of beneficiary households is grounded on the distinction between goods conditioned-on by the program and those that are not. Households will spend the minimum required on goods monitored for program compliance, and residual response is determined by preferences. These preferences, this study posits, are influenced by key program aspects such as granting cash to women and monthly instructional meetings.

The observed impact of *Pantawid Pamilya* on consumption provides credible evidence to the hypothesized response. Impact estimates show that beneficiary households increased their consumption of education-related goods, goods that are necessary for continued program participation. This is a good signal of households’ resolve to perpetuate participation, presumably because they understand the program logic and have positive expectations of its impact on future household welfare.

After spending on goods conditioned-on by the program, *Pantawid Pamilya* households have spent the rest of the additional income on food. Specifically, they prioritized carbohydrates. This choice supports the view that women’s control over resources leads to spending on goods that improve total household welfare, as food is known to be more preferred by women than by men. Since cash grants tend to be lumpy due to the payout cycle,

[24] Due to space constraints, results are not presented but are available upon request.

mothers may opt to stock up on food to ensure sufficient supply until the next pay-out. The obvious choice is rice or corn as it is accessible, storable, and sufficient as stand-alone meal.

The results also show that on average, total household consumption did not increase as a consequence of *Pantawid Pamilya*. This means that some households in the distribution experienced a reduction in total consumption, possibly due to the income-reducing effect of complying with program conditionalities. However, the analysis on heterogeneous impacts illustrates that this income-reducing effect is not prominent among the poorest 20% of households. In fact, among this subsample, total per capita consumption significantly increased. The poorest beneficiaries arguably experienced the biggest increase in income as a consequence of the program and the net change is enough to register an improvement in their total consumption. It also shows that only a minority of beneficiary households experienced a decline in total per capita consumption, as more than 60% of *Pantawid* households belong to the bottom 20% of the income distribution.

The stronger program impact observed on poorer beneficiary households has substantial implications on the program targeting mechanism. If the model used to identify *Pantawid Pamilya* eligible households does not incorporate the relevant factors that determine poverty status, two 'observationally-similar' households can have very different welfare status and there would seem to be unobserved factors that influence program participation. Any effort at isolating the average program impact is effectively compromised. Going back to the model in Section 3, for these Type III households (disguised as Type II) the cash grants are as good as unconditional and they cannot be expected to respond to the conditionalities.

Thus, it is important that the proxy means test model used by the DSWD is updated using better data and guided by recent literature on poverty. The inclusion of barangay characteristics in the revised proxy means test model is a step in this direction. Incorporating results from studies on poverty transitions, such as the distinction between transient and the chronic poor, also helps create a dynamic and richer poverty model. Another important aspect in improving the targeting mechanism is using poverty data and income thresholds that are representative at lower levels of geographical disaggregation. This ensures that the cut-off points used in determining eligibility more closely reflects the welfare status of each locality.

There remains much to understand about the distribution of *Pantawid Pamilya* impact on the target population. As the program expands even more, questions on differential impact should take priority in policy debates as it provides information on which alternative would result to more cost-effective impact at the margin. As studies on the impact of Mexican CCT on consumption show, it is more efficient to intensify program coverage among poor households in the poorest localities than to cover relatively less poor areas [Djebbari and Smith 2008]. This study provides preliminary evidence to support this conclusion.

Another striking, though probably not surprising result from this study is that very few expenditure items are affected by the program. Aside from education, clothing, and carbohydrate foods, none of the remaining expenditure items analyzed is significantly affected. This underscores the fact that *Pantawid Pamilya* households come from a deep state of need. The result also reveals that the level of cash grants received is not enough to give room for consuming beyond basic food items after spending on goods required for program compliance. The implication is that beneficiary households may find it difficult to sustain behavioral change over time due to changing costs of program participation. The value of the peso erodes over time, making education-related goods more expensive. The opportunity cost of sending children to school increases as they age. There is a need for a reexamination of the level of cash grants provided to *Pantawid Pamilya* beneficiaries to ensure that they are able to balance program compliance with household preferences over time. The adjustment of education grants to Php500 per month for students in high school will help cover these opportunity costs and will likely help households sustain induced behavioral changes over time. Any delays in the implementation of this program modification must be avoided.

In addition, some program implementation aspects can also be enhanced to take into account the results from this study. For instance, to lessen inclusion and exclusion errors, barangay assemblies convened to affirm the poverty status of identified households should be strengthened. Transparency on how cash grants are determined and improvement of the schedule of releasing grants would also aid households in making better consumption decisions. This is so because the perception of the persistence of the grants and regularity of pay-outs are shown to influence household consumption response to income shocks [Jappelli and Pistaferri 2010].

As more information is generated on the experimental sample of *Pantawid Pamilya*, other dynamics that influence the observed changes in outcomes, such as externality effects or behavioral changes could be explored. Longitudinal data among treated and control groups allow better investigation of heterogeneous impacts of the program, and of effects beyond the impact of the cash transfer alone [such as in Ribas et al. (2010)]. This enables better analysis of the components that make up the total observed changes in consumption behavior of *Pantawid Pamilya* households.

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Table 1. Program Grant Packages and Conditionalities

Grant type	Eligible Member	Grant amount	Conditionalities
Health	Children aged 0-14 years old	Php500 per month per household or Php6,000 per year	For children 0-5 years old: • Complete all required vaccinations (BCG, OPV, DPT, Hepatitis, and Measles) on the prescribed schedule • Monthly weight monitoring and nutrition counseling for children aged 0-23 months old • Bi-monthly weight monitoring for 24 months to 72 mos. old For children 6-14 years old: • Take deworming pills twice a year (elementary students only)
	Pregnant women		• One pre-natal consultation each trimester • At least one blood pressure and weight monitoring measurement in each trimester • At least one Breastfeeding Counseling Session prior to delivery and within the first six weeks after childbirth • At least one Family Planning Counseling Session prior to delivery and within the first six weeks after childbirth • Delivery by a skilled health professional • At least 1 post-natal care w/in the first 6 weeks after childbirth
	Mother or other designated guardian		• Attend monthly Family Development Sessions (lectures on nutrition, sanitation, responsible parenthood, among others)
Education	Children aged 6 to 14 years old	Php300 per month per child for 10 months or Php3,000 per year; max of 3 beneficiary children	• Enroll in elementary and secondary schools and maintain a class attendance rate of at least 85% per month.
	Children aged 3-5 years old	Same as above if max no. of 6-14 year olds is not yet reached	• Enroll in Day Care Program or Kindergarten and maintain a class attendance rate of at least 85% per month

Source: *Pantawid Pamilyang Pilipino* Program Operations Manual 2012. DSWD.

Table 2. Summary of outcome variables among *Pantawid Pamilya* households (N=3,066)

	Variables	Mean	SD
	Per capita per month expenditure		
1	Total expenditure	1,787.83	987.70
2	Savings[1]	71.25	608.51
3	Food expenditure	1,134.63	458.01
4	Carbohydrate[2] foods	513.42	179.85
5	Protein[3] foods	337.93	235.85
6	Fruits and vegetables	86.74	69.83
7	Other food	196.54	162.95
8	Alcohol and tobacco [4]	102.25	133.48
9	Medicine	34.24	138.77
10	Education [5]	141.29	452.04
11	Clothing	34.03	48.07
12	Other non-food [6]	288.97	324.57
	Shares to total expenditure		
13	Savings	0.0382	0.2509
14	Food expenditure	0.6616	0.1079
15	Carbohydrate foods	0.3190	0.1134
16	Protein foods	0.1850	0.0773
17	Fruits and vegetables	0.0508	0.0370
18	Other food	0.1069	0.0565
19	Alcohol and tobacco	0.0244	0.0294
20	Medicine	0.0154	0.0438
21	Education	0.0270	0.0394
22	Clothing	0.0185	0.0192
23	Other non-food	0.1818	0.0826

Notes:

1 - Savings = Total income - total expenditures

2 - Carbohydrates = Cereals + roots

3 - Protein = Meat + dairy + fish

4 - Alcohol + Tobacco expenditure / members 19 y/o and up

5 - Education expenditure / No. of schooling HH members

6 - Other non-food = Fuel + transportation and comm. + household operations + personal care + recreation + nondurables + durables + taxes + repairs + special occasions + gifts to others + other expenditures

Source of basic data: APIS 2011, National Statistics Office

Table 3. Propensity Score Model estimates
Dependent variable = 1 if Pantawid Pamilya participant

Variables	dy/dx[1]	SE	
HH composition			
Household size	0.0014	0.0016	
No. of HH members 0-2 years old	-0.0050	0.0035	
No. of HH members 3-5 years old	0.0198	0.0031	***
No. of HH members 6-12 years old	0.0199	0.0021	***
No. of HH members 13-18 years old	0.0150	0.0023	***
HH head and spouse characteristics			
=1 if HH head is married	0.0157	0.0083	*
=1 if HH head is male	-0.0018	0.0079	
=1 if HH head is working	0.0153	0.0077	**
=1 if HH head had some elementary	0.0223	0.0061	***
=1 if HH head is elementary grad	0.0232	0.0062	***
=1 if HH head has some high school	0.0145	0.0067	**
=1 if HH head is high school grad	0.0108	0.0065	*
=1 if spouse had some elementary	0.0246	0.0064	***
=1 if spouse is elementary grad	0.0254	0.0063	***
=1 if spouse has some high school	0.0127	0.0065	*
=1 if spouse is high school grad	0.0021	0.0065	
Dwelling characteristics			
=1 if dwelling roof made of light materials	0.0170	0.0044	***
=1 if dwelling walls made of light materials	0.0185	0.0043	***
Floor area of the house (square meters)	-0.0001	0.0001	*
=1 if HH has electricity	-0.0025	0.0048	
Dummies for n-1 categories of toilet			
Shared toilet	0.0041	0.0052	
Closed pit	-0.0034	0.0062	
Open pit	0.0062	0.0082	
Drop/overhang	-0.0066	0.0173	
Pail system	0.0558	0.0191	***
No toilet/field/bush	-0.0004	0.0058	
Dummies for n-1 categories of water source			
Own dwelling, community water system	-0.0138	0.0076	*
Yard/plot	-0.0202	0.0086	**
Public tap	0.0201	0.0071	***
Protected well	0.0004	0.0066	
Unprotected well	0.0096	0.0077	
Undeveloped spring	0.0053	0.0090	
Rivers/stream/pond/lake/dam	-0.0315	0.0150	**
Rainwater	-0.0623	0.0226	***
Tanker/truck/peddler/neighbor	-0.0299	0.0105	***

Table 3. Propensity Score Model estimates
Dependent variable = 1 if Pantawid Pamilya participant

Variables	dy/dx[1]	SE	
Dummies for n-1 categories of tenure			
Own house and lot / owner-like possession	0.0372	0.0407	
rent house/room including lot	-0.0195	0.0432	
Own house, rent lot	0.0737	0.0414	*
Own house, rent-free lot w/ consent of owner	0.0532	0.0408	
Own house, rent-free lot w/o consent of owner	0.0632	0.0413	
Rent-free house and lot w/ consent of owner	0.0320	0.0411	
HH assets			
=1 if HH has at least 1 TV	-0.0176	0.0048	***
=1 if HH has at least 1 DVD player	-0.0036	0.0047	
=1 if HH has at least 1 refrigerator	-0.0445	0.0068	***
=1 if HH has at least 1 washing machine	-0.0337	0.0083	***
=1 if HH has at least 1 oven	-0.0416	0.0110	***
=1 if HH has at least 1 landline/cellphone	-0.0056	0.0038	
=1 if HH has at least 1 stereo/audio player	-0.0147	0.0095	
=1 if HH has at least 1 motorcycle	-0.0028	0.0054	
Other HH characteristics			
=1 if HH has OFW member	-0.0270	0.0101	***
=1 if HH do not have wage income	0.0104	0.0045	**
=1 if HH head is self-employed	0.0221	0.0044	***
=1 if location is classified as rural	0.0323	0.0045	***
=1 if HH has agri land for agri purpose	0.0240	0.0039	***
=1 if HH belongs to income deciles 1-4	0.0336	0.0055	***
=1 if HH is in Set 1 or Set 2 province	0.0513	0.0047	***
Sample size	28,272		
Pseudo-R2	0.2948		

Notes:
*Significant at 10%, **Significant at 5%, ***Significant at 1%
[1] dy/dx is the average marginal effect. For instance, given all possible values of household size and averaging over all observed values of the rest of the covariates, adding one more unit of household size has an effect of increasing the probability of CCT participation by 0.0014.

Source of basic data: APIS 2011, National Statistics Office.

Table 4. After-matching covariate balance results by matching technique (Among total eligible sample)

	Variables in Propensity Score Model	*Nearest neighbor N=1, common, ties*				*Nearest neighbor N=2, cal(0.01) common, ties*				*Radius cal(0.001) common, ties*				*Kernel biweight, bw=0.01 common*			
		Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	fsize1	6.14	6.21	-3.6	0.19	6.14	6.20	-2.9	0.29	6.15	6.20	-2.3	0.40	6.15	6.20	-2.3	0.40
2	kids02yo	0.38	0.38	-0.1	0.98	0.38	0.39	-0.2	0.95	0.38	0.38	1.1	0.66	0.38	0.38	1.1	0.66
3	kids35yo	0.53	0.51	2.4	0.38	0.53	0.53	-0.5	0.86	0.53	0.53	1.1	0.67	0.53	0.53	1.1	0.67
4	kids612yo	1.58	1.64	-5.9	0.04	1.58	1.62	-3.9	0.16	1.59	1.65	-6.1	0.03	1.59	1.65	-6.1	0.03
5	kids1318yo	1.07	1.10	-3.5	0.20	1.07	1.08	-1.1	0.69	1.07	1.06	1.1	0.67	1.07	1.06	1.1	0.67
6	ofw	0.02	0.01	1.2	0.29	0.02	0.01	1.2	0.32	0.02	0.01	1.1	0.36	0.02	0.01	1.1	0.36
7	nonwage	0.42	0.41	0.9	0.74	0.42	0.41	1.0	0.70	0.42	0.42	-0.2	0.94	0.42	0.42	-0.2	0.94
8	semployed	0.54	0.53	0.3	0.90	0.54	0.53	1.4	0.60	0.54	0.53	0.7	0.80	0.54	0.53	0.7	0.80
9	head_married	0.91	0.91	-1.0	0.66	0.91	0.90	0.1	0.95	0.91	0.91	0.1	0.97	0.91	0.91	0.1	0.97
10	hhead_work	0.95	0.95	-0.3	0.86	0.95	0.95	0.5	0.79	0.95	0.95	0.8	0.68	0.95	0.95	0.8	0.68
11	head_male	0.91	0.91	-1.3	0.56	0.91	0.91	0.8	0.72	0.91	0.91	0.1	0.97	0.91	0.91	0.1	0.97
12	hhead_selem	0.37	0.37	-0.5	0.87	0.37	0.37	0.2	0.96	0.37	0.38	-1.3	0.65	0.37	0.38	-1.3	0.65
13	hhead_elemgrad	0.25	0.26	-1.0	0.73	0.25	0.26	-2.0	0.47	0.26	0.26	-1.0	0.70	0.26	0.26	-1.0	0.70
14	hhead_shs	0.14	0.13	2.3	0.37	0.14	0.13	1.5	0.57	0.14	0.13	1.8	0.48	0.14	0.13	1.8	0.48
15	hhead_hsgrad	0.13	0.13	0.6	0.79	0.13	0.13	1.5	0.49	0.13	0.13	-0.3	0.88	0.13	0.13	-0.3	0.88
16	spouse_selem	0.24	0.23	2.9	0.32	0.24	0.25	-1.3	0.67	0.24	0.25	-2.0	0.50	0.24	0.25	-2.0	0.50
17	spouse_elemgrad	0.25	0.25	-1.5	0.60	0.25	0.25	0.4	0.89	0.25	0.26	-1.8	0.52	0.25	0.26	-1.8	0.52
18	spouse_shs	0.15	0.15	1.9	0.47	0.15	0.14	4.3	0.11	0.15	0.15	-0.3	0.92	0.15	0.15	-0.3	0.92
19	spouse_hsgrad	0.14	0.14	0.2	0.94	0.14	0.14	-0.3	0.88	0.14	0.14	0.7	0.77	0.14	0.14	0.7	0.77
20	lroof	0.39	0.39	-0.9	0.75	0.39	0.39	-0.1	0.98	0.39	0.40	-3.9	0.19	0.39	0.40	-3.9	0.19
21	lwalls	0.38	0.40	-4.0	0.17	0.38	0.39	-1.6	0.58	0.38	0.40	-3.8	0.19	0.38	0.40	-3.8	0.19
22	floor	34.07	33.08	2.6	0.14	34.07	33.57	1.3	0.46	34.07	33.75	0.9	0.63	34.07	33.75	0.9	0.63
23	electr	0.63	0.62	4.5	0.13	0.63	0.62	2.3	0.44	0.63	0.63	0.9	0.77	0.63	0.63	0.9	0.77
24	toilet2	0.14	0.15	-3.0	0.25	0.14	0.14	-0.9	0.74	0.13	0.14	-2.8	0.29	0.13	0.14	-2.8	0.29
25	toilet3	0.11	0.11	1.8	0.56	0.11	0.11	1.1	0.73	0.11	0.11	-1.6	0.60	0.11	0.11	-1.6	0.60

Table 4. After-matching covariate balance results by matching technique (Among total eligible sample)

	Variables in Propensity Score Model	*Nearest neighbor N=1, common, ties*				*Nearest neighbor N=2, cal(0.01) common, ties*				*Radius cal(0.001) common, ties*				*Kernel biweight, bw=0.01 common*			
		Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
26	toilet4	0.06	0.07	-6.8	0.04	0.06	0.07	-6.2	0.06	0.06	0.07	-4.9	0.13	0.06	0.07	-4.9	0.13
27	toilet5	0.01	0.01	-0.4	0.90	0.01	0.01	1.1	0.70	0.01	0.01	-3.7	0.24	0.01	0.01	-3.7	0.24
28	toilet6	0.01	0.01	6.1	0.03	0.01	0.01	3.0	0.31	0.01	0.01	5.7	0.06	0.01	0.01	5.7	0.06
29	toilet7	0.15	0.15	-0.2	0.94	0.15	0.15	0.7	0.83	0.15	0.15	-0.6	0.86	0.15	0.15	-0.6	0.86
30	water1	0.13	0.12	1.6	0.44	0.13	0.12	1.5	0.46	0.13	0.12	0.9	0.65	0.13	0.12	0.9	0.65
31	water2	0.06	0.06	0.8	0.75	0.06	0.06	-0.2	0.94	0.06	0.06	-0.1	0.96	0.06	0.06	-0.1	0.96
32	water3	0.18	0.18	2.2	0.46	0.18	0.18	1.3	0.67	0.18	0.17	3.2	0.29	0.18	0.17	3.2	0.29
33	water4	0.29	0.29	0.1	0.98	0.29	0.29	0.9	0.73	0.29	0.28	1.9	0.46	0.29	0.28	1.9	0.46
34	water5	0.12	0.12	1.2	0.69	0.12	0.12	0.5	0.87	0.12	0.11	1.9	0.53	0.12	0.11	1.9	0.53
35	water7	0.07	0.08	-5.8	0.07	0.07	0.08	-5.0	0.12	0.07	0.08	-5.2	0.11	0.07	0.08	-5.2	0.11
36	water8	0.02	0.02	-4.7	0.14	0.02	0.02	-4.1	0.19	0.02	0.02	-1.5	0.63	0.02	0.02	-1.5	0.63
37	water9	0.00	0.00	1.4	0.53	0.00	0.00	0.5	0.84	0.00	0.00	0.0	1.00	0.00	0.00	0.0	1.00
38	water10	0.03	0.03	-0.5	0.83	0.03	0.03	0.7	0.77	0.03	0.04	-2.0	0.44	0.03	0.04	-2.0	0.44
39	tenure1	0.57	0.57	0.3	0.90	0.57	0.57	-0.6	0.81	0.57	0.57	-0.3	0.92	0.57	0.57	-0.3	0.92
40	tenure2	0.01	0.01	-0.2	0.89	0.01	0.01	-0.1	0.95	0.01	0.01	-1.0	0.44	0.01	0.01	-1.0	0.44
41	tenure3	0.04	0.04	1.8	0.53	0.04	0.04	1.6	0.57	0.04	0.04	0.4	0.90	0.04	0.04	0.4	0.90
42	tenure4	0.26	0.27	-2.1	0.47	0.26	0.26	-0.6	0.83	0.26	0.27	-1.7	0.54	0.26	0.27	-1.7	0.54
43	tenure5	0.05	0.05	1.9	0.48	0.05	0.05	-0.5	0.86	0.05	0.04	3.8	0.15	0.05	0.04	3.8	0.15
44	tenure6	0.07	0.07	-0.6	0.80	0.07	0.06	1.3	0.60	0.06	0.06	0.5	0.84	0.06	0.06	0.5	0.84
45	tv	0.39	0.39	-0.1	0.96	0.39	0.39	0.3	0.93	0.39	0.38	0.8	0.77	0.39	0.38	0.8	0.77
46	dvd	0.23	0.23	0.6	0.78	0.23	0.23	0.4	0.88	0.23	0.22	1.3	0.56	0.23	0.22	1.3	0.56
47	ref	0.07	0.06	2.8	0.08	0.07	0.06	1.5	0.35	0.07	0.06	1.5	0.35	0.07	0.06	1.5	0.35
48	wash	0.04	0.03	2.2	0.09	0.04	0.03	2.6	0.04	0.04	0.03	0.9	0.49	0.04	0.03	0.9	0.49
49	oven	0.02	0.01	1.9	0.07	0.02	0.02	1.2	0.28	0.02	0.02	0.8	0.44	0.02	0.02	0.8	0.44
50	phone	0.50	0.49	1.6	0.57	0.50	0.49	3.5	0.21	0.50	0.49	3.2	0.25	0.50	0.49	3.2	0.25

Table 4. After-matching covariate balance results by matching technique (Among total eligible sample)

	Variables in Propensity Score Model	*Nearest neighbor N=1, common, ties*				*Nearest neighbor N=2, cal(0.01) common, ties*				*Radius cal(0.001) common, ties*				*Kernel biweight, bw=0.01 common*			
		Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t	Mean (4Ps=1)	Mean (4Ps=0)	SB (%)	p>t
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
51	stereo	0.02	0.02	1.9	0.16	0.02	0.02	1.4	0.30	0.02	0.02	0.7	0.61	0.02	0.02	0.7	0.61
52	motor	0.10	0.10	1.5	0.47	0.10	0.10	0.6	0.77	0.11	0.10	1.5	0.47	0.11	0.10	1.5	0.47
53	rural	0.83	0.84	-3.0	0.17	0.83	0.84	-2.2	0.31	0.83	0.83	-0.4	0.87	0.83	0.83	-0.4	0.87
54	agri	0.34	0.34	0.0	1.00	0.34	0.33	0.8	0.78	0.34	0.33	0.8	0.77	0.34	0.33	0.8	0.77
55	bottom40	0.89	0.90	-2.7	0.16	0.89	0.90	-2.9	0.13	0.89	0.90	-1.5	0.43	0.89	0.90	-1.5	0.43
56	set12	0.84	0.84	0.7	0.75	0.84	0.84	-0.1	0.97	0.84	0.83	2.8	0.21	0.84	0.83	2.8	0.21
57	r1	0.01	0.01	0.2	0.91	0.01	0.01	0.2	0.91	0.01	0.01	1.1	0.46	0.01	0.01	1.1	0.46
58	r2	0.01	0.01	1.5	0.37	0.01	0.01	1.0	0.55	0.01	0.01	1.3	0.44	0.01	0.01	1.3	0.44
59	r3	0.02	0.03	-0.8	0.62	0.02	0.03	-0.8	0.62	0.02	0.03	-2.0	0.23	0.02	0.03	-2.0	0.23
60	r4a	0.11	0.10	2.7	0.39	0.11	0.10	5.7	0.06	0.11	0.10	3.9	0.20	0.11	0.10	3.9	0.20
61	r5	0.13	0.12	3.1	0.30	0.13	0.12	1.7	0.58	0.13	0.12	2.2	0.47	0.13	0.12	2.2	0.47
62	r6	0.04	0.04	-2.2	0.33	0.04	0.04	-0.6	0.79	0.04	0.04	-1.2	0.60	0.04	0.04	-1.2	0.60
63	r7	0.06	0.06	-1.9	0.45	0.06	0.06	-3.7	0.15	0.06	0.05	2.9	0.23	0.06	0.05	2.9	0.23
64	r8	0.07	0.08	-1.8	0.53	0.07	0.07	-0.7	0.81	0.07	0.07	-0.3	0.92	0.07	0.07	-0.3	0.92
65	r9	0.14	0.13	4.4	0.16	0.14	0.13	3.1	0.33	0.14	0.14	-0.7	0.83	0.14	0.14	-0.7	0.83
66	r10	0.07	0.07	0.7	0.80	0.07	0.07	0.1	0.96	0.07	0.07	1.1	0.68	0.07	0.07	1.1	0.68
67	r11	0.05	0.06	-1.7	0.50	0.05	0.05	-0.8	0.76	0.05	0.06	-1.1	0.65	0.05	0.06	-1.1	0.65
68	r12	0.05	0.06	-3.2	0.21	0.05	0.05	-2.0	0.44	0.05	0.06	-3.5	0.18	0.05	0.06	-3.5	0.18
69	r13	0.02	0.02	-0.1	0.92	0.02	0.02	0.8	0.56	0.02	0.02	0.5	0.70	0.02	0.02	0.5	0.70
70	r14	0.03	0.03	-1.4	0.55	0.03	0.03	-1.9	0.44	0.03	0.03	0.9	0.70	0.03	0.03	0.9	0.70
71	r15	0.06	0.07	-4.5	0.11	0.06	0.07	-4.4	0.11	0.06	0.07	-3.4	0.22	0.06	0.07	-3.4	0.22
72	r16	0.11	0.11	2.0	0.51	0.11	0.11	-0.8	0.81	0.11	0.11	-0.4	0.90	0.11	0.11	-0.4	0.90

Source of basic data: APIS 2011, National Statistics Office

Table 5. Estimated Impact of *Pantawid Pamilya* on Consumption by Matching Technique

Outcome variables	*Among total eligible sample*							
	Nearest neighbor N=1, common ties		*Nearest neighbor* N=2, cal(0.01)		*Radius* cal(0.001)		*Kernel* biweight, bw=0.01	
	ATT	S.E.	ATT	S.E.	ATT	SE	ATT	SE
1	2	3	4	5	6	7	8	9
Per capita per month expenditure								
1 Total expenditure	26.50	30.70	13.45	25.73	-0.90	30.59	-8.25	31.32
2 Savings	7.48	21.39	7.04	17.58	15.22	30.22	9.01	27.01
3 Food expenditure	23.65	13.87 *	20.50	12.12 *	14.72	13.69	10.78	12.27
4 Carbohydrate foods	29.08	5.80 ***	25.00	5.03 ***	25.83	6.30 ***	24.81	5.88 ***
5 Protein foods	-5.26	7.10	-3.00	6.24	-6.72	8.28	-7.87	7.60
6 Fruits and vegetables	2.34	2.12	1.78	1.86	1.45	2.26	0.56	2.31
7 Other food	-2.51	4.54	-3.27	4.07	-5.85	5.75	-6.73	5.02
8 Alcohol and tobacco	-0.59	3.89	2.99	3.44	-4.11	4.73	-2.50	5.42
9 Medicine	1.23	6.39	1.65	4.95	-0.20	6.12	0.24	8.52
10 Education	6.67	14.40	2.85	11.92	5.92	13.97	6.69	14.96
11 Clothing	8.55	1.35 ***	8.75	1.22 ***	7.65	1.36 ***	7.51	1.38 ***
12 Other non-food	-0.16	12.29	-11.46	9.66	-12.18	10.37	-13.53	11.87
Shares to total expenditure								
13 Savings	0.0096	0.0077	0.0127	0.0068 *	0.0143	0.0096	0.0109	0.0095
14 Food expenditure	-0.0014	0.0031	-0.0013	0.0027	0.0003	0.0032	-0.0007	0.0036
15 Carbohydrate foods	0.0039	0.0032	0.0038	0.0029	0.0066	0.0037 *	0.0061	0.0035 *
16 Protein foods	-0.0029	0.0024	-0.0024	0.0022	-0.0035	0.0029	-0.0034	0.0031
17 Fruits and vegetables	-0.0003	0.0012	-0.0005	0.0010	-0.0002	0.0013	-0.0006	0.0014
18 Other food	-0.0021	0.0017	-0.0023	0.0014	-0.0026	0.0019	-0.0027	0.0018
19 Alcohol and tobacco	-0.0002	0.0009	0.0004	0.0008	-0.0009	0.0009	-0.0009	0.0011
20 Medicine	0.0000	0.0013	0.0004	0.0011	0.0007	0.0014	0.0010	0.0014
21 Education	0.0023	0.0012 *	0.0029	0.0010 ***	0.0036	0.0014 ***	0.0036	0.0014 ***
22 Clothing	0.0046	0.0005 ***	0.0048	0.0005 ***	0.0044	0.0006 ***	0.0044	0.0006 ***
23 Other non-food	0.0022	0.0024	0.0004	0.0021	-0.0006	0.0024	-0.0004	0.0027

Notes:
*Significant at 10%, **Significant at 5%, ***Significant at 1%
Estimates are in 2009 Metro Manila pesos. Bias-adjusted robust standard errors using NNMATCH routine in Stata® for nearest neighbour matching and bootstrapped ones (N=100 replications) for radius and kernel matching are reported.

Source of basic data: APIS 2011, National Statistics Office

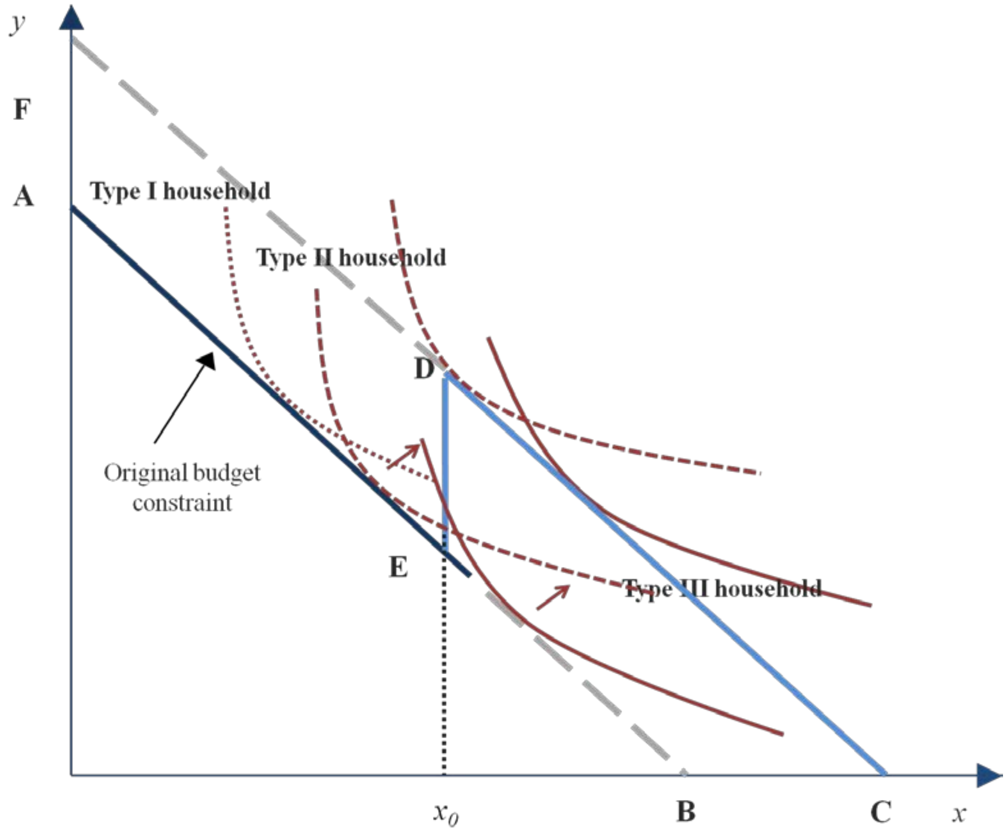
Table 6. Estimated Impact of *Pantawid Pamilya* on Consumption by Matching Technique

Outcome variables	*Among bottom 20% of income distribution*							
	Nearest neighbor N=1, common ties		*Nearest neighbor* N=2, cal(0.01)		*Radius* cal(0.001)		*Kernel* biweight, bw=0.01	
	ATT	S.E.	ATT	S.E.	ATT	SE	ATT	SE
1	2	3	4	5	6	7	8	9
Per capita per month expenditure								
1 Total expenditure	76.03	16.57 ***	65.52	14.49 ***	45.06	19.36 ***	42.60	20.78 **
2 Savings	4.35	11.84	5.70	10.48	19.06	12.50	19.14	13.19
3 Food expenditure	49.18	11.13 ***	43.02	9.82 ***	29.15	12.67 **	28.03	12.79 **
4 Carbohydrate foods	30.96	6.30 ***	27.54	5.65 ***	26.71	6.92 ***	25.82	8.33 ***
5 Protein foods	10.80	5.49 **	9.88	4.85 **	1.56	6.94	1.21	6.07
6 Fruits and vegetables	4.89	2.07 ***	3.06	1.83 *	1.84	2.33	1.53	2.39
7 Other food	2.52	3.10	2.54	2.76	-0.96	3.47	-0.52	3.34
8 Alcohol and tobacco	1.97	4.25	3.67	3.84	-0.80	5.12	-0.58	5.39
9 Medicine	0.88	2.52	1.78	2.19	2.53	3.01	1.63	2.91
10 Education	4.01	6.40	4.46	5.36	3.25	7.66	5.24	7.31
11 Clothing	7.79	0.92 ***	7.35	0.82 ***	6.90	1.10 ***	7.27	0.96 ***
12 Other non-food	13.33	4.11 ***	10.07	3.54 ***	3.10	4.52	4.17	5.35
Shares to total expenditure								
13 Savings	0.0110	0.0080	0.0088	0.0072	0.0157	0.0093 *	0.0157	0.0093 *
14 Food expenditure	-0.0022	0.0037	-0.0024	0.0032	-0.0019	0.0040	-0.0019	0.0049
15 Carbohydrate foods	0.0028	0.0042	0.0023	0.0038	0.0058	0.0051	0.0058	0.0049
16 Protein foods	-0.0016	0.0030	-0.0013	0.0027	-0.0033	0.0040	-0.0035	0.0037
17 Fruits and vegetables	0.0000	0.0016	-0.0010	0.0014	-0.0013	0.0019	-0.0015	0.0017
18 Other food	-0.0033	0.0019 *	-0.0024	0.0017	-0.0031	0.0019	-0.0027	0.0022
19 Alcohol and tobacco	-0.0004	0.0011	-0.0001	0.0010	-0.0005	0.0014	-0.0008	0.0015
20 Medicine	-0.0002	0.0013	0.0010	0.0012	0.0014	0.0015	0.0009	0.0015
21 Education	0.0030	0.0012 ***	0.0030	0.0011 ***	0.0037	0.0014 ***	0.0036	0.0015 ***
22 Clothing	0.0051	0.0007 ***	0.0048	0.0006 ***	0.0048	0.0007 ***	0.0050	0.0008 ***
23 Other non-food	0.0029	0.0028	0.0015	0.0023	0.0002	0.0026	0.0007	0.0026

Notes:
*Significant at 10%, **Significant at 5%, ***Significant at 1%
Estimates are in 2009 Metro Manila pesos. Bias-adjusted robust standard errors using NNMATCH routine in Stata® for nearest neighbour matching and bootstrapped ones (N=100 replications) for radius and kernel matching are reported.

Source of basic data: APIS 2011, National Statistics Office

Figure 1. Impact of CCT on Consumption



Source: Das, Do, and Ozler [2005]

Figure 2. Propensity score distribution of unmatched sample

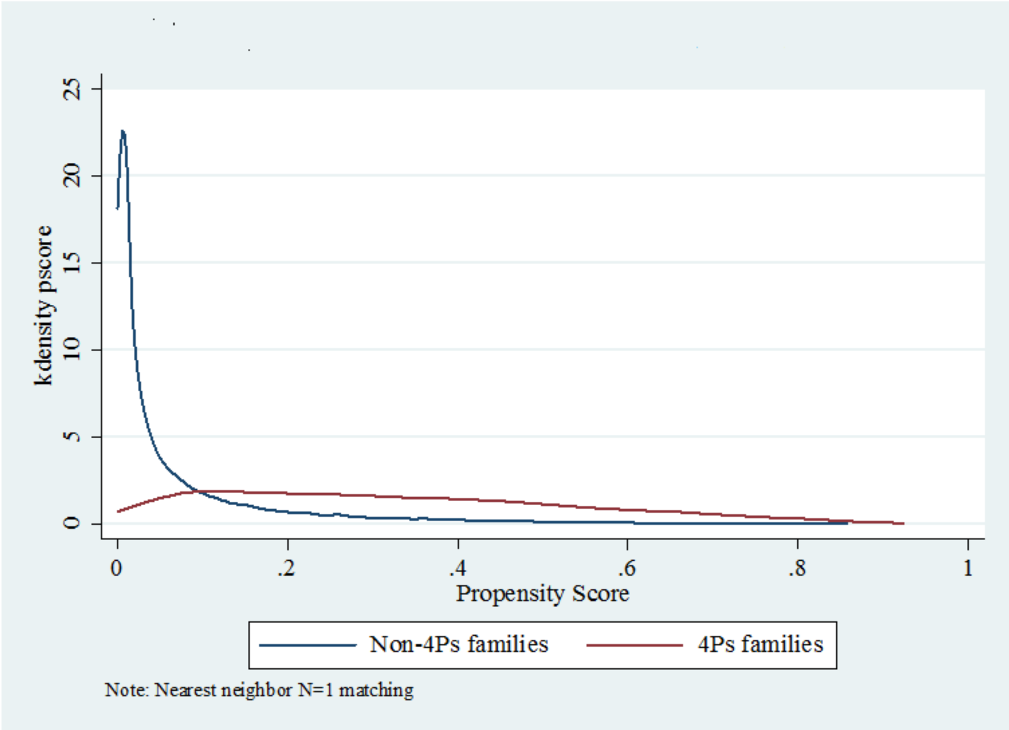


Figure 3. Covariate distribution before and after matching

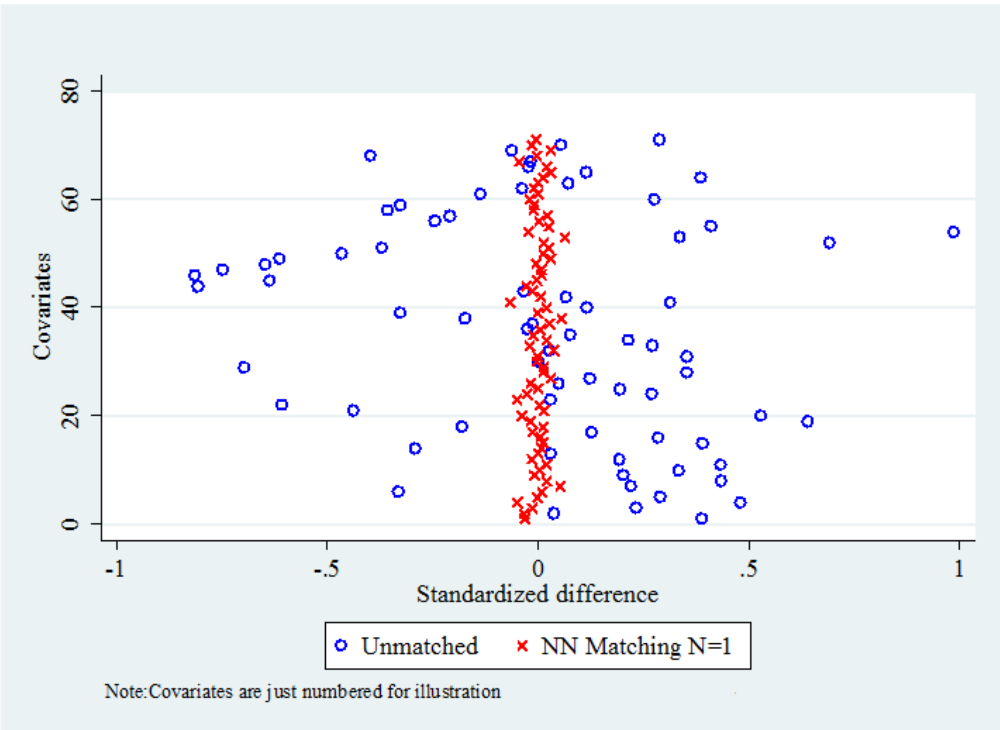


Figure 4. Pr(x) distribution by matching technique (among total eligible sample)