

Received: 7 April 2016

Received in revised form: 5 September 2016

Accepted: 25 October 2016

The Impact of Conditional Cash Transfer on Savings and Other Associated Variables: Evidence from the Philippines' 4Ps Program

Tristan Canare

*Department of Economics, Ateneo de Manila University,
Quezon, Philippines*

Corresponding author: tristan.canare@gmail.com

Abstract

The Philippines is one of the first Asian countries to implement a conditional cash transfer program (CCT). This study aims to find out if the Philippines CCT has an impact on the saving behavior of beneficiaries. Applying the Propensity Score Matching (PSM) methodology to the 2011 Annual Poverty Indicators Survey, results show evidence that CCT has no statistically significant effect on actual savings but has moderate positive impact on savings rate. CCT also has moderate positive impact on the probability of paying off outstanding loans, on the probability of granting loans to others, and on the probability of maintaining a bank deposit.

Keywords: Conditional Cash Transfer, Savings, Propensity Score Matching

1. Introduction

Like most other Conditional Cash Transfer (CCT) programs in the world, the main short-term objectives of the Philippines' *Pamilyang Pantawid Pilipino Program* (4Ps)¹ are to improve utilization of health care for young children and pregnant women, and to increase school enrolment and attendance rates for children. Because it aims to address poverty not just by providing grants, but also by addressing its root causes – lack of education and poor health – the 4Ps has become the cornerstone anti-poverty program of the current government. There are two components of the grant to beneficiary households. The education grant amounts to 300 Philippine Pesos (PhP) per month per child 14 years old and below² for a maximum of three children for 10 months per year, while the health grant is PhP500 per month per household. Thus, beneficiary households can receive a maximum of PhP15,000 per year. The conditions for receiving the full amount of grant include regular visits to a health center for pregnant women and children less than five years old, and meeting a pre-determined school attendance rate (see Fernandez and Olfindo 2011 for an overview of the Philippines CCT program).

The Philippines CCT is one of the most generous such programs in the world. The maximum amount received by beneficiary households is PhP1,400 per month, which is about 23 percent of beneficiaries' income. Earlier CCT programs range from five percent for Brazil to 29 percent for Nicaragua (Chaudhury et al., 2013). As such, one of the frequently asked questions on CCT is how did the beneficiaries use the cash grant. While the main purpose of the grant is to cover direct expenses associated with availment of health services and sending children to school, including the foregone income of the children who used to work, one of 4Ps' explicit objectives is to increase food consumption (Department of Social Welfare and Development, 2012). Initial short-term impact evaluation showed that the 4Ps is meeting its objectives

¹ Loosely translated to English as “Financial assistance for the Filipino family”.

² This was later revised to include high school-aged children.

of making children healthier and increasing enrolment rates; and beneficiary households are spending more on education and health care (Chaudhury et al., 2013). However, there is hardly any effect on aggregate per capita consumption (Chaudhury et al., 2013; Tutor, 2014).

Elsewhere, Hoddinott and Skoufias (2004) found evidence that beneficiaries of the Mexican CCT have higher consumption of calories, while Attanasio and Mesnard (2006) concluded that CCT beneficiaries in Colombia increased their total consumption. Soares et al. (2008) found evidence of a higher per capita consumption among CCT recipients in Paraguay, while De Oliveira et al. (2007) concluded that the Brazilian CCT has a positive impact on expenditures on food and education, but not on aggregate spending. Interestingly, very few of these studies tested for the effect of CCT on savings. Only the Soares et al paper on Paraguayan CCT tested for an d found a positive effect on savings. In the Philippines, Chaudhury et al. (2013) found no impact on presence and amount of savings, but some impact on ownership of some livestock; while Tutor (2014) found some impact on savings as share of expenditure.

This study aims to find out if the Philippines CCT has an impact on the saving behavior of beneficiaries. The outcome variable in this paper is not just limited to savings, which is the difference between income and expenditures, but also on other related variables such as savings rate, amount of bank deposits, incidence and amount of loans, and asset ownership. In what follows, the next section provides a brief description of the Philippines CCT, followed by the methodology used. Results are then presented and discussed before a brief conclusion and summary.

2. The Philippines CCT Program

The specific objectives of the 4Ps program are: to improve health care among pregnant women and young children, to increase enrolment and attendance rates of children in school, to reduce child labor, and to increase food consumption (Department of Social Welfare and Development, 2012). Identification of beneficiaries involves two stages: first is selecting

geographical areas, and second is selecting beneficiaries within these areas. Program areas are identified through poverty incidence, while households are selected based on a Proxy Means Test (PMT). This calculates the households' predicted income based on such variables as characteristics of the household head, asset ownership, housing conditions, housing tenure status, ages of the household members, and location. If the predicted income is below the provincial poverty threshold, the household is a qualified beneficiary.

The program started in 2008 and is being implemented in phases, or sets, with one set being implemented per year. Set 1 households are those in provinces/areas with the highest poverty incidence. Gradually, the program has been expanded to cover almost the entire Philippines. After Set 6 has been implemented in 2013, the program covers almost four million households from more than 41 thousand *barangays*³ in 79 provinces (Department of Social Welfare and Development, 2013).

3. Methodology and Data

The primary data source for this study is the 2011 Annual Poverty Indicators Survey (APIS) while the method applied in determining impact is Propensity Score Matching (PSM). For any impact evaluation problem, the basic challenge is to find an acceptable counterfactual. One of the earliest and widely-used frameworks in impact evaluation, the Rubin potential outcomes model (Rubin 1974), defines impact as the expected value of treatment effect on individual i , $E[T_i]$, where $E[T_i] = E[Y_i(1) - Y_i(0)]$. Here, $Y_i(1)$ and $Y_i(0)$ are the potential outcomes for individual i – $Y_i(1)$ is the outcome for individual i if treatment has been applied and $Y_i(0)$ is the counterfactual, or the outcome for the same individual i had the treatment not been applied. This gives rise to the fundamental problem of impact evaluation – for any individual i , one can observe only one state, either $Y_i(1)$ or $Y_i(0)$ but not both (Holland, 1986).

³ The barangay is the smallest political unit in the Philippines.

According to modern impact evaluation literature, if treatment is assigned randomly, $E[T_i]$ can be approximated by $E[Y_i(1) | Tr = 1] - E[Y_i(0) | Tr = 0]$, where Tr is treatment indicator; i.e. the counterfactual can be estimated by the outcome for the control group. Thus, randomized control trial is generally regarded as the most robust among impact evaluation techniques (Baker, 2000). However, randomization is often not possible due to cost, ethical, logistical, and political considerations. Hence, quasi-experimental methods have been developed in estimating a valid counterfactual.

In this study, treatment assignment in the survey data used is not random because CCT is targeted to the poor in the poorest provinces. Thus, there is a selection problem as only poor households are eligible for the treatment. Hence, we need a quasi-experimental method to construct a valid counterfactual.

3.1 Propensity Score Matching

One of these methods is Propensity Score Matching (PSM). The general idea is to compare outcomes between similar – or matched – observations in the treatment and control groups. Because it is very difficult, or even impossible, to look for observations across treatment and control groups with the same characteristics, Rosenbaum and Rubin (1983) proposed that matching be done on the propensity score, $Pr(X)$, or the probability of being in the treatment group conditional on observable characteristics, X . Two conditions should be established for PSM to produce valid impact estimates (Heckman, Ichimura, and Todd, 1998; Imbens and Wooldridge, 2009). First is the conditional independence assumption (CIA), which states that conditional on X , potential outcomes are independent of treatment assignment; that is, $(Y_i^{Tr=1}, Y_i^{Tr=0}) \perp Tr_i | X_i$. CIA also implies that treatment assignment is determined only by observable characteristics. The assumption on conditional independence cannot be statistically tested, and whether it holds can be justified by data quality and knowledge of how the program was administered (Caliendo and Koepinig, 2008). The second is the assumption of common support. Common support exists if there is an

overlap of propensity score for a sufficient number of observations in the control and treatment groups. Formally, common support exists when $0 < \Pr(Tr_i = 1 | X_i) < 1$. Common support assures that there are observations in the control group that can be matched with observations in the treatment group (Heckman, LaLonde, and Smith, 1999). Rosenbaum and Rubin (1983) also showed that if potential outcomes are independent of treatment assignment conditional on X , then potential outcomes are independent of treatment assignment conditional on $Pr(X)$ when these two assumptions are satisfied.

Satisfying the two assumptions allows for the estimation of the Average Treatment Effect (ATE). However, in practice, when using PSM, only the Average Treatment Effect on the Treated (ATT) is identified because it is limited to matching observations within the range of common support. ATT can also accommodate weaker versions of the two assumptions discussed above. The CIA can be simplified to $Y_i^{Tr=0} \perp Tr_i | X_i$, while the common support can be simplified to $\Pr(Tr_i = 1 | X_i) < 1$ (Khandker et al., 2010). Following Heckman, Ichimura, and Todd (1997), Smith and Todd (2005), and Khandker et al. (2010), ATT is calculated as follows among matched observations within the common support:

$$ATT = \frac{1}{N^{Tr=1}} \left[\sum_{i \in Tr=1} Y_i^{Tr=1} - \sum_{j \in Tr=0} w(i, j) Y_i^{Tr=0} \right] \quad (1)$$

where $N^{Tr=1}$ is the number of treatment observations within the common support and $w(i, j)$ is the weight of each matched control observation.

3.2 Matching Techniques

There are different techniques used in matching treatment and control variables, all with different advantages and disadvantages, usually trade-off between bias and variance. The most common is nearest-neighbor (NN) matching, where treatment observations are matched to the control observation with the closest propensity score. This may be done either one-to-one, or one treatment to n-controls; and either with or without replacement. Matching one treatment unit to n-control observations reduces the variance

but increases potential bias. Meanwhile, matching with replacement decreases potential bias but increases the variance. A disadvantage of the NN matching is that the nearest neighbor may still be “too far”. One solution to this is to restrict the allowed “distance”, or impose a calliper, between matched units. However, this may cause too few matched observations (Caliendo and Koepinig, 2008; Khandker et al., 2010).

This drawback is addressed by calliper or radius matching. Here, a threshold propensity score distance from the treatment observation is imposed. All control observations inside this “radius” is then compared to the treatment unit. A weakness of this, however, is that there could be a high number of dropped control observations, increasing the probability of bias (Khandker et al., 2010).

Most studies using PSM report more than one matching method to test the sensitivity of their results. Nevertheless, as pointed out by Smith (2000), all methods should give the same result asymptotically. The choice becomes more important with smaller sample size because of the bias-variance trade-off. This study, however, uses large number of observations.

3.3 Estimating the Propensity Score

The variables used in estimating the propensity score are essential for PSM to work well. This will determine if CIA holds and if a sufficient region of common support exists. As discussed earlier, CIA is not statistically testable and the researcher should rely on data quality and his/her knowledge of the program. Choosing these variables involve careful balancing between establishing CIA and region of common support. For CIA to hold, only variables that affect both the treatment assignment and outcomes should be included (Blundell and Costas Dias, 2008; Caliendo and Koepinig, 2008). If important variables were not included, that is, if unobserved characteristics determine treatment assignment, CIA will not hold and this leads to biased estimates (Heckman, Ichimura, and Todd, 1997; Khandker et al., 2010). However, only variables that are not affected by the treatment or the

anticipation of it should be included. To ensure this, Caliendo and Koepinig (2008) suggest including only variables that are fixed over time or those measured prior to treatment assignment. Moreover, Heckman, LaLonde, and Smith (1999) also encourage that data from treatment and control groups to come from the same source or questionnaire.

On the other hand, including too much variables can weaken the common support, as this may cause some observations to have a perfect probability of being treated. In this case, units that benefit the most or the least from the treatment may be excluded from the computation of impact (Blundell and Costas Dias, 2008). Moreover, If for some values of X , either $\Pr(X) = 1$ or $\Pr(X) = 0$, matching cannot be performed conditional on these values. There should be some randomness such that observations with similar characteristics are both in treatment and control (Heckman, Ichimura, and Todd, 1998; Caliendo and Koepinig, 2008).

Clearly, selecting variables for estimating the propensity score is a tricky exercise, and there are arguments against both including more and including less. Bryson, Dorsett, and Purdon (2002) points to two reasons why including too much variables is discouraged. First is that it may worsen the common support problem and second is that it can increase the variance of the estimates, although it will not cause them to be biased. Augurzky and Schmidt (2001) also discourage this because it causes higher variance for small samples. On the other hand, Rubin and Thomas (1996) argue that a variable should only be excluded if it absolutely does not affect treatment assignment and the outcome variable, and that researchers should err in the side of inclusion. Another point to consider in choosing covariates is balancing between treatment and control groups. As pointed out by Augurzky and Schmidt (2001), balancing the covariates is another important purpose of estimating the propensity score. Although there is no clear-cut method in the current literature on how to select the variables, a good guide is to choose based on economic theory, previous empirical findings, and knowledge of the program (Caliendo and Koepinig, 2008). Choosing between including

more and less variables may also be based on what “problems” one is trying to address. For instance, in this paper, small sample is not a problem, and so is common support. Balancing of covariates also played a role in including and excluding questionable variables.

In this paper, the basic covariates used in propensity score estimation are the variables used in the PMT in classifying households whether they are eligible or not for the program. Also included are location characteristics, specifically a rural dummy and poverty rate of the province where the household is located. A dummy for households belonging to the bottom four income deciles is also included. As discussed earlier, the 4Ps was implemented gradually, with the poorest provinces getting them first. Other covariates were added keeping in mind that these are determinants of being poor. These include household characteristics, household head characteristics, housing unit characteristics, and asset ownership. Appendix 1 shows the list of variables used in the PMT to classify households as poor or non-poor.

3.4 Outcome Variables

The main outcome of interest is savings; that is, we want to know if CCT affects the savings of CCT beneficiaries. Savings is represented in two ways – one is the difference between total household income and total household expenditures; the other is the difference between total household receipts and total household expenditures (total receipts is income plus non-income receipts). Both household and per capita savings are included as outcome variables. Another outcome variable is savings rate, or the ratio of savings to income. Likewise, household savings rate and per capita savings rate are included.

Variables associated with savings are also included as outcomes, particularly loans, bank deposits and asset ownership. One of these is a dummy variable for households that availed a loan within the last year, and another is a continuous variable for amount of loans availed. Dummy and continuous variables for outstanding loan payments and loans granted to

others were also included as outcomes. We want to test using these variables if CCT beneficiaries used part of their CCT receipts to pay off loans or grant loans to others; or if CCT reduced the need to take out loans. Also included is a constant-weight appliance asset index using household appliance ownership indicators that are available in the APIS⁴. Basically, this variable is the total number of appliance items that the household has. Dummy and continuous variable on bank deposits are also included. Table 1 shows the outcome variables used in this study and their descriptions. It also shows a summary statistics of these variables for 4Ps beneficiaries.

Table 1: Description and summary statistics of the outcome variables for CCT beneficiaries (in Philippine Pesos, except for dummy variables)

Outcome Variable	Description	Mean	SD	Min	Max
savings1	total household income – total household expenditures	1,761.88	14,616.05	-99,384.00	240,697.00
savings1_rate	savings1/total household income	-0.02	0.27	-4.09	0.67
savings2	total household receipts – total household expenditures	5,956.87	15,120.78	-41,818.00	240,697.00
savings2_rate	savings2/total household receipts	0.07	0.16	-0.84	0.71
pcsavings1	per capita savings1	324.01	2,771.36	-26,335.50	48,139.40
pcsavings1_rate	per capita savings1/per capita income	-0.02	0.27	-4.09	0.67
pcsavings2	per capita savings2	1,069.42	2,952.26	-6,969.66	51,250.00
pcsavings2_rate	per capita savings2/per capita receipts	0.07	0.16	-0.84	0.71
Loan	Peso amount of loans availed from other families in the subject year	2,517.18	8,036.54	0.00	189,000.00
payloan	Peso amount of cash loans paid in the subject year	1,215.71	5,543.25	0.00	151,000.00
grantloan	Peso amount of cash loans granted to other families in the subject year	170.48	1,856.59	0.00	50,000.00
bankdep	Amount deposited in banks and investments	246.73	2,403.22	0.00	50,000.00

⁴ These are television, DVD player, refrigerator, washing machine, stove, landline or cellular telephone, radio, and motorcycle.

Table 1: Description and summary statistics of the outcome variables for CCT beneficiaries (in Philippine Pesos, except for dummy variables) (cont.)

Outcome Variable	Description	Mean	SD	Min	Max
assetsum	Number of appliance assets the household owns	2.02	2.08	0	18
loandum	Dummy =1 if household availed a loan in the past year	0.33	0.47	0	1
payloandum	Dummy =1 if payloan >0	0.20	0.40	0	1
grantloandum	Dummy =1 if grantloan >0	0.03	0.17	0	1
bankdepdum	Dummy =1 if bankdepdum >0	0.04	0.19	0	1

3.5 Justifying the Use of APIS and PSM

As discussed earlier, assignment of treatment in the survey data used is non-random, so a quasi-experimental method should be applied. The primary source of data is the 2011 Annual Poverty Indicators Survey (APIS). There are several factors why the 2011 APIS is a suitable dataset to be used in tandem with the PSM method. For one, all variables in the PMT (except one⁵) are in the APIS. It also contains socio-economic variables and other variables on characteristics of the household, the household head, and the housing unit that may affect or predict being poor. Most of these variables do not change much over time, thus it is unlikely that they are affected by being a CCT beneficiary. This suggests that a good propensity score can be estimated because practically all determinants of being a CCT recipient are included – a requirement for CIA to hold and for the estimated impact to be valid.

Moreover, the data collection year is 2011, when the 4Ps was not yet fully implemented. This means that it is easy to find matches of treatment observations in areas where CCT was not yet implemented. Data on control and treatment observations also come from the same questionnaire. The APIS is also a large dataset, making the problem of common support less likely to occur. Being a large dataset also is good for the standard errors and makes it less likely that results will vary across the different matching techniques.

⁵ The PMT variable not in APIS is presence of household help.

4. Results and Discussions

4.1 Savings and Savings Rate

The results of the propensity score estimation is shown in Table 2 while the average treatment effects on the treated (ATT) are shown in Table 3. None of the savings variables – *savings1*, *savings2*, *pcsavings1*, and *pcsavings2* – are significant in any of the matching techniques used. This suggests that CCT has no impact on actual savings, or the difference between income and spending. However, all four savings rate variables – *savings1_rate*, *savings2_rate*, *pcsavings1_rate*, and *pcsavings2_rate* – are significant in all matching techniques. Savings rate is 1.8 to 2.2 percentage points higher for CCT beneficiaries than non-beneficiaries, depending on outcome variable and matching method. The ATT estimates and their standard errors are also very close to each other, indicating that the impact of CCT on savings rate is robust.

Because savings rate equals savings over income, the insignificant savings but significant savings rate variables could suggest that CCT decreased the income of beneficiaries. But this is not true in this case. This was confirmed by applying the same PSM method with various measures of income as outcome variables; and results showed that CCT has no significant effect on income. Similarly, because savings is income less expenditures, a positive impact on savings rate and no impact on savings could also mean that CCT decreases expenditures. However, this was also found to be not the case. By using the same methodology with expenditures as the outcome variable, results show that CCT has no significant impact on expenditures. In fact, it was even positive, as expected, but statistically insignificant. This is similar to the results of Tutor (2014) and Chaudhury et al. (2013), which found no significant impact of Philippines CCT on total household consumption.

A significant impact on savings rate but insignificant effect on actual savings, income, and expenditures may seem atypical at first. However, it just means that CCT households save a bigger part of their income compared

to non-CCT households. Note that although the effect of CCT on savings is statistically insignificant, they are generally positive. Note also that the effect of CCT on savings rate, although statistically significant, is small at 1.8% to 2.2%. Add the fact that income of CCT households is small to begin with. Thus, CCT households do save a bigger part of their income, but this corresponds to actual savings that are hardly different from non-CCT families (1.8% to 2.2% of a low income is a small amount). To support this interpretation, note from Table 3 that the coefficients of the variables *savings1*, *savings2*, *pcsavings1*, and *pcsavings2* are mostly positive but insignificant.

Nevertheless, the impact on saving rate, although moderate, is noteworthy given the savings rate of the CCT beneficiaries. As shown in Table 1, the average savings rate of CCT beneficiaries is negative two percent to seven percent, depending on income measure. If not for CCT, average household savings rate would even be lower. It provides evidence that the CCT program is changing the saving behavior of its beneficiaries; something that complements its original objective, which is to incentivize the availment of health and education services among children.

4.2 Loan Variables and Bank Deposits

The outcome variables *payloandum*, *grantloandum*, and *bankdepdum* are positive and significant in all matching techniques. These indicate that CCT has an impact on the probability that a beneficiary will, respectively, pay off part or all of its outstanding loans, grant loans to other families, and maintain a bank deposit. CCT increases the probability that a beneficiary household will pay part or all its loans by 2.5 to 3.0 percentage points, that a beneficiary household will grant loan to others by 0.8 to 1.1 percentage points, and that a beneficiary household maintains a bank deposit by 1.3 to 1.7 percentage points, depending on matching technique.

However, the corresponding continuous variables of these three binary outcomes turned out insignificant. CCT has no statistically significant impact on amount of outstanding loans paid off, amount of loans granted,

and amount of bank deposits. For loans paid off and loans granted, it is possible that CCT beneficiaries did pay off some outstanding loans and grant loans to others, but the amount of loans paid off and granted is minimal. To support this interpretation, note from Table 3 that the coefficients of the variables *payloan* and *grantloan* are all positive but insignificant.

Moreover, the coefficients of *payloandum* are consistently greater than the coefficients of *grantloandum*, indicating that CCT beneficiaries are more likely to pay off loans than to grant loans to other families. Also, the variables *loan* and *loandum* are both insignificant in all matching techniques, indicating that CCT has no effect on the amount of loans availed by the beneficiaries, nor on their likelihood to avail of a loan. Meanwhile, the significant *bankdepdum* but insignificant *bankdep* outcomes is possibly due to the CCT grants being disbursed through ATM cards. This requires beneficiaries to open bank accounts; but once the grant is deposited, it is withdrawn immediately.

4.3 Some Discussions and Implications

Results show evidence that the Philippines CCT has positive and significant impact on the saving rate of beneficiaries, but insignificant (albeit positive) impact on actual savings. This could imply that CCT negatively impacts income or expenditures. However, applying the same methodology on income and expenditure shows this is not the case. This may seem atypical at first; but it only means that CCT households save a bigger part of their income compared to non-CCT households. Note that the effect of CCT on savings rate, although statistically significant, is small in magnitude. A small effect on savings rate, when applied to a small income, would be a small increase in actual savings, and this might have caused the actual savings variables to be insignificant. Nevertheless, given the low income of CCT beneficiaries, and given their low savings and savings rate that is even negative for some households, any positive change in their saving behavior is noteworthy.

There are also links among the significant outcome variables. The statistically significant positive impact of CCT on saving rate is very similar to the statistically significant positive impact of CCT on the likelihood of paying an outstanding loan and granting a loan to others; and the magnitudes of their effects are similar. Paying off a loan and granting loan to others require saving more of one's income. Another noteworthy link among the outcome variables is that the loan dummies are both positive and significant – CCT increases the likelihood of paying an outstanding loan and granting a loan to others – but the amount of loan paid off and granted are not significantly affected. These are similar to the positive effect of CCT on saving rate, but CCT having no significant impact on amount of actual savings. Again, this may seem atypical at first. If there is significant impact on the likelihood of paying off a loan and granting a loan, there could also be a significant impact on the amount of loan paid and granted. However, similar to the result of savings and saving rate, the results on loans simply says that CCT beneficiaries are more likely to pay off part or all of their loans and grant loan to others, but there is no effect on the amount of the loan paid or granted.

The overall picture of the results provides evidence that the Philippine CCT does impact the saving behavior of its beneficiaries, albeit the magnitude is small. Nevertheless, that there is impact at all is noteworthy. For one, as noted earlier (see Table 1), CCT beneficiaries have low, sometimes even negative savings and savings rate. In fact, using one of the definitions of savings, average saving rate is negative. Thus, any positive effect on saving behavior is notable. Second, affecting saving behavior is not the objective of CCT, but rather to improve the utilization of health and education services among the young in the short run, and address inter-generational poverty in the long run. A positive impact on the saving behavior of beneficiaries is a good complement to its effect on outcomes that it purposefully target.

While this paper, to the author's knowledge, is one of the first to study the short term impact of the Philippine CCT on the saving behavior of beneficiaries, its findings have links to results of existing literature. Chaudhury et al. (2013) found a positive impact of Philippine CCT on ownership of

some livestock. Ownership of livestock is a form of investment; and savings is one of the requirements for one to invest. Using a different methodology, the same paper found a positive impact of CCT on the presence of savings. Moreover, the finding of Tutor (2014) that the Philippine CCT has a positive impact on savings as share of expenditures is very similar to the result of this paper on the effect of CCT on saving rate.

The result of this study has an important policy implication. Results show evidence that aside from the stated short run objectives of the Philippine CCT – which are to increase the utilization of health and education services among poor children – it also has an impact on other outcomes that it did not target to affect. While short term impact evaluation shows that CCT does positively affect the utilization of education and health services, this study shows that it also affects the saving behavior of beneficiaries. This implies that CCT could have unintended effects on beneficiaries. A positive impact on the saving behavior of beneficiaries could be a good unintended effect; but there could be other outcomes that might not be ideal. Some of the common concerns are that CCT in general could discourage work and beneficiaries may just use the transfer to purchase unnecessary goods such as alcoholic drinks. Although these have been debunked empirically for the Philippine CCT by, respectively, Banerjee et al. (2015) and Chaudhury et al. (2013), program implementers should watch out for unintended negative impacts of CCT.

This paper is a short-term impact evaluation of CCT on the saving behavior of beneficiaries; and it found evidence that CCT does affect saving behavior, albeit the magnitude of the effect is small. It would be interesting to do another impact evaluation in the medium term to determine if the effects will be bigger in magnitude. The result of this paper could suggest how the CCT program could be improved further. Although in the short run, the program's effect on saving behavior is minimal, this could add up to a bigger effect in the medium and long term. In the future, CCT program implementers could consider including information dissemination on how savings can be utilized and invested. Program coordinators are meeting beneficiaries on a

regular basis anyway, so disseminating additional information on how to manage saved money will not add too much on costs. It can be included as discussion in one of the meetings with CCT beneficiaries, or informational materials such as flyers could be distributed.

Table 2: Propensity Score Estimation

CCT	Coef.	SE	z-stat	p-value
household size (1)	0.037	0.014	2.670	0.008
number of household members 0 to 5 yrs old (2)	0.139	0.020	7.010	0.000
number of household members 6 to 14 yrs old (3)	0.229	0.015	15.130	0.000
number of household members 15 to 18 yrs old (4)	0.060	0.020	2.970	0.003
number of household members 61 and older (5)	-0.110	0.023	-4.750	0.000
number of household members with no education (5 yrs and up) (6)	-0.092	0.021	-4.480	0.000
number of household members that are elementary graduate (7)	-0.008	0.011	-0.720	0.470
number of household members that are college graduate (8)	-0.165	0.036	-4.560	0.000
single household head (9)	-0.620	0.128	-4.840	0.000
widowed/divorces/separated household head (10)	-0.241	0.050	-4.810	0.000
male household head (11)	-0.076	0.051	-1.490	0.137
household head is employed (12)	0.005	0.052	0.090	0.928
household head has no education (13)	-0.092	0.063	-1.470	0.142
household head is an elementary graduate (14)	0.076	0.029	2.600	0.009
household head is a high school graduate (15)	-0.053	0.034	-1.560	0.120
housing unit roof or wall made of light materials (16)	0.193	0.030	6.450	0.000
housing unit wall made of strong materials (17)	-0.017	0.029	-0.570	0.570
floor area of the housing unit (18)	-0.002	0.000	-4.320	0.000
housing unit has electricity (19)	-0.027	0.033	-0.820	0.412
housing unit has no toilet (20)	0.072	0.037	1.960	0.050
household main water source is piped or dug well (21)	-0.028	0.023	-1.190	0.233
household owns housing unit (22)	0.109	0.246	0.440	0.658
household rents housing unit (23)	-0.149	0.262	-0.570	0.571
household owns house/rent lot (24)	0.444	0.252	1.760	0.078

Table 2: Propensity Score Estimation (cont.)

CCT	Coef.	SE	z-stat	p-value
household owns house/rent-free lot with consent of owner (25)	0.210	0.247	0.850	0.394
household owns house/rent-free lot without consent of owner (26)	0.295	0.251	1.170	0.240
household lives in rent-free house and lot with consent of owner (27)	0.137	0.249	0.550	0.583
household owns a television (28)	-0.147	0.034	-4.370	0.000
household owns a dvd player (29)	-0.011	0.032	-0.350	0.729
household owns a refrigerator (30)	-0.211	0.042	-4.980	0.000
household owns a washing machine (31)	-0.154	0.052	-2.980	0.003
household owns a stove (32)	-0.208	0.063	-3.310	0.001
household owns a phone (33)	-0.051	0.027	-1.910	0.056
household owns a radio (34)	-0.114	0.026	-4.430	0.000
household owns a motorcycle (35)	-0.001	0.036	-0.020	0.981
household has a member working abroad (36)	-0.228	0.060	-3.770	0.000
household has no wage income (37)	-0.063	0.031	-2.070	0.039
household head works for a private household (38)	-0.057	0.086	-0.660	0.508
household head is self-employed without employee (39)	0.164	0.031	5.240	0.000
household is in rural area (40)	0.157	0.030	5.270	0.000
household is an agricultural household (41)	0.230	0.028	8.340	0.000
household belongs to bottom 4 income deciles (42)	0.240	0.033	7.200	0.000
poverty incidence in province where household is located, 2009 (43)	0.017	0.001	19.620	0.000
Constant	-2.746	0.260	-10.550	0.000

Notes: Estimated using probit regression; n=42,062; pseudo r-squared=0.2978. Number in () are variable numbers to be used in future tables.

Table 3: Average Treatment Effect on the Treated of CCT on Various Outcome Variables

	One-to-One (w/ replacement)			One-to-One (w/o replacement)			Nearest Neighbor (N=5)			Nearest Neighbor (N=2)		
	ATT	SE	Abadie-Imbens SE	ATT	SE	Abadie-Imbens SE	ATT	SE	Abadie-Imbens SE	ATT	SE	Abadie-Imbens SE
savings1	26.491	517.290	517.400	160.310	441.700	456.067	201.588	427.214	367.636	238.512	428.415	417.683
savings1_rate	0.021**	0.008	0.009	0.021***	0.007	0.007	0.022***	0.006	0.007	0.020***	0.007	0.007
savings2	-112.465	627.677	561.857	-87.943	510.584	516.956	338.224	458.977	383.483	154.122	485.375	455.830
savings2_rate	0.018***	0.005	0.005	0.018***	0.004	0.004	0.020***	0.004	0.004	0.020***	0.004	0.004
pesavings1	5.802	105.461	103.102	50.530	84.664	82.892	49.784	93.425	65.634	47.435	83.180	79.279
pesavings1_rate	0.021**	0.008	0.009	0.021***	0.007	0.007	0.022***	0.006	0.007	0.020***	0.007	0.007
pesavings2	-12.216	124.770	111.128	15.820	97.698	96.854	93.316	100.163	69.271	48.666	94.915	85.332
pesavings2_rate	0.018***	0.005	0.005	0.018***	0.004	0.004	0.020***	0.004	0.004	0.020***	0.004	0.004
loan	-278.524	394.846	299.766	-410.582	307.621	301.843	-113.373	228.198	195.121	-287.960	283.533	251.608
payloan	40.866	195.460	160.239	17.476	158.208	154.340	133.512	134.931	122.237	68.191	154.318	136.964
grantloan	6.495	53.901	61.274	21.113	49.609	48.432	46.228	41.986	43.797	26.589	47.318	49.498
bankdep	-152.827	128.102	181.803	-105.299	97.410	119.417	-129.461	186.694	94.336	-65.895	94.657	125.665
assetsum	-0.048	0.064	0.054	-0.034	0.055	0.051	-0.017	0.051	0.042	-0.010	0.056	0.047
loandum	0.019	0.013	0.014	0.017	0.012	0.012	0.016	0.011	0.011	0.016	0.012	0.012
payloandum	0.027**	0.011	0.011	0.025**	0.010	0.010	0.027***	0.009	0.009	0.027***	0.010	0.010
grantloandum	0.009**	0.004	0.004	0.009**	0.004	0.004	0.010***	0.004	0.004	0.008**	0.004	0.004
bankdepdum	0.016***	0.005	0.005	0.017***	0.004	0.004	0.015***	0.004	0.004	0.016***	0.004	0.004

Notes: Generated using psmatch2 command in Stata (Leuven and Sianesi 2003). *** significant at 1%, ** significant at 5%, * significant at 10%. psmatch2 ran with “common” and “ties” option.

Table 3: Average Treatment Effect on the Treated of CCT on Various Outcome Variables (cont.)

	Nearest Neighbor (N=5) (cal=0.001)			Nearest Neighbor (N=2) (cal=0.001)			Radius (cal=0.001)	
	ATT	SE	Abadie-Imbens SE	ATT	SE	Abadie-Imbens SE	ATT	SE
savings1	225.821	432.137	355.154	239.756	429.818	420.401	395.587	331.750
savings1_rate	0.021***	0.006	0.007	0.020***	0.007	0.007	0.022***	0.006
savings2	369.515	465.296	371.998	124.098	487.398	460.280	453.859	340.090
savings2_rate	0.019***	0.004	0.004	0.019***	0.004	0.004	0.021***	0.004
pcsavings1	52.007	94.748	65.931	48.456	83.645	80.288	77.328	59.257
pcsavings1_rate	0.021***	0.006	0.007	0.020***	0.007	0.007	0.022***	0.006
pcsavings2	95.152	101.632	69.627	45.699	95.427	86.468	96.176	62.703
pcsavings2_rate	0.019***	0.004	0.004	0.019***	0.004	0.004	0.021***	0.004
loan	-81.314	230.814	195.692	-294.337	284.794	254.041	-127.184	176.778
loandum	0.016	0.011	0.011	0.017	0.012	0.012	0.016	0.010
payloan	133.644	136.846	123.884	65.964	155.243	138.838	176.465	122.676
grantloan	56.470	42.606	40.906	27.969	47.708	50.260	50.264	34.818
bankdep	-128.931	189.532	95.485	-68.410	95.083	127.492	-135.492***	49.741
assetsum	-0.022	0.052	0.043	-0.017	0.056	0.048	-0.042*	0.023
payloandum	0.028***	0.009	0.009	0.028***	0.010	0.010	0.030***	0.010
grantloandum	0.011***	0.004	0.004	0.009**	0.004	0.004	0.010**	0.005
bankdepdum	0.014***	0.004	0.004	0.015***	0.004	0.004	0.013***	0.004

Notes: Generated using psmatch2 command in Stata (Leuven and Sianesi 2003). *** significant at 1%, ** significant at 5%, * significant at 10%. psmatch2 ran with “common” and “ties” option.

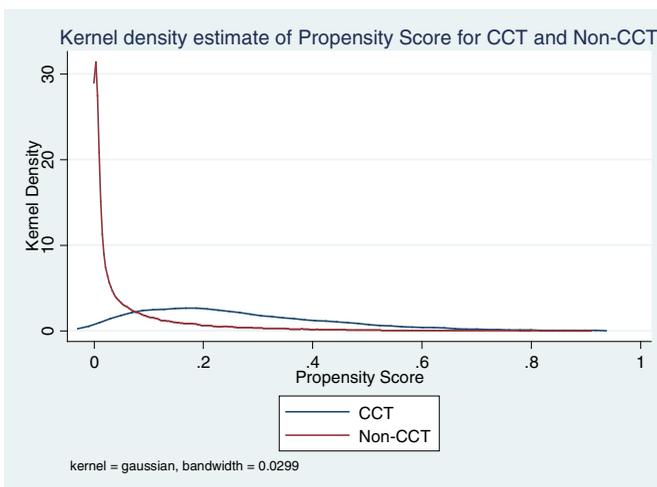
4.4 Balance Test, Standard Errors, and Common Support

Appendix 2 shows the balance test for all matching techniques used. All covariates have standard bias less than 5% and insignificant t-test for all matching techniques, indicating a well-balanced treatment and control groups.

For all nearest neighbor matching, two standard errors were reported: the usual SE and the Abadie and Imbens (2006) heteroskedasticity-consistent analytical SE. Earlier studies using PSM use bootstrapping to calculate standard errors. However, recent literature suggests that bootstrapping does not work with one-to-one and one-to-n nearest neighbor matching. Because the number of control observations matched to a treatment unit does not increase with sample size, consistent estimated SE is not assured with bootstrapping. (Abadie and Imbens, 2008; Blundell and Costas Dias, 2008). Thus, bootstrapping was used only in calliper matching.

The illustration of common support is shown in Figure 1 through the kernel density of the propensity scores for treatment and control observations. A visual examination of the figure shows that the common support is wide enough. The propensity score histograms of each matching technique used are in Appendix 3.

Figure 1: Region of Common Support



4.5 Sensitivity Analysis

While using different matching techniques is in itself a form of sensitivity analysis, the Rosenbaum bounds (Rosenbaum, 2002) was estimated to determine how sensitive the results are to hidden bias, or to unobserved factors that affect treatment assignment. It measures by how much unobserved factors – if they exist – should affect the ratio of the odds of being in treatment to the odds of being in control for them to bias the results. This measure is expressed in terms of a statistic – sometimes called the Gamma factor. Gamma factor of 1.5 means unobserved variables need to change the odds ratio between the probability of being a CCT and a non-CCT household by 50 percent to cause bias in the results. The use of the Rosenbaum bounds merits some clarifications before being used. First, there is no agreement on the threshold level which, if breached indicates sensitivity of results to unobserved covariates. Duvendack and Palmer-Jones (2012) argues that a factor below 2 indicates sensitivity to unobserved factors; while Aakvik (2001) reasons that a factor of 2 – which means that unobserved factors would have to change the odds ratio by 100 percent for it to bias the results – is a very large number given that many of the determinants of treatment assignment is already controlled for. Second, the Rosenbaum bounds only show by how much should unobserved factors affect the odds ratio of treatment and control assignment for them to bias the results; but do not indicate the presence of unobserved factors (DiPrete and Gangl, 2004; Aakvik, 2001). In this study, the Gamma values found range from as low as 1.04 to as high as 2.05, depending on the outcome variables and matching method. This is summarized in Appendix 4.

5. Summary and Conclusions

This study looks at the impact of the Philippines CCT on the saving behavior of beneficiaries. Using Propensity Score Matching and the 2011 Annual Poverty Indicators Survey, it was tested if CCT has an impact on savings, savings rate, loans availed, outstanding loans paid, loans granted to others, bank deposits, and appliance assets. Results provide evidence

that CCT has no statistically significant (although positive) effect on actual savings; but has moderate but robust impact on savings rate. CCT increases savings rate by 1.8 to 2.2 percentage points, depending on outcome variable and matching method. As explained earlier, a significant impact on savings rate but insignificant effect on actual savings, income, and expenditure may seem atypical; however, it just means that CCT households save a larger part of their income compared to non-CCT households. And as noted in the results section, although the savings and per capita savings variables are statistically insignificant, they are mostly positive.

CCT also has moderate and robust effect on the probability that recipient households will pay-off part or all of its outstanding loans, on the probability that recipient households will grant loan to others, and on the probability that recipient households maintain a bank deposit. However, CCT has no significant impact on the amount of loans paid, amount of loans granted, and amount of bank deposits. CCT increases the probability that a beneficiary household will pay part or all its loans by 2.5 to 3.0 percentage points, that a beneficiary household will grant loan to others by 0.8 to 1.1 percentage points, and that a beneficiary household maintains a bank deposit by 1.3 to 1.7 percentage points, depending on matching technique. Moreover, CCT has no effect on the likelihood of availing a loan. Over-all, results show evidence that CCT has moderate positive effect on the saving behavior of beneficiaries. Although moderate, it is still noteworthy given the low saving rate of the poor to begin with. Moreover, CCT is originally aimed at affecting the utilization of health and education services among the poor, and its effect on saving behavior is unintended.

References

- Aakvik, A. (2001). Bounding a matching estimator: the case of a Norwegian training program. *Oxford bulletin of economics and statistics*, 63(1), 115-143.
- Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1), 235-267.
- Abadie, A., & Imbens, G. W. (2008). On the failure of the bootstrap for matching estimators. *Econometrica*, 76(6), 1537-1557.
- Attanasio, O., & Mesnard, A. (2006). The impact of a conditional cash transfer programme on consumption in Colombia. *Fiscal studies*, 27(4), 421-442.
- Augurzky, B., & Schmidt, C. M. (2001). *The propensity score: A means to an end* (IZA Discussion Papers No. 271). Retrieved from <http://ftp.iza.org/dp271.pdf>
- Baker, J. L. (2000). *Evaluating the impact of development projects on poverty: A handbook for practitioners*. Washington, DC: World Bank.
- Banerjee, A. V., Hanna, R., Kreindler, G., & Olken, B. A. (2015). *Debunking the stereotype of the lazy welfare recipient: Evidence from cash transfer programs worldwide* (HKS Working Paper No. 076). Retrieved from <https://research.hks.harvard.edu/publications/getFile.aspx?Id=1290>
- Becker, S.O. & Caliendo, M. (2007). Sensitivity analysis for average treatment effects. *Stata Journal*, 7(1), 71-83.
- Blundell, R., & Dias, M. C. (2009). Alternative approaches to evaluation in empirical microeconomics. *Journal of Human Resources*, 44(3), 565-640.

- Bryson, A., Dorsett, R., & Purdon, S. (2002). *The use of propensity score matching in the evaluation of active labour market policies* (Department for Work and Pensions Working Paper No.4). Retrieved from <http://eprints.lse.ac.uk/4993/>
- Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys*, 22(1), 31-72.
- Chaudhury, N., Friedman, J., & Onishi, J. (2013). *Philippines conditional cash transfer program impact evaluation 2012*. Washington, DC: World Bank.
- De Oliveira, A. M. H. C., Andrade, M. V., Resende, A. C. C., Rodrigues, C. G., Souza, L. D., & Ribas, R. P. (2007). First results of a preliminary evaluation of the bolsa família program. *Evaluation of MDS Policies and Programs Results*, 2, 19-64.
- Department of Social Welfare and Development (2012). *Pantawid pamilyang Pilipino program operations manual 2012*. Manila, the Philippines: Author.
- Department of Social Welfare and Development (2013). *Pantawid pamilyang Pilipino program implementation status report 1st quarter of 2013*. Manila, the Philippines: Author.
- DiPrete, T. A., & Gangl, M. (2004). Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological methodology*, 34(1), 271-310.
- Duvendack, M., & Palmer-Jones, R. (2012). High noon for microfinance impact evaluations: re-investigating the evidence from Bangladesh. *The Journal of Development Studies*, 48(12), 1864-1880.
- Fernandez, L., & Olfindo, R. (2011). Overview of the Philippines' conditional cash transfer program: The pantawid pamilyang Pilipino program. *World Bank Philippine Social Protection Note*, 2.

- Gangl, M. (2003). *Rbounds: Stata module to perform Rosenbaum sensitivity analysis for average treatment effects on the treated*. Retrieved from <https://ideas.repec.org/c/boc/bocode/s438301.html>
- Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64(4), 605-654.
- Heckman, J. J., Ichimura, H., & Todd, P. (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies*, 65(2), 261-294.
- Heckman, J. J., LaLonde, R. J., & Smith, J. A. (1999). The economics and econometrics of active labor market programs. *Handbook of Labor Economics*, 3, 1865-2097.
- Hoddinott, J., & Skoufias, E. (2004). The impact of PROGRESA on food consumption. *Economic Development and Cultural Change*, 53(1), 37-61.
- Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association*, 81(396), 945-960.
- Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5-86.
- Khandker, S. R., Koolwal, G. B., & Samad, H. A. (2009). *Handbook on impact evaluation: quantitative methods and practices*. Washington, DC: World Bank.
- Leuven, E., & Sianesi, B. (2015). *PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing*. Retrieved from <http://ideas.repec.org/c/boc/bocode/s432001.html>.
- Rosenbaum, P. R. (2002). Sensitivity to hidden bias. In P. R. Rosenbaum (Ed.), *Observational studies* (pp. 105-170). New York, NY: Springer.

- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55.
- Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5), 688.
- Rubin, D. B., & Thomas, N. (1996). Matching using estimated propensity scores: relating theory to practice. *Biometrics*, 52(1), 249-264.
- Smith, J. A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of Econometrics*, 125(1), 305-353.
- Soares, F. V., Ribas, R. P., & Hirata, G. I. (2008). *Achievements and shortfalls of conditional cash transfers: Impact evaluation of Paraguay's tekoporã programme* (IPC Evaluation Note No. 3). Retrieved from <http://www.ipc-undp.org/pub/IPCEvaluationNote3.pdf>
- Tutor, M. V. (2014). The impact of Philippines' conditional cash transfer program on consumption. *Philippine Review of Economics*, 51(1), 117-161.

Appendices

Appendix I

PMT Variables

PMT Variables	
Family size	Roof made of light materials
Number of children 0 to 5 years old	Wall made of light materials
Number of children 6 to 14 years old	Wall made of strong materials
Number of children 15 to 18 years old	No toilet facility
Number of family members more than 60 years old	Main source of water supply is tubed/piped or dug well
Number of family members with no education	Availability of electricity at housing unit
Number of family members with elementary degree	Availability of refrigerator
Number of family members with college degree	Availability of washing machine
Agricultural household	Household owns the housing unit
Availability of domestic help at household	Household rents the house
Household head is single	

Appendix II

Balancing Test

Var	One-to-One (w/ replacement)				One-to-One (w/o replacement)				Nearest Neighbor (N=5)						
	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value
1	6.154	6.135	0.900	0.350	0.728	6.154	6.127	1.300	0.490	0.622	6.154	6.149	0.300	0.100	0.922
2	0.919	0.902	1.900	0.670	0.505	0.919	0.894	2.800	0.980	0.325	0.919	0.915	0.400	0.140	0.888
3	2.054	2.070	-1.300	-0.450	0.651	2.054	2.060	-0.500	-0.170	0.863	2.054	2.045	0.800	0.260	0.792
4	0.606	0.616	-1.400	-0.500	0.615	0.606	0.606	0.000	0.020	0.987	0.606	0.607	-0.100	-0.030	0.977
5	0.185	0.180	0.800	0.400	0.693	0.185	0.184	0.200	0.100	0.917	0.185	0.178	1.100	0.540	0.590
6	0.410	0.420	-1.600	-0.530	0.598	0.410	0.417	-1.100	-0.350	0.728	0.410	0.423	-2.100	-0.680	0.495
7	2.541	2.546	-0.300	-0.110	0.912	2.541	2.564	-1.300	-0.510	0.607	2.541	2.569	-1.600	-0.630	0.528
8	0.048	0.043	0.900	0.820	0.410	0.048	0.041	1.200	1.200	0.231	0.048	0.046	0.300	0.310	0.755
9	0.004	0.005	-0.400	-0.390	0.694	0.004	0.004	0.200	0.210	0.835	0.004	0.003	0.600	0.660	0.512
10	0.090	0.089	0.300	0.130	0.893	0.090	0.085	1.400	0.680	0.499	0.090	0.086	1.300	0.600	0.546
11	0.910	0.908	0.500	0.270	0.790	0.910	0.912	-0.600	-0.310	0.754	0.910	0.911	-0.400	-0.210	0.837
12	0.951	0.956	-1.500	-0.910	0.365	0.951	0.954	-1.000	-0.600	0.549	0.951	0.959	-2.500	-1.470	0.141
13	0.053	0.050	1.600	0.580	0.564	0.053	0.052	0.800	0.290	0.774	0.053	0.056	-1.200	-0.420	0.677
14	0.255	0.262	-1.700	-0.610	0.540	0.255	0.266	-2.700	-0.990	0.323	0.255	0.257	-0.600	-0.210	0.833
15	0.131	0.139	-2.200	-0.970	0.331	0.131	0.137	-1.500	-0.680	0.500	0.131	0.137	-1.600	-0.720	0.472
16	0.517	0.505	2.700	0.950	0.345	0.517	0.516	0.300	0.100	0.919	0.517	0.513	0.800	0.300	0.767
17	0.418	0.413	1.200	0.440	0.660	0.418	0.406	2.700	1.010	0.312	0.418	0.412	1.400	0.530	0.593
18	34.072	34.083	0.000	-0.020	0.988	34.072	33.882	0.500	0.290	0.775	34.072	34.356	-0.700	-0.420	0.673
19	0.632	0.637	-1.200	-0.400	0.691	0.632	0.631	0.200	0.050	0.958	0.632	0.626	1.500	0.510	0.608

Var	One-to-One (w/ replacement)					One-to-One (w/o replacement)					Nearest Neighbor (N=5)				
	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value
	20	0.152	0.148	1.400	0.460	0.642	0.152	0.149	1.200	0.390	0.694	0.152	0.153	-0.400	-0.120
21	0.413	0.408	1.000	0.390	0.697	0.413	0.407	1.200	0.470	0.640	0.413	0.405	1.600	0.600	0.550
22	0.569	0.565	0.900	0.360	0.718	0.569	0.570	-0.100	-0.030	0.979	0.569	0.565	1.000	0.380	0.703
23	0.009	0.007	1.200	1.020	0.305	0.009	0.006	1.300	1.180	0.236	0.009	0.008	0.500	0.450	0.652
24	0.044	0.042	1.500	0.500	0.615	0.044	0.040	2.400	0.830	0.409	0.044	0.040	2.300	0.800	0.424
25	0.259	0.260	-0.300	-0.090	0.930	0.259	0.261	-0.300	-0.120	0.907	0.259	0.262	-0.600	-0.200	0.839
26	0.052	0.055	-1.600	-0.570	0.569	0.052	0.053	-0.500	-0.170	0.863	0.052	0.054	-1.100	-0.390	0.697
27	0.065	0.071	-2.600	-1.010	0.311	0.065	0.070	-2.000	-0.760	0.445	0.065	0.070	-2.000	-0.760	0.445
28	0.388	0.383	1.100	0.390	0.694	0.388	0.386	0.400	0.160	0.875	0.388	0.382	1.300	0.480	0.633
29	0.228	0.209	4.200	1.850	0.064	0.228	0.219	2.000	0.890	0.374	0.228	0.215	2.800	1.210	0.226
30	0.066	0.060	1.700	1.050	0.293	0.066	0.062	1.100	0.680	0.498	0.066	0.061	1.400	0.880	0.379
31	0.037	0.033	1.300	0.970	0.330	0.037	0.032	1.500	1.120	0.263	0.037	0.033	1.300	0.930	0.352
32	0.019	0.019	-0.100	-0.090	0.926	0.019	0.021	-0.600	-0.550	0.583	0.019	0.018	0.400	0.380	0.703
33	0.500	0.512	-2.500	-0.920	0.358	0.500	0.498	0.400	0.150	0.878	0.500	0.505	-1.000	-0.370	0.713
34	0.248	0.245	0.500	0.210	0.836	0.248	0.246	0.300	0.120	0.906	0.248	0.244	0.700	0.280	0.781
35	0.105	0.102	1.000	0.460	0.645	0.105	0.102	0.900	0.420	0.675	0.105	0.101	1.200	0.550	0.585
36	0.026	0.022	1.500	1.000	0.318	0.026	0.024	0.800	0.490	0.624	0.026	0.024	0.900	0.570	0.567
37	0.419	0.412	1.500	0.600	0.551	0.419	0.415	1.000	0.390	0.698	0.419	0.420	-0.100	-0.060	0.955
38	0.014	0.016	-1.400	-0.620	0.533	0.014	0.018	-2.600	-1.110	0.265	0.014	0.017	-2.300	-0.980	0.327
39	0.537	0.536	0.100	0.050	0.959	0.537	0.535	0.300	0.130	0.898	0.537	0.535	0.200	0.080	0.935
40	0.830	0.830	0.100	0.030	0.973	0.830	0.837	-1.400	-0.650	0.515	0.830	0.836	-1.200	-0.570	0.570
41	0.649	0.641	1.700	0.640	0.522	0.649	0.641	1.700	0.640	0.522	0.649	0.642	1.600	0.600	0.546
42	0.889	0.901	-2.900	-1.500	0.133	0.889	0.904	-3.500	-1.850	0.065	0.889	0.906	-4.000	-2.110	0.035
43	41.415	41.129	1.900	0.830	0.406	41.415	41.181	1.500	0.680	0.496	41.415	41.197	1.400	0.630	0.526

Var	Nearest Neighbor (N=2)					Nearest Neighbor (N=5) (cal=0.001)					Nearest Neighbor (N=2) (cal=0.001)				
	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value
1	6.154	6.109	2.100	0.800	0.421	6.104	6.084	1.000	0.370	0.713	6.104	6.052	2.500	0.950	0.344
2	0.919	0.908	1.200	0.420	0.671	0.902	0.892	1.200	0.410	0.684	0.902	0.887	1.800	0.630	0.531
3	2.054	2.047	0.600	0.210	0.832	2.025	2.013	1.000	0.360	0.720	2.025	2.014	1.000	0.350	0.729
4	0.606	0.607	-0.100	-0.030	0.974	0.599	0.601	-0.300	-0.110	0.911	0.599	0.602	-0.400	-0.150	0.883
5	0.185	0.177	1.400	0.660	0.508	0.187	0.179	1.400	0.660	0.512	0.187	0.178	1.600	0.760	0.449
6	0.410	0.416	-1.000	-0.320	0.746	0.407	0.413	-1.000	-0.330	0.744	0.407	0.408	-0.200	-0.050	0.960
7	2.541	2.546	-0.300	-0.120	0.906	2.541	2.568	-1.500	-0.590	0.556	2.541	2.554	-0.700	-0.280	0.783
8	0.048	0.050	-0.300	-0.270	0.786	0.049	0.047	0.300	0.310	0.755	0.049	0.051	-0.300	-0.270	0.786
9	0.004	0.004	-0.100	-0.100	0.919	0.004	0.003	0.600	0.660	0.512	0.004	0.004	-0.100	-0.100	0.919
10	0.090	0.087	0.900	0.430	0.670	0.091	0.086	1.700	0.790	0.429	0.091	0.088	1.100	0.520	0.604
11	0.910	0.911	-0.300	-0.160	0.876	0.909	0.911	-0.700	-0.330	0.739	0.909	0.911	-0.600	-0.310	0.753
12	0.951	0.958	-2.200	-1.310	0.189	0.950	0.958	-2.400	-1.410	0.160	0.950	0.957	-2.100	-1.260	0.209
13	0.053	0.051	1.200	0.430	0.666	0.053	0.056	-1.100	-0.390	0.700	0.053	0.051	1.100	0.380	0.707
14	0.255	0.262	-1.700	-0.610	0.540	0.253	0.257	-1.000	-0.360	0.717	0.253	0.261	-2.000	-0.740	0.462
15	0.131	0.136	-1.200	-0.540	0.586	0.133	0.138	-1.300	-0.560	0.576	0.133	0.137	-1.000	-0.430	0.665
16	0.517	0.511	1.300	0.450	0.655	0.513	0.510	0.700	0.240	0.813	0.513	0.507	1.400	0.480	0.634
17	0.418	0.409	2.000	0.760	0.444	0.420	0.415	1.100	0.400	0.690	0.420	0.412	1.700	0.630	0.531
18	34.072	34.335	-0.700	-0.390	0.699	34.121	34.328	-0.500	-0.300	0.762	34.121	34.433	-0.800	-0.450	0.651
19	0.632	0.626	1.600	0.530	0.597	0.635	0.627	1.900	0.620	0.533	0.635	0.630	1.200	0.410	0.679
20	0.152	0.159	-2.300	-0.740	0.460	0.151	0.151	-0.200	-0.060	0.949	0.151	0.158	-2.500	-0.780	0.433
21	0.413	0.406	1.300	0.490	0.622	0.413	0.406	1.300	0.510	0.611	0.413	0.409	0.800	0.290	0.774

Var	Nearest Neighbor (N=2)					Nearest Neighbor (N=5) (cal=0.001)					Nearest Neighbor (N=2) (cal=0.001)				
	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value	Treated	Control	%bias	t-stat	p-value
22	0.569	0.565	0.900	0.360	0.718	0.572	0.565	1.300	0.500	0.618	0.572	0.565	1.400	0.520	0.604
23	0.009	0.007	0.900	0.790	0.428	0.009	0.008	0.600	0.510	0.611	0.009	0.007	0.900	0.790	0.428
24	0.044	0.039	2.900	1.020	0.307	0.044	0.040	2.200	0.760	0.449	0.044	0.040	2.000	0.710	0.480
25	0.259	0.261	-0.500	-0.190	0.850	0.259	0.261	-0.700	-0.240	0.810	0.259	0.261	-0.500	-0.160	0.872
26	0.052	0.057	-2.800	-0.990	0.324	0.051	0.054	-1.500	-0.520	0.603	0.051	0.056	-2.700	-0.940	0.345
27	0.065	0.070	-2.000	-0.760	0.445	0.065	0.070	-2.100	-0.800	0.424	0.065	0.070	-2.400	-0.920	0.356
28	0.388	0.382	1.200	0.450	0.656	0.391	0.384	1.600	0.590	0.553	0.391	0.385	1.400	0.510	0.607
29	0.228	0.212	3.600	1.570	0.116	0.230	0.217	2.900	1.250	0.212	0.230	0.213	3.600	1.560	0.118
30	0.066	0.061	1.400	0.860	0.388	0.067	0.062	1.400	0.890	0.376	0.067	0.062	1.500	0.890	0.373
31	0.037	0.034	0.900	0.690	0.490	0.037	0.033	1.200	0.850	0.394	0.037	0.034	1.000	0.690	0.488
32	0.019	0.019	0.100	0.050	0.963	0.019	0.018	0.400	0.380	0.703	0.019	0.019	0.100	0.050	0.963
33	0.500	0.502	-0.500	-0.170	0.868	0.501	0.509	-1.700	-0.610	0.539	0.501	0.507	-1.100	-0.410	0.681
34	0.248	0.242	1.300	0.550	0.583	0.249	0.246	0.600	0.240	0.808	0.249	0.243	1.300	0.540	0.591
35	0.105	0.099	1.900	0.890	0.375	0.106	0.101	1.300	0.630	0.532	0.106	0.099	1.700	0.780	0.433
36	0.026	0.023	1.200	0.780	0.433	0.026	0.024	1.100	0.690	0.489	0.026	0.023	1.200	0.780	0.433
37	0.419	0.421	-0.300	-0.130	0.897	0.418	0.423	-1.000	-0.380	0.705	0.418	0.424	-1.200	-0.460	0.648
38	0.014	0.017	-1.700	-0.720	0.469	0.015	0.017	-2.100	-0.900	0.367	0.015	0.017	-1.600	-0.670	0.500
39	0.537	0.538	-0.400	-0.140	0.888	0.533	0.535	-0.400	-0.140	0.886	0.533	0.537	-1.000	-0.360	0.718
40	0.830	0.834	-0.700	-0.340	0.733	0.828	0.834	-1.300	-0.600	0.551	0.828	0.832	-0.900	-0.410	0.681
41	0.649	0.648	0.100	0.050	0.957	0.645	0.637	1.700	0.640	0.523	0.645	0.644	0.200	0.080	0.936
42	0.889	0.904	-3.700	-1.930	0.053	0.888	0.904	-4.100	-2.120	0.034	0.888	0.903	-3.700	-1.930	0.053
43	41.415	41.176	1.600	0.700	0.486	41.239	41.027	1.400	0.620	0.538	41.239	41.036	1.300	0.590	0.555

Var	Radius (cal=0.001)				
	Treated	Control	%bias	t-stat	p-value
1	6.104	6.096	0.400	0.150	0.877
2	0.902	0.890	1.500	0.510	0.608
3	2.025	2.019	0.500	0.170	0.865
4	0.599	0.609	-1.400	-0.490	0.624
5	0.187	0.173	2.500	1.170	0.243
6	0.407	0.423	-2.500	-0.810	0.416
7	2.541	2.564	-1.300	-0.500	0.619
8	0.049	0.046	0.500	0.470	0.638
9	0.004	0.003	0.500	0.560	0.574
10	0.091	0.084	2.200	1.070	0.287
11	0.909	0.913	-1.200	-0.610	0.545
12	0.950	0.955	-1.600	-0.910	0.362
13	0.053	0.058	-2.400	-0.810	0.417
14	0.253	0.252	0.200	0.070	0.948
15	0.133	0.136	-0.900	-0.390	0.700
16	0.513	0.511	0.500	0.180	0.861
17	0.420	0.413	1.500	0.550	0.585
18	34.121	34.315	-0.500	-0.290	0.775
19	0.635	0.631	0.900	0.280	0.777
20	0.151	0.149	0.600	0.190	0.850
21	0.413	0.408	0.900	0.330	0.743
22	0.572	0.572	-0.100	-0.030	0.978
23	0.009	0.008	0.700	0.600	0.546
24	0.044	0.040	2.000	0.700	0.483
25	0.259	0.259	0.000	0.010	0.996
26	0.051	0.053	-1.000	-0.350	0.729
27	0.065	0.067	-1.100	-0.430	0.665
28	0.391	0.388	0.800	0.310	0.756
29	0.230	0.223	1.600	0.670	0.503
30	0.067	0.061	1.500	0.920	0.355
31	0.037	0.034	1.000	0.760	0.449
32	0.019	0.018	0.400	0.330	0.739
33	0.501	0.509	-1.600	-0.590	0.558
34	0.249	0.248	0.300	0.130	0.896
35	0.106	0.099	1.900	0.870	0.384

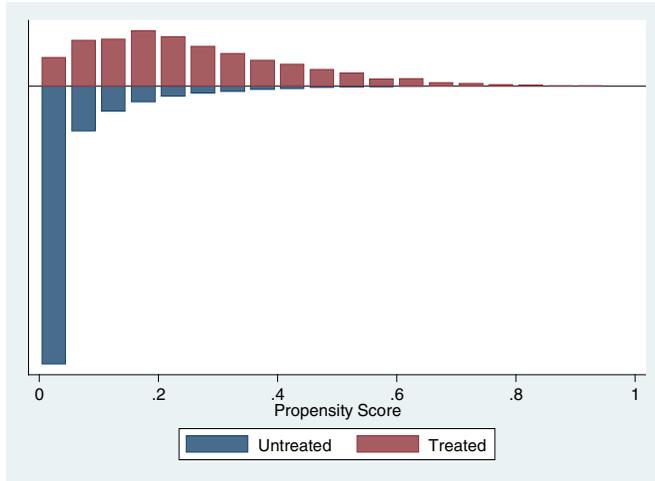
Var	Radius (cal=0.001)				
	Treated	Control	%bias	t-stat	p-value
36	0.026	0.024	1.000	0.610	0.541
37	0.418	0.420	-0.400	-0.160	0.874
38	0.015	0.015	-0.500	-0.210	0.837
39	0.533	0.533	0.100	0.020	0.984
40	0.828	0.831	-0.700	-0.330	0.742
41	0.645	0.639	1.300	0.510	0.614
42	0.888	0.904	-4.000	-2.060	0.039
43	41.239	40.993	1.600	0.710	0.476

Note: Variable numbers are as in Table 3.

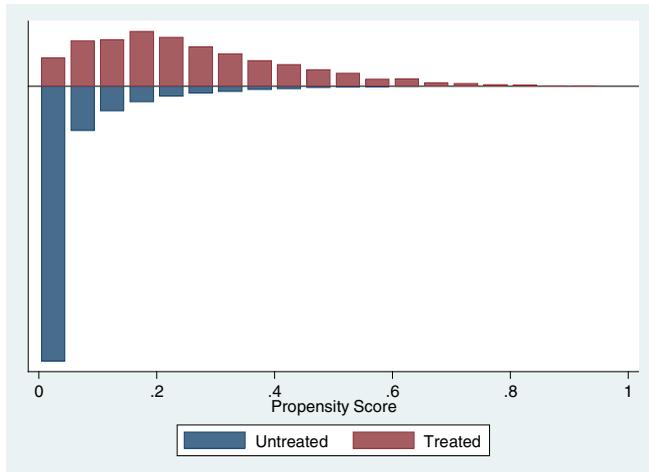
Appendix III

Propensity Score Histograms

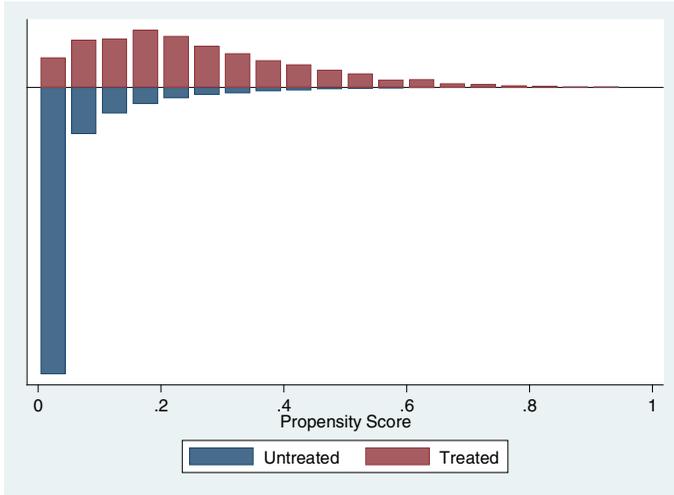
A. Nearest Neighbor One-to-one Without Replacement



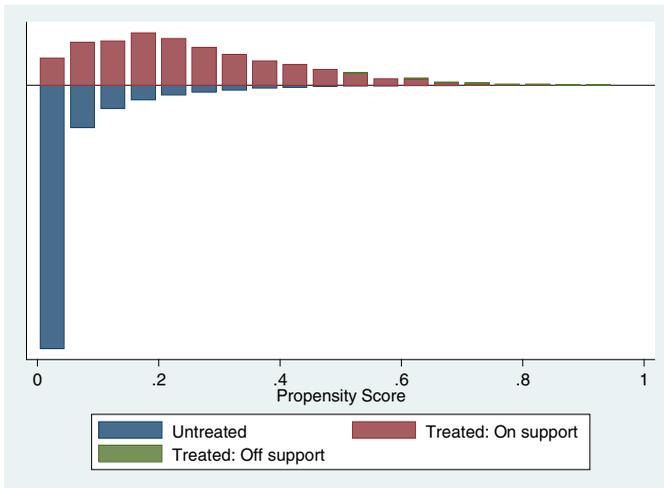
B. Nearest Neighbor One-to-one With Replacement



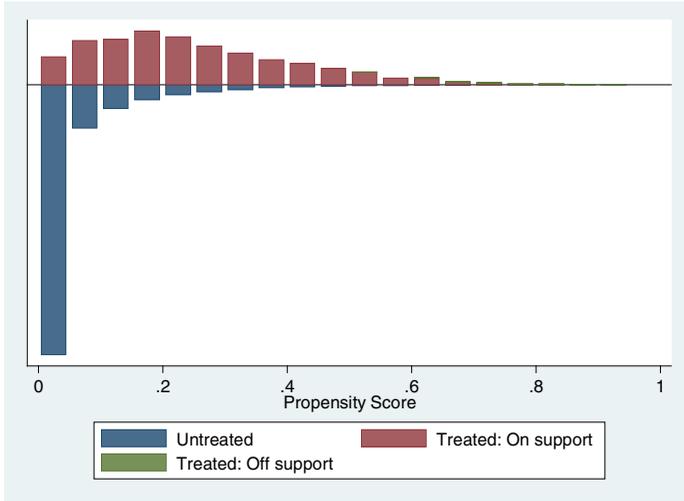
C. Nearest Neighbor One-to-N; N=5



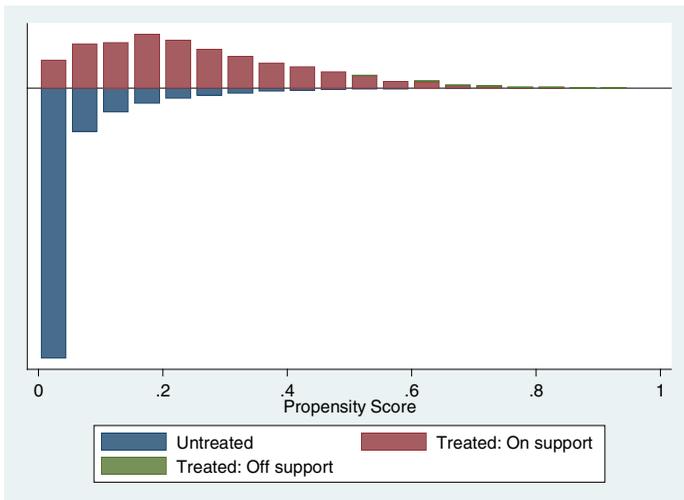
D. Nearest Neighbor One-to-N; N=2



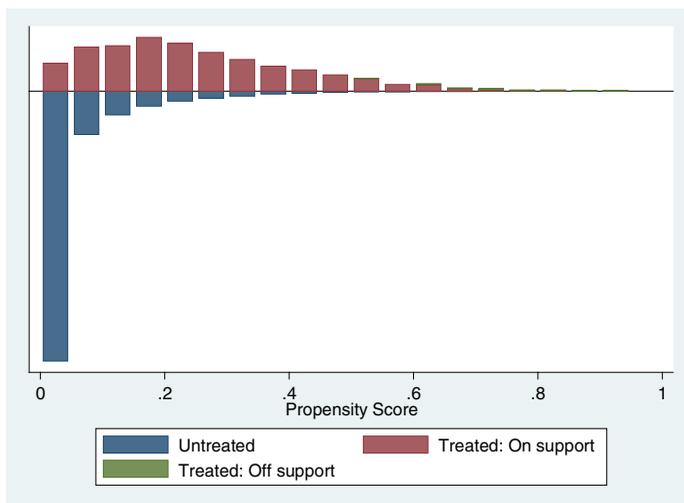
E. Nearest Neighbor One-to-N; N=5; Cal=0.001



F. Nearest Neighbor One-to-N; N=2; Cal=0.001



G. Radius = 0.001



Appendix IV

Rosenbaum bounds Gamma factors, significant outcome variables only

	One-to-One (w/ replacement)	One-to-One (w/o replacement)	Nearest Neighbor (N=5)	Nearest Neighbor (N=2)	Nearest Neighbor (N=5) (cal=0.001)	Nearest Neighbor (N=2) (cal=0.001)	Radius (cal=0.001)
savings1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
savings1_rate	1.05	1.05	1.35	1.20	1.3	1.2	1.50
savings2	N/A	N/A	N/A	N/A	N/A	N/A	N/A
savings2_rate	1.10	1.10	1.20	1.15	1.15	1.15	1.20
pcsavings1	N/A	N/A	N/A	N/A	N/A	N/A	N/A
pcsavings1_rate	1.05	1.05	1.35	1.20	1.3	1.2	1.50
pcsavings2	N/A	N/A	N/A	N/A	N/A	N/A	N/A
pcsavings2_rate	1.10	1.10	1.20	1.15	1.15	1.15	1.20
loan	N/A	N/A	N/A	N/A	N/A	N/A	N/A
loandum	N/A	N/A	N/A	N/A	N/A	N/A	N/A
payloan	N/A	N/A	N/A	N/A	N/A	N/A	N/A
grantloan	N/A	N/A	N/A	N/A	N/A	N/A	N/A
bankdep	N/A	N/A	N/A	N/A	N/A	N/A	N/A
assetsum	N/A	N/A	N/A	N/A	N/A	N/A	N/A
payloandum	1.05	1.05	1.04	1.05	1.04	1.05	1.05
grantloandum	1.15	1.15	1.10	1.15	1.10	1.20	1.15
bankdepdum	1.50	1.55	1.15	1.35	1.10	1.35	2.05

Notes: For savings rate variables – *savings1_rate*, *savings2_rate*, *pcsavings1_rate*, *pcsavings2_rate* – generated using *rbounds* command in Stata (Gangl 2003). For binary outcome variables – *loandum*, *payloandum*, *grantloandum*, and *bankdepdum* – generated using *mhbounds* command in Stata (Becker and Callendo 2007). N/A means outcome variable is insignificant in the corresponding matching technique.