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The unintentional effects of the Conditional Cash Transfers Programs on agriculture: evidence from Peruvian farming households

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evidence from Peruvian farming households*

Cesar Del Pozo Loayza**

Abstract

This paper examines the unintentional effects of Programa Juntos (a Conditional Cash Transfer Program in Peru) on agriculture outcomes using data from household surveys, and a Differences-in-Differences estimator. I found evidence of potential negative effects of program on agriculture; particularly the evidence suggests that program reduces the value of agricultural production and the hectares of land used; these results are opposite to previous empirical evidence for the Latin American context. To explore some causal chains, I estimate the effects of program on labor supply; I found that the program can generates a disincentive effect on adult labor supply for agriculture.

Resumen

Este estudio examina los efectos no intencionales del Programa Juntos (un Programa de Transferencias Condicionadas en Perú) sobre la agricultura, usando encuestas de hogares y el estimador de diferencias en diferencias. Se encuentran posibles efectos negativos del programa en la agricultura; la evidencia sugiere que el programa reduce la producción agrícola y las hectáreas utilizadas; éstos resultados son opuestos a la evidencia previa para latinoamerica. Para explorar cadenas causales, se estimó los efectos del programa sobre la oferta de trabajo, se encuentra que el programa puede generar un efecto disuasorio sobre la oferta laboral de los adultos para la agricultura.

JEL code: C21, D13, J22

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1. Introduction

Conditional Cash Transfers Programs (CCTP) are social interventions with two basic characteristics: (i) Are targeted to the poorest households or individuals; (ii) Cash transfers are conditioned on certain changes on behavior of beneficiaries, usually related with minimum levels of use of health and education services by children. Based on the assumption that human capital is relevant to stimulate the economic growth and social development (Maluccio et al. 2005), the aims of CCTP are to alleviate current poverty in the short-run through monetary transfer, and to reduce poverty in the long-run through increasing human capital of children. The Policy-makers' interest in CCTP has grown enormously in the last years; these programs have become an important instrument to poverty alleviation goal in developing countries. Currently CCTP are implement in several countries of LA[1].

Is usual the perception that cash transfers programs does not have economic impacts because the focus of CCT is on the accumulation of human capital and not on the accumulation of productive capital (Davis et al. 2011). However, recent evidence in the Literature suggests that conditional cash transfer programs (CCTP) can have unintentional effects on productive activities; in particular for rural areas in Latin America, empirical evidence suggests that CCTP could increase agricultural production of beneficiaries households, especially for those who are subsistence farmers (Gertler et al., 2006; Todd et al., 2010).

In Peru, CCTP is called Programa Juntos, this program targets poor households in the whole the country, but most of the beneficiaries are poor farming households in rural areas. As is common in CCTP, women in targeted households receive a transfer of 200 nuevos soles (about USD 70) each two months (around USD 840 per year) the conditionals are related with the participation of children in educational and health services. For the peruvian case, cash transfer is fix per household and substantial as well, cash transfers represent about 28% of household's income. Participation in Programa Juntos is at least four years (extendable by one more four-year term). Programa Juntos are not intended to increase household agricultural production but rather to increase cash income; however, when income increases in poor households and liquidity constraints reduces is possible that CCTP may generate changes in farming household behavior related with productive choices.

This paper explore the hypothesis that Program Juntos can have unintentional effects on agricultural production in the Peruvian context based on households' surveys and using a non-experimental approach by a Difference-in-Differences estimator. To properly control initial differences among treated and control households I combine DD with propensity scores to reduce initial heterogeneity at baseline (Khandker et al., 2010). As opposed to expected results about the potential positive effects of CCTP on production decisions by households, I found that Program Juntos have a negative effect on agricultural production of farming households for the Peruvian context. To understand these results and to explore some causal chains, I also estimate the potential effects of Programa Juntos on labor supply for agriculture activities; I

[1] Progresa/Oportunidades in México; Chile Solidario (Subsidio Unitario Familiar) in Chile; Bono de Desarrollo Humano in Ecuador; Programa Nacional Bolsa Escola, Bolsa Familia, Bolsa Alimentacao y Programa de Eradicao do Trabalho Infantil in Brasil; Programa Familias en Acción in Colombia; Programa de Asignación Familiar in Honduras; Program of Advancement through Health and Education in Jamaica; Red de Protección Social in Nicaragua; Programa Asignación Universal por Hijo in Argentina; Programa Juancito Pinto in Bolivia; Solidaridad, Tarjeta de Asistencia Escolar in DominicRepublic; Red Solidaria in El Salvador; Mi Familia Progresa in Guatemala; Red de Oportunidades in Panama; Tekopora/PROPAIS II in Paraguay, Plan de Atención Nacional de Emergencia Social (Plan de Equidad Social) in Uruguay and Juntos in Peru.

found that Peruvian CCTP generates a potential disincentive effect on labor supply for agriculture.

The paper proceeds as follow: In Section 2, I describe the background that guides this research. In Section 3, I describe the research methodology, which includes the use of databases and outcomes, as well as the identification strategy and empirical methods used. In Section 4, I detail the empirical results. Finally, in Section 5, I discuss briefly the main results of this study.

2. Background

Conditional Cash Transfer Programs and agriculture outcomes: review of related Literature

Agriculture production of the rural and poor households are often limited for liquidity and credit constraints, because are strongly restricted by low productivity and irregular sources of income (Fewick et al. 1999) this is particularly relevant in the case of subsistence farming households (Sadoulet et al., 2001). Considering that the size of the cash transfer is large to average household's income, CCTP have the potential to reduce liquidity constraints because offers a regular flow of cash, and therefore can increase the productive investments in agricultural activities (Todd et al. 2010). For the Peruvian case, 75% of rural population are dedicated to agricultural activities and transfers represent around 28 percent of household´s income in rural areas (Perova et al. 2009).

The promotion of agricultural activities is not a specific objective of CCTPs instead beneficiary farming households may usually use their transfer freely. CCTPs offers non-labor income that increase income of farming households, the additional income can be oriented in two ways: in one hand to consumption of goods and services related with the conditionals of the programs; in the other hand to productive investment, because farming households are both consumption and productive units (Todd et al., 2010). Whether the rural households are liquidity constrained the investment likely around zero, but according with Todd et al. (2010): *"Beneficiaries (of CCTP) are most likely to use cash transfers for productive purposes if they are liquidity constrained and the extra cash helps overcome this constraint".*

Previous empirical evidence on the effects of conditional cash transfers programs on agriculture outcomes in Latin American countries from studies done in the case of *Oportunidades* in Mexico (Gertler et al., 2006; Todd et al., 2010) and *Red de Protección Social* in Nicaragua (Maluccio, 2010). Todd et al., (2010) using an experimental design to estimate the impacts of *Oportunidades* on several agricultural outcomes in Mexico, they find evidence that *Oportunidades* increase per capita value of production to own consumption in three *pesos* per month or about 12% (with respect to the control group). They also find that cash transfers increase per capita land used in 20%, increase in 24% livestock owned by farming households and increase by 11% per capita agricultural spending. Gertler et al., (2006) find evidence that cash transfers increase in 6% land used and in 5% livestock owned. In general, both empirical studies find evidence that *Oportunidades* have a positive impact on agricultural outcomes. Maluccio (2010), finds evidence that *Red de Protección Social* in Nicaragua have a lack effects on agricultural outcomes. In the next table (Table 1), I summarize this empirical evidence for Latin American countries.

Table 1. Literature review of the impacts of conditional cash transfers programs on agriculture.

Programs (Latin American countries)	CCTP		Estimated effects		
	Population target	Estimated % of total Income	Main direction	Magnitude on the main outcomes	Research design
Oportunidades (Mexico) (Todd et al. 2010)	Poorest households in both rural and urban areas	25%	Positive	• Increase agriculture production in 12%. • Increase in 24% livestock owned.	Experimental
Oportunidades (Mexico) (Gertler et al. 2006)			Positive	• Increase in 6% livestock owned.	Experimental
Red de Protección Social (Nicaragua) (Maluccio 2010)	Poorest households in rural areas	18%	None	Few effects on agriculture outcomes (but not significant)	Experimental

Source: Todd et al. (2010), Gertler et al. (2006), Maluccio et al. (2010).

Peruvian CCTP: *Programa Juntos*

The *Programa Juntos* was launched in late 2005 and currently has become the most important development program for poverty alleviation in Peru[2]. The program operates at the national level[3], in 1157 poorest districts in Peru (there are 1834 districts in the whole country). Targeting mechanism for selecting beneficiaries combines both geographic and household targeting, using for it indicators at districts level, such as Poverty Headcount Index and others. By targeting at the household level, program seeks to identify households below poverty line. In addition, program has established a third procedure for validating the selection of potential beneficiaries at the community level (Jones et al., 2007).

A noteworthy aspect is that *Programa Juntos* operates only in rural areas of Peru. Target population segments are households with children under 19 and/or pregnant women. In late 2014, the program was applied to 755.556 households, program delivers a fixed transfer of money from 200 *nuevos soles* (about USD70) each two months. Program deposits cash transfers in individual savings accounts at the *Banco de la Nacion* (National Bank), and are provided for at least four consecutive years (extendable by one more four-year term). Conditionals defined by *Programa Juntos* include a minimum school attendance rate of 85% per children in schooling age (between 6 to 14 years old), health checks for children less than 5 years old (vaccinations and others). Conditionals are verified by program officers every three months; any breach of them causes the suspension of cash transfer. In late 2014, about 5% of beneficiaries were suspended by the program for failure to comply with conditionals.

[2] P*rograma Juntos* budget represent about 30% of total budget of social policy in Peru.
[3] In Appendix 1, I presents the geographic coverage of Programa Juntos.

3. Methodology

Data and agriculture outcomes

In this paper, I use as the main source of data the National Household Surveys (or *ENAHO*, its acronym in Spanish), which is designed and implemented by the National Institute of Statistics (or *INEI*, its acronym in Spanish). *ENAHO* surveys are statistically representative at the national level and have a sub-sample for farming households in rural areas. In addition, using administrative information from *Programa Juntos* at district-level coverage, I could identify the districts enrolled in the program and relate that information to agricultural information from *ENAHO*. I use *ENAHO* 2005 as baseline and *ENAHO* 2009/2010 as a follow-up survey, with this information I am able to analyze the periods before and after program's intervention. I focus on the unintentional effects of *Programa Juntos* on agriculture outcomes of farming households in Peru. The following outcomes are examined three main outcomes: (i) Monetary value of total annual household agricultural production (in Peruvian currency per household); (ii) Hectares of land used to productive purposes (per household); (iii) Monetary value of total annual livestock accumulation (in Peruvian currency per household). In order to isolate the effects of prices over time, the outcomes related to the monetary values are express in real value terms per household using 2001 as price base year.

Identification strategy

The evaluation of the *Programa Juntos* offers critical challenges to the identification of a suitable counterfactual group. The selection of beneficiaries of the program was not randomly assigned; rather I use non-experimental methods to effects estimations. Another critical empirical challenge is related to data structure, because the program does not have a baseline, for it I use two rounds of data collection from household surveys (*ENAHO* 2005 as baseline, and *ENAHO* 2009/2010 as follow-up) to apply a Differences in Differences (DD) analysis. However, this database is not a pure panel data, because a panel between 2005 and 2009/2010 is not available. According to Ravallion (2008), and Chadhury et al., (2006), for this study I pooling comparable cross-section data collected over time. For DD estimation, means of the relevant outcomes need not be calculated for the same sample over time, as long as the sample involves are comparable (Ravallion, 2008). *ENAHO* database ensures comparability over time, because the sample is based on responses to similar questions collected in a similar manner; also, *Programa Juntos* has operating procedures at the district level with the same probabilistic structure and sample as in *ENAHO* databases. I include only the same districts after intervention as before, in which a random sample of districts are taken from the population over several points of time.

Given these challenges in reasonably identifying a comparable control group, I sought to explore the program's targeting rules to select beneficiaries at both district and household levels. At district level, I found that, operationally, the incidence of poverty (Poverty Headcount Index) can be useful in identifying poor districts that are not yet incorporated by *Programa Juntos*, despite being eligible districts. This is particularly true for those districts with a Poverty Headcount Index greater than 50% which could be primarily explained by unobservable factors (Jones et al. 2007). At household level, I explore the participation of beneficiary households in intervention districts, where generally the basic rule of operation is fulfilled; this means that for eligible households considered below the poverty line and with children under 14 years old and/or pregnant women, non-beneficiary households in intervention districts were excluded (these operational rules for targeting process of *Programa Juntos* are showed in Appendix 1). According to the above definitions, I attempted to estimate changes in the outcomes in eligible households in both intervention districts [D=1] (treated households) and non-intervention districts [D=0] (untreated households) overt time.

Empirical methods: Differences-in-Differences

The Differences-in-Differences (DD) estimator takes the mean of outcomes for untreated households as the counterfactual indicator for the mean of these variables for treated households. Assuming that $t = 0$ is the baseline period and $t = 1$ is the follow-up period, then Y_t^T and Y_t^{UT} represent the outcomes for treated households in intervention districts [D=1] and for untreated households in non-interventions district [D=0] in period t. The DD estimator enables one to obtain the Average Treatment Effect on the Treated (ATT) via the following relation: $ATT_{DD} = [Y_1^T - Y_0^T | D = 1] - [Y_1^{UT} - Y_0^{UT} | D = 0]$. Assuming that *ENAHO* 2005 provide a reasonable baseline for *Programa Juntos*, the DD estimator assumes that the main source of bias is caused by unobserved factors (unobserved heterogeneity), these factor are time-invariant and not correlated with treatment status (Ravallion 2008). Last assumption implies that the outcomes in comparison groups remain a common trend, which stays constant over time. Therefore, using a regression scheme, the DD estimator can be expressed as follows:

$$Y_{i,j,t} = \mu + \gamma D_j + \delta t + \alpha_{DD}(D_j * t) + \beta X_{i,j,t}\beta + \epsilon_{i,j,t} \quad (1)$$

For each farming household "i" in a disctict "j" at period t, $Y_{i,t}$ is the vector of variables of interest; D_j is a dummy variable that identifies the intervention districts as designated for *Programa Juntos*; t is a dummy variable that identifies the program intervention period (0: at 2005 and 1: at 2009/2010); $X_{i,j,t}$ represents households and districts characteristics (household expenditure, educational level, age and gender of household head, access to house assets, population density at district level, altitude at district level). $\epsilon_{i,j,t}$ is the error term. Assuming that equation (1) is correctly specified, the error term is uncorrelated with treatment and time variables, i.e.: $Cov(\epsilon_{i,t}, D_i = 0)$ and $Cov(\epsilon_{i,t}, t = 0)$; unobservable characteristics that determine participation in *Programa Juntos* do not vary over time with treatment status (parallel-trend assumption). Thus, the estimated parameter α_{DD} resulting from the interaction between D_j and t is the ATT of program on agriculture outcomes. One of the main advantages of the DD estimator is that it relaxes the assumption of conditional heterogeneity (Khandker et al., 2010). The DD estimator allow a reasonable counterfactual analysis based on the selection of two comparison groups according to unobservable characteristics, assuming a time-invariant selection (Ravallion, 2008).

However, given the identification strategy used in this study it is possible that the fundamental assumption of the DD estimator can be restrictive that is the notion of time-invariant selection bias can be implausible for targeted programs in developing countries (Khandker et al., 2010), if treated households and untreated households are not similar in terms of observed and unobserved characteristics, changes over time in the outcomes may be a function of this differences, in this context DD estimator offers a biases parameters (Jalan et al., 1998). Therefore it is necessary to properly control such initial differences that could correct the potential bias in the DD estimator; for this, a method widely suggested in the literature is the combination of DD estimator with the additional estimation of the probability of participation in a program or called the propensity scores (Khandker et al., 2010). The use of the propensity scores can improve estimations using information on observable characteristics of treated and untreated households. In this sense, first I estimate propensity scores for whole sample and then use DD estimations on the observations that remain in the common support.

According to the above, I model the probability of program participation at both district and household levels using the following probability: $P(X_{i,j}) = Pr(D = 1 | X_{i,j})$. To model the participation in *Programa Juntos* at district level I use poverty index, and to model the participation at household level I use several variables that account for observables socio-economic characteristics that can determine participation in the program, such as household expenditures, household head educational level, household access to assets, household head age, household head gender, and household access to public infrastructure. I also trim the top and bottom of two quartiles of propensity scores values in order to determine the common support region, as those values of the probability of participation that have a positive density within both D=1 and D=0 distributions (usually the top and bottom parts of the distribution) are trimmed to ensure comparability between treated and untreated units. The final common support can be defined by $\hat{S}_P = \{\hat{f}(P) > q_1; \hat{f}(P) < q_2\}$ where q_1 and q_2 are the bottom and top of the quartile propensity scores distribution, respectively.

Robustness Check

As robustness check of previous estimations, I use the Propensity Score Matching (PSM) Methods to estimate the non-parametric effects of the *Programa Juntos* on agricultural outcomes, PSM estimator is based on a single cross-sectional database from *ENAHO* 2009/2010. The PSM is useful to constructs a statistical group that is based on a model of the probability of participation in the *Programa Juntos*, conditional on observed characteristics. The key assumptions for PSM estimations are conditional independence and the presence of a common support (Rosenbaum et al., 1983). The first assumption implies that $0 < Pr(T_i = 1|X_i) < 1$, this condition ensures that treatment observations have comparison observations in the propensity score distribution. Second assumption implies that common support area can inferences be made about causality (Khandker et al., 2010). The PSM estimator for ATT can be written as (Caliendo et al., 2008):

$$ATT_{PSM} = \left[Y_i^T | T = 1, P(X)\right] - \left[Y_j^{UT} | T = 0, P(X)\right] \tag{2}$$

For each farming household “i", Y_i is the vector of outcomes, and $T_{i,t}$ is a dummy that specifies the treatment status of the household (1: if farming household belongs to *Programa Juntos*, 0: otherwise), P(X) is the vector of propensity score values. The PSM estimator differs in three ways: first, in the way that the neighborhood for each treated household is defined; second, in the way the common support problem is handled; and, third, with respect to the weights assigned to comparison households. In this paper, I use two matching algorithms: Nearest-Neighbor Matching (NNM) and Kernel Matching (KM). Using NNM, treated farming household “i" is matched to untreated farming household “j” so that:

$$\left|P(X_i) - P(X_j)\right| = \min_{k \, \epsilon \, \{T=0\}} \{|P(X_i) - P(X_k)|\} \tag{3}$$

Any farming household from the comparison group is chosen as a matching partner from a treated household that is closet in terms of propensity scores (P(X)); in my empirical work I employed a perform 1-to-1 matching without replacement, NNM uses few observations from the comparison group to construct the counterfactual outcome of a treated household. For it, I use a Kernel Matching (KM) estimator, KM is a non-parametric estimator that use weighted averages of all households in the untreated group to construct the counterfactual outcome; thus, one major advantage of the KM approach is the lower variance which is achieved because more information is used (Caliendo et al., 2008). Sample weights depend on the distance between each household from the untreated group and the treated group. The weigtht given to untreated household “i” in proportion to the closeness between “i" and “j”; Y_j^{UT} is weighted by the following equation:

$$w_{ij} = \frac{K\left(\frac{P(X_i) - P(X_j)}{h}\right)}{\sum_{j=1}^{C} K\left(\frac{P(X_i) - P(X_j)}{h}\right)} \tag{4}$$

In equation (4), one choose the kernel function (K) and the bandwidth parameter (h); in my empirical work I use an Epanechnikov Kernel Function and a bandwidth of 0.06 (Sianesi 2001). The bandwidth parameter implies a trade-off between bias and variability (variance), in particular a small bandwidth decrease bias but increase variance.

4. Empirical results

Checking the identification strategy

To mitigate potential bias in the DD estimator, I estimate the Propensity Scores (probability of treatment), those households in the common support were selected then I will process the DD estimation only using treated and untreated households with similar observable characteristics. Results of the Propensity Scores estimation are showed in Appendix 2. Before proceeding with the impact evaluation of *Programa Juntos* on agriculture outcomes, a way to test the suitability the identification strategy is to verify if this strategy is successful in capturing the effects of the program on its own conditionals, such as school attendance and health checks. The following table (Table 2) reports the differences in the means of school attendance ratio and health checks ratio of both treated and untreated groups before and after program intervention. According to the results from a basic mean test, treated households of *Programa Juntos* have a higher rate of school attendance 5% greater than do untreated at follow-up, this difference is significant statistically.

Table 2. Mean test to school attendance (children under 14)

	Treated households [D = 1]	Untreated households [D = 0]	Difference [D = 1] - [D = 0]
Baseline (2005)	62%	62%	0.00 (0.01) [0.26]
Follow-up (2009/2010)	70%	65%	0.05*** (0.01) [3.06]
Difference	0.08*** (0.01) [5.2]	0.03 (0.01) [1.74]	0.05** (0.00) [2.1]

Symbols indicate significance at *** the 1 percent level, ** the 5 percent level, and * the 10 percent level; p- value in parentheses; t-test in brackets.

Treated households have a higher rate of health checks than do untreated at follow-up, this difference is significant statistically (see Table 3). These results suggest that my identification strategy can be considered reasonable for purposes of estimating the effect of *Programa Juntos* on outcomes.

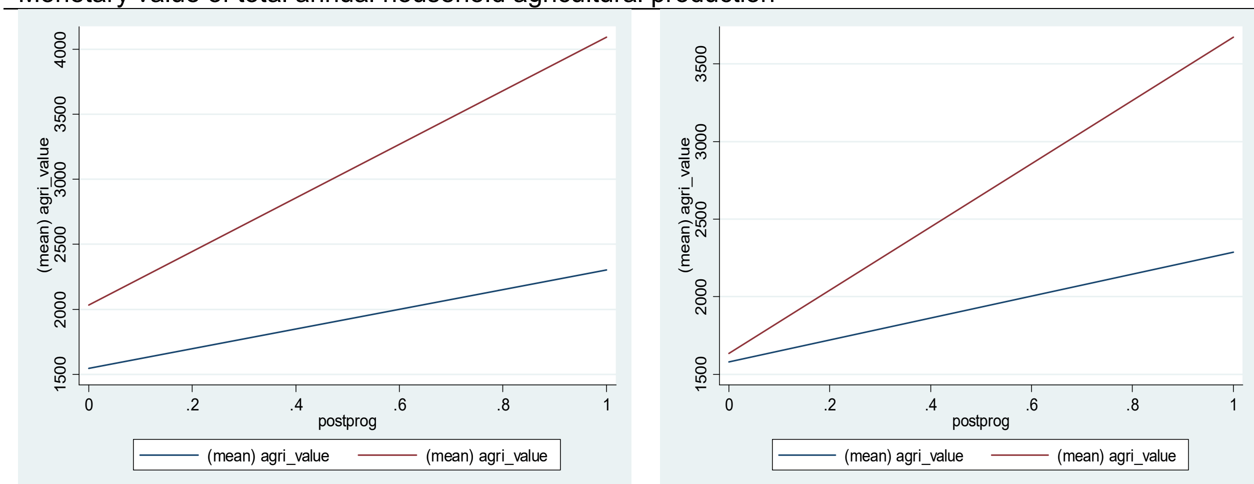
Table 3. Mean test to health checks (children under 5)

	Treated households [D = 1]	Untreated households [D = 0]	Difference [D = 1] - [D = 0]
Baseline (2005)	53%	46%	0.06** (0.03) [2.1]
Follow-up (2009/2010)	56%	34%	0.22*** (0.02) [8.81]
Difference	0.03*** (0.02) [1.19]	-0.12** (0.03) [4.56]	0.16*** (0.03) [4.10]

Symbols indicate significance at *** the 1 percent level, ** the 5 percent level, and * the 10 percent level; p- value in parentheses; t-test in brackets.

I also check whether matching between treated and untreated households based on Propensity Scores is useful to control for initial differences in agriculture outcomes. In the next combined Graph (Graph 1), I show the comparison between treated and untreated farming households before and after matching procedure, this graph shows that the matching selection of control households can be a useful strategy to improve the comparison among farming households.

Monetary value of total annual household agricultural production



Before matching *After matching*

Graph 1: Comparison among farming households before and after matching
Red line untreated households, blue line treated households.
Source: ENAHO 2005-2009/2010

Results from DD and PSM estimators
Table 4 shows the results of the average impact of *Programa Juntos* on indicators related with agricultural production. All values of the Average Treatment Effects on the Treated (ATT) are expressed per rural household and come from Differences in Differences (DD), Differences in Differences with Propensity Scores (DD with PS) and Propensity Score Matching (PSM) estimators, all econometric estimations include control variables to capture farming households heterogeneity: household size, total annual household expenditures, dummies for educational level of household head, household head age, household head gender, altitude (in meters over sea at district level), population density at district levels (inhabitants per km2), and geographical dummies in order to capture market conditions. The first three columns in Table 4 show empirical results from DD models (including the untreated group mean at baseline), and the next three columns show empirical results from PSM (including the untreated group mean at follow-up period).

According to the empirical results, I found evidence of an adverse (negative) impact of *Programa Juntos* on agriculture outcomes by poor and farming households in Peru. Statistically significant result from Difference in Difference estimators (DD and DD with PS) suggest that program reduces between 646 and 790 *nuevos soles* (around USD 226 and USD 276, respectively) the value of annual agricultural production per household. This impact represents a cumulative reduction of about 32% to 38% in agricultural production. As robustness check, empirical results from matching estimators (NNM and KM) offers similar evidence, i.e. program reduces between 1139 and 1208 *nuevos soles* (USD 400 and USD 423, respectively) the value of annual agricultural production. All of these empirical results contradict previous evidence about the impacts of conditional cash transfers programs on agriculture in Latin American and Caribbean context; in particular, Gertler et al., (2006), Todd et al., (2010) both studies found evidence of positive impacts on agriculture (see Table 1).

With respect to outcomes related to the intensification of agricultural production, I found evidence that *Programa Juntos* reduces land use for productive purposes; this result is congruent with previous findings. In particular, statistically significant results from Difference in Difference estimators (DD and DD with PS) suggest that program reduces between 5 and 1,8 hectares of land used per household. If I considered DD (with PS) estimator, the impact represents a cumulative reduction of about 32% of land used by poor and farming households in Peru. Additional empirical evidence from PSM estimators suggests that program reduces in 1,3 and 2.1 hectares the land used for productive purposes per household. These results also contradicts previous empirical research; in particular, Todd et al., (2010) found that cash transfer program in Mexico increases in 2 hectares land used for agriculture per household, which represents an increase of about 20% the land used. Finally, I found no significant evidence of a efects of *Programa Juntos* on the value of livestock accumulation. These results suggest the following question: *Which causal chains can explain this new evidence about potential negative effects of a conditional cash transfer program on agriculture?* I will explore some explanations in the following sub-section.

Table 4. Effects of *Programa Juntos* on agriculture outcomes in Peru

Agriculture outcomes	Differences-in-Differences			Propensity Score Matching		
	Untreated group mean at 2005	DD	DD with PS	Untreated group mean	NNM	KM
Value of annual agricultural production (Peruvian currency)	2034	-646** (261)	-790** (373)	3414	-1208* (660)	-1139* (782)
Hectares of annual land used	5.7	-5*** (1.2)	-1.8** (0.8)	6.3	-1.3 (0.7)	-2.1* (0.8)
Value of annual livestock accumulation (Peruvian currency)	112	-15 (39)	10 (46)	187	-49 (29)	-47* (33)
Observations		6406	3259		1590	1832

NNM: Nearest-Neighbor Matching
KM: Kernel Matching
*Significant at the 10% level;
***Significant at the 5% level.
***Significant at the 1% level.
Note: Robust standard errors in parentheses.

Understanding the negative effects of *Programa Juntos* on agriculture: exploring the effects of CCTP on labor supply

To understand the negative effects of CCTP on agriculture for the Peruvian case, I estimate the additional effects of the program on school assistance and health checks rates (conditionals for the program), also explore the effects on adult labor supply, in particular the effects of program on weekly hours worked by household head and spouse in agriculture activities. These additional effects are estimate based on the database and the identification strategy discussed previously. Table 6 shows the empirical results of the average impact of *Programa Juntos* on additional outcomes – all of which are values of Average Treatment Effects on the Treated (ATT) - which are expressed per farming household, and are obtained via the DD with PS, DD and PSM estimators (include control variables). Results suggest two key concerns about the effects of the *Program Juntos* on poor and rural livelihoods in Peru.

In one hand in Table 6, I show evidence of a strong positive effect of *Programa Juntos* on the program's conditionals. Results from my preferred estimator (DD with PS) suggests that program increase in 15% both the rate of school attendance of children under 14 year old and the rate of health checks for children under 5 years old. All of these results are congruent with previous empirical evidence for Program Juntos (see Perova et al., 2009 and Perova et al., 2011). On another hand, I show evidence that *Programa Juntos* generates a disincentive effect on adult labor supply. Statistically significant results from my preferred estimator (DD with PS) suggest that program reduces in 3 hours weekly hours worked by household head in agricultural activities (a reduction of 8% per week), while the effects on weekly hours worked by the spouse in farming households are also negative but no statistically significant. These results suggest that adult members of farming households reduce labor supply for agricultural activities and therefore a reasonable causal chain to understand the negative effect on production. Last result is congruent with the evidence offers by Fernandez and Saldarriaga (2013) for the Peruvian case, these authors evaluate specifically the impact of the *Programa Juntos* on adult labor supply, they found that program can generates a reduction of 6 hours of work per week by adults members in beneficiary households. According to Earl et al., (2008), when a household receives extra and relevant non-labor income (e.g. cash transfers) the family will tend to reduce their labor supply. An increase in non-labor income will allow the farming households to afford the same bundle of good, while working fewer hours; under these economic conditions, households have the ability to realize a higher level of utility brought on by an outward shift of the budget restriction, resulting in a higher optimal choice of booth leisure and consumption, this effect can be considered as a form of *income-effect*.

Table 6. Impact of *Programa Juntos* on conditionals and adult labor supply

Variables	Differences in Differences			Propensity Score Matching		
	Untreated group mean at 2005	DD	DD with PSM	Untreated gropu mean	NNM	KM
Program's conditionals:						
School assistance (rate)	62%	0.06** (0.02)	0.15** (0.04)	63%	0.05* (0.02)	0.07* (0.02)
Health checks (rate)	47%	0.15*** (0.04)	0.15** (0.07)	40%	0.24*** (0.04)	0.16*** (0.04)
Adult Labor supply:						
Hours worked by household head per week in agriculture	35	-2* (0.9)	-3** (1.4)	34	-1 (1)	-2* (0.9)
Hours worked by spouse per week in agriculture	21	-1 (0.9)	-1 (1.3)	23	1 (1)	1 (0.9)
Observations		6406	3259		1590	1832

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.
Note: Robust standard errors in parentheses.

6. Discussion

This paper examines the unintentional effects of *Programa Juntos* (a conditional cash transfer program in Peru) on agriculture. Using data from National Household Surveys at national level, this database permits me to use a Differences-in-Differences (DD) approach. In order to improve the comparability between treated and untreated farming households I combine Propensity Scores with DD estimator. I found evidence of potential negative effects of *Programa Juntos* on agriculture outcomes; particularly the evidence suggests that program reduces the value of agricultural production and the hectares of land use, these estimations are robust across all econometrics specifications employed. These results are opposite to previous empirical evidence for the Latin American context (Gertler et al., 2006, and Todd et al., 2010), all of these authors found positive effects of conditional cash transfers on agriculture production.

To explore some causal chains of previous results, I also estimate the effects of program on additional outcomes: program's conditionals and adult labor supply. I found that program increase the access to educational and health services of children in beneficiaries, the intentional effects of CCTP are quite positive. However, I found evidence that program reduces adult labor supply for agricultural activities. These results support the hypothesis that conditional cash transfer program can change farming households' behavior related with consumption, production and labor supply. In summary intentional effects of *Programa Juntos* on school attendance, health checks are positive. Nevertheless, unintentional effects of program on agriculture and adult labor supply are negative; a form of income-effect can generate these adverse incentives of program.

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Appendix 1. *Programa Juntos* coverage and targeting mechanism

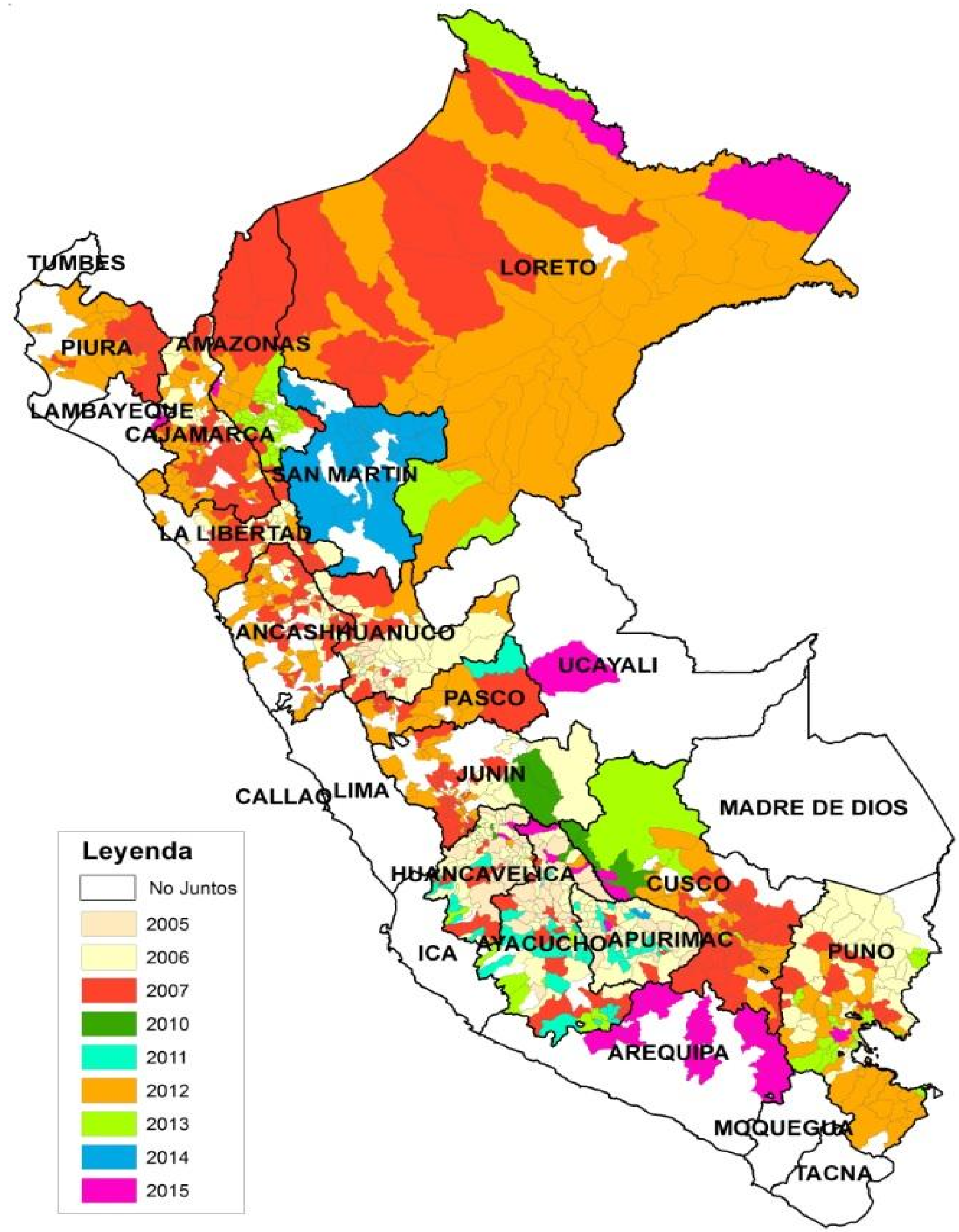


Figure A1.1: Geographic coverage of Programa Juntos

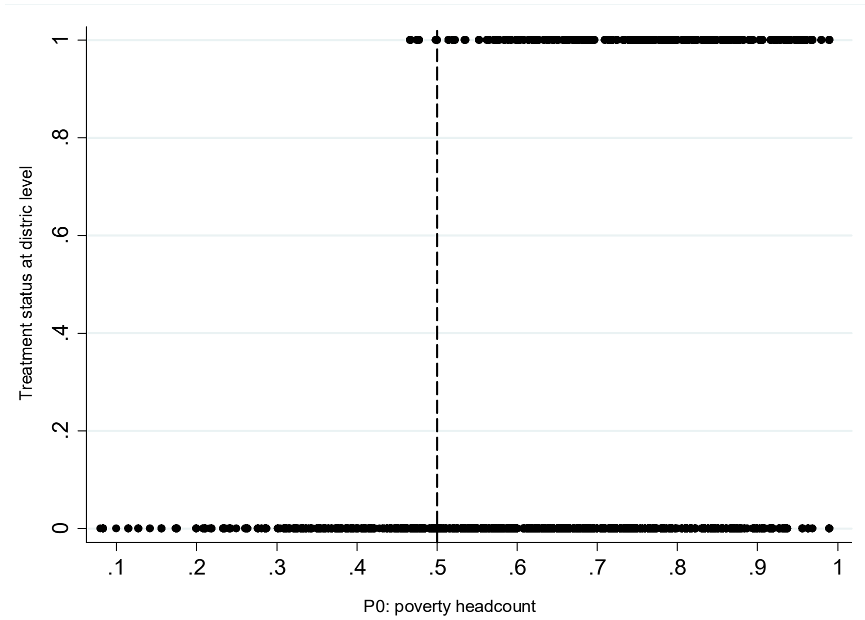


Figure A1.2: Juntos Programme, targeting-mechanism at district level
Notes: Operational rule at district level, Poverty Headcount Index.

Table A1.1: ***Programa Juntos* targeting mechanism**

Targeting-mechanism at household level		Targeting-mechanism at district level		
		Districts with P0[a] ≥ 50%		Districts with P0[a] < 50%
		[D=1]	[D=0]	
Poor households *(below poverty line)*	Households with children under 14 and/or pregnant woman	Target, treated	Target, untreated	No target
	Households without children under 14 and/or pregnant woman	No target	No target	No target
Non-poor households *(above poverty line)*	Households with children under 14 and/or pregnant woman	No target	No target	No target
	Households without children under 14 and/or pregnant woman	No target	No target	No target

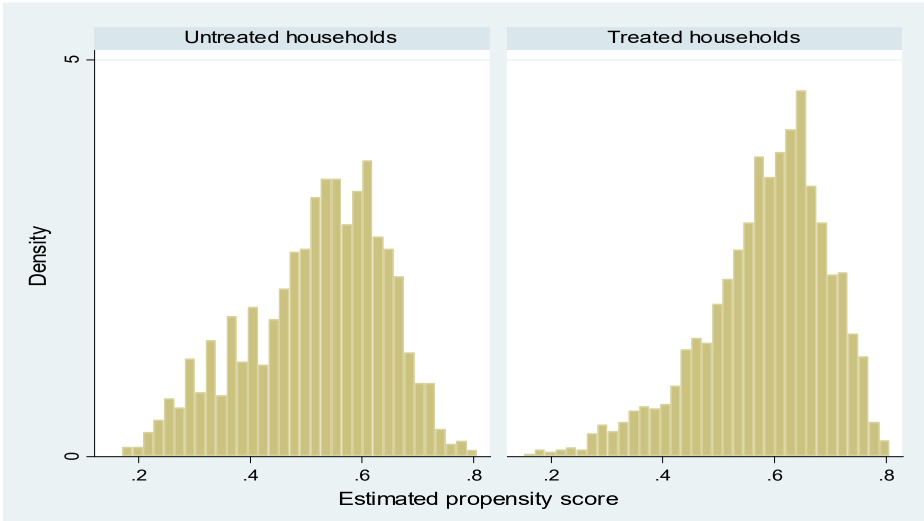
[a] P0: Poverty Headcount Index at district level.
Note: [D=1] intervention districts by *Juntos Programme*; [D=0] non-intervention districts by *Juntos Programme*. Operational rule at household level.

Appendix 2. Propensity Scores

Table A2.1: Logit model with dependend variable: 1 if the farming household belong to Programa Juntos, 0 otherwise

Covariables	Coefficients (S.D.)
Total anual household's expenditure (per cápita)	0,001 (0,00)
Educational level of household head: none	0,119 (0,109)
Educational level of household head: primary	0,088 (0,06)
Household has electricity	-0,14** (0,06)
Fuel to cook: wood	0,241*** (0,05)
Main floor material at home: land	0,558*** (0,07)
Household without sanitation services	0,232*** (0,05)
Household without piped water	0,07* (0,04)
Age of household head	-0,009*** (0,00)
Gender of household head	-0,11 (0,09)
Household has television	-0,162** (0,06)
Poverty Headcount Index at district level	1,579*** (0,41)
Altitude at district level	0,924*** (0,11)
Population density at distric level	-0,003*** (0,00)
District affected by political violence in 80's	0,016* (0,00)
Pseudo R2	0,17
Obs.	6625

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.



Graph A2.1: Propensity score distribution of treated and untreated households.