IDB WORKING PAPER SERIES Nº IDB-WP-802

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The Case of Paraguayan Farmers

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Management Division

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
Lopez, Cesar Augusto.
Agricultural input subsidies and productivity: the case of Paraguayan farmers / Cesar Augusto Lopez, Lina Salazar, Carmine Paolo De Salvo.
p. cm. — (IDB Working Paper Series ; 802)
Includes bibliographic references.
1. Agricultural subsidies-Paraguay. 2. Agricultural productivity-Paraguay. 3. Farmers-Paraguay. I. Salazar, Lina. II. De Salvo, Carmine Paolo. III. Inter-American Development Bank. Environment, Rural Development and Disaster Risk Management Division. IV. Title. V. Series.
IDB-WP-802

http://www.iadb.org

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ABSTRACT

It is a well-known fact that a great majority of countries implement agricultural input subsidies as a tool to boost agricultural productivity and output. However, even though this practice is widely spread and represents a large part of the agricultural budget, little emphasis has been placed on the evaluation of the effectiveness of such schemes. This paper aims to shed light on this issue by exploring the impact of agricultural input subsidies on agricultural productivity. Using a quasi-experimental approach (Propensity Score Matching), this study estimates the impact of receiving an agricultural input donation on the value of production per hectare as a measure of the effect on agricultural productivity. To this end, data from the "Encuesta Permanente de Hogares" of Paraguay, a nationally representative household survey collected in 2012, was utilized. The results provide evidence that agricultural input donations do not have an impact on agricultural productivity or input utilization.

Keywords: Agriculture, input subsidies, productivity, propensity score matching, Paraguay

JEL Classification: H41, O12, O13, Q12, Q18

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I. Introduction

The economy of Paraguay depends largely on the performance of the agricultural sector, with agriculture alone contributing about 20 percent of GDP over the last 10 years.[1] According to Castilleja, Garay and Lovera (2014), Paraguay's average GDP growth rate over the period 2002-2012 (3.6 percent) was higher than most of the countries in the region; however, this growth was very volatile and not sustainable in the long-term. The authors point out that the relatively low investment in infrastructure, and the underdeveloped financial system and capital markets are among the factors limiting economic growth in the country.

The most recent agricultural census (2008) reveals that out of a total of 289,649 farm units occupying 31,086,894 hectares of land in Paraguay, approximately 91 percent were family agricultural units (UAF, its acronym in Spanish) occupying 1,960,081 hectares (6 percent), of which only 4.14 percent had a registered land title.[2] Unlike commercial agriculture, small-scale producers in Paraguay are characterized by low levels of education, lack of access to modern technologies, information and capital, as well as production for family consumption (Gattini, 2011; Arce and Arias, 2015). Given the bimodal, or dualistic, structure of the agricultural system in Paraguay, and the importance of agriculture as a source of income, it is crucial to analyze and understand the effects of government policies in the sector. For example, although total government spending devoted to agricultural-related goods and services is important for agricultural development, there is empirical evidence that suggest that a re-allocation of public resources from "private goods" (subsidies) to "public goods", ceteris paribus, can have significant positive consequences on the performance of the agricultural sector in the long-run (Lopez and Galinato, 2007; Anríquez *et al.,* 2016), and consequently on sustainable economic development.[3]

Impact evaluations are an important tool for the analysis of public policies, and are increasingly being used by policy makers and practitioners for decision-making. Their main objective is to estimate the overall causal effect of an intervention or program, that is, identify whether there is a cause-and-effect relationship between the implementation of a policy and the outcome(s) of interest, estimating the change that can be directly attributable to the intervention. Nevertheless, rigorous impact evaluations in agriculture are limited in developing countries, and

[1] Agricultural value added to GDP includes: forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Based on World Bank national accounts data, and OECD National Accounts data files.

[2] The terms "family agricultural unit", "small farmers", "smallholders", "small-scale producers" and "family farmers" are often used interchangeably. In Paraguay, UFAs are defined as rural households with less than 50 hectares of land in which at least one household member works independently in agricultural activities, either as an employer, self-employed or in the form of unpaid family work (Salcedo and Guzman, 2014).

[3] The authors adopt a broad definition of "public goods" to include both pure public goods—defined as being non-excludable and non-rival in consumption—such as rural infrastructure, and private goods (subsidies) that mitigate the effects of market failures, such as public investments in plant and animal health.

Latin America and the Caribbean (LAC) is not the exception (Gónzales *et al.,* 2010; IEG, 2011; Chirwa and Dorward, 2013; Jayne and Rashid, 2013).

The objective of this case study is to evaluate the impact of government provision of private goods in the form of input donations (i.e. seeds, seedlings or other plant parts, fungicides, insecticides, fertilizers, and other agricultural inputs) on agricultural productivity.[4] For this purpose, we use a sample of small-scale agricultural producers (hereinafter simply referred to as "producers") from the 2012 round of the Paraguayan permanent household survey (EPH, its acronym in Spanish). The dataset used in this evaluation was not designed to evaluate specific agricultural public policies *per se*, but to generate statistics to study the welfare of the population over time; nonetheless, a rigorous quasi-experimental methodology was implemented with the available data to control for selection bias based on observable pre-treatment characteristics for recipients and non-recipients of agricultural input subsidies (or donations) from the government. The main objective of this microeconomic study is to shed some light on the effectiveness of input subsidy programs/projects in Paraguay. The goal is to generate conversations among practitioners, policymakers, and researchers with regards to these types of schemes and their role in promoting sustainable rural development and growth. In addition, we hope to emphasize the need for more and more rigorous impact evaluations of agricultural and rural development programs in LAC.

This study is structured as follows. Section II presents the theoretical justifications for the provision of agricultural input subsidies and a review of the existing empirical evidence of their impacts on agricultural productivity. Section III provides information regarding the characteristics of the agricultural input subsidy scheme to be evaluated. Section IV presents the methodological framework used for the impact assessment. Section V presents the data and provides descriptive statistics of the variables used in the analysis. Section VI presents the main results of the impact evaluation and section VII concludes.

II. Agricultural Input Subsidies: Theory and Evidence

The World Trade Organization (WTO) defines a subsidy as a financial contribution by a government or any public body that confers a benefit to an entity in its territory (Hoda and Ahuja, 2005). Within the agricultural sector, input subsidies have been one of the most common forms of subsidies used as policy instruments in both developed and developing countries, particularly in the 1960s and 1970s (Wiggins and Brooks, 2010; Dorward and Chirwa, 2014). Input subsidies have been implemented with the aim to overcome market failures, increase agricultural productivity, achieve social equity or for political patronage.

[4] Agricultural productivity measured as the value of production (in USD) per hectare.

Under competitive markets, conventional economic theory suggests that subsidies on private goods will cause distortions in the allocation of resources. A subsidy reduces the input price paid by the producer; the subsidy is merely a negative tax. As the price of the input decreases, the quantity demanded for the subsidized input will generally increase. The subsidy therefore, creates a wedge between the price paid by the producer and the price received by input providers. The effects of the subsidy on input demand and supply cause a deadweight loss, violating Pareto efficiency.[5]

Taking into consideration market failures and externalities, some of the concerns regarding subsidized inputs are their potential to distort the relative prices of other factors of production (such as land and labor), leakages, inhibition of the development of private supply networks, high administrative costs, and political manipulation (OECD, 2010). Another major concern is the impact that subsidized inputs have on agricultural development relative to allocating public expenditures towards the provision of public goods (e.g. rural infrastructure, market information, agricultural health). This is the case because government spending on private goods has a crowding-out effect on the supply of public goods due to budget constraints (Lopez and Galinato, 2007). For instance, using data from the rural sector for fifteen countries in LAC, Lopez and Galinato (2007) show that reducing the share of subsidies in the government's budget has, *ceteris paribus*, a large and significant impact on rural per capita income, reduces some undesirable environmental effects, and contributes to poverty reduction in the long-run.

According to the latest data from Agrimonitor, the Inter-American Development Bank's Producer Support Estimate (PSE) database for LAC, the estimated share of producers' gross farm receipts that comes from policy transfers varies across the region, ranging from an average of -32.05 percent in Argentina (2007-2011 period) to 30.19 percent in Jamaica (2006-2012 period).[6] In the case of Paraguay, the average PSE for the period 2007-2013 is 1.98 percent, which means that the estimated total value of policy transfers from consumers and taxpayers to individual agricultural producers represents 1.98 percent of total gross farm receipts.[7]

There is, however, limited empirical evidence concerning the effectiveness and efficiency of input subsidy interventions on agricultural productivity in LAC. In a preliminary evaluation of a fertilizer subsidy scheme in Guatemala, using propensity score matching with

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[5] The size of the deadweight loss and the distribution of benefits from the subsidy depend on the elasticities of demand and supply, as well as on the shifts in the demand and supply curves for the input. Elastic demand and supply tend to be associated with a larger decrease in welfare.

[6] Producer Support Estimate (PSE) (formally producer support equivalent) is the annual monetary value of gross transfers from consumers and taxpayers to agricultural producers, measured at the farm-gate level, arising from policy measures that support agriculture, regardless of their nature, objectives or impacts on farm production or income. PSE is not in itself an indicator of subsidies, but an indicator of policy supports to producers. Gross farm receipts are the value of agricultural production, plus budgetary and other transfers provided to producers.

[7] Gurria, Boyce, and De Salvo (2016).

instrumental variables methodology, IARNA and FAUSAC (2013) found evidence that participation in the program reduced average bean yields by 1.54 quintals per hectare, and had no effects on maize yields compared non-participants. Also, the program had no impact on food security or household income. The experiences of similar types of input subsidy programs in other regions, particularly in sub-Saharan Africa (SSA), have revealed mixed findings. For example, some studies have shown improvements with regards to input use (Carter, Laajaj, & Yang, 2013; Chibwana, Shively, Fisher, Jumbe, & Masters, 2014; Gine, Patel, Cuellar-Martinez, McCoy, & Lauren, 2015), as well as higher yields (Gine, Patel, Cuellar-Martinez, McCoy, & Lauren, 2015). However, the bulk of the evidence from SSA indicates that input subsidy programs are usually Pareto inefficient, that is, the costs generally outweigh the benefits (Jayne and Rashid, 2013).

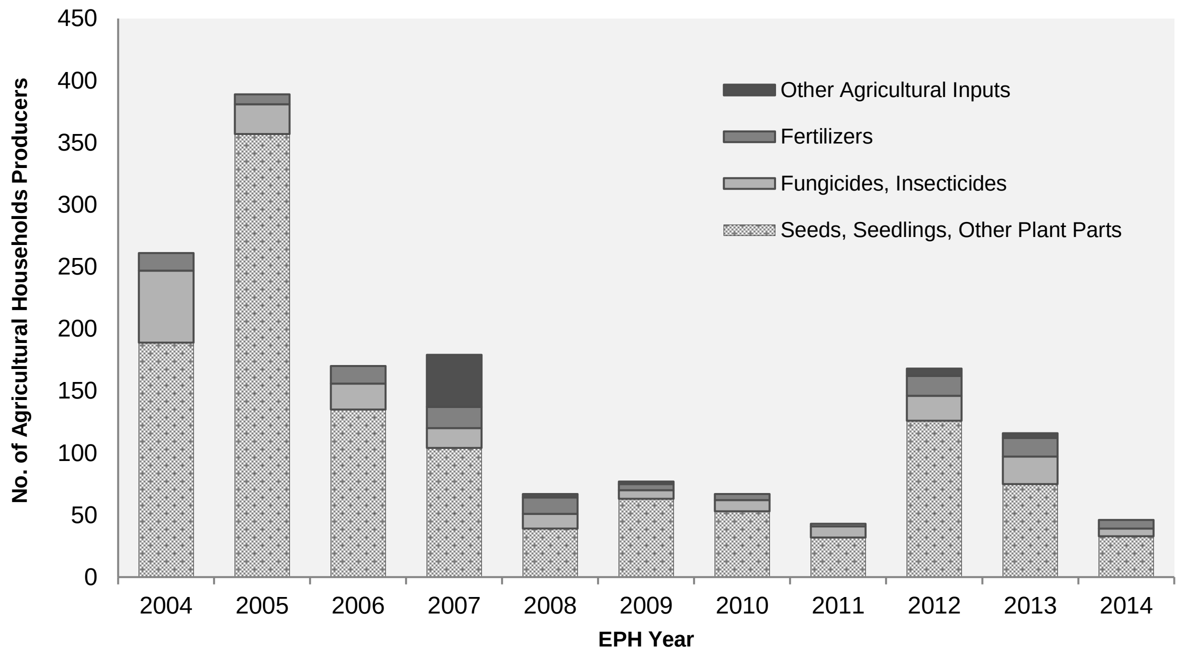
III. Agricultural Input Donations in Paraguay (EPH 2012)

This study assesses the effects of agricultural input donations on agricultural productivity in Paraguay for the year 2012 using the *Encuesta Permanente de Hogares* (EPH). More specifically, we consider the information included in a cross-sectional household survey in which agricultural producers reported receiving donations from the government and/or nongovernmental organizations (NGOs) in the form of agricultural inputs from one or more of the following categories: (i) seeds, seedlings or other plant parts, (ii) fungicides, insecticides, (iii) fertilizers, and (iv) other agricultural inputs. This question has been part of the EPH since 2004 (see Figure 1); however, for this study, we will focus on the observations from 2012.

A limitation of the data used in this analysis is the lack of information regarding the quantity of inputs received. In other words, only category-level data is available for the analysis. Furthermore, it is not possible to trace specific programs or projects through which the subsidies were delivered (for example through direct payments, input vouchers or in-kind transfers with direct distribution). Therefore, treatment in this study is defined as being a recipient of input subsidies from one or more of the above-mentioned categories.

A total of 143 producers reported receiving inputs from at least one of the four categories of agricultural inputs: 123 reported receiving inputs from only one category, 15 reported two categories, and 5 reported three categories. Table 1 presents the total number of agricultural producers receiving donations, by input category, and source (Government, NGOs, others). Most of the farmers, 88 percent, reported receiving seeds, seedlings or plant parts. Furthermore, over 90 percent of the agricultural inputs in this category were reported as government donations. Similarly, for the other three categories of agricultural inputs over 80 percent of donations came from the government rather than from NGOs and other organizations. For the rest of this study, we will limit our analysis to a sub-sample of producers who reported receiving donations from the government (n=119), excluding producers who reported receiving inputs from NGOs and/or other organizations (n=24).

Figure 1—Number of Agricultural Producers Who Reported Receiving Agricultural Input Donations (*EPH: 2004-2014*)



Source: Authors' own elaboration, EPH's 2004-2014

Table 1—Agricultural Input Donations, by Category, Area of Residence, and Provider (EPH 2012)

	Urban	Rural	Total
Seeds, Seedlings, Other Plant Parts	**8**	**118**	**126**
Government*	7	108	115
NGO	1	2	3
Other	0	8	8
Fungicides, Insecticides	**1**	**19**	**20**
Government	1	17	18
NGO	0	2	2
Other	0	0	0
Fertilizers	**0**	**16**	**16**
Government	0	15	15
NGO	0	0	0
Other	0	1	1
Other Agricultural Inputs	**1**	**5**	**6**
Government	0	5	5
NGO	0	0	0
Other	1	0	1

Source: Authors' calculations, EPH 2012
Notes: * Includes Ministry of Agriculture and Livestock (MAG), municipalities and other public institutions.

As previously mentioned, it is not possible to determine specifically from the survey data which program(s) and/or project(s) provided agricultural input donations to these producers; however, from Table 1, it is clear most donations came from the government. Among its institutional objectives and strategic framework, the Paraguayan Ministry of Agriculture and Livestock (MAG, its acronym in Spanish) includes the development of small-scale producers (e.g. family, *campesino*, community, and indigenous agriculture) as key to reducing rural poverty and increasing food security (MAG, 2012).[8] As pointed out by World Bank (2014) and Arce and Arias (2015), there are a number of programs and projects, within and outside of the MAG, without a single hierarchical dependence. In one way or another, these programs and projects support the development of small producers through the transfer of resources; these transfers are usually referred to as “donations”, “non-reimbursable investments” and other “supports”.

Since the nature of the data does not allow us to identify specifically the source of these donations, we will consider the *aggregate* number of government donations as the “intervention” to be evaluated. In other words, even though there are multiple programs and projects involved in the scheme (i.e. donations of agricultural inputs), in this study, our objective is to evaluate whether input donations from the government (regardless of the source) had an impact on the productivity of its beneficiaries or not. This is a caveat to consider when drawing conclusions from the results obtained in the evaluation. Nevertheless, given the characteristics of the input subsidy or donations (e.g. mostly seeds), the interventions share significant similarities in terms of their *theory of change* or logical sequence of effects. This assumption is particularly valid in a geographic and socio-economic context where small producers share similar characteristics and constraints. The details on the programs/projects considered for this study can be found in Appendix A.

IV. Empirical Methodology

The econometric strategy adopted to estimate the impact of agricultural input donations on agricultural productivity is a Propensity Score Matching (PSM) technique. We begin with an overview of the Neyman-Rubin model, a conceptual and statistical framework for analyzing causal effects within experimental and non-experimental studies.[9]

As with every impact evaluation, the main purpose of this study is to estimate the causal effect of the program (i.e. input subsidies) on the population of beneficiaries (i.e. small farmers). True causal effects, however, are difficult to estimate because ideally, we would like to be able to observe and measure both potential outcomes for a given agricultural producer: the outcome

[8] See Table A.1 in Appendix A for a short description of some of the main government programs and projects providing agricultural technical assistance, funding and transfer of resources in 2012.
[9] See Sekhon (2008) for a more in-depth discussion of the Neyman-Rubin model.

of the producer in the presence of the program (observed outcome) and the outcome of the same producer in the absence of the program (counterfactual).

Following the notation of Sekhon (2008), let Y_{i1} denote the potential outcome of unit i in the presence of the treatment, and let Y_{i0} denote the potential outcome of unit i in the absence of the treatment, where $i = 1, \dots, N$ denotes units observed. The individual causal effect of unit i may be written as:

$$\tau_i = Y_{i1} - Y_{i0} \quad (1)$$

The empirical challenge to identifying casual effects, commonly known as the "fundamental problem of causal inference", is one of missing data, or more appropriately, the lack of counterfactual data (Holland, 1986). For any unit i, τ_i in Eq. (1) cannot be observed directly since only one potential outcome can be observed, never both. Similarly, if we extend the logic from a single unit i to a set of units, the average treatment effect (ATE) may be written as:

$$ATE = E(\tau) = E(Y_1) - E(Y_0) \quad (2)$$

Let T_i be a binary treatment variable $T \in \{0,1\}$ equal to 1 if unit i receives the treatment and 0 otherwise. The observed outcome, Y_i, may be written in terms of potential outcomes as:

$$Y_i = T_i Y_{i1} + (1 - T_i) Y_{i0}$$

$$Y_i \equiv Y_i(T_i) = \begin{cases} Y_{i1} \text{ if } T_i = 1 \\ Y_{i0} \text{ if } T_i = 0 \end{cases}$$

The Neyman-Rubin framework states that, under random treatment assignment, an unbiased estimate of the average treatment effect can be calculated by taking the difference between the average outcomes of the treatment and control groups.[10] Stated formally, under random treatment assignment, the expected outcome of the treatment group, $E(Y_{i1} | T_i = 1)$, is equal to the expected outcome of the control group had the control group received the treatment, $E(Y_{i1} | T_i = 0)$, and vice-versa, $E(Y_{i0} | T_i = 0) = E(Y_{i0} | T_i = 1)$. The treatment and control groups created under random treatment assignment are, on average, statistically equivalent across pretreatment observable and unobservable characteristics. Any observed

[10] For the estimate to be unbiased, the Neyman-Rubin model implicitly assumes that the stable unit treatment value assumption (SUTVA) holds. SUTVA assumes treatment status of unit i will not affect the potential outcomes of the other units, and that treatment is homogeneous across units (Rubin, 1980).

differences in the outcome of interest between the treatment and the control groups may be attributed to the treatment alone.[11] Eq. (2) may be rewritten as:

$$\widehat{ATE} = \tau = E(Y_{i1} | T_i = 1) - E(Y_{i0} | T_i = 0) \quad (3)$$

$$= E(Y_i | T_i = 1) - E(Y_i | T_i = 0) \quad (4)$$

However, given the non-experimental nature of our study, agricultural producers who received input donations may differ systematically from producers who did not receive donations. Thus, evaluating the impact of agricultural input donations requires a different econometric approach to find a counterfactual scenario for producers who received donations. In line with recent evaluation literature (Imbens and Rubin, 2015), we employ the propensity score matching (PSM) method to estimate the average treatment effect on the treated (ATET), $E(Y_{i1} - Y_{i0} | T_i = 1)$.[12] The ATET may be rewritten as:

$$\widehat{ATET} = E(\tau | T_i = 1) = E(Y_{i1} - Y_{i0} | T_i = 1)$$

$$= E(Y_{i1} | T_i = 1) - E(Y_{i0} | T_i = 1) \quad (5)$$

Propensity score methods are statistical techniques used in non-experimental research studies to estimate the effect of an intervention by reducing bias due to confounding variables. The propensity score $e(X_i)$ is formally defined as unit i's conditional probability of being treated, given a set of known and observable pretreatment covariates X_i (Rosenbaum and Rubin, 1983),[13]

$$e(X_i) = Pr(T_i = 1 | X_i) = E(T_i | X_i) \quad (6)$$

Further, the authors defined the propensity score as the "coarsest" balancing score $b(X)$, where $b(X)$ is "a function of observed covariates X such that the conditional distribution of X given $b(X)$ is the same for the treated and control units", $X \perp T | b(X)$. Two assumptions are required to construct a valid control group using the propensity score: conditional independence or unconfoundedness, $(\{Y_{i1}, Y_{i0} \perp T_i\} | X_i)$, and overlap, $0 < \Pr(T_i = 1 | X_i) < 1$. Unconfoundedness asserts that when adjusting for differences in observable pre-treatment

[11] For each unit i, we observe the triple (T_i, Y_i, X_i), where X_i is a vector of [observable and unobservable] characteristics or covariates. On average, random assignment balances all potential confounding factors between treatment and control groups, eliminating bias in treatment assignment.

[12] The ATET is the average effect of the treatment on those who get the treatment. See Rubin (1977), Heckman and Robb (1985), Rosembaum (2002), and Imbens (2004) for a more in-depth discussion on estimating average treatment effects.

[13] It is assumed that given the set of pretreatment covariates X_i, treatment T_i is independent:

$$e(x) \equiv pr(T_1, \dots, T_N | X_1, \dots, X_N) = \prod_{i=1}^{N} e(X_i)^{T_i} \{1 - e(X_i)\}^{1 - T_i}$$

covariates, treatment assignment is essentially independent of the potential outcomes (Rubin, 1990). On the other hand, the overlap assumption states that for each set of pre-treatment covariates, there is a positive probability of being treated and not treated. Rosenbaum and Rubin (1983) call “strong ignorability” when both assumptions hold. With this in mind, Eq. (5) may be rewritten as:

$$\begin{aligned}\widehat{ATET} &= E(Y_{i1} | T_i = 1) - E(Y_{i0} | T_i = 1) \\ &= E[E\{Y_{i1} - Y_{i0} | T_i = 1, e(X_i)\}] \\ &= E[E\{Y_{i1} | T_i = 1, e(X_i)\} - E\{Y_{i0} | T_i = 0, e(X_i)\} | T_i = 1] \end{aligned} \tag{7}$$

In experimental studies, the true propensity score is known and defined by the study design (Abadie and Imbens, 2012), however it is not the case for this analysis. Therefore, the propensity score must be estimated using a logit or probit model; in this study, propensity scores are estimated using a probit model. This approach is useful to create balance in observable pretreatment variables between treatment and control groups, however it does not adjust for unobservable confounding variables.[14] Consequently, assuming “strong ignorability”, estimated propensity scores can be used to efficiently estimate the ATET by matching treatment and control units that are as similar as possible based on the (estimated) propensity score.

V. Data and Descriptive Statistics

This evaluation employs cross-sectional micro data for the year 2012 obtained from the *Encuesta Permanente de Hogares* (EPH). EPHs are nationally representative household surveys carried out by the national statistical office of Paraguay, General Directorate of Statistics, Surveys and Censuses (DGEEC, its acronym in Spanish), within the National Secretariat of Planning of Economic and Social Development.

The main objective of this survey is to generate indicators related to employment, unemployment, income and a set of other households and individuals economic and social characteristics. The EPH covers the entire country, except for the departments of *Alto Paraguay* and *Boquerón*, which constitute less than 2 percent of the Paraguayan population. EPH’s sampling strategy follows a two-stage cluster design with stratification at the first stage. The stratification variables are geographic departments (*Asunción* and the other 15 departments) and area of residence (urban and rural), yielding a total of 31 explicit strata. Sample selection is based on “segments” formed using the *Censo Nacional de Población y Viviendas* 2002. These “segments” are clusters representing primary sampling units (PSU) created from census

[14] Rosenbaum (2005) shows that an important task of propensity scores is to minimize unit heterogeneity, as it reduces both sampling variability and sensitivity to unobserved bias.

enumeration areas (*Áreas de Empadronamiento*) containing an average of 30 and 35 homes for urban and rural areas, respectively. Within each stratum, a pre-determined number of PSUs is selected at random, with replacement, and probability proportional to size. Within each selected PSU, a total of 12 households – subsample or secondary sampling units (SSU) - were randomly selected without replacement. These SSUs are regarded as clusters, meaning that every member of selected households was included in the survey (DGEEC, 2013, p. 132). The total sample size for the EPH 2012 was 6,024 households, approximately 66 percent urban (3,972) and 34 percent rural (2,052).

The questionnaire was composed of 8 modules and 229 questions regarding population demographic and household characteristics, international migration, education, health, employment and labor income, as well as independent agricultural and non-agricultural business activities. The agricultural module covered information about agricultural fields, agricultural machinery and equipment used, animal and livestock production, agricultural crops planted and harvested, and expenditures on agricultural inputs, among others. The information collected in the agricultural module refers to the agricultural activities of the 12 months prior to the interview date conducted between October and December of 2012.

The agricultural module is composed of 2,488 households in which at least one member worked independently in agricultural activities, either as an employer, self-employed or in the form of unpaid family work. Furthermore, 1,521 observations reported harvesting during the 12 months prior to the interview date, of which 325 were in urban areas and 1,196 in rural areas. For this evaluation, only rural producers or *campesinos* with complete information on agricultural production were examined.[15] The EPH 2012 includes detailed information on the agricultural activities of 1,184 rural producers. However, after dropping outliers, observations with missing information, and producers receiving donations from NGOs and/or other organizations, the final sample comprises a total of 1,090 producers, 119 in the treatment group and 971 in the control group.[16]

Tables 2 and 3 present summary statistics by treatment status along with t-tests of differences in means before propensity score matching Table 2 includes variables related to the

[15] The sampling design of the EPH 2012 allows for estimates with statistical confidence at the country level, urban and rural levels, and for the departments of *San Pedro, Caaguazú, Itapúa, Alto Paraná,* and *Central.* At the rural level, in addition to the previously mentioned departments, the following departments were grouped into a single category labeled rural "rest": *Concepción, Cordillera, Guairá, Caazapá, Misiones, Paraguarí, Ñeembucú, Amambay, and Canindeyú*.

[16] Two observations were dropped for producers with missing information regarding treatment status (receiving or not receiving agricultural input donations from the government and/or NGOs in the last 12 months). Moreover, 82 additional producers were discarded from the analysis after screening for univariate outliers using the *adjusted* boxplot method for skewed distributions as proposed in Hubert and Vendervieren (2008). This method uses the medcouple, a robust statistical measure of skewness, to adjust the whiskers of the boxplot. Variable distributions were examined for agricultural gross margins, household income, remittances, hectares owned, and agricultural expenditures on labor, inputs, machinery and equipment; these variables had a medcouple below 0.6 in absolute value, and all 82 detected outliers were part of the control group. Similar results were obtained when using the *generalized* boxplot for skewed and heavy-tailed distributions as proposed in Bruffaerts, Verardi, and Vermandele (2014).

demographic and socio-economic characteristics of producers in 2012. Some of the variables from Table 2 will be used as explanatory variables to estimate propensity scores, specified as a Probit model. Table 3 presents variables related to agricultural production, some of which will be used to measure program impact.

In terms of the demographic composition of producers, both groups have an average household size of 4 members and a dependency ratio of approximately 78 percent.[17] In both groups, the average age of the household head is approximately 50 years, of which about 11 percent are single, and the majority (83 percent) speaks mostly *Guaraní* at home. Treated producers have, on average, a significantly lower percentage of female-headed households (14 percent) compared to the control group (21 percent), a significantly larger percentage of literate household heads (92 percent) compared to the control group (83 percent), and a significantly lower percentage of household heads without formal education (1 percent) compared to the control group (7 percent). In both groups, the majority (51 percent) of household heads did not finish elementary school (grades 1-6), while elementary school was the highest level of education completed for approximately 28 percent of them. Furthermore, treated households have, on average, a lower but insignificant percentage of household heads that completed middle school (grades 7-9) and a significantly lower percentage of household heads that completed high school (grades 10-12) compared to the control group. Overall, household heads have an average of 5 years of formal education.

Both groups are similar with regards to household dwelling characteristics. On average, 35 percent of the dwellings have a dirt floor, and 96 percent have access to electricity. One (1) percent of the dwellings in both groups have a landline telephone; meanwhile, a significantly larger percentage of treated households own a cellular phone (93 percent) compared to the control group (87 percent). The great majority of households have a refrigerator (70 percent), but only a few (4 percent) have a computer at home.

With regards to economic characteristics, both groups share similar traits. On average, 27 percent of producers are in extreme poverty, measured as having per capita income below the cost of acquiring a basic food basket per person (336.202 PYG/person per month in 2012). The control group has a significantly larger share of households in extreme poverty (29 percent) compared to the treated group (19 percent). However, based on the *Progress out of Poverty Index* (PPI) score, producers from both groups have, on average, a 45 percent likelihood of living below the national poverty line.[18]

[17] Refers to the ratio dependents [individual < 15 or > 65 years) per working-age population (15-64 years)].
[18] See Schreiner (2012) for details on how the PPI for Paraguay was constructed. To estimate poverty rates, PPI scores were first converted to poverty likelihoods (based on the 100% National poverty line).

Table 2—Descriptive Statistics – *Before Matching*
Demographic and Socio-Economic Characteristics

		Total	Treated	Control	Diff. in Means	t
Household	Household size (# of members)	4.29	4.64	4.25	0.39	1.60
	Dependency ratio	78.54	71.18	79.48	-8.30	-0.9
Head of Household	Age (years)	50.4	51.03	50.35	0.68	0.45
	Female (0,1)	0.21	0.14	0.21	-0.08	-1.8 *
	Single (0,1)	0.11	0.09	0.11	-0.02	-0.5
	Speaks mostly *Guaraní* at home (0,1)	0.83	0.85	0.83	0.02	0.75
	Literacy (0,1)	0.84	0.92	0.83	0.10	3.34 ***
Head of Household Education	**Years of Education (#)**	5.03	5.26	5.01	0.25	0.75
	Formal education (0,1)	0.07	0.01	0.07	-0.06	-5.6 ***
	Elementary/primary incomplete (0,1)	0.51	0.52	0.51	0.01	0.23
	Elementary/primary completed (0,1)	0.28	0.32	0.27	0.05	0.97
	Middle school incomplete (0,1)	0.04	0.09	0.03	0.05	1.79 *
	Middle school completed (0,1)	0.04	0.03	0.04	-0.01	-0.9
	High school/secondary incomplete (0,1)	0.02	0.00	0.03	-0.02	-3.0 ***
	High school/secondary completed (0,1)	0.02	0.01	0.03	-0.02	-2.2 **
	More than secondary education (0,1)	0.02	0.02	0.02	0.00	0.16
Dwelling Characteristics	Dirt floor (0,1)	0.35	0.35	0.35	0.00	0.08
	Electricity (0,1)	0.96	0.97	0.96	0.01	0.44
	Landline phone (0,1)	0.01	0.01	0.01	0.00	-0.5
	Cellular phone (0,1)	0.88	0.93	0.87	0.05	2.04 **
	Computer (0,1)	0.04	0.06	0.04	0.02	0.77
	Refrigerator (0,1)	0.70	0.75	0.70	0.05	1.08
Economic Characteristics	Extreme poverty (0,1)	0.27	0.19	0.29	-0.10	-2.4 **
	Tropical livestock units (TLU)	3.88	4.79	3.77	1.02	1.48
	Progress out of poverty index (PPI) score	47.0	45.84	47.15	-1.30	-0.9
	Remittances (USD/year)	96.7	130.08	92.39	37.69	0.89
	Land under control (ha)	7.01	6.72	7.05	-0.33	-0.4
	Owned (ha)	4.37	4.63	4.34	0.28	0.50
	Rented (ha)	0.14	0.08	0.15	-0.07	-0.9
	Ceded (ha)	1.27	1.34	1.26	0.08	0.21
	Squatting (ha)	0.28	0.16	0.30	-0.14	-0.6
	Municipal and/or communal (ha)	0.95	0.51	1.00	-0.49	-0.7
	n	**1,090**	**119**	**971**		

Source: Authors' own calculations.
Notes: P-values for t-tests obtained by controlling for clusters at the enumeration area level, accounting for stratification at the department level and expansion factors or sampling weights. Significance level at the *** 1%, ** 5%, * 10%.

In addition, according to the *Tropical Livestock Units* (TLU) number, producers own, on average, 4 units of livestock, with no significant differences observed between treated and control groups.[19] In terms of remittances, producers reported receiving, on average, 96.68 USD in 2012, with no significant difference observed between treated (130.08 USD) and control (92.39 USD) groups.[20] Lastly, producers in both groups are also similar in terms of the average number of hectares of land under control (approximately 7 hectares), which includes land owned, rented, ceded, squatted and municipal/communal land.

Table 3 summarizes data on agricultural production. For instance, producers in the treated group worked significantly more hectares (2.8) of land for agricultural production compared to the control group (2.25), on average. In both groups, however, producers worked an average of 51 percent of the total number of hectares under their control. In terms of input expenditures per hectare worked, there are no significant differences between the average expenditures of both groups on agricultural inputs (i.e. seeds, seedlings, plant parts, fungicides and fertilizer), paid labor, and other agricultural production-related expenditures (i.e. oxen rental, transportation costs, storage services, operating costs, land rental, and other); however, on average, the treated group spent significantly more (34 percentage points) on machinery and equipment compared to the control group.

With respect to sales, significantly more producers in the treated group sold at least some of their production (68 percent) compared to the control group (53 percent), and the total value of sales is also significantly higher, on average, for the treated group compared to the control group. However, there is no statistically significant difference in the proportion of production sold between both groups. In the case of production for home-consumption, the treated group allocates less production for this purpose (27 percent) than the control group (34 percent). Yet, the value of production for home-consumption is significantly higher, on average, for the treated group compared to the control group.

'Value of production per hectare, one of our key outcomes of interest, suggest that the productivity of the treatment groups is, on average, not significantly different. The variable 'agricultural gross margin' was estimated by deducting variable costs of production (e.g. inputs, machinery and equipment) from total value of production for the entire agricultural cycle. On average, gross margins are lower for the treatment group (822.53 USD/ha) compared to the control group (1,159.61 USD/ha), however the mean difference is not statistically different.

Lastly, the average total household income for the treated group (7,403.28 USD), is higher than that of the control group (5,943.43 USD), although the difference is non-significant.

[19] Tropical Livestock Units (TLU) are livestock numbers converted to a common unit. Conversion factors are: oxen and other cattle = 0.7, sheep = 0.1, pigs = 0.25, goats = 0.1, horses-donkeys-mules = 0.8, hens-roosters-chickens = 0.01, other poultry animals (ducks, turkeys, geese) = 0.03, rabbits = 0.02, and beehives = 0.001. All animals are counted regardless of age, gender, or purpose.

[20] Official exchange rate: 1USD = 4,424.92 PYG (2012 average). Source: IMF, International Financial Statistics.

In per capita terms, average household income is slightly higher for the treated group, although these difference is also not statistically significant.

Table 3—Descriptive Statistics – *Before Matching*
Agricultural Production

		Total	**Treated**	**Control**	**Diff. in Means**	**t**
Land	Hectares worked (#)	2.31	2.79	2.25	0.54	2.21 **
	Prop. of ha worked (worked/total under control)	0.51	0.51	0.51	0.00	0.17
Input Expenditures	Inputs (USD/ha) (log)	1.69	1.81	1.67	0.14	0.65
	Machinery and equipment (USD/ha) (log)	0.57	0.88	0.54	0.34	2.12 **
	Expenditures on other agri. resources (USD/ha) (log)	0.74	0.80	0.73	0.06	0.37
	Paid labor (USD/ha) (log)	1.31	1.56	1.28	0.28	1.11
Sales	HH sells (0,1)	0.55	0.68	0.53	0.15	2.89 ***
	Proportion of production sold (%)	0.25	0.29	0.24	0.05	1.31
	Value of sales (USD/year)	642.67	841.70	617.15	224.6	1.26
	Value of sales (USD/year) (log)	3.32	4.26	3.20	1.05	2.88 ***
Home Consumption	Prop. of production for home-consumption (%)	0.33	0.27	0.34	-0.07	-2.9 ***
	Value of home-consumption (USD/year)	210.28	275.67	201.90	73.8	2.73 ***
	Value of home-consumption (USD/year) (log)	4.81	5.26	4.75	0.51	3.99 ***
Value of Production	Value of production (USD/ha)	1,172.5	969.4	1,198.5	-229.1	-0.6
	Value of production (USD/ha) (log)	6.23	6.22	6.23	-0.01	-0.1
	Value of production (USD/year)	1,325.5	1,698.9	1,277.6	421.3	1.93 *
	Value of production (USD/year) (log)	6.37	6.92	6.30	0.6	4.27 ***
Gross Margin	Agricultural gross margins (USD/ha)	1132.7	922.5	1159.7	-237.1	-0.7
	Agricultural gross margins (USD/ha) (log)	6.15	6.11	6.15	-0.04	-0.3
Household Income	Household income (USD/year)	6,115.2	7,403.3	5,950.0	1,453.3	1.85 *
	Household income (USD/year) (log)	8.35	8.51	8.33	0.18	1.92 *
	Household income p/c (USD/year)	1,717.2	1,758.7	1,711.9	46.79	0.24
	Household income p/c (USD/year) (log)	7.03	7.12	7.02	0.10	1.14
	n	**1,090**	**119**	**971**		

Source: Authors' own calculations.
Notes: P-values for t-tests obtained by controlling for clusters at the enumeration area level, accounting for stratification at the department level and expansion factors or sampling weights. Significance level at the *** 1%, ** 5%, * 10%.

VI. Results

This section presents the results of the propensity score approach to evaluate the effects of agricultural input donations on agricultural productivity in Paraguay, and describes the main shortcomings faced in the evaluation. The matching process was conducted as follows: First, propensity scores are estimated using the user-written Stata command –pscore–. Second, a variety of propensity score matching algorithms were used to estimate the ATET using the user-written Stata command –psmatch2– based on the propensity scores estimated in the first step.[21]

A. Propensity Score Estimation

Following Rosenbaum & Rubin (1984), the propensity score was estimated using a probit regression model, where the treatment indicator (receiving agricultural input donations) was regressed on pre-treatment (observable) characteristics X_i listed in Table 4. The model accounts for sampling weights (DuGoff, Schuler and Stuart, 2014), and geographic fixed-effects at the department level to reduce possible treatment-selection bias caused by unobservable cluster-level confounders (Arpino and Mealli, 2011). In addition, marginal effects were derived from the probit to analyze the determinants of treatment participation.

As previously mentioned, a major challenge for this evaluation was the lack of information in the EPH on the specific government program(s) and/or project(s) donating agricultural inputs in 2012. However, as pointed out by Arce and Arias (2015), there were a series of government programs and projects in 2012 that provided funding and technical assistance, including the transfer of physical resources. From Table A1 in Appendix A, we can see that they targeted family agriculture, indigenous communities and small rural producers. The inclusion criteria considered variables related to both treatment and outcome(s), and variables correlated with unmeasured confounders. As a first step, we included variables that were easily available in the EPH and known to be exogenous or time-invariant to treatment participation, such as household demographic and socio-economic characteristics.

The results in Table 4 indicate the selected household demographic characteristics are not important determinants of participation in government programs and/or projects providing agricultural input donations (hereafter referred to as program), except for households where the head speaks mostly *Guaraní* at home. The results from the participation model indicate that households where the head speaks mostly *Guaraní* at home are more likely to be recipients of agricultural input donations (5 percent).

Another significant determinant of program participation is the head of household's educational attainment. In general, the results indicate that head of households with higher level of education are more likely to participate in input subsidies programs. With regards to variables capturing socio-economic household characteristics, the results indicate producers in extreme poverty are 8.2 percent less likely to be program participants, while remittances increase the

[21] Different algorithms exist to match pairs of treated and control units using propensity scores, see Caliendo and Kopeinig (2008), and Imbens and Wooldridge (2009).

probability of participation. Finally, households who harvested *poroto* beans and *mandioca* are 5 percentage points more likely to participate in the program.

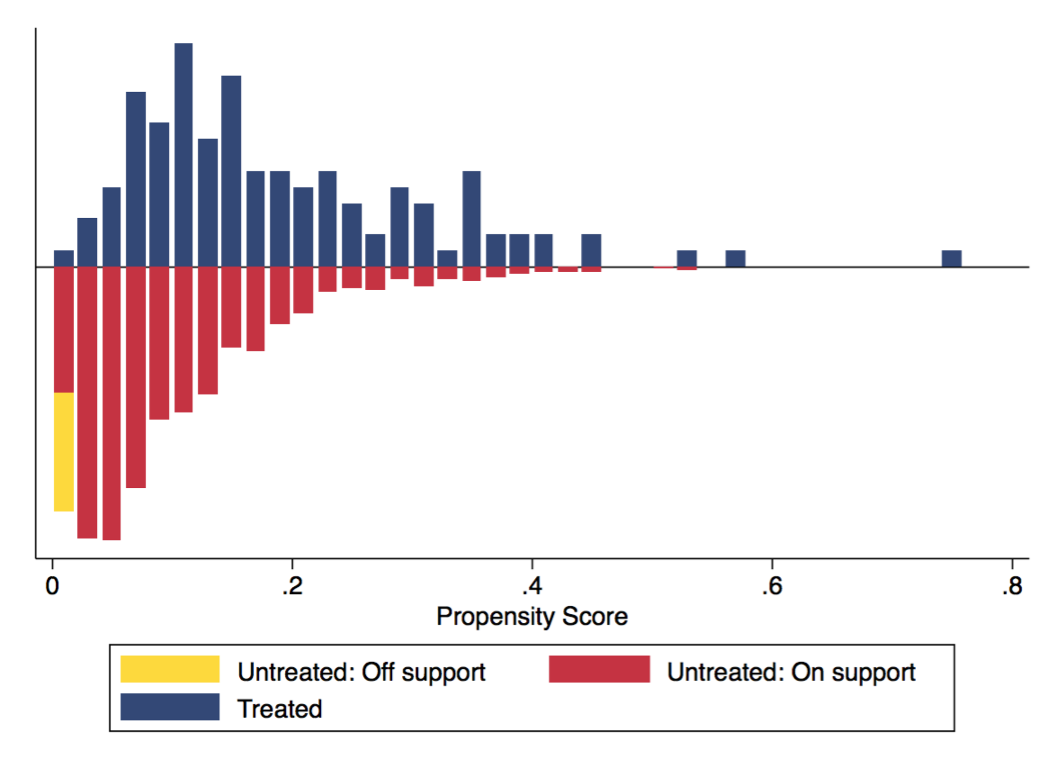
Table 4—EPH 2012 Donations: Participation Model (probit)

Covariates	**Description**	**Marginal Effects**
Household size	Number of family members	0.009 *
Head age	Age of head of household	0.006
Head age-squared	Age-squared of head of household	-0.0001
Head female	Dummy: Female-headed household	0.027
Head catholic	Dummy: Catholic head of household	0.106 **
Head single	Dummy: Single-headed household	-0.005
Head age * Head female	Interaction Variable: Head age * Head female	-0.001
Head speaks mostly *Guaraní* at home	Dummy: Head speaks *mostly* Guaraní at home	0.051
Dependency ratio	Household dependency ratio	-0.00002
Dirt floor	*Dummy*: Household with dirt floor	0.026
Electricity	*Dummy*: Household with electric energy	-0.01
Cellular phone	*Dummy*: Household with cellular phone	0.045
Landline phone	*Dummy*: Household with landline phone	-0.045
Homeownership	*Dummy*: Home owner	0.022
Computer	*Dummy*: Household with computer	0.059
Extreme poverty indicator	*Dummy*: Household in extreme poverty	-0.087 ***
Remittances	*Dummy*: Remittances	0.054 **
Hectares owned	Number of hectares owned	-0.002
Head years of education	Head of HH: Years of education (#)	0.006
Corn	*Dummy*: Household harvested corn (*chipá*, *tupí*, *pororó*)	0.027
Poroto beans	*Dummy:* Household harvested *poroto*	0.057 **
Mandioca	*Dummy:* Household harvested *mandioca*	0.057 *
dptorep1	*Dummy:* Department of San Pedro	-0.071 **
dptorep2	*Dummy:* Department of Caaguazú	-0.011
dptorep3	*Dummy*: Department of Itapúa	0.117 ***
dptorep4	*Dummy*: Department of Alto Paraná	0.021
dptorep5	*Dummy*: Department Central	0.044
	common-support (n)	***1,029***

Source: Authors' own calculations.
Notes: Average marginal effects statistically significant at the *** 1%, ** 5%, * 10% level.

Figure 2 illustrates the distribution of estimated propensity scores across treated and untreated producers before matching, where covariates listed in Table 4 have been used in the specification of the propensity score. We see that while the distributions are similar for both groups, they are right-skewed, with a high percentage of propensity scores close to zero. Propensity scores for the treatment group range from 0.0108 to 0.6522, with a mean of 0.205. For the control group, propensity scores range from 0.0006 to 0.5944, with a mean of 0.1069. Overlap in the distributions indicates substantial range of common support. A total of 74 observations were located outside of this range and therefore removed, all of them from the control group (approximately 7.6 percent of the total sample). In summary, there is common support for 1,026 observations in the data (approximately 87 percent of the original set of rural producers) and for whom causal inferences can be made.

Figure 2—Distribution of Estimated Propensity Scores across Treated and Untreated Producers Before Matching



Source: Authors' own elaboration.

B. Propensity Score-Matching (PSM)

For robustness, propensity scores of producers in treated and control groups are matched using nearest neighbor, radius, kernel and local linear regression (LLR) algorithms. The nearest-neighbor (NN) algorithm constructs the counterfactual by matching the propensity score of each treated observation to the control observation with the closest (nearest) propensity score. NN matching can be performed with or without replacement and with k-nearest neighbors (for this evaluation, we perform 1-nearest matching with and without replacement, as well as 3-nearest and 5-nearest matching with replacement). Similarly, the radius algorithm uses a specified tolerance level on the maximum propensity score distance or "caliper" to match treated observations with all control observations within the given caliper. A caliper of 0.01 was used in the case of nearest neighbor matching, and 0.01 for radius matching. Lastly, the counterfactual for each treated observation is constructed using the kernel and LLR matching algorithm by using the weighted average of the outcome(s) of virtually all control observations, depending on the specified kernel function. Weights are inversely proportional to the distance between each control and treated observation.[22] In small samples, the choice of matching algorithm involves a trade-off between bias and efficiency (Caliendo and Kopeinig, 2008).

In Table 5, we assess the quality of propensity score matching by analyzing the standardized percentage bias (% bias) and two-sample *t*-statistic across pre-treatment covariates, before and after matching. The (% bias) statistic checks for balance in covariates across treated and untreated groups in the matched sample and, unlike the *t*-statistic, it is not influenced by sample size (Austin, 2009; Harder *et al.*, 2010).[23] Before matching, large (absolute) standardized biases are observed between treatment groups across most covariates in the model. Absolute standardized bias for the unmatched sample ranges from 0.1 to 44 percent, with a mean and medium percentage bias of 12.1 and 8.1, respectively; these differences between groups are also identified by the two-sample *t*-statistics across covariates. After matching, we observe a significant (% bias) reduction in the covariates across the different matching algorithms, except for LLR. Based on these statistics, we are more confident with regards to the quality of the econometric approach in identifying a proper counterfactual. More specifically, we will concentrate on the results obtained from NN- (with replacement), radius-, and kernel-based matching algorithms.

[22] See Caliendo and Kopeinig (2008), and Imbens and Wooldridge (2009) for a more detailed discussion of each matching algorithm.

[23] The standardized bias for a covariate (continuous or binary) is defined as the difference in means between treatment groups in units of pooled standard deviation. In general, the absolute standardized bias across covariates is expected to be less than 0.05 (or 5 percent) in the matched sample(s) (Rosenbaum and Rubin, 1983). Although not a rule-of-thumb, the maximum (% bias) threshold has been suggested to be around 10 to 25 percent (D'Agostino, 1998); a large standardized bias indicates significant differences between treatment groups.

Table 5—Standardized (% bias) Difference in Means: Before & After PS Matching

Matching algorithms	before matching		*with caliper (0.01)* (1) **NN (1)**		(2) **NN (1)** w/out repl.		(3) **NN (3)**		(4) **NN (5)**		(5) **Radius** [a] cal(0.01)		(6) **Kernel** [a]		(7) **LLR** [a]	
			% bias & t-test after matching													
	% bias	**t**	**% bias**	**t**	**% bias**	**t**	**% bias**	**t**	**% bias**	**t**	**% bias**	**t**	**% bias**	**t**	**% bias**	**t**
Number of family members	**18.8**	2.0**	**12.0**	0.9	4.9	0.4	-4.5	-0.3	-0.3	0.0	0.4	0.0	3.2	0.2	2.0	0.9
Age of head of household	-1.8	-0.2	**-5.6**	-0.4	-1.9	-0.2	-4.8	-0.4	**-5.8**	-0.5	-4.3	-0.3	-4.1	-0.3	**-5.6**	-0.4
Age-squared of head of household	-4.4	-0.4	**-5.4**	-0.4	-1.5	-0.1	-4.3	-0.4	**-5.3**	-0.4	-3.5	-0.3	-3.9	-0.3	**-5.4**	-0.4
Dummy: Female-headed household	**-11.3**	-1.1	**13.4**	1.1	4.5	0.4	3.7	0.3	1.4	0.1	**5.6**	0.5	4.0	0.3	**13.4**	1.1
Dummy: Catholic Head of household	**8.9**	0.9	**-8.5**	-0.8	**-8.5**	-0.8	**-7.1**	-0.7	**-9.4**	-0.9	**-9.1**	-0.9	**-6.7**	-0.6	**-8.5**	-0.8
Dummy: Single-headed household	**-7.5**	-0.7	3.1	0.3	-3.1	-0.2	-2.0	-0.2	**-10.4**	-0.8	-4.2	-0.3	**-5.7**	-0.4	3.1	0.3
Head age * Head female	**-15.9**	-1.5	**12.8**	1.2	5.0	0.4	0.8	0.1	-2.1	-0.2	1.6	0.1	0.5	0.0	**12.8**	1.2
Dummy: Head speaks mostly Guaraní at home	**5.5**	0.6	**17.1**	1.2	**9.8**	0.7	3.3	0.3	4.9	0.4	1.4	0.1	1.2	0.1	**17.1**	1.2
Dependency ratio	**-7.5**	-0.8	3.4	0.3	-4.5	-0.3	**-10.3**	-0.8	-3.5	-0.3	-1.1	-0.1	-2.4	-0.2	3.4	0.3
Dummy: Dirt floor	**10.6**	1.1	-3.6	-0.3	1.8	0.1	-2.1	-0.2	3.7	0.3	**12.9**	1.0	**10.9**	0.8	-3.6	-0.3
Dummy: Electric energy	-3.0	-0.3	**-13.3**	-1.2	**-13.3**	-1.2	**-8.9**	-0.7	**-8.0**	-0.6	**-8.8**	-0.7	**-7.5**	-0.6	**-13.3**	-1.2
Dummy: Cellular phone	**8.7**	0.9	**5.8**	0.5	2.9	0.2	1.9	0.2	-1.2	-0.1	-4.6	-0.4	-0.8	-0.1	**5.8**	0.5
Dummy: Landline phone	-0.4	0.0	**9.3**	1.0	**9.3**	1.0	0.0	0.0	3.7	0.3	3.1	0.3	3.2	0.3	**9.3**	1.0
Dummy: Home owner	**7.7**	0.8	-3.2	-0.3	0.0	0.0	2.1	0.2	3.9	0.3	**6.0**	0.5	**5.8**	0.5	-3.2	-0.3
Dummy: Computer	**8.1**	0.9	**7.4**	0.6	**11.1**	0.9	2.5	0.2	0.7	0.1	-1.9	-0.1	1.7	0.1	**7.4**	0.6
Dummy: Extreme poverty	**-15.3**	-1.5	-4.0	-0.3	0.0	0.0	0.7	0.1	**6.4**	0.5	**6.0**	0.5	2.6	0.2	-4.0	-0.3
Dummy: Remittances	**23.6**	2.6***	**-10.7**	-0.7	**-10.7**	-0.7	**-7.5**	-0.5	-4.8	-0.3	-4.2	-0.3	-2.9	-0.2	**-10.7**	-0.7
Number of hectares owned	1.4	0.1	**-9.7**	-0.7	-4.9	-0.4	-4.9	-0.4	**-5.7**	-0.4	**-8.5**	-0.6	-4.9	-0.4	**-9.7**	-0.7
Head years of education (#)	-0.1	0.0	**-8.3**	-0.6	**5.5**	-0.4	**-7.6**	-0.6	**-8.4**	-0.6	**-12.9**	-1.0	**-10.8**	-0.8	**-8.3**	-0.6
Dummy: Household harvested corn (*chipá*, *tupí*, *pororó*)	**27.7**	2.7***	**-6.4**	-0.6	**-6.4**	-0.6	-1.4	-0.1	2.6	0.2	3.9	0.3	**5.2**	0.4	**-6.4**	-0.6
Dummy: Household harvested *poroto*	**33.9**	3.3***	3.7	0.3	3.7	0.3	4.7	0.4	**6.8**	0.5	4.4	0.4	**8.5**	0.7	3.7	0.3
Dummy: Household harvested *mandioca*	**13.1**	1.3	2.7	0.2	0.0	0.0	2.7	0.2	-1.5	-0.1	**-5.5**	-0.5	-4.3	-0.4	2.7	0.2
Dummy: Department of San Pedro	**-32.5**	-3.0***	0.0	0.0	-2.3	-0.2	-3.1	-0.3	0.5	0.0	**-7.1**	-0.6	**-10.2**	-0.9	0.0	0.0
Dummy: Department of Caaguazú	**-5.6**	-0.6	**-8.0**	-0.6	**-14.0**	-1.0	**-8.6**	-0.7	**-7.7**	-0.6	-2.5	-0.2	-1.6	-0.1	**-8.0**	-0.6
Dummy: Department of Itapúa	**44.0**	5.2***	-4.2	-0.3	-2.1	1.0	3.2	0.2	**5.8**	0.4	**6.9**	0.5	**7.6**	0.5	-4.2	-0.3
Dummy: Department of Alto Paraná	-3.0	-0.3	**11.4**	1.0	1.4	1.0	**7.6**	0.6	3.8	0.3	2.1	0.2	-0.6	0.0	**11.4**	1.0
Dummy: Department Central	**-5.2**	-0.5	**-10.1**	-0.7	**-5.1**	-0.4	-3.4	-0.3	-2.0	-0.2	0.7	0.1	2.1	0.2	**-10.1**	-0.7
Mean Bias	12.1		7.5		5.5		4.2		4.5		4.9		4.5		7.5	
Median Bias	8.1		7.4		4.9		3.4		3.9		4.3		4		7.4	

Source*:* Authors' own calculations.
Notes*:* Estimated standardized differences in absolute value. Significance level at the *** 1%, ** 5%, * 10%.
[a] Bootstrap standard errors based on 1,000 replications.

C. Impacts

Table 6 shows the results of the different PS matching algorithms and the estimated effects of agricultural input donations on agricultural productivity and related outcomes. Overall, the results indicate agricultural input donations did not have significant impacts on agricultural input expenditures per hectare, value of agricultural production per hectare or agricultural gross margin of program beneficiaries in 2012.

With regards to input expenditures, the results from our preferred matching algorithms (columns 1, 3-6) show no statistical difference between the average expenditures of beneficiaries in terms of agricultural machinery and equipment per hectare, agricultural inputs (i.e. seeds, seedlings, plant parts, fungicides and fertilizers), other agricultural resources per hectare, as well as paid labor per hectare, relative to the control group.

Also, the results from the different matching algorithms suggest that agricultural input donations had a significant impact on the total value of agricultural production for the 2011-2012 agricultural cycle (measured in USD); however, this increase did not translate to statistically significant impacts on the value of production per hectare (an indicator of productivity) and gross margin per hectare for program beneficiaries. These results are in line with Ramirez, Bedoya, and Zubieta (2015) who use data from the EPH 2002-2012 and found no effects of agricultural input donations (used as a proxy for technical assistance) on the technical efficiency of Paraguayan producers working on traditional crops (cotton, sugar cane, tobacco, sesame, soya and corn).

Table 6—The Effects of Agricultural Input Donations for Different Matching Algorithms

	Matching Algorithms	(1) NN (1) [a]	(2) NN (1) w/o repl..[a]	(3) NN (3) [a]	(5) NN (5) [a]	(6) Radius [b] cal (0.01)	(7) Kernel [b]	(8) LLR [b]
OUTCOMES								
Input Expenditures	Inputs (USD/ha) (log)	-0.06 (0.24)	-0.21 (0.22)	-0.06 (0.19)	-0.07 (0.19)	-0.01 (0.17)	-0.01 (0.17)	-0.03 (0.17)
	Machinery and equipment (USD/ha) (log)	0.16 (0.21)	0.09 (0.20)	0.11 (0.17)	0.15 (0.17)	0.23 (0.16)	0.19 (0.16)	0.17 (0.16)
	Expenditures on other agri. resources (USD/ha) (log)	0.03 (0.23)	-0.09 (0.22)	-0.06 (0.19)	-0.10 (0.18)	-0.07 (0.19)	0.01 (0.17)	-0.04 (0.17)
	Paid labor (USD/ha) (log)	0.16 (0.28)	0.16 (0.27)	0.17 (0.23)	0.07 (0.23)	0.01 (0.23)	0.08 (0.22)	0.09 (0.21)
Value of Production	Value of production (USD/ha)	302.40 (248.27)	-244.14 (562.61)	-180.75 (351.27)	-106.40 (318.20)	8.26 (260.28)	12.46 (242.67)	6.37 (242.01)
	Value of production (USD/ha) (log)	0.23 (0.12)	0.12 (0.12)	0.05 (0.11)	0.02 (0.10)	0.02 (0.09)	0.01 (0.09)	0.02 (0.09)
	Value of production (USD/year)	385.53 (374.74)	219.16 (344.91)	277.41 (262.64)	84.49 (254.98)	156.12 (239.97)	195.05 (235.20)	196.46 (222.79)
	Value of production (USD/year) (log)	0.35** (0.16)	0.29* (0.15)	0.28** (0.13)	0.21* (0.13)	0.22* (0.12)	0.26** (0.12)	0.26** (0.12)
Gross Margin	Agricultural gross margin (USD/ha)	286.86 (237.24)	-255.75 (558.04)	-195.15 (343.55)	-119.98 (309.55)	-6.05 (240.85)	0.02 (241.55)	-3.20 (230.36)
	Agricultural gross margin (USD/ha) (log)	0.26* (0.15)	0.16 (0.14)	0.07 (0.12)	0.02 (0.12)	0.00 (0.11)	0.01 (0.11)	0.01 (0.11)

Source: Authors' estimations.
Notes: ATETs statistically significant at the *** 1%, ** 5%, * 10% level.
[a] Nearest-neighbor matching with caliper (0.01).
[b] Bootstrap standard errors with 1,000 replications.

VII. Conclusion

Most countries in Latin America and the Caribbean (LAC) implement input subsidy schemes with the objective to boost agricultural productivity and therefore, rural income. In fact, the amount allocated to these programs represents an important portion of the total budget of agricultural programs in the region (Lopez and Galinato, 2007; Anríquez *et al.,* 2016). Despite this, the effectiveness and efficiency of these programs is rarely evaluated using rigorous analysis, thus creating a tendency to maintain the status quo. This case study aims to reduce this knowledge gap by examining the impact of providing agricultural input donations on the productivity of small-scale rural agricultural producers in Paraguay in 2012. Several matching algorithms were performed on the propensity scores estimated from a fixed-effects probit model using the micro data-set *Encuesta Permanente de Hogares* (EPH) 2012.

The impact analysis presented in this paper offers several useful insights regarding our understanding of the behavior of rural producers who are exposed to agricultural input subsidies in Paraguay. The results derived from the different matching methods indicate that there is no evidence of statistically significant and robust effects of agricultural input donations on input expenditures per hectare, value of production per hectare, and agricultural gross margins of program beneficiaries in 2012. Based on this, agricultural input subsidies do not appear to have an impact on agricultural productivity. This study is an important step towards developing a stock of knowledge to rigorously assess the effectiveness of this type of interventions.

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Appendix

Table A1—Summary of Government Programs and Projects in Agriculture Technical Assistance, Financing and Transfer of Resources (2010-2012)

Program Name	Objective	Period	Geographic Coverage	Components/Key Activities	Beneficiaries	Source of Information
Programa de Fomento de la Producción de Alimentos por la Agricultura Familiar (PPA)	• Increase the national production of quality food • Promote access to these foods • Support communities in socioeconomic activities (organization, technology, production, basic services, access, marketing) • Improve the incomes of family farmers	2010-2020	Nationwide coverage: 17 departments	• **Technical assistance** for production, marketing and organization • Provision of basic inputs for food production (**seeds for crops for home consumption**, small tools) • Transfer of incentives for the adoption of production technologies • Management of community services through coordination with other institutions (water, energy, roads, health, education)	• **Family Farmers** • **Indigenous communities** • **Rural households in extreme poverty**; and • Other families belonging to family agriculture through organizations	Arce and Arias (2015)
Modernization of Agricultural Supports Public Management (PAGRO)	• Contribute to the improvement of productivity and income increase of small and medium size producers	2007-2015	Nationwide coverage	• Administration and supervision • Support to technology adoption: increasing the adoption rate of environmentally appropriate agriculture technologies with positive economic returns • **Direct supports to family farming:** partially and temporarily compensate for income drop due to the elimination of supports for the supply of inputs by MAG and its decentralized institutions	• Small and medium-scale producers • Family farming	Arce and Arias (2015)
Proyecto de Desarrollo Rural Sostenible (PRODERS)	• Improve the quality of life of **small farmers and indigenous communities** in the project area in a sustainable fashion, through support measures that can strengthen community organizations and the management of natural resources, increasing the socioeconomic situation of producers and communities	2008-2013	Departments of San Pedro and Caaguazú	• **Technical assistance,** training and organizational strengthening • **Transfer of financial resources to peasants and indigenous communities** • Extension and adaptive research • Investment fund • Animal health improvement • Project management, monitoring, and evaluation	• **Small rural farmers and indigenous communities**	Arce and Arias (2015); Ministerio de Agricultura y Ganadería de Paraguay (2012)
Proyecto de Empoderamiento de las Organizaciones de los Pobres Rurales y Armonización de Inversiones - Proyecto Paraguay Rural (PPR)	• Ensure that small rural farmers and their organizations are strengthened, with access to productive resources and to the **technical and financial services** already available in the project area, and incorporating beneficiaries in the national socioeconomic development process	2007-2013	Departments of Concepción, San Pedro, Guairá, Caaguazú and Caazapá	• Building and strengthening of social capital: grouping project activities and actions for the strengthening of organizations: ○ Subcomponent for the empowerment of social and economic organizations with a **focus on gender** ○ Subcomponent of pre-investment in agribusiness and non-farm opportunities. • Coordination of productive investments, including actions to provide a **supply of technical and financial resources** to ensure the development of business plans • Policy dialogue and partnerships: includes activities for policy dialogue and knowledge management for rural development	• **Rural poor households** who in part are landless agriculture workers and in part farmers that belong to weak organizations • In some cases, cooperatives that have endured difficult circumstances	Arce and Arias (2015); Ministerio de Agricultura y Ganadería de Paraguay (2012)
Proyecto Seguridad Alimentaria para Agricultores de Escasos Recursos (2KR)	• Improving the productivity of small farmers by providing fertilizer for cultivation of the main agricultural areas of Paraguay.	2005-*indefinite period*	Throughout the Country	• Donations and sale of agricultural machinery, equipment, and inputs. • Financing for the development of socioeconomic projects.	• Small, resource-poor farmers	TIC (2012)