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WHEN A SHORT-TERM ANALYSIS IS NOT A SHORT-TERM APPROACH. IMPACTS OF AGRICULTURAL TECHNOLOGY ADOPTION IN BOLIVIA

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ABSTRACT

This paper presents the results of an impact evaluation for the CRIAR program, implemented in rural areas in Bolivia. The objective of this program is to increase the agricultural income and food security of smallholder farmers through productivity gains that result from technological adoption. We use data obtained from a sample of 1,287 households-817 beneficiaries and 470 controls- interviewed specifically for this evaluation, and rely on a methodology of Propensity Score Matching. Overall, the main impacts of the program are observed in short- and medium-term variables, including crop diversification, input use and expenditures, and variables related to sales and home consumption. For the medium-term variables, the program had a positive impact on sales at the farm gate, market sales, agricultural income from sales, and a decrease in the proportion of production allocated for home consumption. The program also had a significant and positive impact on the food security of beneficiary households. For the long-term indicators, the analysis did not identify significant impacts on productivity variables. The lack of productivity impacts is probably due to the short period after program implementation, which corresponds to only one agricultural cycle. This length of time may have not been sufficient for farmers to gain experience and knowledge with regards to their effective use of the newly acquired technologies or to adjust the production process through input changes.

Keywords: Technology Adoption; Food Security; Productivity; Propensity Score Matching; Bolivia.

JEL classifications: O13, O33, Q12, Q18

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I. Introduction

The agricultural sector plays a fundamental role in the Bolivian economy. This sector represents about 9% of the Gross Domestic Product (GDP) and employs about 40.3% of the labor force at the national level (FAOSTAT, 2014). The agricultural area in Bolivia is 3.1 million hectares of cultivated land which has been increasing significantly, expanding more than 20% from 2005 (Finance Ministry of Bolivia, 2014). This cultivated land represents about 3% of the total area of the country, out of which only 3% is arable and 10% is irrigated.

Bolivia presents a wide gap between the different productive systems that characterize the agricultural sector. Out of the 775,000 productive agricultural units in the country, 6% belong to medium and large producers while 94% belong to smallholder producers who use their land for family farming[1]. On one hand, large and medium producers rely on modern agricultural systems characterized for being capital intensive with high levels of mechanization, access to modern technologies and credit, and oriented towards exports. These units of production are mainly located in the east side of the country and produce crops such as soy, rice, sugar cane and livestock. In contrast, the family farming systems are characterized for having small parcels oriented towards home consumption, and for having low access to credit and modern productive technologies. These units of production are mainly located in the Valleys and the Altiplano producing staple crops such as potatoes, corn and cereals.

Despite the increasing expansion and the high potential of the agricultural sector, Bolivia is one of the countries with the lowest levels of agricultural productivity in the Latin America and Caribbean (LAC) region. The agricultural yields from cereal production, for example, correspond to only 57% of the average yields in South America and for the case of tubers; it reaches only 39% (FAO, 2012). Moreover, from 2006 to 2011, Bolivia was the only country in the region that presented a negative growth in total factor productivity (IFPRI, 2003). The low levels of agricultural productivity of the country are directly related to the low levels of income and the high levels of food insecurity, particularly in rural areas. Regarding income, Bolivia is one of the countries with the lowest per capita income in the region, 51% of the Bolivian population is below the poverty line, and this increases to 66% in rural areas (National Institute

[1] Jornadanet.com. 2013. "Bolivia se insertara en actividades por Año de Agricultura Familiar". La Paz, November 2013. URL: http://www.jornadanet.com/n.php?a=97329-1.

of Statistic-INE- 2009). Regarding food insecurity, Bolivia is the second country with the highest rate of malnutrition in South America at 21% (IFPRI, 2013)[2]. Moreover, 89% of the municipalities are classified by the Ministry of Agriculture as having high or medium levels of vulnerability to food insecurity (Ministry of Rural Development and Land, 2013)[3].

The main causes that lead to these low levels of agricultural productivity in Bolivia are diverse. The principal causes are: (i) low levels of investment in productive infrastructure (Hameleers, Antezana y Paz, 2011); (ii) lack of access to credit and financing in rural areas (Tejerina y Navajas 2006; Fretes-Cibils et al., 2006); and (iii) insufficient levels of innovation and technological transfer (SBI 2009; Hameleers et al., 2011).

In this context, the Government of Bolivia requested a loan from the Inter-American Development Bank in 2009 in order to implement the "*Programa de Apoyos Directos para la Creación de Iniciativas Agroalimentarias Rurales*" CRIAR). The objective of the program is to increase agricultural income and reduce food vulnerability of smallholder rural producers through two components: (i) direct support for the adoption of agricultural technologies, and (ii) support for productive entrepreneurships.

This study assesses the impact of the first component of CRIAR using a quasi-experimental approach to identify the effects of program participation in short- and medium-term indicators. Given the period of program execution, beneficiary producers were able to use their newly acquired technology only during one agricultural cycle, at most. Therefore, the impacts of technological adoption that can be attributed to program participation correspond mainly to short- and medim-term effects. However, despite this caveat, some long-term indicators have also been included in the analysis. The overall objective of this study is to provide rigorous empirical evidence on the effectiveness of agricultural programs that promote technology adoption through mechanisms that aim to counteract specific market failures. Specifically, this study analyzes the variables that characterize the technological adoption process from

[2] International Food Policy Research Institute (IFPRI) en base al Global Hunger Index 2013.
[3] Based on the Vulnerability Assesment Map (VAM) of the Bolivian Ministry of Rural Development and Land (MDRyT). This is a methodology developed by the World Food Program of the United Nations to establish the degree of vulnerability to food insecurity for a given population or geographic area. This scale categorized the municipalities in three levels of food insecurity: (VAM=1: low; VAM=2: medium; VAM=3:high).

smallholder farmers' perspective as well as the relationship that exists between technology adoption, agricultural productivity and food security.

The remainder of this paper is structured as follows. Section II presents a review of the literature regarding market failures that limit agricultural technology adoption in developing countries and the effectiveness of the interventions that aim to overcome such failures. Section III describes the CRIAR program and the executing mechanisms undertaken in order to address market failures in the Bolivian context. Section IV presents the identification strategy and the following section describes the methodology used to identify the program's impact. Section VI provides descriptive statistics of the data used in the analysis. Section VII provides the main results of the evaluation in the outcomes of interest and section VIII concludes.

II. Market Failures and Agricultural Technology Adoption

The technology adoption literature suggests various reasons that justify the provision of public services in support of technology transfer from an economic perspective. These reasons are mainly related to the presence of market failures that limit technological adoption despite the existence of private economic benefits (Jack, 2009). Specifically, Feder, Just and Zilberman (1985) identify the following market failures that limit technology adoption: (i) credit constraints; (ii) risk aversion; (iii) information asymmetries; (iv) shortage of technology providers or dysfunctional supply (thin markets); (v) low levels of human capital; (vi) poor access to infrastructure; and (vii) lack of complementary inputs. In this context, CRIAR was designed to address the first five barriers noted above.

This section presents a review of the literature and provides evidence on the presence of the aforementioned barriers and the negative impacts these might cause in the process of technology adoption in different contexts. It also presents evidence on the effectiveness of interventions that promote technology adoption by addressing some of these market failures through the provision of public goods.

The presence of liquidity constraints and credit restrictions is one of the principal factors that limit smallholder farmers' technology adoption, particularly in rural areas where financial markets are thin or non-existent. Specifically, for the case of Bolivia, Tejerina and Navajas (2006) estimate that only 7% of households have access to financial credit and 10% have savings in formal financial institutions. These percentages are lower in the case of poor households: only 5.3% have access to formal credit and 4.5% have formal financial savings. In the case of rural areas, the situation worsens as only 21.4% of the formal financial institutions in Bolivia are located in these areas (Fretes-Cibils et al., 2006). Conventionally, it is assumed that credit restrictions only affect the adoption of technologies that require a significant initial investment (indivisible investments). However, diverse studies corroborate the relationship that exists between the presence of credit constraints and the adoption of technologies that do not require a significant initial investment (Feder, Just and Zilberman, 1985; Uaiene, 2008; Dercon y Christiaensen, 2007). For instance, Simtowe y Zeller (2006) find that having access to credit increases the adoption of modern varieties of corn in Malawi. Also, Moser and Barrett (2003) provide evidence that liquidity constraints diminish the probability of adopting new technologies for smallholder rice producers in Madagascar.

The second type of market failure is risk aversion. This factor limits technology adoption because producers prefer to have certainty regarding the future yields that will be obtained with new technologies before incurring the initial cost. Thus, producers tend to postpone technology investments until they can confirm the benefits associated with the adoption of such technologies through experience from other farmers (Feder, 1980). Several studies provide evidence on the negative impact of risk aversion on technology adoption. Abadi Ghadim, Pannell y Burton (2005) show that risk aversion reduces technology adoption for chick-pea producers in Australia. Besley and Case (1994) show that farmers are less likely to adopt high-yielding cotton varieties when there is uncertainty about the economic benefits associated with them. The authors also find that farmers prefer to wait for other farmers to adopt the technology in order to learn from them and confirm their expectations.

The lack of information or information asymmetries is the third factor that limits the adoption of economically profitable technologies. Lack of information limits technology adoption not only because agricultural producers lack knowledge on the effective use of these technologies, but also because they lack information regarding location of private providers or additional costs of production. For instance, in the case of Nepal, Joshi and Pandey (2005) show that farmers' perceptions regarding different rice varieties influence adoption decisions. Therefore, the authors conclude that it is important to disseminate information broadly using different methods to form accurate perceptions of the technologies to be promoted among farmers. This is also confirmed by Adesina and Zinnah (1993) in Sierra Leone and Adesina and Baidu-Forson (1995) in Burkina Faso and Guinea. Similarly, Conley and Udry (2004) demonstrate the importance of learning and information effects on the technological adoption in Ghana. Specifically, the authors show that pineapple producers change their input use patterns only when they gain access to information regarding production yields from neighboring farmers. Foster and Rosenzweig (1996) also confirm that the lack of knowledge and imperfect information about high yielding varieties in India are important barriers for technological adoption. In the case of Bolivia, Bentley et. al (2011) measure the effect of farmers field schools where free information regarding plant health and agricultural practices is provided to farmers. The authors find that adoption rates are high (about 82%) for producers who received the information.

Another barrier that limits technological adoption is related to the shortage of private technology providers or a dysfunctional supply. The presence of thin markets of technology providers in rural regions is mainly caused by the small population density spread in remote and large areas without accessible roads and high transaction costs (IFAD, 2003). Therefore, it is not profitable for technology providers to be located in areas under these conditions without certainty about potential demand. On the other hand, it is difficult for farmers to reach technology providers as these are primarily located in urban or suburban areas.

The next barrier that limits technology adoption among smallholder farmers is the low levels of human capital characterized by low education levels and lack of technical assistance. This barrier restricts the effective use of technologies and therefore, the extraction of economic benefits related to adoption. In the case of India, Foster and Rosezweig (1996) find that households with at least one adult who finished primary school have a higher probability of adopting high yielding seeds. Similarly, using information from agricultural producers in the US, Huffman and Evenson (1993) confirm that education contributes to total factor productivity. The authors also find evidence that formal educational and technical assistance provided by rural extension workers can be substitutes.

The CRIAR program was designed to address some of these market failures and barriers that limit technological adoption by small farmers in rural areas in Bolivia. Specifically, the program aims to reduce the barriers related to liquidity constraints, risk aversion, asymmetric information, shortage of supply and low human capital. Empirical studies that provide rigorous evidence on the impact of similar programs in Latin America is scarce and presents mixed or inconclusive results, particularly with regards to smallholder producers.

Lopez and Maffioli (2008) analyze the impact of a livestock program that aims to increase livestock productivity among Uruguayan producers through technology adoption. The impact evaluation of the program "*Livestock Pilot Project I*" demonstrates that program participation led to positive impacts on the adoption of management practices. However, the authors do not find any significant impact on productivity or specialization. Gonzalez et. al. (2009) evaluate the impact of an agricultural technology transfer program "*Technological Support in the Agricultural Sector*", that aims to reduce the barriers that limit technology adoption among farmers in the Dominican Republic. The study presents evidence that the adoption of promoted technologies increases productivity levels for beneficiary producers of rice and livestock. However, the authors do not find evidence of the impact of the program on other types of producers.

Cerdán-Infantes et al (2008) analyze the impact of the PROSAP program in Argentina. This program provides extension services to grape producers financed with public resources. The authors find that the program increased the adoption of high quality varieties of grapes. Finally, Maffioli et. al (2013) evaluate the impact of the "*Programa de Reconversion y Fomento de la Granja*"(PREDEG) in Uruguay. The program provides co-financing to encourage technology adoption and boost agricultural production by smallholder and medium-size farmers. The authors find that the program increased the density of fruit planting and the adoption of improved varieties but do not find evidence of effects on productivity which is attributed to the short period of study.

Overall, the literature provides evidence on the existence of market failures and barriers that limit technology adoption in rural areas, particularly for smallholder producers. To overcome these barriers there are various types of intervention that aim to increase technological adoption rates and therefore, agricultural productivity. However, rigorous empirical studies that aim to identify a proper counterfactual to measure programs' impact present mixed evidence on the effectiveness of these interventions in Latin America. In the case of Bolivia, most of the studies that analyze technology adoption in rural settings are based on qualitative or historical analysis of particular case studies. Yet, even the few studies that use quantitative techniques, these do not identify a proper counterfactual to measure the causal impact of the intervention in the outcomes of interest (Godoy, Morduch, y Bravo 1998; Heffernan et al. 2008; Bentley et al. 2011).

This study aims to reduce the knowledge gap about the effectiveness of interventions that address market failures in order to boost technological adoption and therefore, agricultural productivity, income and food security in Latin America, particularly in Bolivia. To our knowledge, this is the first impact evaluation study that rigorously measures the effect of this type of interventions on food security in the LAC region.

III. The CRIAR Program

This study presents the results of the impact evaluation of the "*Programa de Apoyos Directos para la Creación de Iniciativas Agroalimentarias Rurales*" (CRIAR) executed by the Ministry of Rural Development and Land (MDRyT) in Bolivia. The total cost of the program was US$25 million dollars of which US$20 million dollars were financed with a loan from the Inter-American Development Bank (IDB). Although the program was approved in 2009 by the IDB, the implementation did not fully start until 2011 with a peak in 2012-2013. The overall objective of CRIAR was to improve agricultural income and reduce food insecurity of smallholder producers in rural areas in Bolivia. The program had two components: (i) direct support for the adoption of agricultural technologies, and (ii) support for productive entrepreneurships.

The first component of CRIAR provided non-reimbursable vouchers that financed 90% of the total cost of an agricultural technology chosen by the producer. The voucher also covered personalized technical assistance on the use of the selected technology in the field. To this date, the program has given 17,663 non-reimbursable vouchers to finance one of the following technologies: modern irrigation systems, traditional irrigation, fruit dehydrators, mills, pulp machines, silos, weed cutters, destemmers, electric fences, greenhouses and livestock technologies. The second component of CRIAR aimed to partially finance the cost of productive projects or entrepreneurships presented by smallholder farmers associations through business plans. The goal to finance 80 entrepreneurships was not achieved due to difficulties in the identification and consolidation of farmers associations with enough managerial capabilities to execute productive plans and commercialization schemes. For this reason, this paper focuses on the evaluation of the first component of CRIAR.

The program was implemented in five departments of Bolivia (La Paz, Cochabamba, Chuquisaca, Tarija and Potosí), focusing on 33 municipalities and 1,355 communities. The targeting of the program was based on the following criteria: (i) vulnerability to food insecurity measured with the "Vulnerability Assessment Map" (VAM); (ii) productive agricultural capacity[4]; and (iii) territorial continuity to simplify program execution. The cost of the technology covered by the program amounts to US$900, the remaining US$100 was covered by the producer. The technologies offered by the program could be divided into six groups: greenhouses, planting, harvest, post-harvest and livestock technologies. The most highly demanded technologies were for planting (76%) which mainly included modern irrigation equipment and post-harvest technologies (12%) that included mills, fruit dehydrators and silos.

The implementation of CRIAR was focused at the community level. As a first step in the implementation process, the program's executing unit contacted community leaders from the different areas to evaluate the producers' interest to participate in the program. Next, once the communities expressed their interest to participate in CRIAR, the community leader provided a list of potential beneficiaries from the community with relevant information (community roster). The executing unit then implemented technological *ferias*[5] in the field. In these *ferias* smallholder producers who were included in the community roster could approach different technology providers. Overall, 33 *ferias* were organized –one per benefited municipality- that lasted about three days each. These *ferias* were located in strategic places within the municipalities in order to be accessible for the different participant communities. During the *ferias*, the executing unit verified the eligibility of each producer and then delivered the vouchers. The producers used the vouchers during the *feria* to sign a contract of purchase with the selected provider for the chosen technology. The private provider selected by the producer had 45 working days to deliver the technology to the producer in the field. The producers were eligible based on the following criteria: (i) to present a valid identification card; (ii) to belong to the

[4] Under this criterion, mining communities were excluded from the program.
[5] Fairs.

community roster; (iii) to have agriculture as the principal economic activity; and (iv) to be a smallholder producer with less than 35 hectares of land.

Once the producers received the technology, the executing unit provided a personalized training in the field regarding the use and operation of the purchased technologies. This training aimed to foster an appropriate and effective use of the technology among farmers. Ultimately, an in-situ verification of the process of delivery and technical assistance was conducted by a private company to all benefited producers. The full cost of the technology was paid to the private provider once the verification company certified the process of delivery by the executing unit of the program.

In the specific case of CRIAR, the implementation of the program was focused on addressing the market failures that limit technological adoption for smallholder producers without creating market distortions. Specifically, the provision of a voucher that partially covers the cost of an agricultural technology aims to ease liquidity and credit constraints. On the other hand, the provision of technical assistance in the field aims to reduce the barriers related to risk aversion and low levels of human capital that limit the effective use of the technologies. Lastly, the implementation of technology ferias aimed to reduce information asymmetries and eliminate problems related to shortage of supply and thin markets by providing a physical space where demand (small farmers) and supply (technology private providers) could carry out the commercial exchange.

While the main objective of the program is to increase income and food security for beneficiary households, it is also important to understand the mechanisms through which these objectives will be fulfilled. In other words, it is crucial to identify the short- and medium-term effects that might cause the long-term impacts on outcomes related to income and food security. A priori, it is expected that technology adoption might have an impact on land allocation as farmers will transform their portfolio of crops from traditional to higher-value crops increasing their future agricultural income due to higher value of sales. Overtime, it is expected that producers acquire more experience and knowledge about the appropriate use and operation of the technology which will be translated into higher productivity (*learning by doing*). This productivity increase will also improve agricultural income as higher productivity means higher yields and therefore more sales from own harvest production. Finally, the impacts on productivity and income would improve household food security. The following sections will focus on the impact of the program on a set of indicators that capture short-term, medium-term and long-term effects.

IV. Counterfactual Identification

As with every impact evaluation, the principal problem to identify the causal effect of the program is the lack of information. Specifically, it is impossible to observe the indicator of interest (*Y*), at the same moment in time (*t=1*) for beneficiaries (*i*) with and without treatment (*CRIAR=1; CRIAR=0*) because by definition, all the beneficiaries received the program. .

$$Impact = [Yi\ (t = 1, CRIAR = 1) - Yi(t = 1, CRIAR = 0)] \quad (1)$$

Therefore, the term $Yi(t = 1, CRIAR = 0)$ is not observable because there is only information about the beneficiaries with the program $Yi\ (t = 1, CRIAR = 1)$, consequently the principal challenge consists in the identification of a counterfactual group (*j*) comparable to the treatment or beneficiary group (*i*). In other words, the control group of non-beneficiary households comparable to treated households in all their characteristics. The identification of a counterfactual will allow us to measure the average impact of the program for the treated households by comparing them with the control households.

$$Impact = [Yi\ (t = 1, CRIAR = 1) - Yj(t = 1, CRIAR = 0)] \quad (2)$$

The ideal scenario to create a control group consists on a random assignment to treatment. This ensures that treated and control households are, on average, statistically similar on all observable and unobservable characteristics. Therefore, any difference in the outcome indicators between both groups is due to participation in the program. Unfortunately, this scenario must be ruled out for this evaluation because participation in CRIAR was not randomly assigned. Moreover, the lack of baseline information makes it more difficult to identify a control group for CRIAR.

Specifically for this evaluation, the identification strategy consists on different phases that focus on replicating the selection process into CRIAR at the community and the household levels. At the community level, we identified the communities that fulfilled all the initial eligibility conditions with regards to high vulnerability to food insecurity, agricultural productive capacity, territorial continuity and that belonged to the treated municipalities. These criteria corresponds to the original conditions that determine eligibility of participant communities. Secondly, using administrative data and local knowledge from the program's executing unit, we identified control communities that fulfilled the eligibility criteria, that did not reject participation into the program and that were located within a radius of 5 kilometers from benefited communities. This proximity criterion used to select the control communities resembled the decision-making of the executing unit that was considered for selection of beneficiary communities to facilitate the logistics of program implementation (territorial continuity). Moreover, the proximity criterion assures that beneficiary and control communities have similar geographic, climatic and productive characteristics as well as with regards to access to markets and infrastructure.

Next, to determine the comparability at the household level, we perform a careful analysis of the administrative data collected by the executing unit during the creation of the roster of beneficiary households at the technology *ferias*. The administrative data contains information regarding land extension, cultivated crops and other general characteristics of the treated households. The analysis of these variables allowed us to identify a prototype of beneficiary households and elaborate a short list of questions that determined whether control households fulfilled these characteristics and therefore, could be comparable. The administration of this list of questions was part of the data collection process which allowed us to have a pre-screening of the control households and determined at first glance their comparability to treatment households.

Lastly, once the pre-screening was confirmed, the interviewer proceeded with the administration of a comprehensive agricultural household survey. The questionnaire was administered to a representative sample of beneficiary and non-beneficiary households that fulfilled the eligibility criteria and the pre-screening. The questionnaire includes all the possible variables needed to identify a proper counterfactual, including key variables that capture the process of socialization and dissemination of CRIAR as these could have determined the participation of beneficiary producers to a great extent. For instance, variables that capture participation in agricultural associations were included because the socialization of the program used these organizations as part of their dissemination strategy. Also, information that captures distance to the *feria* location was included using GPS, as the *ferias* were the physical place were vouchers were delivered and exchanged. The data collected was later used to apply a Propensity

Score Matching methodology to statistically identify non-beneficiary households that were comparable to treated households.

Overall, the strategy to establish a proper counterfactual consisted in identifying households that fulfilled all the eligibility criteria and were located in non-beneficiary communities that were comparable to the beneficiary communities. This was achieved by replicating as closely as possible the original process of selection into the CRIAR program. The lack of intervention in the communities selected in the control group was mainly due to the limited resources available for program implementation rather than to other factors that could bias the estimation of the program effect. Simply, the lack of financial resources did not allow extending the program participation to all communities within a given municipality. It is worth mentioning that communities that rejected participation into the program were excluded from the analysis despite their similarity to benefited communities in order to avoid self-selection bias at the community level. In other words, it is expected that households within communities that rejected the program could be intrinsically different to treated households and therefore, non-comparable. In consequence, the control group selected consists of a group of households that belong to non-beneficiary communities that were not offered to participate in the program because of limited resources but would have been interested to participate in CRIAR.

V. Methodology

This impact evaluation was designed and executed ex post. There was neither an impact evaluation design nor a baseline prior to program implementation. However, the data collection strategy was designed with the objective of conducting this study. Therefore, we were able to design strategies prior and during the fieldwork for identifying a control group that resembled the treatment group as closely as possible. To this end, the identification strategy consisted on four steps that resembled as closely as possible the selection process used by the executing unit in the execution of CRIAR: (i) fulfillment of criteria that determined eligibility at the community level; (ii) fulfillment of criteria that determined eligibility at the household level; (iii) pre-screening of key features that defined a prototype of program beneficiaries in the field; and (iv) implementation of Propensity Score Matching (PSM) to identify more rigorously a group of comparable non-beneficiary households and to eliminate any estimate bias arising from observable characteristics that might affect treatment allocation. This section describes the methodology in detail.

The parameter of interest in an impact evaluation is the average treatment effect on the treated (ATT):

$$ATT = [Yi\ (t = 1, CRIAR = 1) - Yi(t = 1, CRIAR = 0)] \quad (3)$$

Where $Yi\ (t = 1, CRIAR = 1)$ is the average value of the outcome of interest for treated households and $Yi(t = 1, CRIAR = 0)$ is the average value of the outcome for the control group. However, as mentioned above, it is impossible to observe the average value of the indicator for treated units under the absence of the program, which corresponds to the second term of equation (3). Because of this lack of information, it is necessary to identify a control group (j) in order to measure the impact of the program as follows:

$$\widehat{ATT} = [Yi\ (t = 1, CRIAR = 1) - Yj(t = 1, CRIAR = 0)] \quad (4)$$

The Propensity Score, which represents the conditional probability of participation into the program, identifies a counterfactual group of non-beneficiaries based on a set of observable characteristics. This method allows us to calculate a score for each of the treated and control units based on these observable variables, thus solving the problem of dimensionality. Once this score is obtained, an area of common support is identified and observations outside that area are removed. This ensures comparability between the treated and control group ($X \in S$) (Heckman, Ichimura and Todd, 1998). In mathematical notation:

$$E[Yi(t = 1, CRIAR = 0|CRIAR = 1, X \in S) = E[Yj(t = 1, CRIAR = 0|CRIAR = 0, X \in S)] \quad (5)$$

Assuming that an appropriate control group is identified, the impact of CRIAR is determined as follows:

$$Impact = E[Yi(t = 1, CRIAR = 1) - Yj(t = 1, CRIAR = 0)], X \in S \quad (6)$$

Finally, once the propensity score is estimated, the treatment effect is obtained by averaging the difference between the beneficiaries and control groups, using different methodologies for matching treated and untreated units. In short, the basic intuition is to match units through statistical processes based on exogenous observable characteristics (X) that determine the participation into the program.

The treatment effect estimations of the PSM are consistent as long as certain conditions are met. First, all differences between treated and control units must be explained exclusively by observable characteristics. This assumption is known as the conditional independence assumption or *unconfoundedness*, and is expressed as follows:

$$\left((Y_i, Y_j\ ) \perp CRIAR \,\middle|\, X\right) \quad (7)$$

This means that the PSM can be used to identify the control group as long as this conditional independence assumption prevails (Rosenbaum and Rubin, 1983).

Second, the common support assumption requires that, for each value of X, there is always a positive probability of being treated[6]:

$$0 < P(CRIAR|X) < 1 \quad (8)$$

By requiring sufficient overlap in the characteristics of the treated and control units, this condition guarantees the existence of comparable units.

If these two conditions are met ("*Strong Ignorability*"), then $\left[(Y_i, Y_j\ ) \perp CRIAR\middle|\Pr(X)\right]$, where $\Pr(X)$ is the conditional probability of participating in CRIAR, given certain observable characteristics (X) (Rosembaum and Rubin, 1983).

For this evaluation, the compliance with these conditions is based on the identification process of the control group. As discussed previously, the identification of this group was designed carefully following a strategy that attempted to replicate the original selection process using administrative data collected by the executing unit during the implementation of CRIAR, as well as data obtained on the field exclusively for this evaluation. On the other hand, with regards to the unobservable variables, taking the communities outside the coverage area of CRIAR, and discarding those who refused voluntarily to be part of the program ensures that there are not unobservable variables that affect treatment participation.

[6] By definition and rules of probability, this implies that the probability of not receiving treatment also lies between 0 and 1.

VI. Data and Background

This section presents the descriptive statistics of the data collected in the field exclusively for the impact evaluation of CRIAR. This analysis provides an overview of the socio-demographic, economic and agricultural background of program beneficiaries. It also presents a comparison between the beneficiaries and control group on key variables used later for the econometric analysis.

The data used for this study was collected by a private firm in the departments of Chuquisaca, La Paz, Cochabamba, Tarija and Potosí. An agricultural household survey was administered between November 2013 and January 2014. The questionnaire included a total of 1,287 households located in 35[7] municipalities and 176 communities (see Annex A). The sample interviewed for this purpose included a total of 817 beneficiary and 470 control households, selected from a list of beneficiary and non-beneficiaries communities which met the program eligibility criteria. A questionnaire was applied to every agricultural household in the sample.

The questionnaire, implemented in the field by the firm with the support of the executing unit and the IDB team, included 11 modules and 215 questions containing socio-demographic information of the households, education, occupation and income, information about agricultural land, crops, input use, agricultural production, access to associations or cooperatives, housing conditions and poverty, food security, and specific details about CRIAR. In addition, community-level questionnaires were applied to 170 community leaders that included 11 modules and 150 questions. This questionnaire contained information regarding population, basic community services, infrastructure and communication, accessibility to markets and nearby towns, sources of community income, seasonality of the agricultural activities, and main characteristics of agricultural and livestock production.

The information collected in the survey refers to the agricultural cycle comprised between July 2012 and June 2013. The questions asked cover information about the whole agricultural cycle – land preparation, sowing and harvesting- for all the different crops planted by the farmers. Given that the majority of the technologies financed by the program were delivered during the

[7] The two additional municipalities (just 33 municipalities participated in CRIAR, see section 3) are due to households that, when surveyed, were located in neighbor municipalities.

second semester of 2012 (80%) and only 49% of the beneficiaries had access to the technology for the entire agricultural cycle, the focus of this analysis is to capture the effect of CRIAR in short-term outcomes. A priori, it is not expected to identify significant impacts on variables of medium or long term such as income or productivity. However, these variables are also analyzed. Tables 1 and 2 present the descriptive statistics for both the beneficiary and control households in the sample. Table 1 presents the descriptive statistics of variables related to socio-economic status, household demographics, and access to social capital and distance to important places. These variables are exogenous to program participation and will be used to estimate the propensity score. Table 2 presents the agricultural variables that will be used to measure the impact of CRIAR.

Regarding the demographic composition of the sample, households have an average of 4 household members, 50% of which are age dependents (under 15 or over 65 years old). Heads of households are mostly men (89%) who considered themselves indigenous or native (74%). The average education for the head of household is 4.7 years; 14% of them do not have any level of formal education, 41% have incomplete primary, 22% have complete primary school, 14% have incomplete secondary education and 9% have complete secondary education. The treated households present lower percentage of heads of household without formal education and a higher percentage with secondary education compared to the control group. However, in the case of primary education both groups are alike. The treated households are, on average, larger, with younger heads of household (4 years younger than the control), a higher percentage of indigenous or native households (5%), a higher percentage of female-headed households (6%), a lower percentage of single heads of household (11%), and a higher percentage of its members carrying out some type of agricultural work (10%).

With respect to the household dwellings, the prototype of households in the sample has two rooms (including a dining room) and most of them have dirt floor (63%). While access to electricity is rather widespread with 76% of households using electricity in their homes, only 15% have a refrigerator. With regards to access to information, the main means of access are radio and television (89% and 58% respectively). Access to information via internet or having a computer is extremely rare and corresponds to 2% of households in the sample. On average, households in the treated group show better housing conditions compared with the control group.

Table 1: Descriptive Statistics – Socio-Economic Status of Households

	Variables (units)	Total	Treated	Control	Diff. in Means
Household	Household Size (# members)	4.23	4.39	3.97	0.42***
	Dependency Ratio	1.05	1.04	1.08	0.04
	Members in agricultural work (%)	0.26	0.3	0.2	0.10***
Head of Household	Age (years)	50.39	48.97	52.86	3.89***
	Woman (0,1)	0.11	0.09	0.15	0.06***
	Single (0,1)	0.21	0.16	0.27	0.11***
	Indigenous or native (0,1)	0.74	0.76	0.71	0.05**
Education of the Head of Household	Education (years)	4.74	5.21	3.92	1.29***
	HH without formal education (0,1)	0.14	0.11	0.21	0.10***
	HH with primary incomplete (0,1)	0.41	0.43	0.42	0.01
	HH with primary complete (0,1)	0.22	0.22	0.22	0
	HH with secondary incomplete (0,1)	0.14	0.16	0.1	0.06***
	HH with secondary complete (0,1)	0.07	0.09	0.04	0.05***
	HH with more than secondary (0,1)	0.02	0.03	0.01	0.01
House Characteristics	Size (number of rooms)	2.51	2.63	2.32	0.31***
	Dirt floor (0,1)	0.63	0.6	0.68	0.08***
	House with electric energy (0,1)	0.76	0.78	0.72	0.06**
	House with freezer (0,1)	0.15	0.15	0.14	0.01
	Radio as main source of information (0,1)	0.89	0.9	0.87	0.03*
	TV as main source of information (0,1)	0.58	0.62	0.5	0.12***
	Internet as main source of information (0,1)	0.02	0.01	0.03	0.02***
Associativity	Household belongs to an agric. cooperative (0,1)	0.08	0.11	0.04	0.07***
Economic Status	Agriculture as main source of income (0,1)	0.7	0.71	0.67	0.05
	Agricultural income (% of total income)	0.56	0.57	0.56	0.01
	Access to formal credit (0,1)	0.08	0.09	0.07	0.02
	Voluntary savings (0,1)	0.06	0.07	0.04	0.03
	Remittances (US$ year/HH)	394.5	369.28	438.34	69.06
	TLU	4.89	4.8	5.06	0.26
	Household with land tenure (0,1)	0.99	0.99	0.99	0
	Land owned by HH (Has)	2.35	2.29	2.45	0.16
	PPI Score	29.32	29.6	28.84	0.76
Access to *Ferias*	Time to paved road (logs)	1.95	1.98	1.91	0.07
	Distance to *feria* CRIAR (km)	13.78	12.62	15.82	3.2***
	N	**1,287**	**817**	**470**	

Difference in means is significant at the *** 1%, ** 5%, * 10% level

Regarding social capital variables, participation to agricultural cooperatives differs significantly between treated and control households. Specifically, the treated group has a higher percentage of households who belong to a cooperative or an agricultural association (7%).

With respect to the economic status, 70% of the households have agriculture as the main source of income, and it represents on average 56% of the total household income. The average extent of land owned by households is 2.35 hectares and the index number of cattle in *TLU* (*Total Livestock Units*) shows that, on average, households have 5 livestock units. Regarding access to credit and financial services, only 8% of households reported having received formal credit and 6% reported having voluntary savings in financial institutions. The remittances received by households in the sample amounted to US$394 per year on average. The *Progress out of Poverty Index* (*PPI* index; see Appendix B for details) which captures the probability that a household has an income below the poverty line shows that for this sample, the probability equals 83%, with no significant differences between the beneficiary group and control group. None of the economic variables present significant differences in means between the treated and control groups.

Finally, as expected, households in the treated group are 3.2 km closer to the technology *ferias* held by the executing unit. This difference is statistically significant between both means. On the other hand, the difference in time to a paved road is not statistically significant between the two groups.

The context described above confirms the existence of various types of barriers that can potentially limit technological adoption by small farmers in Bolivia. In particular, the inaccessibility to credit markets, the lack of access to information, the presence of liquidity constraints and the low level of education are the most important.

With respect to agricultural production (Table 2), the extent of the plots worked by these farmers reaches 2.11 hectares on average, 43% of farmers work one hectare or less of land, 34% work between 1 to 3 hectares, 13% work between 3 to 5 hectares, and the remaining 10% work between 5 to 10 hectares. None of the variables related to extension of agricultural land show significant differences between treatment and control groups.

In regards to the portfolio of crops cultivated by the farmers, 28% of households reported working traditional crops exclusively. The average proportion of land allocated to traditional crops in the sample is 66%[8] of total land cultivated. Only 19% of farmers in the sample have

[8] Traditional crops are rice, barley, corn, quinoa, wheat, *oca*, potato and cassava.

modern irrigation systems on their land, and it covers about 10% of the total land worked. With respect to the use and application of inputs, 91% of households apply organic fertilizer, 41% use chemical fertilizer, 49% use insecticides, 25% apply herbicides and 24% use fungicides. In turn, 88% used agricultural machinery and equipment[9], and 41% used paid labor for agricultural work. Compared with the control group, beneficiary households show a higher use of modern irrigation systems, a higher proportion of land allocated to non-traditional crops, a higher use of agricultural machinery as well as insecticides and herbicides. Expenditures on fertilizers, insecticides, herbicides and fungicides, as well as expenditures on machinery and agricultural equipment are also higher, on average, for treated households. The difference in labor expenses, however, is not significant between the two groups.

The agricultural production of these households is mainly used for home consumption. Specifically, 36% is destined for home consumption while 24% is sold. The remaining is distributed among seeds (10%), losses (10%), animal consumption (8%) and other uses (12%). Within households that sell at least one crop (74%), 50% sell in the market, and the rest sell their production on the farm to intermediaries. Regarding the variables of production use and allocation, the treated group has a higher proportion of households that sell their produce (both in markets and on the farm), higher proportion of production sold, and a higher proportion of the output destined for market sales compared with control households. At the same time, income from agricultural sales of beneficiary households is US$233 higher than for the control group. Finally, beneficiary households show a lower proportion of their production destined to home consumption.

[9] Agricultural machinery and equipment comprise cultivators, weed cutters, mechanical harvesters, hammer mills (gas or electric), irrigation and solar pumps.

Table 2: Descriptive Statistics – Agricultural Production and Food Security

	Variables (unit)	Total	Treated	Controls	Diff. in Means
Land	Hectares worked (Has)	2.11	2.09	2.16	0.07
	Proportion of hectares worked (Has/totalHas)	0.82	0.83	0.81	0.02
Crop Portfolio	Traditional Crops (0,1)	0.28	0.24	0.36	0.12***
	Proportion of land with traditional crops (%)	0.66	0.62	0.74	0.13***
Irrigation	Modern Irrigation (0,1)	0.19	0.23	0.11	0.12***
	Proportion of land with modern irrigation	0.10	0.13	0.05	0.07***
Input Use	Use of fertilizer (0,1)	0.91	0.91	0.91	0.00
	Use of chemical fertilizer (0,1)	0.41	0.39	0.43	0.04
	Use of insecticide (0,1)	0.49	0.45	0.55	0.10***
	Use of herbicide (0,1)	0.25	0.26	0.23	0.03**
	Use of fungicide (0,1)	0.24	0.26	0.22	0.04
	Use of machinery and equipment (0,1)	0.88	0.91	0.83	0.08
	Use of paid labor (0,1)	0.41	0.42	0.39	0.02
Input Expenditures	Machinery and equipment (US$/HA (logs))	0.93	1.01	0.81	0.20**
	Paid labor (US$/HA (logs))	2.15	2.23	2.01	0.22
	Inputs - FIHF (US$/HA (logs))	4.37	4.52	4.12	0.39***
Sales	HH sales (0,1)	0.74	0.77	0.69	0.08***
	Proportion of production sold (%)	0.24	0.25	0.21	0.05***
	HH sales in the market (0,1)	0.50	0.52	0.47	0.05**
	Proportion of production sold in the market	0.32	0.33	0.30	0.03**
	HH sales in farm (0,1)	0.50	0.53	0.46	0.07**
	Proportion of production sold on-farm (%)	0.20	0.20	0.19	0.01
	Agricultural Income from Sales (US$/HH)	538.04	619.65	396.18	223.47***
	Agricultural Income from Sales (logs)	4.08	4.31	3.69	0.63***
Home Consumption	Proportion home-consumption (%)	0.36	0.34	0.39	0.05***
Value of Production	Value of production US$/HA (logs)	7.69	7.79	7.52	0.28***
Gross Margins	Gross Margins US$/HA (logs)	7.08	7.14	6.97	0.17
Food Insecurity	Food Insecurity (FAO Index)	0.58	0.57	0.59	0.02*
	N	**1,287**	**817**	**470**	

Difference in means is significant at the *** 1%, ** 5%, * 10% level

On average, the value of agricultural production is US$2,186 per hectare while the agricultural gross margin is US$1,187 per hectare. The treated group shows a higher value of production and gross margins, although the mean difference is statistically significant only in the case of the value of production.

In order to obtain a measure of food security at the household level we use the index of food insecurity developed by FAO and based on the Latin American and Caribbean Food Security

Scale (ELCSA by the Spanish acronym). This index consists of a list of 15 questions that capture the degree of households' accessibility to food capturing objective (number of meals per day, variety of food) and subjective assessments (concern for food deprivation)[10]. According to this index, 58% of households in the sample are food insecure; this percentage is 2 points lower for the treated households compared to the control group.

Lastly, table 3 shows the descriptive statistics at the community level from the questionnaire applied to community leaders. The variables related to basic infrastructure and public services indicate that only 8% of the communities have a public hospital or health center, 84% have primary school and only 1% have a formal financial institution within the community. With respect to communication and transportation, 41% of communities have public transportation and 12% have a paved road that connects with the provincial capital. The average travel time from these communities to the largest market in the area is 133 minutes (2.2 hours)[11]. Finally, variables referring to agricultural and productive activities show that 98% of communities consider agriculture as their main source of income, 15% of them have an association or agricultural cooperative, 58% have access to water for irrigation, and 46% have water for irrigation continuously throughout the year.

Table 3: Descriptive Statistics – Communities Characteristics

Variables (unit)	**Total**	**Treated**	**Control**	**Diff. in Means**
Community with hospital or health center (0,1)	0.08	0.09	0.07	0.02
Community with primary school (0,1)	0.84	0.84	0.85	0.01
Community with formal financial institution (0,1)	0.01	0.01	0.00	0.01
Community with public transportation (0,1)	0.41	0.40	0.48	0.09
Community with paved road (0,1)	0.12	0.13	0.09	0.04
Time between community and nearest market (min.)	132.78	129.63	145.61	15.98
Community with agricultural cooperative (0,1)	0.15	0.17	0.06	0.11
Community with agriculture as main source of income (0,1)	0.98	0.98	0.97	0.01
Community has access to water for irrigation (0,1)	0.58	0.60	0.48	0.12
Community has access to water for irrigation throughout the year (0,1)	0.46	0.46	0.45	0.01
N	**167**	**134**	**33**	

Difference in means is significant at the *** 1%, ** 5%, * 10% level

[10] At an international symposium organized by the FAO in 2012, this index was chosen as the most robust, reliable and scientifically valid from 5 other proposals discussed. Also, the index is one of the fastest and cost-effective when collecting information on the field.

[11] This is considered under the most common means of transport for each community.

The last column of table 3 presents the difference in means between treated and control communities. The evidence shows that the selection process was successful as control communities are comparable to the treated ones. Specifically, the differences in means between treated and controls are small in magnitude, and none of them is statistically significant.

VII. Results

VII.I Propensity Score Estimation

This section presents the results to the participation model used to estimate the propensity score. As mentioned, the propensity score represents the probability of participating in CRIAR, therefore, the definition and estimation of the participation model is the first step for the PSM estimation. Towards this end, a binary choice model must be estimated in which the dependent variable is $Y = 1$ for treated households and $Y = 0$ for the controls. The independent variables in this regression will be included in the vector X. In general, this vector should be composed by variables that determine participation in CRIAR but which are not affected by program participation (exogenous variables). The vector X should include variables that capture the eligibility criteria as well as variables that control for possible self-selection bias (education, social capital, etc.) and administrative selection bias (distance to the nearest road or market).

In order to select which variables to include in the participation model, a careful analysis of the socio-demographic, economic and agricultural household variables in the sample was done. Specifically, variables related to household composition, head of household characteristics (gender, age, education, etc.), and wealth (access to credit, savings, household assets, remittances, household livestock, PPI score) were included in the participation model. This set of variables attempt to capture the demographic and socio-economic status of the households. Furthermore, geographic fixed effects were included at the municipality level as a proxy to control for climatic and soil quality. These variables also represent a basic criterion for eligibility of communities in the program. Finally, we included variables related to the processes of diffusion and socialization of CRIAR, such as distance to program dissemination events (*ferias*) and participation in agricultural associations. It is considered that these variables are crucial determinants of participation in the model as the process of socialization and dissemination of CRIAR was performed through the *ferias* as well as through agricultural associations. Therefore, it is expected that these variables have influenced to a large extent, the participation of beneficiary households.

The following equation presents the estimated participation model that predicts the probability of being a beneficiary of CRIAR:

$$\Pr(CRIAR = 1|X) = \alpha + \beta \sum Z_i + \delta \sum HH_i + \rho A_i + \gamma \sum W_i + \tau \sum D_i + \varphi \sum G_i + \varepsilon_i \quad (9)$$

Where:

- $\Pr(CRIAR = 1|X)$ is the probability that household i participates in CRIAR, given a vector of observable characteristics X.
- Z_i is a vector of socio-demographic characteristics that capture household composition. It includes number of household members, proportion of women, dependency ratio, and proportion of household members in non-farm paid activities.
- HH_i is a vector of head of household characteristics including age, gender, marital status, education and indigenous origin.
- A_i is a variable that captures the associativity of the household members to agricultural associations.
- W_i is a vector that captures the economic characteristics of the household, including remittances, access to credit through formal institutions, access to voluntary savings, household livestock and PPI score.
- D_i is a vector of variables that capture the accessibility to roads and distance to CRIAR *ferias*. Since the *ferias* were the most important processes of diffusion and socialization of CRIAR, it is expected that this variable is an important determinant of household participation. To calculate the distance from the household dwelling to the *ferias*, we used the geographical coordinates using GPS data. A squared term is included to capture nonlinear effects.
- G_i is a vector of dummy variables for each municipality (fixed effects). There are 35 provinces in the sample.
- α β δ ρ γ τ φ are the vectors of coefficients to be estimated in the model; and
- ε_i is the error term.

Table 4 presents the results of the estimation for the participation model. The results using a PROBIT model show that variables of household composition and characteristics of the head of household are not an important determinant of program participation. This is not surprising given the homogeneity of the households in the sample. The only significant coefficients in this group of variables are household size, marital status and indigenous origin of the head of household. Specifically, household size has a positive effect on the probability of participation in CRIAR. Regarding the characteristics of the head of household, households with indigenous head of household are more likely to participate in the program (7%), while households with single head of household are less likely to receive the program (-12%).

With regards to the variables that capture the economic status of the household, the results show that liquidity constraints are an important determinant of program participation. Specifically, households with voluntary savings are more likely to be treated (11%), as did those with a higher PPI score –which indicates less probability of having an income below the poverty line-. The variable of remittances has a negative impact on the probability of being treated.

Finally, it is further observed that variables that capture the process of program socialization and dissemination are the most relevant in the model. Specifically, households that belong to an agricultural cooperative are 19% more likely to participate in the program. Also, distance to the *ferias* has a negative effect on the probability of program participation. Specifically, for each additional kilometer between the household dwelling and the *feria*, the probability of participation is reduced by 2%. This effect is not linear and decreases with the distance (the coefficient of distance squared is positive and statistically significant).

Table 4: CRIAR Participation Model (PROBIT)

	Variable	Marginal Effects
Household Composition	Size	0.012**
	Proportion of women	-0.069
	Dependency ratio	-0.014
	Members in non-agricultural work.	0.067
Head of Household Characteristics.	Age	-0.007
	Age (squared)	0.001
	Woman	0.065
	Single	-0.122***
	Indigenous	0.071**
Head of Household Education	Primary incomplete	-0.067
	Primary complete	-0.039
	Secondary incomplete	0.03
	Secondary complete	0.003
	More than secondary	-0.016
	No formal education	*Base*
Associativity	Member of an agricultural cooperative	0.190***
Remittances, Credit and Savings	Remittances received	-0.001*
	HH with formal credit	0.022
	HH with savings	0.114**
Welfare and Assets	TLU	-0.001
	PPI score	0.003**
Access to *Ferias*	Time to a paved road (logs)	-0.012
	Distance to *feria* CRIAR (km.)	-0.021***
	Distance to *feria* CRIAR (km.) (sq.)	0.001***
Fixed Effects	Fixed effects at the municipality level	yes
	N	**1,287**

*** p<0.01, ** p<0.05, * p<0.1

Note: we report the average marginal effects.

Figure 1 shows the distribution of the estimated propensity scores, and exhibits two main characteristics. First, for the control group, there are more observations with propensity scores close to 0, i.e., there is a higher percentage of farmers in the control group that are less likely to participate compared to the treatment group. The opposite happens in the case of the treated group, which has a higher percentage of households with scores close to 1. Second, there is an important overlap of the Propensity Scores between the treatment and control groups. This means that observable variables are highly comparable between the two groups.

Under the assumption of common support, observations without comparable units are removed from the analysis. This happens for households in the control group whose propensity score takes a very low value of the score (white bars in figure 1) and for households in the treatment group whose propensity score takes a very high value (black bar in figure 1).

Figure 1: Distribution of the Propensity Score between Treated and Controls

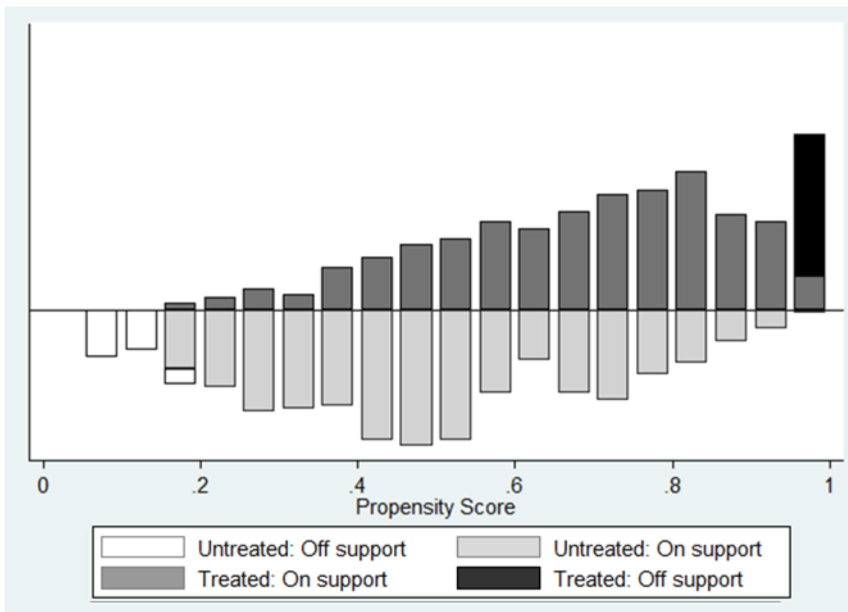
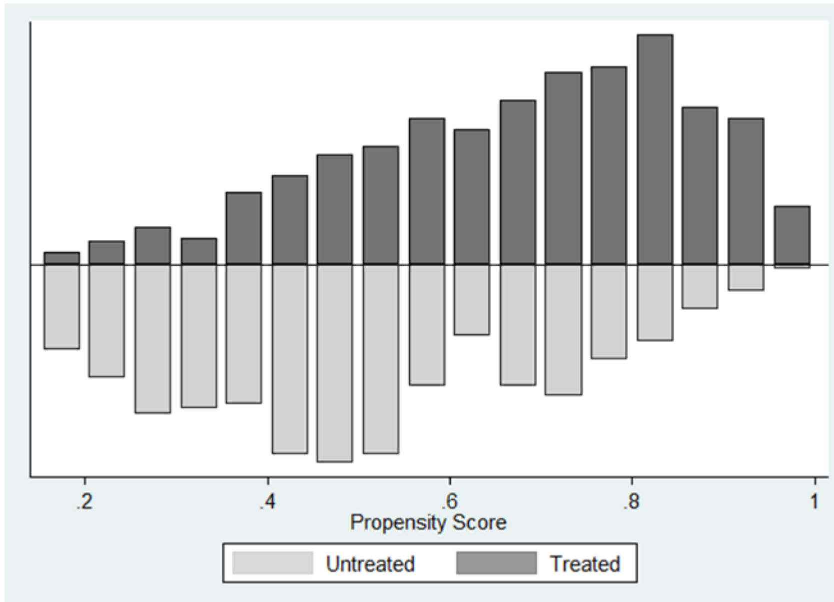


Figure 2 shows the distribution of the propensity scores between the treated and control groups that result when observations outside the area of common support are removed. For the treated group, 32% of the observations are eliminated (265 observations), while 4% (18 observations) of the control group are removed. This figure shows that the distribution of the propensity score is more homogeneous between treated and control groups when the observations within the common support are considered. It also confirms that there is a significant area of common support between the scores of the treated and control groups, which guarantees the comparability between the two groups. Specifically, 78% of the observations are located within the area of common support.

Figure 2: Distribution of the Propensity Score between Treated and Controls in the Common Support Area



VII.II Matching

Once the participation model is estimated, we proceed to match treated with control units using the value of the propensity scores. The most commonly used algorithms for matching are the Nearest Neighbor, Radius, Kernel and Local Linear Regression (LLR). The Nearest Neighbor algorithm matches each treated unit with the control unit with the closest value of the propensity score. The most frequently used specifications of the Nearest Neighbor take one or five control units for the comparison of each treated unit. The Radius algorithm specifies a "caliper" or maximum propensity score distance by which a match can be made. The basic idea of radius matching is that it uses not only the nearest neighbor but all the comparison group members within a given radius. In the case where the value of the propensity score is outside the defined radius, then the control unit is considered not comparable to the treated unit. Finally, Kernel and LLR are nonparametric matching estimators that compare the outcome of each treated unit to a weighted average of the outcomes of all the untreated units, with a highest weight being placed on those control units with scores closest to the treated –it assigns a weight which is inversely proportional to the distance between the propensity score and the corresponding control treated unit- (Fan 1992 & 1993; Todd, 1999).

The basic trade-offs between these algorithms are basically efficiency versus accurate comparability. Algorithms that consider only the closest observations can obtain counterfactuals more comparable to the respective treated unit, but they lose efficiency by discarding the rest of control units. This efficiency is the main feature of the algorithms that use all the sample observations to construct a counterfactual, as Kernel and LLR, although these can lose some accuracy in the comparability (Imbens and Wooldridge, 2009; Caliendo and Kopeinig, 2005).

The quality of the matching is determined by calculating the baseline differences in means between the treated and control group ex-post. Therefore, it is expected that initial differences are eliminated after matching is performed. Table 5 presents the descriptive statistics for the treated and control observations, which lie in the area of common support. These observations are later use to perform the matching. Notice that the ex-ante significant differences between treated and control groups –Table 1 in Section 6- are completely removed once the matching is performed. This confirms the quality of the method when it comes to identifying a counterfactual comparable to the treated group.

With regards to variables that capture short-term effects, the program had a significant impact on the allocation of crops Beneficiaries have a higher probability of cultivating non-traditional crops of higher value added (8%) and they allocate 11% more land for these crops. The program also has a positive impact on the use of inputs. Specifically, beneficiaries are more likely to use insecticides (a probability of 10% higher), herbicides (6%), fungicides (9%), agricultural machinery and equipment (15%) and paid labor force (14%). Moreover, compared to non-beneficiaries, treated households spend more on inputs, labor and agricultural machinery.

Table 5: Treated and Control Units after the Matching

	Variables (unit)	Total	Treated	Control	Diff. in Means
Household	Size (number of persons)	4.41	4.35	4.48	0.13
	Dependency Ratio	1.04	1.05	1.04	0.01
	Prop. of members in agricultural work	0.31	0.31	0.31	0.00
Head of Household	Age	48.30	48.77	47.83	0.94
	Woman (0,1)	0.09	0.09	0.09	0.01
	Single (0,1)	0.16	0.15	0.17	0.01
	Indigenous or native (0,1)	0.78	0.76	0.80	0.04
Education of the Head of Household	Education (years)	5.61	5.54	5.68	0.14
	HH without formal education (0,1)	0.10	0.10	0.09	0.02
	HH with primary incomplete (0,1)	0.37	0.37	0.37	0.00
	HH with primary complete (0,1)	0.21	0.21	0.22	0.01
	HH with secondary incomplete (0,1)	0.20	0.19	0.20	0.02
	HH with secondary complete (0,1)	0.10	0.10	0.09	0.02
	HH with more than secondary (0,1)	0.03	0.03	0.03	0.00
House Characteristics	Size (number of rooms)	2.45	2.56	2.34	0.22
	Dirt floor (0,1)	0.65	0.63	0.68	0.05
	House with electric energy (0,1)	0.79	0.79	0.79	0.00
	House with freezer (0,1)	0.14	0.14	0.14	0.00
	Radio as main source of information (0,1)	0.89	0.89	0.89	0.01
	TV as main source of information (0,1)	0.63	0.64	0.61	0.03
	Internet as main source of information (0,1)	0.02	0.03	0.01	0.02
Associativity	Household belongs to an agric. cooperative (0,1)	0.10	0.11	0.10	0.02
Economic Status	Agriculture as main source of income (0,1)	0.70	0.71	0.68	0.03
	Agricultural income (prop. of total income)	0.54	0.56	0.52	0.04
	Access to formal credit (0,1)	0.08	0.07	0.08	0.01
	Voluntary savings (0,1)	0.06	0.06	0.06	0.01
	Migration remittances received (US$ year/HH)	303.97	304.97	302.97	2.00
	TLU	4.50	4.58	4.42	0.16
	HH with own plot (0,1)	0.99	0.99	0.99	0
	Own hectares	2.32	2.30	2.34	0.02
	PPI Score	28.91	29.56	28.27	1.29
Access to *Ferias*	Time to paved road (logs)	1.83	1.79	1.87	0.08
	Distance to *feria* CRIAR (km.)	12.61	13.22	12.00	1.22
	N	**1,004**	**552**	**452**	

Difference in means is significant at the *** 1%, ** 5%, * 10%, level

Finally, once the algorithm to perform the matching is chosen, the average treatment effect on the treated (ATT) is obtained by averaging the differences between each treated unit and the controls. Table 6 shows the impact of the program for different matching algorithms. The results are robust to different specifications, both in terms of magnitude and statistical significance.

As part of the analysis, we have divided the outcome variables into short-, medium and long-term. Short-term variables include crop allocation, input use and expenditures on inputs. These variables represent the first effects that are expected to take place in the production unit in order to achieve significant impacts on medium and long-term variables, such as sales, productivity, food security and income. *A priori*, it is highly likely that given the short period of implementation of the technology by the beneficiary farmers (one agricultural cycle), the results should be visible only for short-term variables. However, the results show that the program had a significant impact not only on short-term but also in medium-term variables. Finally, except for the food security index, no significant impacts were found in the long-term indicators.

Overall, the impact of the program on short-term variables can be summarized as follows. Beneficiary households changed their crop portfolio moving from traditional and low value crops to higher value crops. They are also spending a higher amount on inputs, labor and farm equipment compared with non-beneficiaries (control group).

The program also had a positive impact on medium-term variables. With regards the variables that capture production use and allocation, beneficiaries are more likely to sell their produce (10%) and to sell a higher proportion of their harvest (7%). The results also show a significant impact of the program on market sales. Specifically, the program has an impact of 16% in the probability of selling at the market, while the proportion of production assigned to sale at the markets is 10% higher for beneficiaries with respect to the control group. Also, as a result of the program, the proportion of production allocated for home consumption is 10% lower for beneficiary households. For the agricultural income from sales, the impact of the program is 70%, which corresponds to approximately $279 on average per household. These results show that beneficiary households assigning a greater proportion of its production to sales and a smaller proportion to home consumption. This is reflected in a higher income from sales of agricultural produce.

For the long-term variables, the results show that the program had a significant impact on food security. Specifically, the results show that participation in CRIAR reduced the vulnerability to food insecurity for beneficiary households by 4%. Furthermore, no significant impacts were found in the long-term variables used as proxy for productivity, such as the value of production or gross margins. This suggests that improvements in food security are primarily driven by higher income from production sales rather than productivity gains. This result is not surprising given the short period of use of technologies by beneficiary farmers. At the time of the survey, approximately 49% of beneficiaries had access to the technology for a full agricultural cycle, while 51% had access to technology for less time. According to the literature that analyzes technology adoption programs (De Janvry et. al., 2010), results in variables like value of production and gross margins are expected to take longer time to present significant changes. Farmers require a learning period to optimize the use of the technology, as well as to make a proper adjustment to production factors. The results obtained in this study are in line with this premise.

Table 6: Impacts of CRIAR – Short Term Variables

	Variables (unit)	(I) PSM (Kernel)	(II) PSM (LLR)	(III) PSM (Radius 0.001)	(IV) PSM (Near Neigh 5)	(V) PSM (Near Neigh 1)
Short-Term Outcomes						
Crop Portfolio	Non Traditional Crops (0,1)	0.083**	0.080**	0.117***	0.080*	0.092**
	Proportion of land with non-traditional crops	0.107***	0.108***	0.133***	0.090***	0.085**
Use of Inputs	Use of fertilizer (0,1)	-0.021	-0.026	-0.026	-0.015	-0.022
	Use of chemical fertilizer (0,1)	0.040	0.035	-0.044	0.048	0.052
	Use of insecticide (0,1)	0.098**	0.092**	0.089**	0.080**	0.097*
	Use of herbicide (0,1)	0.063**	0.064**	0.023	0.039	0.022
	Use of fungicide (0,1)	0.086***	0.083***	0.074**	0.076**	0.061**
	Use of machinery and equipment (0,1)	0.147***	0.145***	0.076***	0.179***	0.169***
	Use of paid labor (0,1)	0.136***	0.140***	0.107**	0.107**	0.109*
Expenditure on Inputs	Expenses in machinery and equipment US$/HA (logs)	0.709***	0.722***	0.295**	0.481*	0.513**
	Expenses in paid labor US$/HA (logs)	0.854***	0.888***	0.721**	0.742**	0.659*
	Expenses in inputs - FIHF US$/HA (logs)	0.456**	0.473*	0.282**	0.426**	0.631***
	N	1,004	989	989	797	722

Note: standard errors are bootstraped

*** p<0.01, ** p<0.05, * p<0.1

Table 6 (cont.): Impacts of CRIAR – Medium and Long Term Variables

	Variables (units)	(I) PSM (Kernel)	(II) PSM (LLR)	(III) PSM (Radius 0.001)	(IV) PSM (Near Neigh 5)	(V) PSM (Near Neigh 1)
Mid-Term Outcomes						
Sales	HH sales (0,1)	0.104***	0.084**	0.104***	0.148**	0.150***
	Proportion of production sold	0.066***	0.060***	0.061***	0.068**	0.072**
	HH sales in the market (0,1)	0.160***	0.172***	0.105***	0.171**	0.187***
	Proportion of production sold in the market	0.096**	0.102***	0.057**	0.085*	0.090*
	HH sales in farm (0,1)	-0.011	-0.040	0.052*	0.040	0.034
	Proportion of production sold in the farm	-0.026	-0.021	0.011	0.013	0.010
	Agricultural Income from Sales (US$/HH)	279.154***	274.594***	308.634***	262.573**	302.923***
	Agricultural Income from Sales (logs)	0.822***	0.710***	0.926***	1.128***	1.185***
On-farm Consumption	Proportion allocated to on-farm consumption	-0.101***	-0.088***	-0.072***	-0.076***	-0.071**
Long-Term Outcomes						
Value of Production	Value of production US$/HA (logs)	0.026	0.017	0.063	0.063	0.086
Gross Margins	Gross Margins US$/HA (logs)	-0.150	-0.155	-0.014	-0.014	0.071
Food Insecurity	Food Insecurity (FAO Index)	-0.037**	-0.029**	-0.021**	-0.054***	-0.095**
	N	1,004	989	989	797	722

Nota: los errores standard fueron calculados mediante *Bootstrap*

*** p<0.01, ** p<0.05, * p<0.1

VIII. Conclusion

This paper presents the results of the impact evaluation of CRIAR, using a quasi-experimental methodology of Propensity Score Matching. The CRIAR program was implemented in rural areas in Bolivia with the objective of increasing agricultural income and food security for smallholder farmers through productivity gains that result from technological adoption.

The main impacts of the program are observed in short- and medium-term variables, including crop diversification, input use and expenditures on inputs, and variables related to sales and home consumption. The results presented use different estimations and show a positive impact of CRIAR on land extension allocated to non-traditional higher-valued crops, and an increase in the use and expenditures of agricultural inputs. Also, the program had a positive impact on the proportion of production destined for market sales. All these results are robust to different specifications of the PSM. The program also had a positive impact on incomes from sales of agricultural production and food security, which a priori, had been identified as medium to long-term impacts. To the best of our knowledge, this is the first study to provide rigorous empirical evidence on the impact of interventions that aim to promote the adoption of agricultural technologies on food security, particularly in Bolivia.

With regards to variables related to productivity, this study did not find any significant impacts on either value of production or agricultural gross margins. The lack of productivity impacts is probably caused by the short period of program implementation, which corresponds to one agricultural cycle. This length of time may have not been sufficient for farmers to gain experience and knowledge in regards to the effective use of the technologies or to adjust the production process through input changes. Therefore, it is expected that a long-term analysis could provide further evidence of program impacts on productivity gains. Nevertheless, the results obtained from these analyses on short-term and medium-term variables provide evidence that the mechanisms for achieving these long-term goals is generating important results through these intermediate variables. We also expect to perform a future impact evaluation of the program in order to analyze whether the expected long-term results will finally take place.

This study confirms the importance of analyzing the process of technology adoption carefully. It is worth analyzing the short- and medium-term mechanisms through which it is expected to have impacts in the long-term. The analysis of these intermediate variables permits to study the entire process of technological adoption and the first step mechanisms that should be generated to achieve an impact on long-term variables. By contrast, a focus limited to long-term variables could generate partial or erroneous conclusions about the evolution of the objectives of these interventions.

ANNEX A: LIST OF MUNICIPALITIES

MUNICIPALITY	NUMBER OF HOUSEHOLDS
Alalay	42
Alcalá	4
Anzaldo	52
Aucapata	20
Ayata	29
Bermejo	38
Chuma	4
Colquechaca	51
Colquiri	63
Combaya	39
El Puente	33
El Villar	8
Ichoca	56
Icla	33
Inquisivi	76
Malla	21
Mizque	94
Mocomuco	30
Mojocoya	85
Ocurí	36
Padilla	8
Pocoata	26
Quiabaya	30
Quime	49
Ravelo	45
San Lorenzo	4
Sopachuy	24
Tarabuco	5
Tarija	58
Tarvita	27
Tomina	16
Uriondo	61
Vila Vila	22
Yaco	57
Zudañez	41
Total	**1,287**

ANNEX B: PPI SCORECARD FOR BOLIVIA

INDICATOR	ANSWER	POINTS
1. How many household members are there?	A. Seven or more	0
	B. Six	7
	C. Five	11
	D. Four	16
	E. Three	17
	F. Two	26
	G. One	35
2. How many household members ages 6 to 17 currently attend school at the level and grade that they enrolled in for this calendar year?	A. Not all	0
	B. All	2
	C. No children ages 6 to 17	4
3. What is the main construction material of the floors of the residence?	A. Earth, bricks, or other	0
	B. Wooden planks, cement, hardwood floors, parquet, rugs or carpets	4
	C. Tile (mosaic, stone, or ceramic)	10
4. What is the main fuel used for cooking?	A. Firewood, dung/manure, kerosene, LPG in a cylinder, or other	0
	B. Piped-in natural gas, electricity, or does not cook	7
5. Does the household own, have, or use a refrigerator or freezer?	A. No	0
	B. Yes	5
6. Does the household own, have, or use a dining-room set (table and chairs)?	A. No	0
	B. Yes	5
7. Does the household own, have, or use a television?	A. No	0
	B. Yes	10
8. Does the household own, have, or use a VCR or DVD player?	A. No	0
	B. Yes	6
9. Does the household own, have, or use a stereo or hi-fi system?	A. No	0
	B. Yes	5
10. Are any household members employed in blue-collar or white-collar jobs?	A. No	0
	B. Yes	13

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