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Unraveling the Threads of Decentralized Community-Based Irrigation Systems in Bolivia

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Inter-American Development Bank
Environment, Rural Development, and Disaster Risk Management Division

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Cesar Augusto Lopez [i] Lina Salazar [ii]

Abstract

Irrigation is a key determinant of agricultural productivity, income, and sustainable development. This paper estimates the impact of the National Irrigation Program with a Watershed Approach (PRONAREC) on the value of agricultural production, investments in complementary technologies, household income, and water resource management in rural communities in Bolivia. We use a unique cross-sectional data set collected from a sample of 1,682 farmers (583 beneficiaries and 1,099 controls) for the 2014-2015 agricultural cycle. To evaluate the effects of the program, we exploit special features of the program design by comparing two rounds of program participants: treated communities are those that received the program first, while control communities are those that were in the pipeline to receive the treatment at a later period. The strategy controls for program placement and self-selection bias at the community level, and we control for self-selection based on observable characteristics with the implementation of Propensity Score Matching. The results show that participation in the program improved the value of agricultural production, and it triggered a deeper process of technological change that led to investments in complementary inputs. Additionally, there is evidence PRONAREC has strengthened farmers' access to markets, increased household incomes, promoted the formalization of water users' associations, and improved the organization and management of irrigation systems. Nevertheless, the lack of effects on agricultural productivity suggests program beneficiaries are in the upward sloping curve of the learning process.

Keywords: Agriculture; irrigation; technology adoption; productivity; propensity score matching, water resource management, Bolivia

JEL classification: O13; O33; Q12; Q15; Q16; Q25

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1. Introduction

Agriculture is an important and dynamic sector for the Bolivian economy. In 2015, agriculture contributed US$1.506 billion to Bolivia's economy, equivalent to 9.7 percent of its gross domestic product (GDP, 2005 prices) (FAOSTAT, 2016). The sector employs approximately 30 percent of Bolivia's labor force and 80 percent in rural areas (ECLAC/FAO/IICA, 2012; INE, 2014). However, agricultural productivity remains relatively low in Bolivia compared to other countries in the region (Hameleers et al., 2011; Kay, 2011; World Bank, 2011). In fact, Bolivia is the only country in the region with negative growth in agricultural total factor productivity for the period 2006-2011 (Nin-Pratt et al., 2015). Part of the problem seems to be the lack of access to modern technologies, such as irrigation (Viceministerio de Riego, 2007). The 2013 agricultural census shows that 9 percent (approximately 249,000 hectares) of agricultural land was under irrigation during the summer of 2012-2013, and 17 percent (about 17,800 hectares) during the winter of 2012 (INE, 2015).

Through a series of projects and initiatives beginning in the mid 1990s, the Inter-American Development Bank has continuously supported the efforts of the Bolivian government to expand irrigated areas, as well as to create favorable conditions for improving the efficiency of public investments in community-based irrigation systems. Initially, from 1996 to 2005, the government implemented the National Irrigation Program (PRONAR) which financed a total of 158 small-scale irrigation projects covering about 22,000 hectares. Further, in 2009, the Government implemented the first phase of the National Irrigation Program with a Watershed Approach (PRONAREC), followed by a second phase approved in 2013.[1] The general objective of PRONAREC is to boost agricultural income and productivity of rural households by expanding the area of farm land under irrigation and improving efficiency in the use and distribution of water for agricultural purposes through the development of community-based irrigation systems.[2]

Despite the importance of community-based irrigation systems in Bolivia (Saldías et al., 2012; VRHR-MMAyA, 2013), to the best of our knowledge, the only systemic attempt at evaluating their effects has been made by Andersen et al. (2015). Using administrative data and national household surveys, the authors evaluate the impact of PRONAR and PRONAREC on the vulnerability of agricultural households through the implementation of propensity score matching

[1] Both phases of PRONAREC were financed by the Inter-American Development Bank for a total of US$34.3 million and US$57 million. The entity responsible for the implementation of PRONAREC is the Ministry of Environment and Water (Ministerio de Medio Ambiente y Agua—MMAyA) through the Vice Ministry of Water Resources and Irrigation (Viceministerio de Recursos Hídricos y Riego—VRHR).

[2] Community-based development refers to the active participation of beneficiaries (communities, its members, and their social capital) in the design and management of projects (Mansuri and Rao, 2004).

in combination with difference-in-differences.[3] Specifically, they analyzed vulnerability using two indicators: per capita income and an index of income diversification. The results from their evaluation suggest irrigation systems financed by PRONAR and PRONAREC had no impacts on the resilience of agricultural households. However, as the authors point out, the results from their quantitative analysis are likely to be biased due to significant limitations in the data, especially since they were unable to identify direct beneficiaries of PRONAR and PRONAREC.

This case study aims to reduce this knowledge gap by conducting an impact evaluation of a community-based irrigation program (PRONAREC) on agricultural income, productivity, and water resource management. Specifically, we seek to examine whether access to public infrastructure generates sufficient incentives to trigger private investment that leads to increased agricultural productivity and income among small farmers using a quasi-experimental approach. Further, we investigate whether the program affects the management and organization of irrigation systems, which consequently should enhance the efficiency in the use and distribution of water for irrigation. The main contribution of this paper is to provide further evidence on the effectiveness of agricultural programs promoting the adoption of community-based irrigation systems. The results present evidence of a positive impact on agricultural technology adoption, production, income, and water resource management.

The rest of the paper is organized as follows: Section 2 provides a summary of the empirical evidence from rigorous impact evaluations. Section 3 introduces the program and presents the theory of change. Section 4 describes the data used in the analysis and an assessment of the comparability between treatment and control groups. Section 5 presents the methodological framework used for the identification of program impacts. In Section 6, we discuss the main findings of the impact evaluation and Section 7 concludes.

2. Empirical Evidence from Impact Evaluations

There is an extensive theoretical and empirical literature that investigates the adoption and diffusion of agricultural innovations, including adoption constraints and their impacts (Feder, Just and Zilberman, 1985; Feder and Umali, 1993; Sunding and Zilberman, 2001; Lee 2005; Foster and Rosenzweig, 2010). In the case of the adoption of irrigation technologies, Dillon (2011a) finds that while access to irrigation has a significant impact on agricultural production in northern Mali, the scale of the irrigation scheme may have differential effects on the welfare of producers. More specifically, using a propensity score matching (PSM) technique, the author finds

[3] By vulnerability, the authors refer to the “inability to anticipate, cope with, resist, and recover from the impacts of … shocks and stresses of all types” (Andersen et al., 2015).

small-scale irrigation to have a significant effect on agricultural production and income; however, the impact on consumption per capita was significant only for large-scale irrigators. Dillon (2008, 2011b) implemented a combination of PSM and difference-in-differences (DD) on a sample of small-scale irrigators from the same area and finds similar effects on agricultural production. Moreover, concerning welfare gains, the author finds evidence of an increase in household consumption (27-30 percent), savings through livestock accumulation, and an increase in the likelihood of beneficiaries to engage in informal food-sharing (20 percent) relative to farmers without irrigation. Kuwornu and Owusu (2012) find that access to irrigation has a positive impact on household consumption per capita in northern Ghana. However, Zeweld et al. (2015) finds that participation in small-scale surface irrigation projects in Ethiopia had no effect on food consumption, livestock resources or expenditures on education and health.[4] Del Carpio, Loayza and Datar (2011) evaluate the impact of an irrigation rehabilitation project along the Peruvian coast. They find a significant increase in the value of production (72 percent) and value of sales (83 percent) of treated producers in the top 25th percentile (larger farms) and a decline (about 65 percent) in the bottom 25th percentile.[5]

Far less studied is the impact of irrigation on the adoption of complementary inputs and technologies, particularly on sustainable agricultural practices. Zeweld et al. (2015) find that small-scale surface irrigation schemes had a significant effect on asset accumulation and expenditures on agricultural inputs (e.g., chemical fertilizers and improved seeds). Such synergy or complementarity between irrigation and inputs of production and other agricultural technologies has been suggested and discussed in the literature. For instance, Lipton et al. (2003) point out water availability highly influences the demand for modern agricultural inputs; thus, access to irrigation can contribute to the stabilization of farm output in the long-run. Further, while there is growing concern of the association between irrigation and the overutilization of modern inputs (i.e., chemical fertilizer) and its effects on the environment, policies that promote irrigation water efficiency, such as community-based irrigation management, can influence input efficiency and sustainability (Alauddin and Quiggin, 2008; Aregay and Minjuan, 2012).

However, most studies in the literature focus on the analysis of irrigation interventions that take place at the farm-level rather than at the community-level. Community-based irrigation systems are typically more complex, as they often require further private investments, and

[4] Both, Kuwornu and Owusu (2012) and Zeweld et al. (2015), evaluate the effects of access to irrigation using PSM.

[5] The authors evaluate the effectiveness of the project using a spatial regression discontinuity (RD) and DD design. They find positive effects in the bottom percentile. However, the effects were not related to an increase in agricultural production, but through employment opportunities in larger farms.

therefore, a deeper analysis of the adoption process is necessary. Empirical evidence on the effectiveness of irrigation management transfer (IMT) and participatory irrigation management (PIM) interventions on farm-level outcomes has produced mixed results mostly derived from either qualitative assessments or from studies that fail to establish an appropriate counterfactual (Vermillion, 1997; Garces-Restrepo, Vermillion, and Muñoz, 2007; Merrey, 2015; Senanayake, Mukherji, and Giordano, 2015).[6] Nevertheless, the literature shows positive effects of IMT/PIM on operational and financial performance, increasing the area under irrigation, and reducing public expenditures for irrigation (Vermillion, 1997). WUAs also seem to be effective at performing basic canal operation and maintenance functions (Garces-Restrepo, Vermillion, and Muñoz, 2007). However, as mentioned, rigorous empirical evidence about IMT/PIM impacts is very limited (Senanayake, Mukherji, and Giordano, 2015). In fact, we were able to identify only two impact evaluations on the effects of IMT/PIM on farm productivity in the Philippines and China.

Using a PSM and instrumental variable (IV) approach, Bandyopadhyay, Shyamsundar and Xie (2007) examine a reservoir-based irrigation system in the island of Luzon, Philippines, by evaluating the impact of IMT on the performance of irrigation systems and rice yields. In terms of the performance of systems managed by irrigation associations, although the effects on the development of maintenance plans and fee collection are less clear, the authors find strong evidence that IMT promotes canal maintenance activities. At the farm level, they find a significant increase in rice yields (2-6 percent) compared to farmers in non-IMT areas. Furthermore, using a stochastic production frontier analysis, the authors show that the increase in productivity is associated with an improvement in the technical efficiency of rice producers.[7] In a more recent study of villages in northern China, Huang (2014) evaluates the effects of IMT on the performance of irrigation systems managed by WUAs or contractors and its impact on rice and wheat production.[8] Following an IV approach, the author finds positive and significant effects of WUAs on maintenance expenditures (37 percent), timely water delivery (share of water delivered timely increased by 25 percentage points), irrigated area (41 percentage points), and rate of water fee

[6] Although the two concepts are interrelated and often used interchangeably, IMT refers to the reallocation of responsibility and authority of publicly owned irrigation systems from governmental to non-governmental agencies, such as water users' associations (WUAs). On the other hand, PIM refers to the participation of WUAs in the development of irrigation systems, along with the government (Vermillion and Sagardoy, 1999).
[7] The authors assume 'allocative efficiency' in rice production considering that the area of study is one of the most developed rice producing regions in the country.
[8] In China, WUAs are typically established at the village-level, as these are the basic hydrological units for irrigation management purposes. Some villages engage in *contracting*, a form of management in which contractors are hired to operate or maintain part of the village's canal system. WUAs and *contracting*, China's version of water management reform, emerged in the northern side of the country between 1995 and 2004 as alternatives to traditional forms of *collective management* of irrigation systems by village officials (Huang et al., 2009).

collection (24 percentage points). However, the author did not find evidence of an impact on water use efficiency or crop production.

3. Theory of Change: The National Irrigation Program with a Watershed Approach

The National Irrigation Program with a Watershed Approach (PRONAREC) promotes an integrated water-resources management (IWRM) framework from a community-based approach.[9] This program aims to boost farmers' income and productivity by enhancing the efficiency of water use, increasing land under irrigation and enhancing management of water resources. To achieve its objectives, the program financed public infrastructure investments for the construction and rehabilitation of community-based irrigation systems. It also provided technical assistance for the use and maintenance of the irrigation infrastructure, as well as for the adoption of new and more profitable agricultural practices. It is important to mention that the program financed only communal-public infrastructure. As such, farmers were responsible for making private on-farm investments to capture the benefits of the program fully. These investments included on-farm irrigation channels, pipes, irrigation pumps and other investments as needed.

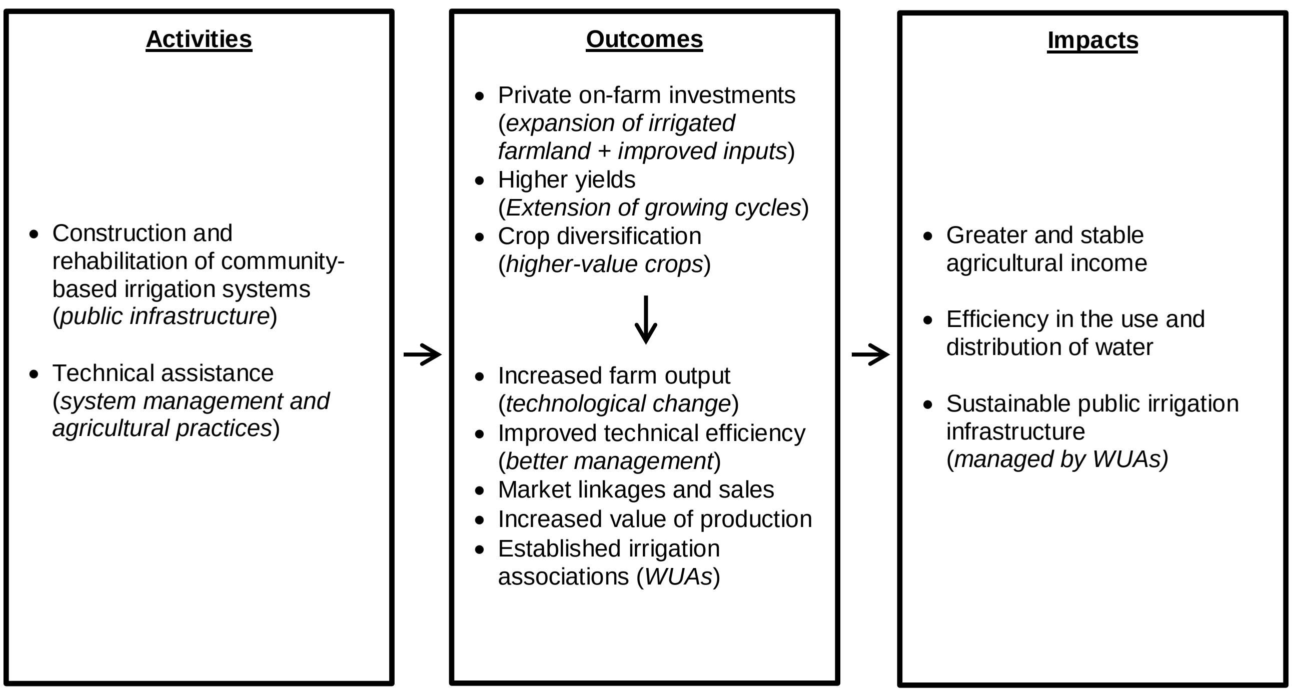
The literature recognizes the existence of several obstacles that hinder the adoption of agricultural technologies, including liquidity constraints and access to credit, problems of access to information or asymmetric information, risk aversion, input and output market inefficiencies, among others (Feder et al., 1985; Jack, 2013). PRONAREC seeks to reduce barriers that hinder the adoption of irrigation technologies. First, in relation to liquidity constraints, the program financed the investment for the development of irrigation infrastructure for communities in rural areas. Second, an important part of the program was the provision of specialized technical assistance, particularly focused on water management. The technical assistance was expected to provide the necessary knowledge regarding the efficient and effective management of the system to ensure resource savings and improving productivity. Third, risk aversion limits the adoption of agricultural technologies as producers prefer certainty about the economic returns generated by the technology prior to making the investment. Therefore, producers may postpone investment until they can confirm the productivity gains associated with the technology through the experience of other producers (Besley and Case, 1994; Foster and Rosenzweig, 1995). For this reason, the technical training component of the program also provided assistance related to

[9] IWRM is defined as an on-going "process which promotes the coordinated development and management of water, land and related resources, in order to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems" (GWP, 2000).

agricultural diversification towards high-value crops, including input and output markets, crop types, and crop cycle.

Figure 1 illustrates the theory of change, which describes how program activities are expected to produce a series of outcomes and their causal effects on final results. The main activities financed by the program include: (i) financing of community infrastructure for the development for irrigation systems (i.e. water dams, irrigations channels); (ii) technical assistance for the management of the infrastructure and the efficient use of water resources; and (iii) technical assistance for the adoption of new agricultural practices (i.e. higher value crops). Access to public irrigation infrastructure is expected to trigger private farm-level investments in order to increase land under irrigation. These private investments include the construction of on-farm channels, water pumps, water pipes, etc. In other words, to fully capture the benefits from community irrigation systems, farmers must have undertaken complementary on-farm private investments.

Figure 1—Theory of Change



The implementation of on-farm private investments and the expansion of land under irrigation are expected to raise the value of agricultural production twofold. First, higher value of production can result from higher yields caused by an increase in the number of harvests per agricultural season. Less dependability on rain-fed agriculture allows farmers to harvest more than one season and therefore, increase production. Second, an increase in the value of production can result from a crop portfolio transformation: less risky agriculture due to access to irrigation generates incentives for farmers to plant crops with higher market value. This agricultural transformation is reinforced through the technical assistance and training provided to program beneficiaries on marketing and agro-economic practices, and to WUAs on plot irrigation, watershed protection, management, and system operation and maintenance. Finally, access to irrigation is expected to strengthen farmers' linkages with markets as increased agricultural production can be allocated to market sales, boosting agricultural productivity and income.

The implementation of PRONAREC began in 2009 by the Bolivian Ministry of Environment and Water (MMAyA) and its Vice Ministry for Water Resources and Irrigation (VRHR). The program has been implemented in two phases. The first phase (PRONAREC I), with a total cost of US$35.8 million, started the construction and rehabilitation of infrastructure for irrigation systems in 2010. The program financed a total of 54 community-based irrigation systems (projects) that covered more than 9,000 hectares of incremental land and benefited 10,500 families, approximately. The projects were spread throughout Bolivia in the departments of Cochabamba, La Paz, Chuquisaca, Oruro, Potosi, Santa Cruz, and Tarija. Projects from the first phase finalized their construction on different dates ranging from 2011-2015. At the time of data collection, 48 projects had finalized construction and have been operative for at least one agricultural cycle.[10] The second phase of the program (PRONAREC II), with a total cost of US$77 million, started the construction of public irrigation infrastructure in 2014, and it is currently under implementation. An estimated total of 75 community-based irrigation systems, covering more than 10,500 hectares of land and benefiting approximately 13,192 families, will be financed by PRONAREC II.[11] Figure 2 presents the geographical location of the projects considered in this study (PRONAREC I and II).[12]

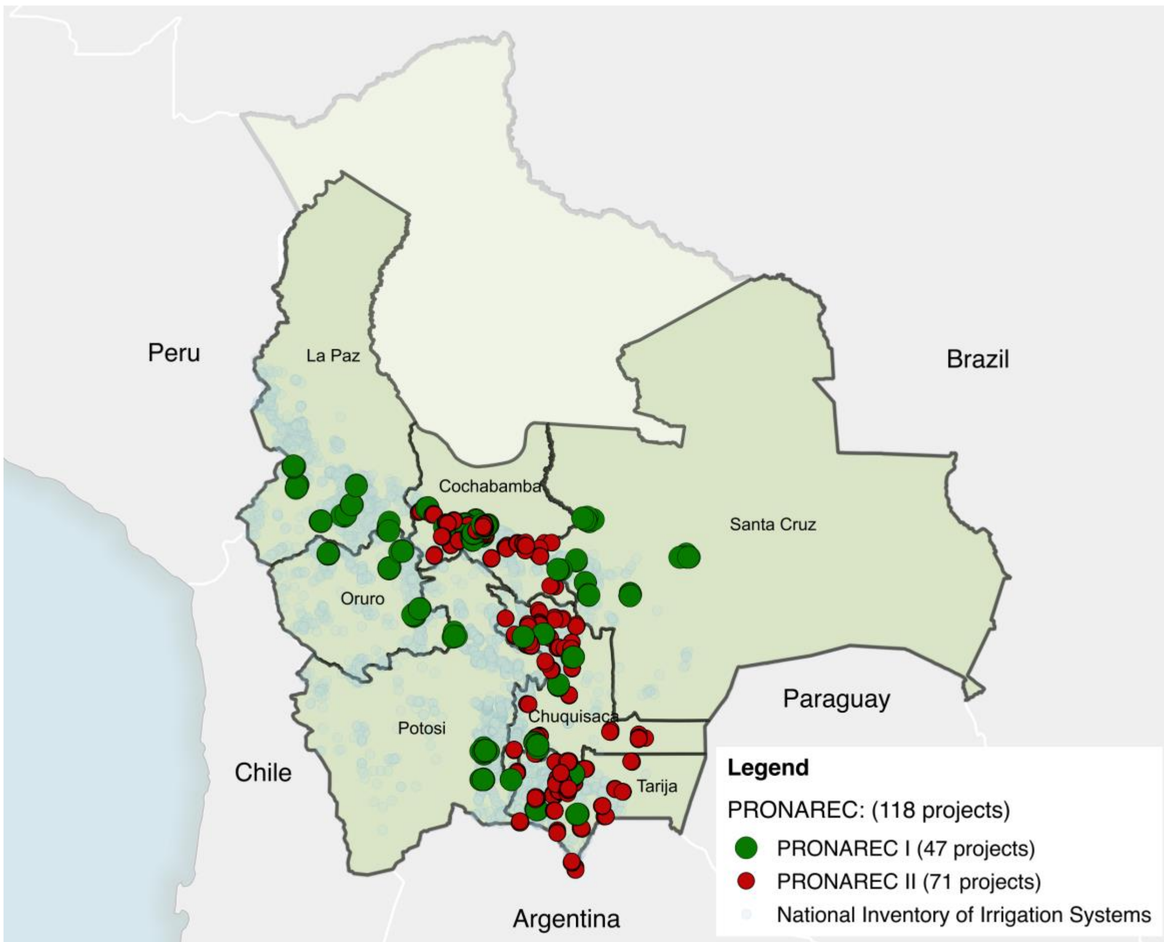
Eligible beneficiaries of PRONAREC were communities with established or in the process of establishing WUAs that fulfilled certain criteria: (i) proof of legal status, (ii) evidence of access to water rights for irrigation granted by SENARI, (iii) a signed agreement with the local government to operate and maintain the irrigation infrastructure, (iv) commitment to contribute at least 10%

[10] These projects will be considered the beneficiary group. Projects from PRONAREC I that were still under construction at the time of data collection have been excluded from the analysis.
[11] The projects from this second phase will be considered the *control group*, as benefits from the irrigation systems have not materialized at the time of data collection.
[12] Most of the projects funded by PRONAREC II were reviewed, approved, and prioritized within the first two years of program implementation (2014 and 2015). By June 2016, construction of the first set of projects (39 irrigation systems) had finalized (this set represents *initial* beneficiaries of PRONAREC II); the second set (32 irrigation systems) were completed after July 2016 (this represents the *final* set of beneficiaries of PRONAREC II). Together, *initial* and *final* beneficiaries of PRONAREC II will be used as the control group to assess the impact of PRONAREC I.

of the system's cost (in cash or in-kind) and to fully cover all other operating, maintenance, and investment depreciation costs.

Eligible communities submitted the required documentation to justify the projects' viability from an environmental, technical, legal, and socio-economic perspective. Also, the proposals included a watershed management plan. Ultimately, the final review and approval of the projects were performed by the Governorates, the National Fund for Productive Investment and the VRHR.

Figure 2—Geographical Location of Sample Beneficiaries



Source*:* Authors' own elaboration.
Notes: Shapefiles for the National Inventory of Irrigation Systems obtained from GeoSIRH (2015).

4. Data

The dataset analyzed in this study was collected using an agricultural household survey designed to examine the effects of PRONAREC. The data were gathered in December 2015 from a representative sample of households from beneficiary communities of PRONAREC I and II across seven departments (Chuquisaca, Cochabamba, La Paz, Oruro, Potosí, Santa Cruz, and

Tarija.[13] The questionnaire consists of 15 modules covering information about demographic and household characteristics, identification and location of agricultural holdings, land use, crop types, farmland investments, livestock, agricultural machinery and equipment, technical assistance, among others. Overall, the survey captures all the necessary information to conduct the proposed analysis, including an innovative set of modules collecting information about the characteristics and management of irrigation systems (e.g., system features and organizational structure), and WUAs. Questions regarding agricultural activities refer to the agricultural cycle from July 2014 to June 2015.

The sample of analysis consists of 47 projects of PRONAREC I and 71 projects of PRONAREC II, with a total of 583 and 1,099 producers surveyed (n = 1,682), respectively.[14] All of the irrigation systems financed by PRONAREC I and analyzed in this study were completed and were fully operational for at least one agricultural cycle by the time of data collection.[15] After dropping outliers and production units that reported not having any agricultural production for the agricultural cycle 2014-2015, the final dataset used in our analysis is composed of 1,591 observations (543 beneficiaries from PRONAREC I and 1,048 from PRONAREC II).[16] Tables 1 through 8 present a summary of descriptive statistics and two-sample t-statistics for the treatment groups. Tables 1 and 2 summarize demographic and socio-economic characteristics, Table 3 examine geographical areas (e.g., agroecological zones) and cultivated land, Tables 4 through 6 present descriptive statistics associated with agricultural production, and Tables 7 and 8 provide an overview of variables related to irrigation system management, irrigation technical assistance, water rights and usage.

[13] The survey was developed and carried out by the consulting firm Centro de Estudios y Proyectos (CEP S.R.L.) under the supervision of the project executing unit, UCEP-PRONAREC, of the Viceministerio de Recursos Hídricos y Riego del Ministerio de Medio Ambiente y Agua (VRHR-MMAyA) and the IDB.

[14] The sample size and power calculation for the evaluation of PRONAREC considered the fact that the intervention was implemented at a cluster-level (i.e. community). This approach assumes that, relative to producers belonging to different communities, the behavior of producers in any given community will be correlated. Thus, variability of information obtained in the sample depends on the distribution of sampled units among different communities. For this reason, the sampling strategy followed a clustered design where the primary sampling units (PSU), or clusters, are the beneficiary communities of PRONAREC. From each community, a sample of 12 households was randomly selected. The parameters ρ (intra-cluster correlation = 0.14), δ (standardized effect size = 0.24), and R_{l2}^2 (proportion of explained variation = 0.32) were obtained from the variable *value of production per hectare* from the impact evaluation of CRIAR (Salazar et al. 2015). The CRIAR program was implemented in rural areas of Bolivia similar to those of PRONAREC. The total number of clusters in the sample (118) was based on the number of projects of PRONAREC I (47) with completed and functional irrigation systems, and projects of PRONAREC II (71) that were still in the pipeline. Given these parameters, *Optimal Design* software reports that 12 is the minimum number of observations that must be included per cluster to achieve the desired level of statistical power (taking the commonly accepted level of 0.80). The final sample included an adjustment of 5% to account for non-response.

[15] Particularly, one system had been operating for four cycles, nine systems for three, thirteen for two cycles, and the remaining twenty-four for one full agricultural cycle; none of the irrigation systems financed by PRONAREC II were completed or operational.

[16] A total of 66 observations were dropped from the dataset as they reported not having any agricultural production during the 2014-2015 agricultural cycle. An additional 13 observations (outliers) were excluded from the analysis as they reported working on less than 0.001 hectares of land.

4.1 Descriptive Statistics

A preliminary analysis of comparability between treatment and control units shows that producers from both groups share similarities in household characteristics (see Table 1). The average household in the sample has four members, half of them are women, and have a dependency ratio of approximately 60 percent (Table 1).[17] Regarding head of household characteristics, there are significant, yet small, differences in the age, marital status, ethnic background, and years of education of the head of household between groups. Relative to the control group, household heads in the treated group are, on average, two years older, and a smaller proportion of them are single (4 percentage points, pp). Household heads in the sample have an average of 5 years of education, but those in the treated group have approximately an additional year of schooling. Regarding ethnic background, 77 percent of household heads identified themselves as native indigenous (*Naciones y Pueblos Indígenas Originarios Campesinos*, NyPIOC) the percentage was 10 points higher in the case of the treated group.

While most household members (5 years and older) dedicate at least some amount of time to agricultural activities, particularly crop production (86 percent) and animal husbandry (64 percent), the share is lower for the treated group (5 and 6 pp, respectively) compared with the control group. With respect to dwelling characteristics and accessibility, both groups share multiple similarities. In particular, 83 percent of households reported having access to electricity, 74 percent have a cellular phone, and 71 percent have a television. However, with regards to flooring material, 45 percent of the households in the treated group reported having a dirt floor, which is significantly higher with respect to the control group by 11 percentage points. *Accessibility* of households is measured as the average amount of time, in minutes, which normally takes producers to reach: (*i*) the nearest route or (paved) road passable year-round, (*ii*) the nearest market or *feria* to buy or sell food products, and (*iii*) the main source of water for drinking and cooking. On average, it takes producers approximately 38 minutes to reach the nearest road, 92 minutes to reach the nearest market or *feria*, and about 3.8 minutes to reach the main source of water for drinking and cooking. There are no statistically significant differences between both groups for any of these variables.

[17] Dependency ratio refers to the ratio of household dependents (individuals < 15 and > 65 years) per working-age member (15-64 years).

Table 1—Descriptive Statistics: Demographic and Socio-Economic Characteristics

	Mean			Diff. in
	Total	Treated	Control	Means
Household characteristics				
Household size (# members)	4.18	4.21	4.17	0.04
Dependency ratio	0.60	0.60	0.60	-0.01
Female (% household)	0.49	0.49	0.49	0.00
Head of household characteristics				
Age (years)	52.04	53.39	51.34	2.05 **
Female (0,1)	0.17	0.15	0.18	-0.03
Single (0,1)	0.10	0.07	0.11	-0.04 **
Indigenous (0,1)	0.77	0.84	0.74	0.10 *
Years of education (#)	5.16	5.70	4.88	0.82 **
Occupation of household members (5 years and older)				
Crop production (%)	0.86	0.83	0.88	-0.05 ***
Animal husbandry and processing (%)	0.64	0.60	0.66	-0.06 *
Dwelling characteristics				
Dirt floor (0,1)	0.38	0.45	0.34	0.11 *
Electricity (0,1)	0.83	0.86	0.81	0.04
Cellular phone (0,1)	0.74	0.78	0.72	0.06 *
Television (0,1)	0.71	0.70	0.71	-0.01
Accessibility (time to)				
Route or road passable year-round (min)	38.49	42.19	36.57	5.62
Closest market or *feria* to buy/sell food (min)	92.10	99.10	88.48	10.62
Main source of drinking/cooking water (min)	3.79	3.67	3.85	-0.18
Associability (social capital) 2014-2015 ag. cycle §				
Water users' associations (WUAs)	0.89	0.93	0.88	0.05 *
Agricultural cooperative or association (0,1)	0.46	0.42	0.48	-0.06
Non-agricultural association or organization (0,1)	0.13	0.10	0.14	-0.04
Economic characteristics				
PPI score: Below national poverty line (%)	30.43	32.82	29.19	3.63
Total household income (US$) ‡	3,942.29	4,654.07	3,573.50	1,080.57 *
Off-farm income (US$)	1,080.04	954.30	1,145.19	-190.90
Agricultural income (US$)	2,402.14	3,083.20	2,049.27	1,033.93 *
Agricultural production (% of total income)	0.62	0.60	0.63	-0.04
Tropical livestock units (TLUs)	9.04	8.82	9.15	-0.32
Bank account (0,1)	0.16	0.17	0.15	0.01
Voluntary savings (0,1)	0.16	0.17	0.16	0.01
Credit constrained (0,1) †	0.18	0.19	0.17	0.02
Total landholding (ha)	4.31	6.43	3.21	3.21 **
Land owned (ha)	4.22	6.28	3.15	3.13 **
Land owned (% total landholding)	0.96	0.96	0.96	0.00
Altitude and agroecological zones (AEZ)				
Altitude (MASL) - at the plot level	2,432.56	2,708.84	2,289.42	419.43 **
AEZ: Altiplano (high plateau) (0,1)	0.09	0.25	0.01	0.24 ***
AEZ: Andean valleys (0,1)	0.85	0.65	0.96	-0.31 ***
AEZ: Tropical (0,1)	0.06	0.10	0.04	0.07
n	1,591	543	1,048	

Source*:* Authors' own calculations

Notes: Cluster-robust standard errors at the community-level. T-test for difference in means statistically significant at the *** 1%, ** 5%, * 10% level. *§* The dummy variable for agricultural association takes the value of 1 if any member of the household participated in any agricultural, livestock or agroindustry association (excluding WUAs), 0 otherwise. Non-agricultural association takes the value of 1 if any member of the household participated in other associations (e.g., artisanal, social, tourism), 0 otherwise. ‡ Total income derived from off-farm income, remittances, agricultural production (excluding losses), and livestock revenue (home consumption and sales). † Credit constrained takes the value of 1 if the household requested credit from a formal financial institution, but the request was either denied or the amount of credit offered to the household was lower than the amount requested, 0 otherwise.

Over the last three decades, growing attention and recognition has been given to the concept of "social capital" and its role on economic growth and sustainable development (Sorensen, 2000; Winters et al., 2001; Atria and Siles, 2004). This is particularly important given that social capital—namely *associability*—may be one of the most important resource endowments of small-scale farmers in developing countries. For the purpose of this study, social capital was assessed using a set of dummy variables indicating whether someone in the household participated in any organization, either agricultural or non-agricultural. This preliminary analysis indicates that the most important source of social capital in this sample comes from associative schemes formed with the purpose of coordinating the management of water resources, namely participation in WUAs. On average, 89 percent of farmers were part of a WUA (93 percent in the treated group and 87 percent in the control group) during the 2014-15 agricultural cycle. Interestingly, on average, the proportion of the sample participating in other types of agricultural and non-agricultural organizations and/or associations is smaller (46 percent and 13 percent, respectively).

Households in both groups share similar economic characteristics. According to the *progress of out poverty index* (PPI) score, on average, the likelihood of households living below the national poverty line is about 30 percent.[18] Average household income and agricultural income was US$3,942 and US$2,402, respectively; that is, agriculture represents the largest source of income for the majority of households in the sample. Farmers own an average of approximately 9 *tropical livestock units* (TLUs),[19] and are characterized by having low access to (formal) financial services (e.g., bank account, savings, credit). Regarding land ownership, households in the sample have an average of 4.31 hectares; however, the treated group possesses about twice as much land area (6.43 ha) than the control group (3.21 ha).

The majority of beneficiaries of PRONAREC I are located between the Andean valleys (65 percent) and the Altiplano (25 percent), while beneficiaries of PRONAREC II are mostly located in the Andean valleys (96 percent). This is reflected as a significant difference in the average altitude of the treated relative to the control group (419.4 meters above sea level, MASL).

[18] The PPI is a poverty measurement tool created by the Grameen Foundation to estimate the likelihood that a household is living below a poverty line (either national or international). The PPI is specially designed, by country, based on the most recent national household expenditure or income surveys. So far, 45 PPIs have been developed for 45 countries. The PPI score is derived from the answers to 10 questions regarding the characteristics and asset ownership of households. All the questions from the 2007 PPI for Bolivia were incorporated in PRONAREC's survey.

[19] TLUs are livestock numbers, across species, converted to a common unit, where 1 TLU is commonly taken to represent 1 mature cow of 250kg. Conversion factors are: cattle = 0.7, pigs = 0.25, sheep = 0.1, goats = 0.1, birds = 0.01, horses = 0.8, donkeys = 0.7, oxen = 0.7, beehives = 0.001.

Table 2. Descriptive Statistics: Agricultural Input Use and Production

	Mean			Diff. in Means
	Total	Treated	Control	
Input use				
Fungicide (0,1)	0.29	0.28	0.29	-0.01
Herbicide (0,1)	0.31	0.28	0.33	-0.05
Insecticide (0,1)	0.34	0.34	0.35	-0.01
Chemical fertilizer (0,1)	0.26	0.20	0.30	-0.10 **
Organic fertilizer, *guano,* manure, chicken manure (0,1)	0.67	0.69	0.66	0.03
Improved or certified seeds (0,1)	0.19	0.28	0.15	0.12 ***
Animal traction for production (0,1)	0.65	0.56	0.69	-0.13 **
Agricultural Machinery (0,1)	0.78	0.81	0.76	0.05
Tractor (0,1)	0.77	0.81	0.74	0.07
Paid labor (0,1)	0.69	0.66	0.71	-0.05
Input expenditures				
Inputs (US$) ‡	559.71	661.84	506.80	155.04 **
Animal traction (yoke) (US$)	45.06	46.12	44.51	1.61
Tractor (US$)	106.65	131.52	93.76	37.77 **
Paid labor (US$)	621.83	756.72	551.94	204.78
Expenditures on the irrigation of plots (US$) §	41.58	64.05	29.93	34.12 ***
Irrigation equipment/maintenance (US$)	24.59	40.59	16.30	24.29 **
Water service (US$)	13.05	14.41	12.34	2.07
Energy (US$)	3.94	9.05	1.29	7.76 *
Agricultural land				
Harvested physical area (ha)	2.13	2.58	1.90	0.68
Under rainfed agriculture (ha)	1.07	1.26	0.97	0.29
Under irrigation (ha)	1.06	1.31	0.93	0.39
Harvested area (ha)	2.24	2.64	2.03	0.61
Under rainfed agriculture (ha)	1.11	1.27	1.02	0.25
Under irrigation (ha)	1.14	1.37	1.02	0.35
Harvested area under irrigation (%)	0.65	0.74	0.61	0.14 **
Land Intensification: Harvested/physical harvested area (%)	1.11	1.06	1.13	-0.06 **
Crop portfolio				
Traditional crops (0,1) †	0.90	0.90	0.89	0.01
Prop. of land with traditional crops (%)	0.69	0.68	0.70	-0.02
Produced traditional crops exclusively (0,1)	0.38	0.35	0.39	-0.04
Non-traditional crops (0,1)	0.62	0.65	0.61	0.04
Value of agricultural production				
Value of production (US$)	2,466.05	3,169.80	2,101.41	1,068.40 *
Value of production (US$/ha) (harvested)	2,120.48	2,287.42	2,033.98	253.44
Sales				
Sells (0,1)	0.74	0.73	0.75	-0.02
Sold *most* of a crop in a *feria*/market (0,1)	0.48	0.53	0.45	0.09
Value of sales (US$)	1,597.65	2,308.53	1,229.32	1,079.21 **
Proportion of agricultural production dedicated to:				
Home consumption (%)	0.29	0.27	0.30	-0.04
Animal consumption (%)	0.14	0.15	0.14	0.01
Losses (%)	0.05	0.06	0.04	0.02 **
Transformation (sub-products) (%)	0.02	0.02	0.02	0.01
Sold (%)	0.45	0.45	0.45	0.00
Seeds (%)	0.06	0.05	0.06	-0.01
Agricultural Gross margins				
Gross margins (US$)	1,242.93	1,687.20	1,012.74	674.46
n	1,591	543	1,048	

Source*:* Authors' own calculations.

Notes: Cluster-robust standard errors at the community-level. ‡ Inputs (US$) includes expenditures on fungicides, herbicides, insecticides, chemical and organic fertilizer, agro-chemicals, seeds, animal traction (yoke), and tractor. § Expenditures on the irrigation of plots includes expenditures on equipment, maintenance, water service, and energy; it does not include expenditures on labor for irrigation. † Traditional crops: rice, barley, corn, quinoa, wheat, sorghum, oats, oca, potatoes, yucca, papaliza, tuna or beans (*fríjol*/*poroto*), 0 otherwise.

T-test for difference in means statistically significant at the *** 1%, ** 5%, * 10% level.

Table 2 presents descriptive statistics of agricultural input use, expenditures, and production. On average, there are significant differences in the share of the treated group who reported using chemical fertilizer (-10 pp), improved or certified seeds (12 pp), and animal traction (-13 pp), relative to the control group. No differences in the use of other inputs (i.e. fungicides, herbicides, insecticides, organic fertilizer, agricultural machinery/equipment or paid labor) were found. Further, compared to the control group, beneficiaries of PRONAREC I spent significantly more on variable inputs of production (US$155.04), the utilization of tractors (US$37.77), and irrigation of plots (US$34.12), particularly on equipment or maintenance and energy.

In this study, the difference between the variables *harvested physical area (ha)* and *harvested area (ha)* is subtle yet important. *Harvested physical area (ha)* refers to the physical area planted and harvested during the 2014-2015 agricultural cycle. On the other hand, *harvested area (ha)* quantifies the total amount of land planted and cultivated during the same cycle. For instance, if a producer reported cultivating twice in a 2-hectare plot, the variable *harvested physical area (ha)* would take the value of "2", while the variable *harvested area (ha)* would take the value of "4." Land intensification is then defined as the ratio of *harvested area* to *harvested physical area (ha)*.

On average, producers harvested approximately 2 hectares of land, about 65 percent under irrigation.[20] The share of harvested area under irrigation is significantly larger for the treated group (14 pp) relative to the control group. The average land intensification is 1.11, which indicates an increase in the frequency of cropping cycles, an expected effect of irrigation; however, the treated group has a significantly lower rate of land-use intensification (6 pp) compared to the control group. Although this might seem strange at first, the result is likely a reflection of the differences in the geographic location of beneficiaries of PRONAREC I and II. As mentioned earlier, a significant share of beneficiaries of PRONAREC I are located in the Altiplano, where during the winter time (April to October), land is unsuitable for agriculture (Garcia et al., 2007).

Overall, no significant differences are found in terms of the crop portfolio between both groups. On average, 90 percent cultivated at least one traditional crop (69 percent of the land was cultivated with traditional crops), 38 percent produced traditional crops exclusively, and 62 percent cultivated at least one non-traditional crop. Value of production in the sample averaged approximately US$2,466, most of which was sold (45 percent) or used for home consumption (29 percent). Even though the majority of producers in both groups reported selling at least some of

[20] Most of the land is used for agricultural production (e.g., seasonal and permanent crops).

their production (about 74 percent), the value of sales for the treated group is significantly larger compared to the control group (US$1,079). Average agricultural gross margins in the sample was US$1,242.93.[21]

Table 3—Descriptive Statistics: Infrastructure and Management of Irrigation Systems

	Mean			Diff. in Means
	Total	Treated	Control	
Agricultural infrastructure investments – 2014-15 ag. cycle				
Total investments (US$)	102.14	118.62	93.60	25.02
Investments in irrigation (US$)	55.35	60.15	52.86	7.30
Other investments (e.g., *pozos, cercas*) (US$)	34.63	43.37	30.10	13.27
Communal investments (US$)	12.16	15.09	10.64	4.46
Area equipped with irrigation §				
On-farm irrigation (0,1)	0.73	0.83	0.67	0.16 ***
Total landholding equipped with irrigation (ha)	1.27	1.59	1.11	0.48 *
Prop. landholding equipped with irrigation (%)	0.60	0.68	0.56	0.12 **
Modern irrigation system (0,1)	0.07	0.08	0.06	0.02
Land equipped with modern irrigation (ha)	0.12	0.12	0.12	0.00
Prop. land with modern irrigation (%)	0.06	0.07	0.06	0.01
Traditional irrigation system (0,1)	0.67	0.77	0.62	0.16 **
Land equipped with traditional irrigation (ha)	1.15	1.48	0.99	0.49 *
Prop. land with traditional irrigation (%)	0.66	0.76	0.61	0.15 **
Community watershed and irrigation board				
Watershed Committee was formed (0,1)	0.39	0.49	0.34	0.15 ***
HH belongs to a WUA (0,1)	0.91	0.93	0.90	0.04
Formalized WUA (0,1)	0.83	0.89	0.80	0.09 ***
Irrigation system management ‡				
Norms (0,1)	0.58	0.74	0.50	0.23 ***
Irrigation turns (0,1)	0.63	0.85	0.51	0.34 ***
Organization at the system-level				
Statutes and regulations (0,1)	0.50	0.60	0.45	0.14 **
Manuals (0,1)	0.39	0.47	0.35	0.12 **
Irrigation System Features				
Dam (0,1)	0.25	0.27	0.23	0.04
Intake structure (0,1)	0.55	0.78	0.43	0.35 ***
Conveyance system (0,1)	0.24	0.32	0.20	0.12 ***
Main line (0,1)	0.46	0.58	0.40	0.18 ***
Distribution system (0,1)	0.48	0.64	0.40	0.24 ***
Hydrant (0,1)	0.18	0.31	0.12	0.19 ***
Well (0,1)	0.15	0.20	0.12	0.08
Pumping station (0,1)	0.08	0.13	0.06	0.07 *
n	1,591	543	1,048	

Source*:* Authors' own calculations.
Notes: Cluster-robust standard errors at the community-level.
§ Modern systems include drip, micro and sprinkler irrigation, while traditional systems include gravity-fed, submersion and flood irrigation. ‡ *Norms* refer to customary rules for the management of irrigation systems (e.g. allocation and distribution of water, rights and obligations, forms of organization, etc.) (Gerbrandy and Hoogendam, 1998). *Irrigation turns* refers to the form of expression (at the individual-, family-, or community-level) of the right or access to water within an irrigation system that operates based on a rotational water delivery following a schedule designed for the efficient and equitable distribution of water (Gaceta Oficial de Bolivia, 2006).
T-test for difference in means statistically significant at the *** 1%, ** 5%, * 10% level.

[21] Agricultural gross margins were obtained by deducting total input costs (i.e., fungicide, herbicide, insecticide, chemical fertilizer, organic fertilizer, other agrochemicals, paid labor, tractor, seeds, animal traction, and irrigation) from the value of production.

Lastly, Table 3 reports descriptive statistics related to on-farm infrastructure investments and management of irrigation systems. Producers in the sample invested an average of US$102 on agricultural infrastructure (US$55 for irrigation), and 73 percent have on-farm irrigation. As expected, beneficiaries of PRONAREC I have a significantly larger land area equipped for irrigation (1.59 ha) compared to the control group (1.11 ha), mostly traditional irrigation.

Naturally, most of the variables related to the organizational structure and management of irrigation systems are significantly different for the treated group compared to the control group, given the treated group has been exposed to the program and its benefits for at least one agricultural cycle.

5. Empirical Approach to the Identification of Causal Effects

The main objective of this case study is to estimate the causal effect of the PRONAREC program. In an ideal impact evaluation scenario, we would like to observe the "potential outcomes" of each program participant: the outcome of a farmer with the program and its counterfactual (outcome without the program). If this was possible, a simple difference between the two outcomes would reveal the true (individual-level) impact of the program. However, it is not possible to observe the same unit of analysis with and without the program. Hence, the "fundamental problem facing inference for causal effects" is that of missing data or a counterfactual (Rubin, 1974, 1978; Holland, 1986). Consequently, empirical research focuses on estimating average treatment effects by constructing a credible and rigorously defined control group as a proxy of the counterfactual (Imbens, 2004).

In the case of PRONAREC, given that treatment was not randomly assigned, selection bias is likely to come from three main sources: (i) program placement; (ii) self-selection at the community-level; and (iii) self-selection at the individual (farmer) level.[22] However, special features of the program design are used to address these issues. Specifically, we exploit the gradual implementation or phase-in nature of the program: beneficiary communities of PRONAREC I represent the treated group, and future beneficiary communities (PRONAREC II) represent the control group. PRONAREC I began implementation in the year 2009 and PRONAREC II began implementation in the year 2014. Thus, for evaluation purposes, we identify projects from PRONAREC I that had been operative for at least one agricultural cycle and projects from PRONAREC II which are under construction. Beneficiary communities from both phases self-selected themselves into the program and went through the same selection process. The

[22] Bias due to endogenous placement arises due to non-random assignment of the treatment (for instance, following an eligibility criterion). Self-selection arises in any situation in which individuals (or communities) voluntarily choose to participate in the program.

main difference between both groups is related to the timing of the intervention. Hence, by comparing selected beneficiary projects that receive the program at different moments in time, we are addressing the potential bias of program placement and self-selection at the community-level.

In addition, we control for self-selection bias at the individual-level using propensity score matching (PSM) (Imbens and Rubin, 2015).[23] PSM is a quasi-experimental evaluation technique widely applied in empirical research for program evaluation. Matching methods rely on pre-treatment observable characteristics and statistical techniques to construct a credible and rigorously defined control group for the unbiased assessment of treatment effects under the assumption of unconfoundedness (Rubin, 1974; Rosenbaum and Rubin, 1983; Imbens, 2015).[24] Since not all of the producers in the sample within beneficiary communities of PRONAREC I are connected to the irrigation systems financed by the program (Table 3), the estimation of interest is the *intent-to-treat* (ITT): the average impact of being assigned to the treatment group or the first phase of the program[25]. Using a probit (or logit) regression model to predict the propensity score, ITTs are estimated using a variety of propensity score matching techniques.[26] It is important to keep in mind, however, that the PSM methodology assumes there is no selection bias based on unobservable characteristics; a violation of this assumption would undermine the validity of the results.

6. Results

In this section, we discuss the results of the propensity score matching analysis. This includes an assessment of the participation model and the distribution of the estimated propensity scores, assessment of measure covariate balance after matching, and the impacts of the program on the outcomes of interest. Propensity score matching is in effect a two-stage process. The first-stage being the specification and estimation of the propensity scores using a probit or logit model to predict the likelihood of participation for each producer. The second stage corresponds to the estimation of average treatment effects using different matching algorithms on the basis of the propensity scores.[27]

[23] The propensity score represents the likelihood of program participation conditional on a set of exogenous and observable pre-treatment characteristics.
[24] See Rubin (1994, 1977), Heckman and Robb (1985), Rosembaum (2002), and Imbens (2004) for an in-depth discussion of average treatment effects.
[25] About 83% of the beneficiary farmers of PRONAREC I have on-farm irrigation.
[26] See Appendix for a summary of the Neyman-Rubin model, the conceptual and statistical framework for analyzing causal effects in experimental or quasi-experimental research designs. See Sekhon (2008) for a more in-depth discussion of the model, and Cerulli (2015) for a brief overview of the theoretical and applied econometrics for the evaluation of socio-economic programs.
[27] Balance in measured covariates does not indicate balance in unmeasured covariates. The presence of unmeasured confounders would result in biased estimates of treatment effects (Rosenbaum, 2002; Carnegie et al., 2016).

Table 4—Likelihood of PRONAREC Participation

Covariates	(1) Margins
Household characteristics	
Household size (# of members)	0.004
	(0.006)
Electricity (0,1)	0.137***
	(0.032)
Dirt floor (0,1)	0.009
	(0.025)
Cellular phone (0,1)	0.022
	(0.026)
Head of household characteristics	
Age (years)	0.003***
	(0.001)
Single (0,1)	-0.015
	(0.039)
Female (0,1)	0.009
	(0.030)
Indigenous (0,1)	0.056**
	(0.028)
Years of formal education (#)	0.012***
	(0.003)
Economic characteristics	
Land owned (ha)	0.008***
	(0.002)
Land owned (ha)-squared	-3.50e-05*
	(1.79e-05)
Bank account (0,1)	0.036
	(0.029)
Accessibility (time to)	
Reliable road (min)(log)	0.008
	(0.022)
Reliable road x altitude (MASL)	1.06e-05
	(8.68e-06)
Community characteristics	
Number of families in the community (#)	1.13e-05
	(4.32e-05)
Altitude (MASL) - at the plot level	6.17e-05**
	(3.08e-05)
AEZ: Inter-Andean valleys (0,1)	-0.542***
	(0.059)
AEZ: Tropical (0,1)	-0.222***
	(0.080)
Associability (social capital) before 2009 §	
Agricultural association or WUA (0,1)	-0.006
	(0.022)
Non-agricultural association/organization (0,1)	0.014
	(0.032)
n	1,591
Log likelihood	-808.09
$p > \chi^2$	0.00
Pseudo R^2	0.209
Correctly classified (%)	75.81

Source: Authors' own calculations.

Notes: Agroecological zone-level reference group = Altiplano. The dependent variable takes the value of 1 if the household is a beneficiary of PRONAREC I, 0 otherwise. Column 1 reports average marginal effects at the means of covariates. § The variables of participation in agricultural and non-agricultural associations or organizations included in the probit regression model were modified to reflect participation before 2009.
Standard errors in parentheses. Statistical significance level at *** p<0.01, ** p<0.05, * p<0.1.

6.1 First-Stage: Propensity Score Model Specification and Estimation

For the propensity score model specification, we followed the guidelines described in Heinrich et al*.* (2010). We included variables that are explicitly part of the eligibility criteria, time-invariant, exogenous pre-treatment covariates (i.e., variables not affected by participation, or the anticipation of participation), and covariates related to treatment status and outcome variables. Also, we incorporated variables that determined eligibility criteria such as land ownership and associability. Additional variables that capture household's economic status and accessibility were also included, as these might have played an important role in the household's decision to participate.

The results from the participation model reported in Table 4 show that having access to electricity, characteristics of the head of household (age, educational attainment, and ethnic background), landholdings, altitude, and agroecological zones influence program participation. More specifically, households with electricity are 13.7 pp more likely to participate in PRONAREC I relative to households without electricity at home. Being indigenous increases the likelihood of participation by 5.56 pp, and having an additional year of education increases the probability of participation by 1.22 pp. The probability of participation increases by 0.8 pp per hectare of land owned, however, the results indicate diminishing marginal effects on the likelihood of participation.

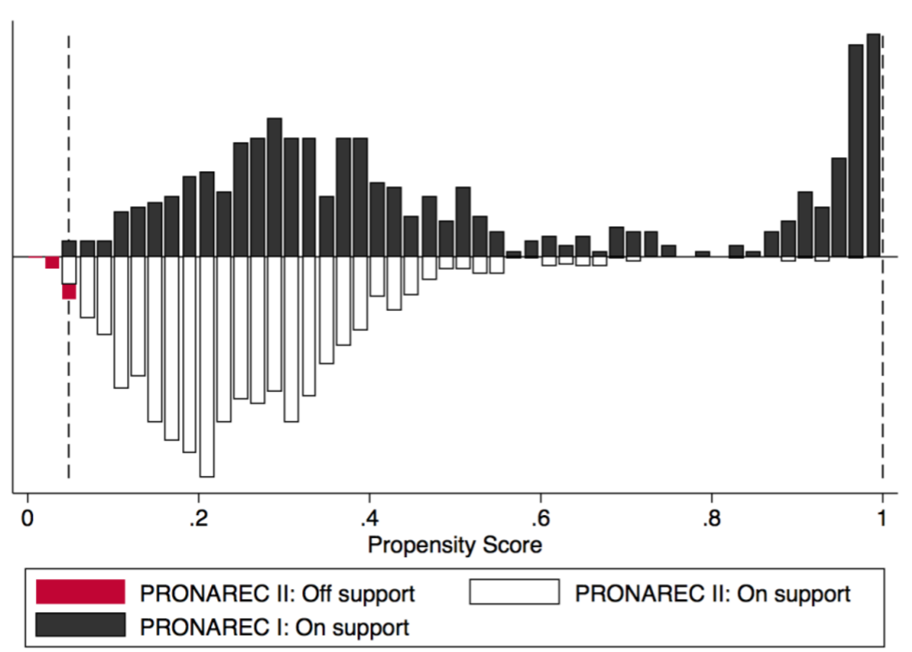
With regards to agroecological zones, the probability of participation decreases in the Andean valleys (54.2 pp) and tropical lowlands (22.2 pp), compared to the Altiplano. On the other hand, neither gender of the head of household nor access to social capital (measured as participation in agricultural and non-agricultural associations) affect the probability of program participation.

Once the propensity score is estimated for each producer by a first-stage probit regression, the next step in the implementation of the methodology is to verify the "common support" or overlap condition (Garrido et al., 2014). Figure 3 illustrates a histogram of the estimated propensity scores for both treatment groups before matching. The overlap in the distribution of propensity scores lies between [0.0470383, 0.9999219] in the treated group and between [0.0191598, 0.9646696] in the control group. The region of common support is determined to be within the range [0.04703831, 0.99992188]. A total of twelve observations (0.75 percent of the sample)—all of them part of the control group—lie outside of the region and will be discarded from the analysis.[28] In terms of the balancing property of the propensity score, after

[28] Caliendo and Kopeinig (2008) note that one method of defining the region of common support is to apply the 'minima and maxima comparison' by deleting all observations "whose propensity score is smaller than the minimum and larger than the maximum in the opposite group", which in this case would be [0.0478568, 0.9663905]. Following this approach, 88 observations are outside of this

splitting the sample in 9 equally spaced blocks, the algorithm found no statistical difference in the average propensity score of treated and control observations within each block, as well as on the mean of each covariate from the model.

Figure 3—Distribution of Estimated Propensity Scores Before Matching



Source*:* Authors' own elaboration.
Notes: Vertical dashed lines mark the region of common support [0.04703831, 0.99992188] determined by the user-written Stata command –*pscore*– (Becker and Ichino, 2002).

6.2 Second-Stage: Propensity Score Matching

The next step in the implementation of the methodology is to use the propensity score to match treated and control observations. The choice of matching method involves a tradeoff between bias and efficiency (Caliendo and Kopeinig, 2008).[29] As a robustness check, we performed this process using several matching algorithms (i.e., nearest-neighbor, radius, kernel, and local linear regression) to produce point estimates.[30] The nearest-neighbor (NN) algorithm

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region of common support which correspond to 76 treated and 12 controls (5% of the sample). However, the region of common support used and reported in this analysis is based on the output obtained from the user-written Stata command –pscore– (Becker and Ichino, 2002) which selected 0.9999231 as the upper bound of the region. Following this approach, a total of 87 observations are outside the region of common support. The results using both approaches are similar. These results are not shown in this paper due to limited space, but are available upon request. Also, it is important to mention that the sampling design considered a sample loss of 5%.

[29] See Caliendo and Kopeinig (2008) for a general overview of different matching algorithms, and Heckman et al. (1997), Imbens (2004), Smith and Todd (2005), and Imbens and Wooldridge (2009) for technical details.

[30] The propensity score matching was performed using the user-written Stata command –*psmatch2*– (Leuven and Sianesi, 2003).

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 implemented with or without replacement and with *k*-nearest neighbors. For this evaluation, we performed 1-nearest neighbor matching with and without replacement, as well as 3-nearest and 5-nearest neighbor matching with replacement. Following a similar approach as NN matching, the radius algorithm uses a pre-specified tolerance level on the maximum propensity score distance or "caliper" to perform the matching of treated observations with all those control observations that fall within the caliper bandwidth. Based on the literature, a caliper of 25 percent (Rosenbaum and Rubin, 1985) and 20 percent (Cochran and Rubin, 1973; Austin, 2011) of the pooled standard deviation (sd_p) of the sample estimated propensity scores were chosen. Also, a combination of NN matching with caliper was implemented.[31] Lastly, the counterfactual for each treated observation was constructed using kernel and Local Linear Regression (LLR), both with the default bandwidth of 0.06, as well as 0.01 (Heckman et al.,1997).[32]

While there is no consensus in the literature on how much imbalance is acceptable when implementing PSM (Harder et al., 2010; Garrido et al., 2014), a rule of thumb is to consider a matched sample to be adequately balanced if the Rubins' B is less than 25 percent and the Rubin's R is between 0.5 and 2 (Rubin, 2001). The Rubins' B statistic is the absolute standardized difference of the means of the linear index of the propensity score between the treated and matched control group and the Rubin's R is the ratio of the variance of the propensity score of the treated and matched control group (Rubin, 2001). Intuitively, these statistics are testing the similarity of the covariate distributions across treatment groups. For the sample of analysis, the Rubins' B before matching is 103.50 percent and the Rubin's R is 7.24, which indicate a highly unbalanced sample with large initial bias. The rest of the analysis will be based on the results obtained from the set of matched samples satisfying the Rubins' B and Rubin's R criteria. In particular, NN 1:1 without replacement and caliper ($0.25sd_p$, $0.1sd_p$, 0.01), radius matching with caliper (0.25sdp and $0.2sd_p$), and kernel matching with a 0.01 bandwidth constitutes our set of preferred matching algorithms.[33]

[31] In addition, both NN and radius matching were implemented using calipers equal to $0.1sd_p$, $0.3sd_p$, 0.01, and 0.001. Further, the option –ties– was specified for all matching algorithms, thus matching not only the NN but also other controls with identical propensity scores (Abadie et al*.,* 2004).
[32] Abadie and Imbens (2008) show that the calculation of bootstrapped standard errors is not valid for the standard NN matching estimators with replacement and a fixed number of neighbors (e.g., one, three or five), since they are not asymptotically linear estimators of average treatment effects. However, as the number of matches increases, estimators become asymptotically linear, as it is in the case of radius-, kernel, and LLR-based matching techniques (Abadie and Imbens, 2008; Ham, Li and Reagan, 2011).
[33] Results of the overall measures of covariate imbalance for the complete set of matching techniques is available in Table A1 of the Appendix. ATT estimates from the complete set of matching are omitted due to limited space, but are available upon request.

Table 5—Overall Measures of Covariate Imbalance Before and After Matching

Matching algorithm	No. of observations: Total	Treated	Control	*Pseudo* R^2	$p > \chi^2$	Mean bias (%)	Median bias (%)	Rubins' B (%)	Rubin's R
Unmatched sample	1,579	543	1,036	0.21	0.00	20.82	15.51	103.50	7.24
NN 1:1 (no repl., cal=0.25sd_p)	750	375	375	0.00	1.00	2.88	2.86	14.31	0.78
NN 1:1 (no repl., cal=0.1sd_p)	746	373	373	0.00	1.00	3.51	3.13	15.80	0.92
NN 1:1 (no repl., cal=0.01)	732	366	366	0.00	1.00	2.18	2.00	15.05	1.19
Radius (cal=0.25sd_p) †	1,500	464	1,036	0.01	0.99	4.23	4.09	19.37	1.10
Radius (cal=0.2sd_p) †	1,499	463	1,036	0.01	0.99	4.12	4.06	19.57	1.13
Radius (cal=0.01) †	1,466	436	1,030	0.00	1.00	3.20	2.66	16.01	0.95
Kernel (epan, bw=0.01) †	1,466	436	1,030	0.00	1.00	3.31	2.87	16.57	0.96

Source: Authors' own calculations.
Notes: NN = nearest-neighbor; no repl. = without replacement; cal = caliper; epan = epanechnikov kernel. $p > \chi^2$ = *p*-value of the likelihood-ratio test; sd_p = pooled standard deviation of the estimated propensity scores (0.2327087); bw = bandwidth.
† Cluster bootstrapped standard errors with 500 replications.

Relative balance, comparability and quality of matched samples can be assessed through the examination of the *standardized percentage bias* (% bias) (Rosenbaum and Rubin, 1985). Results of the overall measures of covariate imbalance for our preferred set of matching algorithms are shown in Table 5. Unlike t-tests, absolute standardized mean differences are not sensitive to sample size. This allows researchers to compare the difference in means across measured covariates between treated and control observations in the matched sample with that in the unmatched sample as a percentage of the square root of the average of the sample variances in both groups (Austin, 2009). Specifically, an average absolute standardized difference closer to 0 indicates small differences between treated and control groups in matched samples.[34]

The absolute standardized mean differences in covariates were significantly reduced for this set of preferred matching techniques. This implies the quality of matching was superior for these algorithms as they significantly reduced biases from observable characteristics. Specifically, the average absolute standardized bias of the unmatched sample is 20.82 percent, while under PSM, the average absolute standardized bias for the preferred set of matching techniques ranges from 2.18 to 4.23 percent. Similarly, the median absolute standardized bias was reduced from 15.51 for the unmatched sample to between 2.00 to 4.09 for this preferred set.

The *pseudo* R^2, which indicates how well the covariates in the model explain the participation probability, is fairly low for the set of preferred matching algorithms (less than or equal to 0.01) compared to the unmatched sample (0.21). This indicates that there are no systemic differences in the distribution of covariates between groups after matching. Also, while the p-value of the likelihood-ratio test of the joint significance of all the regressors before matching

[34] Exact balance in covariates is a property of randomized controlled trials (RCT) with large sample sizes. In the case of observational studies, and also of RCTs with small samples, some degree of imbalance can be expected (Austin, 2009).

is less than 0.00 (failing to reject the null hypothesis of joint insignificance), the p-values after matching (≥ 0.99) suggest joint insignificance of all regressors.

Table 6—Remaining Covariate Imbalance After Matching

Covariates	% bias (before matching)	Matching algorithm: NN 1:1 (no repl., cal=0.25sd$_p$)	NN 1:1 (no repl., cal=0.1sd$_p$)	NN 1:1 (no repl., cal=0.01)	Radius† (cal=0.25sd$_p$)	Radius† (cal=0.2sd$_p$)	Radius† (cal=0.01)	Kernel† (epan, bw=0.01)
		% bias (after matching)						
Household characteristics								
Household size (# of members)	1.4	1.6	3.1	0.5	8.4	8.6	4.7	4.2
Electricity (0,1)	10.8*	2.9	5.8	4.5	-1.1	-2.3	-2.4	-2.2
Dirt floor (0,1)	22.5*	-3.8	-2.8	-1.7	-7.4	-8.0	-5.8	-6.1
Cellular phone (0,1)	13.0*	5.6	5.6	3.8	0.8	1.1	-1.1	-0.9
Head of household characteristics								
Age (years)	13.9*	-2.3	-1.9	-1.0	-1.7	-0.9	-3.6	-3.4
Single (0,1)	-14.3*	0.0	0.0	-1.9	-7.1	-7.7	-5.5	-5.7
Female (0,1)	-8.2	0.0	-0.7	0.7	-6.0	-4.5	-1.6	-2.0
Indigenous (0,1)	23.8*	-6.6	-7.3	-6.7	-0.3	-1.7	-1.3	-1.3
Years of formal education (#)	19.6*	4.4	4.5	1.7	7.2	7.2	4.2	3.8
Economic characteristics								
Land owned (ha)	24.4*	0.0	2.7	1.0	8.6	8.5	6.0	6.2
Land owned (ha)-squared	16.7*	-0.9	3.1	2.1	5.2	4.2	2.9	3.0
Bank account (0,1)	3.3	4.4	7.3	2.2	5.4	5.4	5.6	6.5
Accessibility (time to)								
Reliable road (min)(log)	26.4*	4.4	3.9	2.1	2.2	2.2	4.5	5.6
Reliable road x altitude (MASL)	48.4*	1.1	0.9	-0.6	-1.0	-1.4	1.8	2.3
Community characteristics								
Families in the community (#)	-0.7	0.0	0.9	-3.3	0.4	0.3	-1.2	-1.6
Altitude (MASL) - at the plot level	45.5*	-2.8	-2.7	-0.3	-3.3	-3.9	-2.1	-2.5
AEZ: Andean valleys (0,1)	-84.3*	5.1	5.1	2.2	-2.0	-0.8	2.3	2.7
AEZ: Tropical (0,1)	26.2*	-5.3	-5.4	-3.3	9.0	6.8	1.2	0.6
Associability (social capital)								
Agricultural org or WUA (0,1)	-6.8	3.8	3.8	1.1	4.9	5.7	5.5	5.3
Non-agricultural association (0,1)	-6.1	2.5	2.5	2.6	-2.5	-1.1	0.6	0.2

Source*:* Authors' own calculations.
Notes*:* NN = nearest-neighbor; no repl = without replacement; cal = caliper; epan = epanechnikov kernel; sd$_p$ = pooled standard deviation of the estimated propensity scores (0.2327087); bw = bandwidth. * Indicates absolute value of standardized bias greater than 10 percent.
† Cluster bootstrapped standard errors with 500 replications.

Table 6 presents a summary of the standardized percentage bias across measured covariates in the unmatched and matched samples for the selected set of preferred matching techniques. For the unmatched sample, a total of 14 out of the 20 covariates have an absolute standardized bias greater than 10 percent; the largest differences being for the Andean valleys agroecological zone dummy (-84.3 percent), the interaction between time to a reliable route/road and altitude (48.4 percent), altitude (45.5 percent), and time to a reliable route/road (26.4 percent). Only three covariates in the unmatched sample had an absolute standardized percentage bias of less than 5 percent. After PSM, there is a substantial improvement in the balance of each covariate, indicating that the balancing property of the PSM methodology has been adequately satisfied.

6.3 Program Impacts

This section presents the impacts of PRONAREC I on the outcomes of interest. Tables 7 and 8 report estimates of the ITT obtained from the set of preferred matching techniques.

The parameter estimates in Table 7 examine the effects on agricultural input use, production, and total household income. The results indicate that PRONAREC I had a positive impact on the use of improved seeds and agricultural machinery during the 2014-2015 agricultural cycle. On average, beneficiaries of PRONAREC I are more likely to use improved or certified seeds (80-90 percent), and agricultural machinery (7-19 percent), especially a tractor (11-20 percent). Further, they are less likely to use animal traction (7-18 percent) compared to the control group. These results are significant and robust across matching algorithms. While the effects of the program on land intensification are negative, the results are rather small (4 pp) and not robust; this is likely as a consequence of the extreme temperatures in the Altiplano during winter, which makes the region unsuitable for agricultural production even when irrigation is available.

As expected, the program also had significant effects on aggregate expenditures dedicated to the irrigation of plots (between US$30-US$40)—especially expenditures on equipment or maintenance—an increase of approximately 160 percent relative to the control groups' expenditures on irrigation. The impacts on irrigation expenditures are robust across different matching techniques. Similarly, the results show program participation had a significant impact on investments in on-farm irrigation infrastructure: total landholding equipped for irrigation is significantly higher for beneficiaries of PRONAREC I (0.4-0.5 hectares), an increase of approximately 35-45 percent with respect to the control group. Further, beneficiaries of PRONAREC I have a larger proportion of their land equipped with irrigation (15-17 pp), and a greater number of hectares equipped with irrigation were under production during the 2014-2015 cycle (0.4-0.45 hectares). Overall, beneficiaries of PRONAREC I are 24 percent more likely (16-18 pp) to have irrigation compared to the control group. Finally, PRONAREC I had positive impacts on expenditures on variable inputs of production (34-47 percent), including tractors (35-55 percent), and these results are robust across specifications.

The program was also expected to have an impact on the composition of farmers' crop portfolios by shifting production patterns from traditional to higher-value crops. However, using the proportion of land dedicated to non-traditional crops as a proxy, we do not have any evidence of crop diversification for the period under study. On the other hand, ITT estimates in Table 7 reveal that beneficiaries of PRONAREC I are relatively better connected to markets as a result of the program. Treated farmers are more likely to sell their products in a market or *feria* (10-16 pp), an increase of approximately 20-30 percent relative to the control group.[35] Further, there is evidence suggesting beneficiaries of PRONAREC I allocated less production to home-consumption.

On average, the intervention had a significant positive impact on the value of agricultural production (US$1,250-US$1,550), an increase of approximately 60-70 percent compared to the control group. On the other hand, there is no evidence of an impact on the value of production per hectare (a proxy of productivity). However, we have some evidence of a positive effect on average gross margins (US$867-US$987), with an increase of roughly 86 to 98 percent as a result of the program. Figure 4 compares the composition and destination of agricultural production between beneficiaries of PRONAREC I and II during the 2014-2015 cycle. Beneficiaries of PRONAREC I produced and sold a larger share and mix of fruits, vegetables, and grains (rice and sorghum). In contrast, beneficiaries of PRONAREC II focused extensively on the production of potatoes and corn, with a smaller production of non-traditional crops.

The results presented at the bottom portion of Table 7 reports the effects of PRONAREC on household welfare. The output shows a significant positive ITT on total household income (US$1,240-US$1,580), mostly derived from agricultural sales. The increase in income represents an average gain of about 35-45 percent relative to the control group.

So far, the results indicate that access to PRONAREC has triggered a modernization process, creating a dynamic cycle of technological change. Specifically, beneficiaries have invested in other modern technologies (i.e., improved seeds and tractor) and inputs. Also, treated farmers are more connected to markets and report higher income. In sum, the investments have improved market connections, increased sales and income. There is also evidence that beneficiaries of PRONAREC I are still in the "learning by doing" stage of the technology adoption, as these results do not reflect an impact on the value of production per hectare.

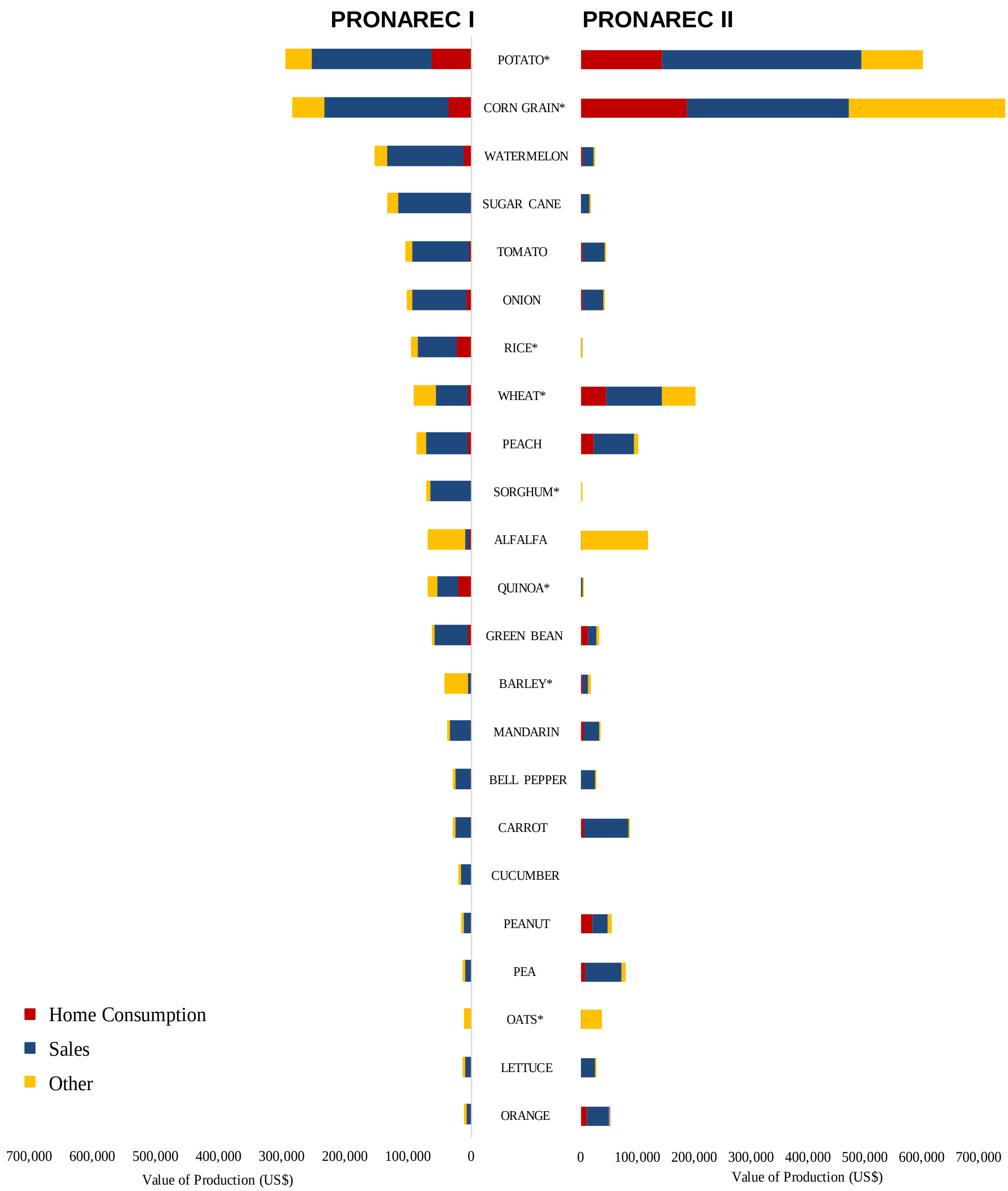
[35] From the data, it is not possible to identify the exact proportion of production sold in a *feria* (market) vs *rescatista* (wholesale merchant). The questionnaire asked producers (crop by crop) to specify whether *most* of the production was sold in: (1) a *feria* (within and outside the community), (2) a *rescatista*, or (3) other; no other information was collected. For instance, if a producer sold 60 percent of crop *i in* a *feria* and the other 40% to a *rescatista*, the only information we know about the composition of this sale is that *most* of that crop was sold in a *feria*. Therefore, this variable is only a proxy and the results should be interpreted with caution.

Table 7—Impacts of PRONAREC on Agricultural Input Use, Production, and Income

	Matching algorithm						
ITT estimates	NN 1:1 (no repl., cal=0.25sd_p)	NN 1:1 (no repl., cal=0.1sd_p)	NN 1:1 (no repl., cal=0.01)	Radius† (cal=0.25sd_p)	Radius† (cal=0.2sd_p)	Radius† (cal=0.01)	Kernel† (epan, bw=0.01)
Input use							
Fungicide (0,1)	0.02	0.01	0.01	0.01	0.01	0.00	0.00
Herbicide (0,1)	0.05	0.05	0.05	0.01	0.02	-0.01	-0.01
Insecticide (0,1)	0.03	0.03	0.03	0.05	0.05	0.05	0.05
Chemical fertilizer (0,1)	-0.03	-0.03	-0.04	-0.03	-0.02	-0.03	-0.03
Organic fertilizer/*guano*/manure (0,1)	0.02	0.02	0.02	-0.04	-0.04	-0.01	-0.01
Improved or certified seeds (0,1)	0.13***	0.11***	0.13***	0.13**	0.13**	0.12**	0.11**
Animal traction (oxen) (0,1)	-0.09**	-0.09***	-0.09**	-0.17**	-0.17**	-0.16**	-0.16**
Agricultural machinery (0,1)	0.06**	0.06*	0.05*	0.15*	0.15*	0.13*	0.13*
Tractor (0,1)	0.08***	0.078**	0.07**	0.15*	0.15*	0.13*	0.13*
Paid labor (0,1)	0.01	0.01	0.00	-0.01	-0.02	-0.03	-0.03
Physical cultivated (ha)	0.30	0.24	0.13	0.72	0.76	0.36	0.36
Hectares worked (ha)	0.28	0.22	0.11	0.63	0.68	0.30	0.30
Land Intensification: worked/physical (%)	-0.03	-0.03	-0.03	-0.04**	-0.04*	-0.04*	-0.04*
Input expenditures							
Expenditures on the irrigation of plots (US$)	45.54***	41.54***	44.95***	32.82**	32.89**	32.41**	33.37**
Water service (US$)	1.65	1.66	2.47	2.85	2.61	2.84	3.12
Energy (US$)	5.05	5.15	4.99	7.42	7.46	4.47	4.49
Irrigation equipment/maintenance (US$)	38.71***	34.62***	37.37***	21.96*	22.74*	25.02**	25.68**
Inputs (US$) ‡	184.60***	184.10***	172.60***	235.00***	243.0***	208.1**	208.4**
Tractor (US$)	32.02***	35.25***	31.48***	51.61**	51.66**	44.65**	44.79**
Paid labor (US$)	464.40	227.00	295.70	311.30	302.20	157.20	156.00
Area equipped for irrigation							
On-farm irrigation (0,1)	0.16***	0.16***	0.17***	0.17***	0.17***	0.18***	0.18***
Total landholding equipped for irrigation (ha)	0.43**	0.43**	0.45**	0.51*	0.52*	0.42	0.40
Equipped for irrigation (% landholding)	0.15***	0.15***	0.16***	0.16***	0.16***	0.17***	0.17***
Worked under irrigation (ha)	0.40**	0.38**	0.42**	0.46*	0.46*	0.39	0.38
Crop portfolio							
Non-traditional crops (0,1)	-0.01	0.00	-0.01	0.01	0.01	0.00	-0.01
Land w/ non-traditional crops (% worked)	0.00	0.00	0.00	0.03	0.03	0.02	0.02
Sales							
Sells (0,1)	0.04	0.04	0.03	0.08*	0.08*	0.07	0.07
Sold *most* of a crop in a *feria*/market (0,1)	0.10***	0.10***	0.09**	0.16**	0.16**	0.14**	0.14**
Agricultural production							
Value of production (US$)	1,296***	1,436***	1,304**	1,558**	1,539**	1,256**	1,268**
Home consumption (% total production)	-0.05**	-0.05**	-0.03	-0.10**	-0.09**	-0.09**	-0.09**
Sales (% total production)	0.05	0.05*	0.04	0.08*	0.07*	0.06	0.06
Value of production (US$/ha worked)	462.90	500.70	419.30	385.80	403.50	348.90	382.80
Agricultural gross margins (US$)	606.30	938.70*	795.60	987.10*	969.40*	867.70*	880.00*
Total household income §							
Total Household Income (US$)	1,387***	1,583***	1,357**	1,543**	1,529**	1,237*	1,246*
Off-farm income (US$)	-141.90	-78.07	-194.10	-135.70	-149.60	-188.10	-191.50
Value of production							
Home consumption (US$)	-21.71	-23.54	-17.36	-13.69	-9.33	-59.16	-57.26
Animal consumption (US$)	-97.19	-95.43	-106.50	-47.28	-48.29	-79.26	-83.66
Seeds (US$)	-15.86	-14.59	-19.06	0.15	1.06	-4.71	-1.79
Sales (US$)	1,359***	1,498***	1,388***	1,523***	1,498***	1,301**	1,310**
Consumption of livestock owned (US$)	61.59***	67.64***	69.28***	49.85*	53.18**	56.84**	56.86**
Livestock sold (US$)	173.8***	159.7**	161.6**	81.54	110.50	160.5*	158.40

Source*:* Authors' own calculations.
Notes*:* NN = nearest-neighbor; repl = replacement; cal = caliper; epan = epanechnikov kernel; sd_p = pooled standard deviation of the estimated propensity scores (0.23270874); bw = bandwidth. ITT estimates statistically significant at the *** 1%, ** 5%, * 10% level.
† Cluster bootstrapped standard errors with 500 replications.
‡ Includes expenditures on fungicides, herbicides, insecticides, fertilizer, other agrochemicals, seeds, animal traction, and tractors.
§ Total income derived from off-farm income, remittances, agricultural production (excluding losses), and livestock revenue (home consumption and sales).

Figure 4—Value of Agricultural Production (US$), by Crop and Program Phase



Source: PRONAREC's 2014-2015 Agricultural Household Survey.
Notes: Exchange rate: 1 Boliviano = 0.15 US$ (2014-2015 average). List includes only the set of crops with the highest values (US$).
* Traditional crop.

Lastly, Table 8 presents the effects of program participation on the management and organization of irrigation systems. On average, beneficiaries of PRONAREC I are more likely to have formalized a WUA (12-15 percent), and to be part of the WUA (5 percent). Also, treated farmers are significantly more likely to report belonging to irrigation systems with better-structured forms of management and organization, including norms (50 percent), irrigation turns (57 percent), statues and regulations governing WUAs (36 percent), and technical manuals for the operation and maintenance of the system (42 percent). These results are highly significant and robust across matching specifications. These findings are crucial for the sustainability of the investments in irrigation infrastructure at the community- and farm-level, as WUAs are expected to enhance the efficiency in the use and distribution of water for irrigation.

Table 8—Impacts of PRONAREC on the Management and Organization of Irrigation Systems

	Matching algorithm						
ITT estimates	NN 1:1 (no repl., cal=0.25sd$_p$)	NN 1:1 (no repl., cal=0.1sd$_p$)	NN 1:1 (no repl., cal=0.01)	Radius† (cal=0.25sd$_p$)	Radius† (cal=0.2sd$_p$)	Radius† (cal=0.01)	Kernel† (epan, bw=0.01)
Community watershed and irrigation board							
Watershed committee was formed (0,1)	0.11***	0.10***	0.11***	0.08	0.08	0.09*	0.10*
Formalized WUA (0,1)	0.10***	0.10***	0.10***	0.12***	0.12***	0.11***	0.12***
HH belongs to a WUA (0,1)	0.05**	0.05**	0.04**	0.07***	0.06**	0.06**	0.06***
Irrigation system management ‡							
Norms (0,1)	0.27***	0.27***	0.28***	0.27***	0.26***	0.28***	0.28***
Irrigation turns (0,1)	0.32***	0.33***	0.33***	0.31***	0.31***	0.33***	0.33***
Irrigation system organization							
Statutes and regulations (0,1)	0.18***	0.19***	0.18***	0.17***	0.16***	0.19***	0.19***
Manuals (0,1)	0.17***	0.18***	0.16***	0.15***	0.15***	0.15***	0.16***

Source*:* Authors' own calculations.
Notes: NN = nearest-neighbor; repl = replacement; cal = caliper; epan = epanechnikov kernel; sd$_p$ = pooled standard deviation of the estimated propensity scores (0.23270874); bw = bandwidth. ITT estimates statistically significant at the *** 1%, ** 5%, * 10% level.
‡ *Norms* refer to customary rules for the management of irrigation systems (e.g. allocation and distribution of water, rights and obligations, forms of organization, etc.) (Gerbrandy and Hoogendam, 1998). Irrigation *turns* refers to the form of expression (at the individual-, family-, or community-level) of the right or access to water within an irrigation system that operates based on a rotational water delivery following a schedule designed for the efficient and equitable distribution of water (Gaceta Oficial de Bolivia, 2006).
† Cluster bootstrapped standard errors with 500 replications.

7. Conclusion

This study evaluates the impact of the first phase of Bolivia's National Irrigation Program with a Watershed Approach (PRONAREC, for its acronym in Spanish) on a set of agricultural and water resource management outcomes. For this purpose, detailed cross-sectional data from an agricultural household survey was collected and analyzed. To measure program effectiveness, we exploit unique features of the program design (phased roll-out). Specifically, by comparing a representative sample of farmers from beneficiary communities of the first phase of the program (PRONAREC I) with farmers from beneficiary communities of the second phase of the program

(PRONAREC II). This strategy combined with propensity score matching (PSM) allows us to control for program placement and self-selection bias.

The results of the impact evaluation indicate that program beneficiaries are undergoing significant structural changes. In particular, there is evidence of a trickling-down process towards the adoption of complementary technologies. More specifically, farmers did not only make on-farm investments on irrigation infrastructure but also increased expenditures on improved or certified seeds and modern agricultural machinery. Modernization also translated into greater access to markets, an improvement of farm sales, and an increase in total household income. Nevertheless, the lack of significant impacts on agricultural productivity suggests that farmers are still in the upward sloping part of the learning curve. Regarding outcomes related to the organization and management of irrigation systems, the results suggest that beneficiary communities of PRONAREC I have more advanced and better structured irrigation systems, including formalized WUAs and water rights for irrigation. To our knowledge, this is the first time a rigorous impact evaluation of communal irrigation systems has been conducted in Bolivia addressing both, productive and managerial outcomes. Such assessment is essential because the governance of communal irrigation systems is a complex and dynamic structure that relies on a series of informal and formal norms, regulations, cultural traits, etc. Also, governance has been widely acknowledged to play a crucial role in the sustainability of irrigation systems (Redman et al. 2004; Saldías et al., 2012; McGinnis and Ostrom, 2014).

Overall, these results suggest that communal irrigation systems can produce effects at the agricultural, economic and governance levels. The impacts caused by irrigation systems generate a snowball effect that improves adoption of more modern technologies, creating a virtuous cycle for agricultural innovation. Nevertheless, the causal chain to develop these impacts is rather complex and must be analyzed carefully using appropriate indicators at all levels of the causal chain, and considering timing and temporality for capturing diverse types of effects.

Lastly, given that the general objective of the program is to increase income by boosting agricultural productivity, enhancing the efficiency of water use, and improving the management of water resources for irrigation purposes, stochastic frontier analysis (SFA) would be a suitable complement to this study (Bravo-Ureta, 2014). By combining PSM and SFA to control for selection bias (Green, 2010), our ongoing research objective is to analyze the effects of PRONAREC I on technological change and technical efficiency.[36] This analysis will allow us to corroborate whether

[36] Technological change refers to a shift in the production frontier caused by the application of knowledge (whether embodied or disembodied in physical inputs, or through the introduction of an entirely new set of processes and inputs), and technical efficiency refers to the "ability to avoid waste", either through output-augmentation (maximizing production given the set of available technology and inputs) or input-conservation orientation (minimizing input usage given the set of available technology and output production) (Carlson et al. 1993).

the modernization of irrigation systems generates effects on efficiency and technological changes at the farmer level.

An important caveat to keep in mind when considering the validity of PSM results concerns the potential presence of unobservable characteristics. If unobservable characteristics affect program participation and outcomes, PSM analysis produces biased estimates of ATTs. An approach widely applied in the evaluation literature, when panel data is available, is difference-in-differences (DD) (Imbens and Wooldridge, 2009). DD methods can mitigate selection bias arising from time-invariant and individual-specific unobserved characteristics. It is also possible to combine evaluation methods, such as matching and DD (Stuart et al., 2014). Given the drawbacks associated with cross-sectional data, a more detailed analysis using panel data techniques will be useful to complement this study. Also, by analyzing long-term impacts, future research will aim to provide valuable insights about the sustainability of these type of investments which is of crucial importance for policymakers.

References

Abadie, A., Drukker, D., Herr, J. L., & Imbens, G. W. (2004). Implementing Matching Estimators for Average Treatment Effects in Stata. *Stata Journal*, 4, 290-311.

Abadie, A., & Imbens, G. W. (2008). On the Failure of the Bootstrap for Matching Estimators. *Econometrica*, 76(6), 1537-1557.

Abadie, A., & Imbens, G. W. (2016). Matching on the Estimated Propensity Score. *Econometrica*, 84, 781–807.

Alauddin, M., & Quiggin, J. (2008). Agricultural Intensification, Irrigation and the Environment in South Asia: Issues and Policy Options. *Ecological Economics*, 65(1), 111-124.

Andersen, L. E., Cardona, M., & Romero, D. (2015). Do Irrigation Programs Make Poor Rural Communities in Bolivia Less Vulnerable to Climatic and other Shocks? *Revista Latinoamericana de Desarrollo Económico*, (24), 9-46.

Aregay, F. A., & Minjuan, Z. (2012). Impact of Irrigation on Fertilizer Use Decision of Farmers in China: A Case Study in Weihe River Basin. *Journal of Sustainable Development*, 5(4), 74.

Atria, R., & Siles, M. (2004). *Social Capital and Poverty Reduction in Latin America and the Caribbean: Towards a New Paradigm* (Vol. 71). United Nations Publications.

Austin, P. C. (2009). Balance Diagnostics for Comparing the Distribution of Baseline Covariates Between Treatment Groups in Propensity-Score Matched Samples. *Statistics in Medicine*, 28(25), 3083-3107.

Austin, P. C. (2011). Optimal Caliper Widths for Propensity-Score Matching When Estimating Differences in Means and Differences in Proportions in Observational Studies. *Pharmaceutical Statistics*, 10(2), 150-161.

Bandyopadhyay, S., Shyamsundar, P., & Xie, M. (2007). Yield Impact of Irrigation Management Transfer: Story from the Philippines. *World Bank Policy Research Working Paper*, (4298).

Becker, S. O., & Ichino, A. (2002). Estimation of Average Treatment Effects Based on Propensity Scores. *The Stata Journal*, 2(4), 358-377.

Besley, T., & Case, A. (1994). *Diffusion as a Learning Process: Evidence from HYV Cotton*. Working Papers. Research Program in Development Studies. Woodroow Wilson School of Public and International Affairs, Princeton University.

Bravo-Ureta, B. E. (2014). Stochastic Frontiers, Productivity Effects and Development Projects. *Economics and Business Letters*, 3(1), 51-58.

Caliendo, M., & Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. J*ournal of Economic Surveys*, 22(1), 31-72.

Carnegie, N. B., Harada, M., & Hill, J. L. (2016). Assessing Sensitivity to Unmeasured Confounding Using a Simulated Potential Confounder. *Journal of Research on Educational Effectiveness*, *9*(3), 395-420.

Carlson, G. A., Zilberman, D., & Miranowski, J. A. (Eds.). (1993). *Agricultural and Environmental Resource Economics*. New York: Oxford University Press.

CBDHDD (2009). *Informe de la Sociedad Civil para el EPU Bolivia: Un Informe Sobre los Derechos Humanos en Bolivia*. Capítulo Boliviano de Derechos Humanos, Democracia y Desarrollo, La Paz.

Cerulli, G. (2015). Econometric Evaluation of Socio-Economic Programs. *Advanced Studies in Theoretical and Applied Econometrics Series*, *49.*

Cochran, W. G., & Rubin, D. B. (1973). Controlling Bias in Observational Studies: A Review. *Sankhyā: The Indian Journal of Statistics*, Series A, 417-446.

Del Carpio, X. V., Loayza, N., & Datar, G. (2011). Is Irrigation Rehabilitation Good for Poor Farmers? An Impact Evaluation of a Non-Experimental Irrigation Project in Peru. *Journal of Agricultural Economics*, 62(2), 449-473.

Dillon, A. (2008). *Access to Irrigation and the Escape from Poverty: Evidence from Northern Mali*. IFPRI Discussion Paper 872, International Food Policy Research Institute, Washington DC.

Dillon, A. (2011a). Do Differences in the Scale of Irrigation Projects Generate Different Impacts on Poverty and Production? *Journal of Agricultural Economics*, 62(2), 474-492.

Dillon, A. (2011b). The Effect of Irrigation on Poverty Reduction, Asset Accumulation, and Informal Insurance: Evidence from Northern Mali. *World Development*, 39(12), 2165-2175.

ECLAC/FAO/IICA (2012). *The Outlook for Agriculture and Rural Development in the Americas: A Perspective on Latin America and the Caribbean 2013*. Santiago, Chile.

FAOSTAT (2015). FAO Database: Value Added, Agriculture, Forestry and Fishing (Value US$).

Feder, G., & Umali, D. L. (1993). The Adoption of Agricultural Innovations: A Review. *Technological Forecasting and Social Change*, 43(3), 215-239.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change*, 33(2), 255-298.

Foster, A. D., & Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy*, 103(6), 1176-1209.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of Technology Adoption. *Annual Review of Economics*, 2.

Gaceta Oficial de Bolivia. (2006). *Bolivia: Reglamento a la Ley Nº 2878 de Promocion y Apoyo al Sector Riego para la Producción Agropecuaria y Forestal Marco Institucional, DS Nº 28817, 2 de agosto de 2006*. Estado Plurinacional de Bolivia

Garces-Restrepo, C., Vermillion, D., & Muñoz, G. (2007*). Irrigation Management Transfer: Worldwide Efforts and Results*. FAO Water Report No. 32, Food and Agriculture Organization of the United Nations, Rome.

García, M., Raes, D., Jacobsen, S. E., & Michel, T. (2007). Agroclimatic Constraints for Rainfed Agriculture in the Bolivian Altiplano. *Journal of Arid Environments*, 71(1), 109-121.

Garrido, M. M., Kelley, A. S., Paris, J., Roza, K., Meier, D. E., Morrison, R. S., & Aldridge, M. D. (2014). Methods for Constructing and Assessing Propensity Scores. *Health Services Research*, 49(5), 1701-1720.

GeoSIRH (2015). *Nacional: Mapa Inventario de Sistemas de Riego*. (August 28). Instituto de Datos Espaciales, Viceministerio de Recursos Hídricos y Riego. Retrieved March 2017 from the World Wide Web: http://geosirh.riegobolivia.org/maps/158.

Gerbrandy, G. & Hoogendam, P. (1998). *Aguas y Acequias: Los Derechos al Agua y la Gestión Campesina de Riego en los Andes Bolivianos*. Cochabamba: PEIRAV–Plural Editores

GWP (2000*). Integrated Water Resource Management*. TAC Background Paper No. 4, Global Water Partnership Secretariat, Stockholm.

Ham, J. C., Li, X., & Reagan, P. B. (2011). Matching and Semi-Parametric IV Estimation, a Distance-Based Measure of Migration, and The Wages of Young Men. *Journal of Econometrics*, 161(2), 208-227.

Hameleers, A., Antezana, S. and Paz, B., (2011). *Agricultural Human Investment Strategies: Towards Strengthening the Farmers Innovation Capacity (FIC) Case Study: Bolivia.* FAO, page 33.

Harder, V. S., Stuart, E. A., & Anthony, J. C. (2010). Propensity Score Techniques and the Assessment of Measured Covariate Balance to Test Causal Associations in Psychological Research. *Psychological Methods*, 15(3), 234.

Heckman J.J., Ichimura H., & Todd P. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies*, 64, 605–54.

Heckman, J. J., & Robb, R. (1985). Alternative Methods for Evaluating the Impact of Interventions: An Overview. *Journal of Econometrics*, 30(1), 239-267.

Heinrich, C., Maffioli, A., & Vazquez, G. (2010). *A Primer for Applying Propensity-Score Matching.* Technical Note No. IDB-TN-161. Inter-American Development Bank.

Holland, P. W. (1986). Statistics and Causal Inference. *Journal of the American Statistical Association*, 81(396), 945-960.

Huang, Q. (2014). Impact Evaluation of the Irrigation Management Reform in Northern China. *Water Resources Research*, 50(5), 4323-4340.

Huang, Q., Rozelle, S., Wang, J., & Huang, J. (2009). Water Management Institutional Reform: A Representative Look at Northern China. *Agricultural Water Management*, 96(2), 215-225.

Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *Review of Economics and Statistics*, 86(1), 4-29.

Imbens, G. W. (2015). Matching Methods in Practice: Three Examples. *Journal of Human Resources*, 50(2), 373-419.

Imbens, G.W., & Wooldridge., J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature*, 47(1), 5-86.

INE (2014). Estadísticas Sociales: Pobreza Desigualdad y Desarrollo Humana. <http://www.ine.gob.bo/>

INE (2015). *Censo Agropecuario 2013: Bolivia*: Instituto Nacional de Estadística.

Jack, B. K. (2013). *Constraints on the Adoption of Agricultural Technologies in Developing Countries.* Literature Review, Agricultural Technology Adoption Initiative, J-PAL (MIT) and CEGA (UC Berkeley).

Kay, C. (2011). Rural Poverty Reduction Policies in Honduras, Nicaragua and Bolivia: Lessons From a Comparative Analysis. *European Journal of Development Research*, 23(2), 249-265.

Kohl, B. (2003). Democratizing Decentralization in Bolivia: The Law of Popular Participation. *Journal of Planning Education and Research*, 23(2), 153-164.

Kuwornu, J. K., & Owusu, E. S. (2012). Irrigation Access and Per Capita Consumption Expenditure in Farm Households: Evidence from Ghana. *Journal of Development and Agricultural Economics*, 4(3), 78-92.

Lee, D. R. (2005). Agricultural Sustainability and Technology Adoption: Issues and Policies for Developing Countries. *American Journal of Agricultural Economics*, 87(5), 1325-1334.

Leuven, E., & Sianesi, B. (2003). PSMATCH2: Stata Module to Perform full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. *Statistical Software Components,* S432001. Boston College Department of Economics, revised 19 Jan 2015.

Lipton, M., Litchfield, J., & Faurès, J. M. (2003). The Effects of Irrigation on Poverty: A Framework for Analysis. *Water Policy*, 5(5-6), 413-427.

Mansuri, G., & Rao, V. (2004). Community-Based and –Driven Development: A Critical Review. *The World Bank Research Observer*, 19(1), 1-39.

McGinnis, M. D., & Ostrom, E. (2014). Social-Ecological System Framework: Initial Changes and Continuing Challenges. *Ecology and Society*, 19(2), 30.

Merrey, D.J. 2015. *An Evaluation of CGIAR Centers' Impact Assessment Work on Irrigation and Water Management Research*. Rome, Italy, Standing Panel on Impact Assessment (SPIA), CGIAR Independent Science and Partnership Council (ISPC).

Nin-Pratt, A., Falconi, C., Ludena, C.E., Martel, P. (2015). *Productivity and the Performance of Agriculture in Latin America and the Caribbean: From the Lost Decade to the Commodity Boom*. IADB Working Paper No. WP-608. Inter-American Development Bank, Washington, DC.

Raitzer, D. A., & Ryan, J. G. (2008). State of the Art in Impact Assessment of Policy-Oriented International Agricultural Research. *Evidence & Policy: A Journal of Research, Debate and Practice*, 4(1), 5-30.

Redman, C. L., Grove, J. M., & Kuby, L. H. (2004). Integrating Social Science into the Long-Term Ecological Research (LTER) Network: Social Dimensions of Ecological Change and Ecological Dimensions of Social Change. *Ecosystems*, 7(2), 161-171.

Rosenbaum, P. (2002). Covariance Adjustment in Randomized Experiments and Observational Studies. *Statistical Science*, 17(3), 286 – 327.

Rosenbaum, P., & Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70(1), 41-55.

Rosenbaum, P., & Rubin, D. B. (1985). Constructing a Control Group using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *The American Statistician*, 39(1), 33-38.

Rubin, D. B. (1990). Formal Modes of Statistical Inference for Causal Effects. *Journal of Statistical Planning and Inference*, 25, 279–292

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, Vol 66(5), 688-701.

Rubin, D. B. (1977). Assignment to Treatment Group on the Basis of a Covariate. *Journal of Educational and Behavioral statistics*, 2(1), 1-26.

Rubin, D. B. (1978). Bayesian Inference for Causal Effects: The Role of Randomization. *Annals of Statistics,* 6(1), 34-58.

Rubin, D. B. (2001). Using Propensity Scores to Help Design Observational Studies: Application to the Tobacco Litigation. *Health Services and Outcomes Research Methodology*, 2(3), 169-188. Chicago

Salazar, L., Aramburu, J., González, M., & Winters, P. (2015). Food Security and Productivity: Impacts of Technology Adoption in Small Subsistence Farmers in Bolivia. *Inter-American Development Bank*, IDB Working Paper Seires No. IDB-WP-567.

Saldías, C., Boelens, R., Wegerich, K., & Speelman, S. (2012). Losing the Watershed Focus: A Look at Complex Community-Managed Irrigation Systems in Bolivia. Water International, 37(7), 744-759.

Schultz, T. W. (1975). The Value of the Ability to Deal with Disequilibria. *Journal of Economic Literature*, 13(3), 827-846.

Sekhon, J. (2008). The Neyman-Rubin Model of Causal Inference and Estimation via Matching Methods. *The Oxford Handbook of Political Methodology*, 271-299.

Senanayake, N., Mukherji, A., & Giordano, M. (2015). Re-visiting What We Know About Irrigation Management Transfer: A Review of the Evidence. *Agricultural Water Management*, 149, 175-186.

Smith, J. A., & Todd, P. E. (2005). Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators? *Journal of Econometrics*, 125(1), 305-353.

Sorensen, C. (2000). *Social Capital and Rural Development: A Discussion of Issues.* World Bank, Social Capital Initiative Working Paper No. 10.

Sunding, D., & Zilberman, D. (2001). *The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector*. Handbook of Agricultural Economics, 1, 207-261.

Vermillion, D.L. (1997). *Impacts of Irrigation Management Transfer: A Review of the Evidence*. In: IWMI Research Report 11. International Water Management Institute, Colombo, Sri Lanka.

Vermillion, D. L., & Sagardoy, J. A. (1999). *Transfer of Irrigation Management Services: Guidelines*. FAO Irrigation and Drainage Paper No. 58, FAO, Rome.

Viceministerio de Riego (2007). Plan Nacional de Desarrollo del Riego ... "para vivir bien" 2007-2011. Ministerio del Agua, La Paz, Bolivia.

VRHR-MMAyA. (2013). *Inventario Nacional de Sistemas de Riego 2012*. Viceministerio de Recursos Hídricos y Riego del Ministerio de Medio Ambiente y Agua, Cochabamba, Bolivia.

Walker, T., J. Ryan, and T. Kelley. 2010. Impact Assessment of Policy-Oriented International Agricultural Research: Evidence and Insights from Case Studies. *World Development*, 38(10), 1453-1461.

Winters, P., Corral, L., & Gordillo, G. (2001). *Rural Livelihood Strategies and Social Capital in Latin America: Implications for Rural Development Projects.* University of New England, Graduate School of Agricultural and Resource Economics.

World Bank (2011). *Plurinational State of Bolivia: Agriculture Public Expenditure Review*. Report No. 59696.

Zeweld, W., Huylenbroeck, G. V., Hidgot, A., Chandrakanth, M. G., & Speelman, S. (2015). Adoption of Small-Scale Irrigation and Its Livelihood Impacts in Northern Ethiopia. *Irrigation and Drainage*, 64(5), 655-668.

Appendix

Following the notation of Cerulli (2015), let Y_{1i} denote the potential outcome of unit i in the presence of the treatment, and let Y_{0i} denote the potential outcome of the same unit in the absence of the treatment, where $i = 1 \dots, N$ denotes units observed. The treatment effect (τ) of unit i may be written as:

$$\tau_i = Y_{1i} - Y_{0i} \qquad (1)$$

For any unit i, τ_i in Eq. (1) can never be observed and measured directly. The Neyman-Rubin framework states that, under random treatment assignment, an unbiased estimate of the average treatment effect (ATE) can be calculated by taking the difference between the average outcomes of the treatment and control groups.[37]

Propensity score methods are statistical techniques used in non-experimental research studies to estimate the causal effect of an intervention by reducing the bias due to confounding variables. The propensity score is formally defined as unit i's conditional probability of being treated given a vector of exogenous and observable pretreatment covariates (Rosenbaum and Rubin, 1983).[38] Further, the authors defined the propensity score as the "coarsest" balancing score $b(X)$, where $b(X)$ is "a function of observed (pre-treatment) covariates X such that the conditional distribution of X given $b(X)$ is the same for the treated and control units." Two assumptions are required to construct a valid control group using the propensity score: conditional independence (or unconfoundedness) and overlap. These assumptions are commonly referred to as the assumption of "strong ignorability" (Rosenbaum and Rubin, 1983). Unconfoundedness asserts that when adjusting for differences in observable pre-treatment 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. In experimental studies, the true propensity score is known and defined by the study design (Abadie and Imbens, 2016). However, in the case of non-experimental studies, such as this evaluation of PRONAREC I, the propensity score must be estimated using a logit or a probit model. This approach aims to create statistical balance in observable pre-treatment covariates between treatment and control groups.[39] Consequently, assuming "strong ignorability", estimated propensity scores can be used to efficiently estimate ATT by matching treatment and control units that are as similar as possible based on the propensity score. Since making private on-farm investments to connect a plot to the irrigation system was voluntary and not every producer within beneficiary communities of PRONAREC I have irrigation (Table 3), the estimated parameter should capture an *intent-to-treat* (ITT) effect.

[37] 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, 1978).

[38] It is assumed that given the set of pretreatment covariates X_i, treatment T_i is independent (Rosenbaum and Rubin, 1983):

$$e(X_i) \equiv pr(D_1, \dots, D_N | X_1, \dots, X_N) = \prod_{i=1}^{N} e(X_i)^{D_i} \{1 - e(X_i)\}^{1-D_i}$$

[39] Rosenbaum and Rubin (1983) shows that an important task of propensity scores is to minimize unit heterogeneity, as it reduces both sampling variability and sensitivity to unobserved bias. However, PSM cannot adjust for unobserved differences between groups.

Table A1—Overall Measures of Covariate Imbalance Before and After Matching

	No. of observations			*Pseudo*		Mean	Median	Rubins' B	Rubin's
Matching algorithm	Total	Treated	Control	R^2	$p > \chi^2$	bias (%)	bias (%)	(%)	R
Unmatched sample	1,579	543	1,036	0.21	0.00	20.82	15.51	103.50	7.24
NN 1:1 (repl., cal=0.3sd_p)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:1 (repl., cal=0.25sd_p)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:1 (repl., cal=0.2sd_p)	741	463	278	0.02	0.44	6.69	7.02	**29.76***	1.07
NN 1:1 (repl., cal=0.1sd_p)	733	455	278	0.02	0.39	7.46	7.35	**30.67***	1.01
NN 1:1 (repl., cal=0.01)	714	436	278	0.01	0.79	6.44	5.98	**26.15***	1.01
NN 1:1 (repl., cal=0.001)	600	339	261	0.02	0.66	4.01	3.46	**30.29***	1.63
NN 1:1 (repl., no cal)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:1 (no repl., cal=0.3sd_p)	750	375	375	0.01	1.00	3.33	2.92	16.67	0.93
NN 1:1 (no repl., cal=0.25sd_p)	750	375	375	0.00	1.00	2.88	2.86	14.31	0.78
NN 1:1 (no repl., cal=0.2sd_p)	748	374	374	0.00	1.00	2.92	2.71	15.01	**0.44***
NN 1:1 (no repl., cal=0.1sd_p)	746	373	373	0.00	1.00	3.51	3.13	15.80	0.92
NN 1:1 (no repl., cal=0.01)	732	366	366	0.00	1.00	2.18	2.00	15.05	1.19
NN 1:1 (no repl., cal=0.001)	620	310	310	0.01	0.98	3.00	2.55	24.30	1.41
NN 1:1 (no repl., no cal)	928	464	464	0.05	0.00	7.92	5.61	**52.13***	**5.55***
NN 1:3 (cal=0.3sd_p)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:3 (cal=0.25sd_p)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:3 (cal=0.2sd_p)	733	455	278	0.02	0.44	6.69	7.02	**29.76***	1.07
NN 1:3 (cal =0.1sd_p)	714	436	278	0.02	0.39	7.46	7.35	**30.67***	1.01
NN 1:3 (cal=0.01)	714	436	278	0.01	0.79	6.44	5.98	**26.15***	1.01
NN 1:3 (cal=0.001)	600	339	261	0.02	0.66	4.01	3.46	**30.29***	1.63
NN 1:3 (no cal)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:5 (cal=0.3sd_p)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:5 (cal=0.25sd_p)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
NN 1:5 (cal=0.2sd_p)	741	463	278	0.02	0.44	6.69	7.02	**29.76***	1.07
NN 1:5 (cal=0.1sd_p)	733	455	278	0.02	0.39	7.46	7.35	**30.67***	1.01
NN 1:5 (cal=0.01)	714	436	278	0.01	0.79	6.44	5.98	**26.15***	1.01
NN 1:5 (cal=0.001)	600	339	261	0.02	0.66	4.01	3.46	**30.29***	1.63
NN 1:5 (no cal)	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05
Radius (cal=0.3sd_p) †	1,500	464	1,036	0.01	0.98	4.20	4.03	19.79	1.14
Radius (cal=0.25sd_p) †	1,500	464	1,036	0.01	0.99	4.23	4.09	19.37	1.10
Radius (cal=0.2sd_p) †	1,499	463	1,036	0.01	0.99	4.12	4.06	19.57	1.13
Radius (cal=0.1sd_p) †	1,490	455	1,035	0.01	0.99	4.20	4.12	19.46	0.97
Radius (cal=0.01) †	1,466	436	1,030	0.00	1.00	3.20	2.66	16.01	0.95
Radius (cal=0.001) †	1,145	339	806	0.01	0.95	3.54	2.96	**25.17***	1.07
Kernel (epan, bw=0.01) †	1,466	436	1,030	0.00	1.00	3.31	2.87	16.57	0.96
Kernel (epan, bw=0.06) †	1,500	464	1,036	0.01	0.99	4.15	4.16	19.28	1.10
LLR (epan, bw=0.01) †	742	464	278	0.02	0.42	6.71	7.22	**29.97***	1.05

Source: Authors' own calculations.

Notes: NN = nearest-neighbor; repl. (no repl.) = with (without) replacement; cal = caliper; epan = epanechnikov kernel; $p > \chi^2$ = *p*-value of the likelihood-ratio test; sd_p = pooled standard deviation of the estimated propensity scores (0**.**23270874**)**; bw = bandwidth; LLR = local-linear regression.
* Indicates Rubins' B > 25 percent or Rubin's R outside [0.5, 2].
† Cluster bootstrapped standard errors with 500 replications.