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Evaluating the Impacts of an Agricultural Technology Adoption Program using a Randomized Control Trial

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"Evaluating the Impacts of an Agricultural Technology Adoption Program using a Randomized Control Trial"

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Tesis de Maestría en Economía de

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"Evaluación de impacto de un programa agrícola de adopción tecnológica haciendo uso del método experimental"

Resumen

El presente trabajo evalúa los impactos de la adopción de tecnología agrícola en un conjunto de resultados que incluyen el ingreso de los hogares, la seguridad alimentaria, y diferentes medidas de productividad. En particular, se evalúa el Programa Agrícola de Innovación Tecnológica (PATCA) en la República Dominicana, que tuvo como objetivo aumentar la productividad agrícola y los ingresos de los pequeños agricultores mediante el fomento de la adopción tecnológica. Este trabajo hace uso de la asignación aleatoria del programa para inducir una variación exógena en la adopción de tecnología. Se utiliza una encuesta integral de hogares para una muestra de 2.214 agricultores, incluidos beneficiarios directos, beneficiarios indirectos y controles. Las estimaciones de 2SLS indican que la adopción de una tecnología agrícola provista por el programa PATCA mejoró el estado de seguridad alimentaria de los hogares beneficiarios en alrededor de 19%, aunque no se encontraron efectos en los ingresos del hogar. Se encuentran diferentes patrones de adopción e impactos en las medidas de productividad para cada una de las dos tecnologías analizadas (riego y rehabilitación de pastizales). La inferencia se basa en un método de corrección de Bonferroni que controla por pruebas múltiples. Además, una evaluación preliminar de los efectos indirectos no validó las hipótesis de que podrían producirse efectos indirectos a nivel geográfico.

Palabras clave: adopción de tecnología; agricultura; efectos indirectos; productividad; evaluación de políticas

"Evaluating the Impacts of an Agricultural Technology Adoption Program using a Randomized Control Trial"

Abstract

In this paper, I evaluate the impacts of agricultural technology adoption on a set of outcomes including household income, food security, and different measures of productivity. In particular, I evaluate the Agricultural Program for Technological Innovation (PATCA) in the Dominican Republic, which aimed to increase agricultural productivity and income of small-farmers by encouraging technological adoption. I exploit the random assignment of the program in order to induce exogenous variation in technology adoption. I use a comprehensive household survey for a sample of 2,214 farmers including direct beneficiaries, indirect beneficiaries and controls. 2SLS estimates that account for the presence of non-compliance indicate that the adoption of an agricultural technology provided by the PATCA program improved the food security status of beneficiary households by around 19%, although no effects are found on household income. Different patterns of adoption and impacts on productivity measures are found for each of the two technologies analyzed (irrigation and grassland rehabilitation). Inference is based on a Bonferroni correction method that accounts for multiple outcomes testing. Also, a preliminary assessment of spillover effects did not validate the hypotheses that indirect effects might take place at the geographical level.

Keywords: technology adoption; agriculture; spillover effects; productivity; policy evaluation

*Códigos JEL: [**C26, C93, D13, D24, O13, O33, Q12, Q16**]*

Evaluating the Impacts of an Agricultural Technology Adoption Program using a Randomized Control Trial [*,†]

Julian Aramburu

July 3, 2019

Abstract

In this paper I evaluate the impacts of agricultural technology adoption on a set of outcomes including household income, food security, and different measures of productivity. In particular, I evaluate the Agricultural Program for Technological Innovation (PATCA) in the Dominican Republic, which aimed to increase agricultural productivity and income of small-farmers by encouraging technological adoption. I exploit the random assignment of the program in order to induce exogenous variation in technology adoption. I use a comprehensive household survey for a sample of 2,214 farmers including direct beneficiaries, indirect beneficiaries and controls. 2SLS estimates that account for the presence of non-compliance indicate that the adoption of an agricultural technology provided by the PATCA program improved the food security status of beneficiary households by around 19%, although no effects are found on household income. Different patterns of adoption and impacts on productivity measures are found for each of the two technologies analyzed (irrigation and grassland rehabilitation). Inference is based on a Bonferroni correction method that accounts for multiple outcomes testing. Also, a preliminary assessment of spillover effects did not validate the hypotheses that indirect effects might take place at the geographical level.

1 Introduction

Low agricultural productivity is considered one of the main obstacles to eradicate poverty in the rural areas (JPAL, (2013)). Studying how individuals are able to escape poverty is a central issue of economic development theory. Since agricultural growth will depend more and more on yield-increasing technological change (Foster and Rosenzweig, (2010)), studying the impacts of the adoption of agricultural technologies becomes relevant.

[*] I thank Lina Salazar, Senior Economist at the Inter-American Development Bank (IADB), who allowed me to use the data for this paper and helped me understand the implementation of the program. The IADB collected (through a private outsourced company) and owns this data. I plan to extend this research agenda using a third round of data (to be collected this year, 2019) in order to perform a geographical and social network spillover effects analysis of the program (see sections 2 and 5 for more details about this), as well as to address some questions and technical issues I leave open in this version of the paper due to time constraints. This paper is part of a joint work with Lina Salazar (IADB), Alessandro Maffioli (IADB), Lucas Figal Garone (IADB) and Cesar Lopez (IADB). An updated working paper version of this project (as of July 2019) can be found here.

In this paper, I aim to provide empirical evidence on the effectiveness of a program that aimed to increase agricultural productivity and rural income by promoting the adoption of agricultural technologies. Specifically, using data from a technology adoption program that was randomly assigned to small farmers in the Dominican Republic, I explore whether irrigation and grassland rehabilitation technologies have positive impacts on productivity, income and food security.

In order to provide a source of exogenous variation to the technology adoption as well as to account for the presence of non-compliance, I use the randomly assigned treatment as an instrument for the adoption of the agricultural technology. Additionally, the randomization design allows studying the existence of direct and indirect impacts –spillovers- of the program.

I find that the adoption of an agricultural technology provided by the PATCA program improved the food security status of beneficiary households by around 19%. On the contrary, I do not find significant effects of technology adoption on income.

Given that the sample is representative of the two most demanded technologies of the program (irrigation and grassland rehabilitation), I analyze the impacts separately on a different set of outcome variables. The results for the grassland technology show that the adoption of the technology fostered a switch from a lower to a better quality of pasture, which improves the quality of the livestock feeding in beneficiary plots. It also increased the annual livestock sales income and livestock product sales income, increased the probability of having improved breed livestock in 17% and the percentage of improved breed over total livestock in 23%, and decreased the probability of being food insecure by 29%. On the contrary, no impacts are found for the irrigation technology. The statistic significance of these results was obtained by correcting the p-values by the Bonferroni method in order to account for multiple testing.

The presence of geographic spillover effects is nonexistent in this study, as suggested by the adoption model. Being geographically close to beneficiary households does not increase the probability of technology adoption. Furthermore, the results of the Probit suggest that the major limitation for technology adoption is a liquidity constraint, basically access to savings, credits and cash from remittances.

The remaining of the paper is structured as follows. Section 2 describes the context and the program to be analyzed as well as the randomization design. Section 3 describes the data to be used in the analysis and presents the balancing tests that corroborate the success of the randomization approach. Section 4 presents the econometric methodology followed by the results in section 5. Finally, section 6 concludes and describes the future research I plan to continue with this project.

2 Literature Review

Many policies that aim to alleviate poverty for rural population have come in the form of conditional cash-transfers or subsidized agricultural inputs without a clear exit strategy; this increases governments' fiscal burden and sometimes even fails to promote long-term livelihood strategies (Chirwa and Dorward, 2013; Dorward, 2009). There is a substantial body of economic literature indicating that public investment in direct distribution of large-scale inputs has a low social return, restricts private sector investment, and delays the adoption of more efficient technologies (IARNA and FAUSAC, 2013; Jayne and Rashid, 2013; Lopez et al., 2017; Macours et al., 2018; Valdés, 2012). These findings combined with high fiscal costs, inappropriate targeting of programs' benefits, and the absence of an exit strategy have raised questions about the effectiveness of such interventions (Banful, 2011). In an attempt to overcome these issues, recent input subsidy programs have introduced the so-called "smart subsidies" to promote the adoption of innovations among smallholder farmers in developing counties (Baltzer and Hansen, 2011; Carter et al., 2016; Chirwa and Dorward, 2013).[1]

The body of evidence on the effectiveness of agricultural input subsidy schemes in developing countries has increased in the last decades; however, these evaluations have produced mixed conclusions. In Sub-Saharan Africa, the results from detailed and rigorous evaluations indicate one-time targeted input subsidies may or may not have positive treatment effects that persist beyond the season in which the subsidy was offered (Carter et al., 2016; Duflo et al., 2011). Also, while input subsidies can raise food production within one growing season, the impacts may be lower than commonly presumed due to various factors (e.g., crowding out of commercial input demand, lower production and income effects from late fertilizer delivery, non-responsive soils, poor management practices, insufficient use of complementary inputs) (Jayne and Rashid, 2013).

[1] "Smart subsidies" define alternative subsidy strategies that favor market solutions to promote the development of input or technology markets, target the poorest producers (Tiba and Prakash, 2011), and arise in response to specific market failures in the rural sector (Feder et al., 1985). However, the difficulty to adequately target farmers and the distorting effects that may occur in the private sector remain the most significant obstacles in the design, implementation, and effectiveness of such interventions (Sheahan, 2014; Ricker-Gilbert et al., 2011; Jayne and Rashid, 2013).

For instance, Dercon and Christiaensen (2005) find that credit constraints, lack of insurance, and the risk of possible low consumption outcomes when harvests fail, discourage the application of fertilizer. Further, the empirical evidence suggests input subsidy schemes are more effective when they easy actual technological gaps compared to subsidies for inputs and practices that are widely known and disseminated (Macours et al., 2018).

Evidence from LAC shows that "smart subsidies" for the promotion and adoption of technologies have positive effects on income and productivity, mainly when these interventions target small producers with market mechanisms that have credible exit strategies. In Bolivia, technology adoption vouchers increase the productivity, income and food security of smallholder farmers (Salazar et al., 2015). Positive effects on income and productivity are also found in similar programs implemented in Nicaragua, Argentina, Uruguay and the Dominican Republic (Flores et al., 2014; Gonzalez et al., 2009; Maffioli and Mullally, 2014; Rossi, 2013). Cost-sharing interventions, which involves government-farmer partnerships to fund the provision of goods and services through the private sector, have also led to significant effects on technology adoption. For example, partially public-funded private extension services in Uruguay increased the adoption of certified fruit varieties (Maffioli et al., 2013), and public expenditures for the development of community-based irrigation systems in Bolivia triggered a broader process of technological change reflected in private investments in on-farm irrigation and complementary inputs (Lopez and Salazar, 2017).

Several empirical studies have found direct positive effects of agricultural technology adoption on income and poverty reduction associated with growth in yields and labor productivity (Asfaw et al., 2012; Berrecil and Abdulai, 2010; de Janvry and Sadoulet, 2009; Hagos et al., 2010; Kassie et al., 2011; Mendola, 2007; Minten and Barrett, 2008). In a recent review of agricultural field experiments in developing countries, de Janvry et al. (2017b) find that while the majority of studies have focused on the adoption, diffusion, and impact of technological and institutional innovations, there is still room in the literature to gain a better understanding of how public policies can improve the productivity and welfare of smallholder farmers. For example, there is evidence that smallholder farm households' demand for some innovations (e.g., improved seeds, weather index insurance) tends to be highly price elastic around zero: technology take-up rates are high when short-term subsidy rates to induce technology take-up are high, but take-up rates fall rapidly to low levels when the subsidy rate is reduced (Cai et al., 2016; de Janvry et al., 2017b; Glennerster and Suri, 2015; Karlan et al., 2014; and Mobarak and Rosenzweig, 2013).

Agricultural interventions in developing countries may generate substantial indirect or spillovers effects (as a result of geographical and social ties among farmers), local environmental externalities, and general equilibrium effects (Bandiera and Rasul, 2006; Beaman et al., 2014; BenYishay and Mobarak, 2015; Carter et al., 2014; Cole and Fernando, 2016; Conley and Udry, 2010; de Janvry et al., 2017b; Oster and Thornton, 2012). A limited number of studies have focused on analyzing the spillover effects of agricultural TAP. Holloway et al. (2002) found strong positive neighboring effects concerning the adoption of HYVs in Bangladesh. Using Bayesian spatial probit estimation, the inclusion of neighborhood effects increases the marginal probability of adoption relative to the traditional (non-spatial) probit model. In Ghana, Conley and Udry (2010) examines the context of pineapple farmers and find that they learn from the experience of their neighbors. Their findings imply that, in the production of new crops, farmers tend to follow the more successful and experienced neighbors regarding the use of inputs and are more likely to follow this pattern when they have little experience of their own.

Using household-level panel data from India, Foster and Rosenzweig (1995) present a simple learning model that examines the presence of social learning spillovers in the adoption of highyielding seed varieties (HYVs) associated with the Green Revolution. Their empirical evidence confirms the presence of free-riding behavior and provides some support for the use of public subsidies to promote technology adoption among early adopters. In Mozambique, Bandiera and Rasul (2006) demonstrated that social networks play an important role in the decision of farmers to adopt a new crop, sunflower seeds. The authors found an inverse-U relationship between the probability that a farmer grows sunflowers and the number of known adopters in his or her social network: the propensity to adopt increases at a decreasing rate when there are a few adopters in the network, but the marginal effect of having one more adopter is negative where there are many adopters in the network. The authors point out that while, intuitively, adoption decision should be positively correlated with the number of adopters in the social network, theoretically, the sign of the relationship is ambiguous: "On the one hand, the benefit of adopting in the current period is higher when there are many adopters in the network because of the information they provide. On the other hand, having many adopters in the network increases incentives to delay adoption strategically and free ride on the knowledge accumulated by others. If strategic delay considerations prevail, a farmers' propensity to adopt decreases as the number of adopters among his network increase" (Bandiera and Rasul, 2006). Maertens (2010) analyze the role of social networks in the adoption of Bt cotton in India and finds that knowledge about the profitability of a new technology is vital in the adoption decision of farmers. Knowledge may come from experimentation, observation of other farmers' past inputs and outputs, and talking to informed parties such as company representatives and input dealers. Nonetheless, the effect of information flows via social learning are stronger and more active within homogenous populations with fairly uniform growing conditions, where the performance of the new technology is not sensitive to unobserved or imperfectly observed individual characteristics (e.g., organic composition and other features of the soil) (Munshi, 2004). This aim of this paper is to measure the direct effects of an agricultural TAP on the productivity and income of smallholder farmers, as well as to estimate the geographical and social spillover effects that might have been caused by the intervention.

3 The PATCA Program and Experiment Design

3.1 Study setting and experimental design

PATCA II aimed to improve the agricultural productivity and income of beneficiary farmers by facilitating technological adoption. To achieve this objective, the program provided nonreimbursable vouchers to finance a portion—between 33 and 59 percent—of the total cost of an agricultural technology chosen by the farmer, including technical assistance[2]. The technologies offered by the program included land-leveling, irrigation (drip, sprinkler, and micro-sprinkler), green-houses, mulching, post-harvest management equipment, and pasture and grassland conservation & rehabilitation. However, only five of the technologies (i.e., pasture and grassland conservation & rehabilitation, greenhouses, post-harvest management, drip irrigation, and sprinkler irrigation) were randomized as the other three technologies did not have enough demand. This paper will focus on evaluating the impacts of pasture and grassland conservation & rehabilitation and irrigation technologies, which together comprise over 80 percent of the program's total demand. The maximum amount financed by the program was US$3,650 for pasture and grassland conservation & rehabilitation, and US$3,500 for irrigation.

[2]Each farmer was able to choose only one technology.

The program targeted agricultural and livestock producers who met the following eligibility criteria: (i) be a citizen of the Dominican Republic with valid identification card (cédula); (ii) have legal proof of land tenure;[3] (iii) have agricultural or livestock production as the main economic activity; (iv) be a smallholder producer;[4] (v) have their farmland outside of protected areas; (vi) present evidence showing ability to cover the remaining cost (cash or in-kind) of the technology; and (vii) not a beneficiary of PATCA I. For farmland located in irrigation districts, producers were required to submit either proof of water payment (e.g., water bill or certificate of endorsement from the National Institute of Hydraulic Resources (INDRHI), or a certification from a competent authority showing there were no Water User's Associations nor the INDRHI operating in the area. PATCA II was expected to be of national scope with an implementation period of five-years (2012-2015). The total cost of the project was US$34.3 million to target 9,000 farmers approximately. Following an extensive national campaign (local radio stations, street advertising, press, local TV, brochures) in 2010, a total of 21,032 pre-registered producers were eligible to participate in the program (universe).[5] The excess demand encouraged government officials from the MA to implement a randomized controlled trial (RCT) to ensure transparency in the allocation of resources.

3.2 Experimental Design

The chosen experimental design considered the objective of identifying: (1) the direct effects; and (2) spillovers or indirect effects of the program. The direct effect is the average treatment effect of the program on the treated; that is, the impact of the program on those who received the benefits. The unbiased estimate of direct treatment effects requires a control group of producers not exposed to the program, directly or indirectly. The spillover effects refer primarily to the impact on

[3]Eligible forms of tenure: official property title, agrarian reform title, or be a legal tenant.

[4]The financial support provided to each program beneficiary had a specific cap (i.e., land area, dollar amount) for each technology, ranging from a minimum area of 629 squared-meters for greenhouses to a maximum of 25 hectares of improved pastures. The program financed an average of 8.6 hectares (minimum = 0.63, maximum = 12.6) for beneficiaries of improved pastures, and an average of 1.5 hectares (minimum = 0.4, maximum = 1.87) for beneficiaries of irrigation technologies.

[5]The campaign's material stated: (1) the period of pre-registration (November-December 2010), (2) registration location (regional offices located in Agricultural Banks around the country), (4) the program's requirements, and (3) that no applications would be accepted after the pre-registration period. Also, Agricultural Support Agents (AAA) participated in the campaign by convening local community leaders. Established in regional offices throughout the country, AAA's fulfilled the function of the "main point of contact" for program beneficiaries. Some of their responsibilities included: assisting with the promotion and dissemination of the program, filling pre-registration applications, verification of environmental data, provision of environmental technical assistance, supervision of compliance with the established criteria and procedures of the program.

nontreated farmers located in geographical proximity to treated farmers or by non-treated farmers who belong to the social network of the treated farmers. Specifically, spillovers are the effects of the program on producers in close geographical or social proximity to program beneficiaries but who do not themselves receive the intervention (Benjamin-Chung et al., 2018). Overall, TAP can generate positive externalities, general equilibrium effects, or behavioral effects from the interaction between treated and non-treated producers (Angelucci and De Giorgi, 2009; Angelucci and Di Maro, 2015). In the case of PATCA II, we expect non-beneficiary producers to be influenced by treated producers after realizing the benefits obtained from the adoption of technologies offered by the program. Measuring spillover effects requires the identification of a contaminated control group indirectly exposed to the treatment either through geographical or social proximity to program beneficiaries. The contaminated and uncontaminated control groups can be obtained by implementing a two-stage randomization design where the first-stage randomization takes place at the geographical level (the unit at which the spillover is expected to take place), and the second-stage at the individual level (Angelucci and Maro, 2015). The Dominican Republic is divided into three macro-regions (north, southwest, and southeast) and sub-divided into ten administrative regions.[6] Politically, these regions are composed of a National District and 31 provinces (ONE, 2017). The Ministry of Agriculture (MA) implements its interventions through eight Regional Agricultural Directorates (RADs) across 29 zones, and 134 sub-zones (Ministerio de Agricultura, 2017).[7] These sub-zones are geographic units that share similar agricultural conditions and correspond to the main unit of analysis within the MA; however, they do not necessarily match administrative regions. The 21,032 producers in the universe of PATCA II are located across 129 sub-zones (approximately 96 percent of all subzones) across the RADs.

In 2012, authorities from the MA conducted lotteries nationwide through each of the RADs to select the beneficiaries from PATCA II.[8] These lotteries took place in public spaces, such as schools, auditoriums, and regional agricultural offices; each session was widely advertised and community leaders, farmers, as well as local authorities across the regions, were invited to participate in order assure transparency. Many communities located far away from the lottery sessions sent a

[6] North Cibao (I), South Cibao (II), Cibao Northeast (III), Northwest Cibao (IV), Valdesia (V), Enriquillo (VI), El Valley (VII), Yuma (VIII), Higuamo (IX), and Ozama or Metropolitana (X).

[7] North, Northwest, South, Southwest, North Central, Northeast, East, and Central.

[8] The central core (CTP) in charge of the project's execution was headquartered in Santo Domingo and operated nationally through the RADs. The CTP's responsibilities include planning, supervision, technical and environmental control of all the activities related to the program.

designated farmer to witness the process. Also, public notaries were present to register and legalize the selection process.

To measure the direct and spillover effects, the random assignment of treatment followed a two-stage without replacement design using a tombola (a spinning container used as a lottery device). In the first-stage, sub-zones were randomly selected to participate in the program. Approximately, 80 percent of the sub-zones were selected into the treatment group while the remaining 20 percent represented the uncontaminated counterfactual.[9] Further, the treatment group was sub-divided into four cohorts, one for each year of the program's implementation period. The random drawing of balls from the tombola determined the assignment and order of sub-zones to treatment cohorts for each RAD. For example, in the Central RAD, fourteen subzones were randomly drawn from the tombola in the first-stage, of which the first set of four balls (sub-zones) constitute the first cohort. The second set of four became the second cohort, the third set of three the third cohort, and the last three formed the fourth cohort; leaving the remaining four sub-zones in the tombola as part of the control group (Figure 1). The second stage consisted in randomly assigning eligible farmers located within treated sub-zones (selected in the first-stage) into the treatment for each of the technologies with high demand (i.e., grassland rehabilitation & improvement, drip irrigation, sprinkler irrigation, greenhouses, and post-harvest management). Specifically, the random selection of program beneficiaries in the second-stage was based on a set of established quotas for each technology (according to budget availability set by the MA), a limited supply of technologies, and the number of beneficiaries and sub-zones per region. Based on these restrictions, three of the technologies (i.e., land leveling, mulching, and micro-sprinkler irrigation) were not randomized, and all of the farmers that requested these technologies were automatically assigned to treatment. For the set of technologies with high demand, a separate lottery was carried out for each technology using the tombola and a set of numbered balls representing the last digit (between [0,9]) of the identification card of producers. That is, the treatment group (direct beneficiaries) in the second-stage was determined by randomly drawing balls without replacement, until reaching the quota established per technology. After the selection process, a complete list of program beneficiaries was made available in the same locations where the lotteries took place, as well as on the MA's official website.

[9]The number of sub-zones to treat was determined previously to the lottery to maintain a similar number of treated sub-zones per RAD as well as to assure an uncontaminated counterfactual at the RAD level (control sub-zones in the first-stage).

This stratified two-stage cluster randomization process allowed us to divide the universe of eligible producers into three treatment groups: (i) direct beneficiaries (DB), (ii) indirect beneficiaries (or contaminated control group) (IB), and (iii) pure controls (uncontaminated counterfactual). The group of direct beneficiaries is composed of farmers located in treated subzones (first-stage) and whose last digit of the cédula was selected for treatment in the second-stage. Similarly, the group of indirect beneficiaries is composed of farmers in treated sub-zones but not selected for treatment. Lastly, the group of pure controls is composed of all the eligible farmers in the untreated sub-zones. A total of 7,975 eligible farmers (20.7 percent women) in the universe are direct beneficiaries (Table 1). Pasture and grassland rehabilitation & improvement (henceforth referred to as "improved pastures") and irrigation (drip and sprinkler) were the technologies with the highest demand, representing almost 75 percent of the total in the universe.

Randomly dividing the universe of sub-zones between treated and untreated as well as the universe of eligible farmers between direct beneficiaries, indirect beneficiaries, and pure controls, was done with the purpose of measuring both direct and spillover effects that might take place at the geographical level. The direct effect will be estimated by comparing direct beneficiaries with the pure control group, and geographical spillover effects will be estimated by comparing indirect beneficiaries with the control group (Figure 2).

3.3 Program Implementation

Following the randomization process, the government expected to provide vouchers to 7,975 direct beneficiaries throughout the country. However, due to budgetary restrictions during the implementation phase, the program's geographical scope was limited to the North and Southwest RADs (hereafter referred to as 'regions') (Figure 3).[10] Only 26.4 percent (5,558) of the producers in the program's universe are located within these regions (1,836 direct beneficiaries, 2,428 indirect beneficiaries, and 1,294 controls). Moreover, only 745 farmers from the North and Southwest regions were included in the baseline, thus limiting the sample space to consider for the follow-up survey.[11] By the end of 2014, the number of effectively treated beneficiaries was 1,014, including 666 with

[10]The North region covered the provinces of Espaillat, Puerto Plata, and Santiago de los Caballeros, and the Southwest region covered Azua, Elias Piña, and San Juan.

[11]By limiting the analysis to the North and Southwest regions, it is clear that the sample size available in the baseline survey would not allow for a meaningful evaluation of any of the technologies under consideration. For the two technologies under consideration, only 508 eligible farmers from the North and Southwest regions were interviewed at baseline (245 direct beneficiaries, 127 indirect beneficiaries, and 136 controls).

improved pastures and 317 with irrigation (drip, sprinkler, or micro-sprinkler).[12] By effectively treated, we refer to those farmers who were selected as direct beneficiaries and received the technologies as of December 31, 2014. However, not all the farmers received the technology as requested in the randomization process, as some decided to opt for a different technology (e.g., micro-sprinkler instead of sprinkler irrigation). Our analysis will focus on effectively treated beneficiaries who were randomly assigned to receive improved pastures and who received improved pastures, and farmers randomly assigned to drip or sprinkler irrigation and who received an irrigation technology (drip, sprinkler or micro-sprinkler).[13] Also, we consider only those famers that were treated as of May 2014 to allow for program impacts to occur. Accounting for these adjustments, a total of 487 direct beneficiaries in the North and Southwest regions received the technologies (effectively treated) between 2012 and May 2014 (denoted DB-ET, direct beneficiaries-effectively treated), 340 received improved pastures and 147 received irrigation (drip, sprinkler, or micro-sprinkler). The remaining of the direct beneficiaries (denoted DB-IT, direct beneficiaries-intended to be treated) are those direct beneficiaries randomly assigned to treatment but who never received the benefits of the program. Also, indirect beneficiaries (IB) are considered as such if they belong to a sub-zone with at least one DB-ET.

To increase the availability of control producers and to better represent the heterogeneity of the population, the follow-up sample included 13 additional pure control sub-zones across five regions. Five of the additional control sub-zones belong to the Northwest, four to the North Central, two to the South, and the remaining two additional control sub-zones belong to the Central and Northeast regions[14]

Given the similarity between the irrigation technologies (drip, sprinkler, and microsprinkler) relative to the rest of the technologies that were randomized in the second-stage of the experiment, and the reduced sample space, these irrigation technologies were grouped together as one technology to estimate the sample size required to evaluate the effectiveness of "irrigation". The follow-up sample was representative of the three treatment groups (direct beneficiaries, indirect

[12] The remaining 31 beneficiaries received greenhouses (n=1), post-harvest management (n=27), and mulching (n=3). Given the limited number of treated farmers with greenhouses and post-management harvest technologies, it is not possible to evaluate their effectiveness; these observations are not part of the analysis.

[13] Farmers that requested micro-sprinkler irrigation are excluded from the analysis since that technology was not randomized, as described in Section 3.1. However, DB farmers of drip or sprinkler irrigation who received micro-sprinkler irrigation are included in the analysis as they were randomly assigned to treatment.

[14] According to the information in the baseline, these additional control sub-zones behave similarly to the North and Southwest RADs, and, with the exception of two sub-zones, they also share geographic borders.

beneficiaries, and controls) and both technologies (improved pastures and irrigation) in the North and Southwest regions. Data collection took place between May and July 2015 concerning the 2014 agricultural cycle.

To measure social network spillovers, the survey instrument for the follow-up included an additional module with questions related to the exchange of agricultural knowledge and information (e.g., technologies, inputs, prices, marketing) among farmers. Specifically, each producer, regardless of treatment status, was asked to identify a list of three farmers with whom they typically exchange (provide or receive) agricultural information in the region. Field supervisors were then responsible for randomly selecting one of the farmers in the social network of each producer by following a set of instructions that involved using the Kish selection grid method (Kish, 1949); however, survey data was collected only for the set of farmers in the social network of effectively treated beneficiaries (i.e., DB-ET).

4 Descriptive Data and Randomization Check

This section describes the dataset used for the empirical estimations. The primary purpose of this section is to assess the validity of the randomization strategy and to confirm the comparability between treatment and control groups. The data collection strategy was composed of two rounds of surveys collecting a comprehensive agricultural household questionnaire with detailed information regarding agricultural production, input use, land allocation, livestock production, household socio-economic characteristics, income sources, food security, among others.

The baseline data was collected in 2012 and gathers information prior to program implementation for the agricultural cycle from January to December 2011. The sampling strategy considered all the original eligible producers that participated in the raffles as implementation problems were not foreseen back then. Hence, the baseline survey was administered to a representative sample of program direct beneficiaries, indirect beneficiaries and control groups by technology. A total of 3,735 eligible producers from the eight regions –1,879 direct beneficiaries, 842 indirect beneficiaries and 1,014 pure controls– were interviewed. The full set of descriptive statistics for the whole baseline sample is presented in Table 4, including outcomes and control variables to be used in subsequent estimations. The t-test of differences in means confirms the validity of the randomization process. Specifically, only two variables present statistically significant differences in means but the magnitudes are rather small.

Table 5 shows the descriptive statistics for treatment and control groups located in the two regions of analysis (North and Southwest) at the baseline. The t-test for difference in means, in the last column, confirms the comparability between treated and control groups. In fact, the results are very similar to the ones presented for the whole sample. Specifically, no variables present statistically significant differences at 5% level and only three variables present significant differences at 10% level; however, the magnitudes are fairly small (between 1% to 5%). The assessment of the baseline characteristics provides strong support that corroborates the validity of the randomization process and the comparability between treatment and control groups in the regions of analysis.

The second round of data or follow-up survey was collected in the year of 2016, in regards to the agricultural cycle from January to December, 2015. As mentioned previously, the baseline data was representative of the PATCA program at the national level by technology. However, it was not representative at the regional level. In fact, for the two technologies considered in the analysis, only 518 eligible farmers from the treated regions (North and Southwest) were interviewed at the baseline[15]. Therefore, the sample for the follow-up survey had to be adjusted in order to be representative for the three groups of farmers (DB, IB, controls), for both of the technologies considered (modern irrigation and grass rehabilitation) in the regions of analysis (North and Southwest). The sample consisted of a total of 2,214 observations, and it was designed to be representative at the technology level. Table 6 presents the distribution of the final sample size by groups of farmers and by technology.

5 Empirical Strategy

The main objective in this paper is to identify the causal relationship of adopting an agricultural technology provided by the PATCA on different outcome variables. Formally, estimating the following equation captures the impact of adopting an agricultural technology on the outcome variable:

$$Y_i = \alpha + \beta Adopt_i + \gamma X_i + \varepsilon_i \tag{1}$$

[15] 255 direct beneficiaries, 127 indirect beneficiaries and 136 controls.

where Y_i represents the outcomes of interest for the household i; $Adopt_i$ is a dummy variable that takes the value of 1 if the household i adopts the technology provided by the PATCA Program, and 0 otherwise; X_i is a matrix of household i pre-treatment characteristics described in Table 5; and ε_i is an individual error term.

The parameter β will be estimated consistently under the presence of perfect compliance, which means that all farmers assigned to PATCA adopted the technology and all farmers assigned to control did not. This was clearly not the case in this particular scenario. As mentioned in Section 2 and mainly generated by problems in the program implementation, not all selected beneficiaries adopted the technology while some controls adopted it. Hence, adoption is an endogenous variable.

To solve the problem of partial compliance and endogeneity of adoption, I implement an instrumental variable methodology using two-stage least squares (2SLS) (Angrist and Pischke (2009)). Specifically, the endogenous variable of technology adoption will be instrumented by using the exogenous variable of random assignment to PATCA, as follows:

$$Adopt_i = \theta + \lambda PATCA_i + \gamma X_i + \mu_i \tag{2}$$

where the dependent variable is a dummy variable equal to one if the farmer adopted the agricultural technology (i.e. irrigation or grassland rehabilitation), PATCA is a dummy variable equal to one if the farmer was selected in the draft lottery, the coefficient λ represents the probability of adoption given that the farmer was selected in PATCA, X_i is a matrix of household i pre-treatment characteristics described in Table 5, and μ_i is the error term.

The second stage corresponds to estimating the impact of adopting an agricultural technology in the main outcomes of interest, as follows:

$$Y_i = \alpha + \beta \widehat{Adopt}_i + \gamma X_i + \varepsilon_i \tag{3}$$

Where, Y represents the main outcomes of interest (agricultural productivity, income and food security), $\hat{\beta}$ is the estimate of β and identifies the effect of adopting a specific technology, $\widehat{Adopt}$ is the instrumented variable for adoption decision, and ε_i is the error term. As shown in Angrist et al. (1996), the 2SLS estimator of β in (3) will recover the Local Average Treatment Effect (LATE), which is the parameter that estimates the effect of technology adoption on those farmers whose adoption was influenced by the lottery assignment (the compliers).

For completeness, I also estimate the Intention to Treat (ITT) parameter by estimating δ in the following equation:

$$Y_i = \alpha + \delta PATCA_i + \gamma X_i + \varepsilon_i \tag{4}$$

where all the variables were described above.

The results to the first, second stage (LATE) and ITT estimates are presented in the following section.

6 Results

Considering that the sample is representative at the technology level, I use technology-specific outcomes in order to analyze the impacts of irrigation and grassland technologies separately. Outcomes for grassland rehabilitation technology include: (i) hectares planted with natural grass; (ii) hectares planted with improved pasture; (iii) Tropical Livestock Units (TLU) index to proxy for livestock production; (iv) livestock sales income; and (v) production of improved breed livestock, among others. On the other hand, outcomes for irrigation technology include: (i) value of production per hectare as a proxy for productivity; (ii) labor and input expenditures; (iii) gross margins per hectare; and (iv) number of hectares sown. Additionally, an analysis of adoption on agricultural income and food insecurity will be presented using the whole sample.

6.1 First Stage Estimations

As mentioned previously, technological adoption might be endogenous. However, the random assignment of the PATCA program provides a natural experiment and therefore, a source of exogenous variation to instrument technological adoption. Table 7 presents the results to the first stage estimation. The results confirm that the instrument (assignment to PATCA) is relevant as evidenced by the significance levels of the coefficients and the F-test statistic. Specifically, the estimates suggest that households that have been randomly selected into the program are 57% more likely to adopt an agricultural technology relative to the control group. Households that enrolled for the grassland technology are 69% more likely to adopt the technology relative to the control group, while those selected for irrigation are 45% more likely to adopt it as a result of the program. All these three effects are highly significant (1% level). Note that, although compliance can be lower compared to other randomized control trials, in this case this includes the fact that many farmers did not adopt the technology because of failures in the implementation of the program, as mentioned in section 2, subsection 2.3.

6.2 ITT and LATE Estimations

Tables 8 to 10 show the main results of this paper for the LATE and ITT estimates, with and without covariates. Tables 8 to 10 have the following structure: columns (1) and (2) show the results of the estimation of the ITT parameter δ in equation (4) by Ordinary Least Squares (OLS), while columns (3) and (4) show the estimation of the LATE parameter β in equation (3) by 2SLS. I comment on the LATE estimates, the ITT results are shown for completeness only. Columns (2) and (4) include the covariates described in section 3 as controls. All models report both robust standard errors and robust standard errors by clustering at the subzone level.

Especially for tables 9 and 10 where I analyze the impacts of the program for each technology separately, I show the impact on multiple outcome variables. In order to account for and to correct any bias generated by repeated testing effects, I report significance values obtained using the Bonferroni correction, using the user-written command by Jones, Molitor and Reif (2018). Although this is considered to be a conservative approach[16], I consider it a good one in order to prevent me from obtaining results that were found by random error.

Something that is worth mentioning before proceeding is that, throughout the different regressions, I find that precision for the estimates disappears as I cluster standard errors at the subzone level. Indeed, in some cases the standar errors behave strangely. This is something that is definitely worth to explore later. In particular, I am analyzing the sample calculations performed for the follow up survey in order to see whether this loss in significance can be due to a failure in including more subzones in the sample. The maximum number of clusters in the sample is 41. To the best of my knowledge, there is no consensus in the literature about the minimum number of clusters necessary to trust clustered standard errors. Although I've seen papers mentioning that the minimum is 50 (Cameron and Miller, 2015), in which case my clustered standard errors should

[16]Indeed, for some of my estimates significance is lost after performing the Bonferroni correction.

not be taken as the correct ones, I've found other papers mentioning that 30 clusters is already enough to obtain clustered standard errors (Cameron, Gelbach and Miller, 2008).

Given this, I report significance levels based on unclustered standard errors, although this is something that I need to study in more detail.

Table 8 presents the impact estimates of technology adoption on household income and food security using the pooled sample for irrigation and grassland rehabilitation. To measure food security at the household level I use the FAO index based on the Latin American and Caribbean Food Security Scale (ELCSA by the Spanish acronym) (FAO, 2012), which consists of 15 questions that capture the degree of households' accessibility to food[17]. Although I do not find any significant impacts on agricultural income, households that adopted an agricultural technology improved food security status. Specifically, the coefficient of the FAO Index indicates a reduction of 19% in the probability of being food insecure by beneficiary households. The mean at the baseline was 29%, so this representas a 65% reduction in the food insecurity status of the households.

Table 9 shows the results of the estimations for the grassland rehabilitation technology. The results confirm that adopting this technology reduced the number of hectares planted with natural grass by 3.6, while increased the number of hectares with improved pasture by 2.5. These results can be interpreted as a switch from a lower to a better quality of pasture, which in turn improves the quality of livestock feeding. The results on the TLU index (to proxy for livestock production) indicate that technology adoption increases this index in 5.2 points (39% increase with respect to the baseline).

Adoption of the grassland technology also increased the annual livestock sales income and the annual livestock products sales income in between 0.85 and 0.81 log points (equivalent to 133% and 124%) respectively, although the significance of these estimates is marginal. In addition, it increased the probability of having improved breed livestock in 17% and the percentage of improved breed over total livestock in 23%.

The results for the food insecurity index analyzed for the grassland rehabilitation indicate that adopting this technology reduces the food insecurity status of beneficiary households by 29%.

Last, it is worth to mention that the results obtained for the grassland technology are in line with what the literature has found for similar programs (Mullally et al. (2014)).

Table 10 presents the results of the estimations for the irrigation technology. In contraposition

[17] See Annex A for more details about the construction of this index.

to the livestock technology, no significant impacts are found for irrigation. This absence of impacts for this technology is puzzling. By reading the documentation of the program, one possibility that arises here is that this technology is one that requires more specific knowledge and higher maintenance costs and skills compared to the grassland technology. Unfortunately, there is no information in the database I have regarding any of these aspects for the technology, which limits the understanding of this absence of effects.

Before concluding this section, and since I focus mainly on LATE estimates, it is important to justify that the exclusion restriction is satisfied. This would be violated, for example, if the program affected agricultural outcomes even if the farmer did not receive the voucher, perhaps through extension services/technical advice. Given the implementation of the program as described in section 2, this could not be possible given the inseparability and personal nature of the voucher. As opposed to other similar agricultural programs, the "soft" component of the voucher, that included technical assistance, was provided at the farmer level and not to a group of farmers.

6.3 Indirect Effects - Spillovers

This section of the analysis focuses on measuring spillover effects that might have taken place at the geographical level (the subzones). As previously mentioned, I present a very preliminary analysis of spillover effects. As part of my research agenda, I will analyze the presence of spillover effects generated within the social network as well. For this I plan to use a third round of data, to be collected this year, 2019, which includes a detailed section of the social networks of the farmers.

As mentioned, the PATCA randomization design allows measuring the spillovers that might have occurred among farmers who did not benefit from the program but whose geographical proximity to treated farmers may have influenced technology adoption (indirect beneficiaries). Hence, by comparing the adoption rates between untreated households located in treated subzones (indirect beneficiaries) and the control group I can recover the geographical spillover effects. For this purpose, the following equation is estimated:

$$Pr[Adopt = 1|X]_i = \alpha + \beta Indirect_i + \gamma X_i + \varepsilon_i \tag{5}$$

where $Pr[Adopt = 1|X]_i$ indicates the probability that household i adopts a technology from PATCA; $Indirect_i$ is a dummy variable that takes the value of 1 if household i was randomly assigned to the indirect beneficiary group (untreated farmers in treated subzones) and 0 if it was assigned to the control group; X_i is the matrix of pre-treatment characteristics, and ε_i is an individual error term assumed to be uncorrelated with $Indirect_i$.

Table 11 presents the results of the estimation of the adoption equation in (4) using a Probit model. Column (1) estimates the model for the pooled sample, while columns (2) and (3) estimate the adoption model for the grassland and the irrigation technologies separately.

Results show that being randomly assigned into the indirect beneficiary group is not a significant determinant of adopting a technology provided by the program, which suggests the non-existence of spillover effects at the geographical level. On the other hand, in the pooled sample specification, the economic characteristics of the households seem to play a major role in encouraging technology adoption, which validates the hypothesis that liquidity constraints might be one of the most important aspects limiting technology adoption. This relationship is rather strong in the case of livestock technology where having savings increases the probability of technology adoption by 73%, having access to credit by 66%, and having access to remittances by 90%.

7 Conclusion

This paper evaluates the direct impacts of the PATCA program in the Dominican Republic. The study exploits the random assignment of the program to identify the causal effects of adopting an agricultural technology on different outcomes of interest. In order to provide a source of exogenous variation to the technology adoption as well as to account for the presence of non-compliance, I use the randomly assigned treatment as an instrument for the adoption of the agricultural technology. Additionally, the randomization design allows studying the existence of direct and indirect impacts –spillovers- of the program.

Regarding the direct impacts of the program, I find that the adoption of an agricultural technology provided by the PATCA program improved the food security status of beneficiary households by around 19%.

The results for the grassland technology show that the adoption of the technology fostered a switch from a lower to a better quality of pasture, which improves the quality of the livestock feeding in beneficiary plots. It also increased the annual livestock sales income and livestock product sales income, increased the probability of having improved breed livestock in 17% and the percentage of improved breed over total livestock in 23%, and decreased the probability of being food insecure by 29%. On the contrary, no impacts are found for the irrigation technology. For all these estimates, inference is based on a Bonferroni correction method that accounts for multiple outcomes testing.

The presence of geographic spillover effects is nonexistent in this study, as suggested by the adoption model. Being geographically close to beneficiary households does not increase the probability of technology adoption. Furthermore, the results of the Probit suggest that the major limitation for technology adoption is a liquidity constraint, basically access to savings, credits and cash from remittances. However, it is worth mentioning that the analysis of spillover effects must be done more carefully and extensively, and this is part of another paper I will work on once the third round of data becomes available.

To conclude, it is worth mentioning some limitations and future extensions of this analysis.

First of all, this type of data can be subject to a huge amount of measurement error. For example, data on income and productivity are very hard to collect precisely on the field. This can have an impact on the estimates obtained here through an attenuation bias. Another limitation consists on just having a dichotomic measure of treatment. This prevents me from analyzing the impacts of different degrees of exposure to the treatment. One possibility I explored consisted of measuring the percentage of land devoted to the technology provided by the program, although the nature of these technologies prevents me from doing this analysis (irrigation technology is easily transferrable between plots and grassland technologies covered the majority of the plots worked by these farmers). Another interesting analysis would consist of identifying the effects of exposure to the program by time. One would expect that those who are exposed for a longer time to have stronger effects given the learning by doing process that is present in these types of technologies.

Finally, further analysis should be done on the mechanisms behind the results presented here. Of particular interest would be to explore why the irrigation technology did not have any impacts on beneficiaries. Also, I examined how impacts for the grassland technology vary with background characteristics (heterogeneous treatment effects), in particular with education of the head of the household and plot extension, although no claer patters were found.

I leave all these issues and open questions for a future version of this paper.

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Figures

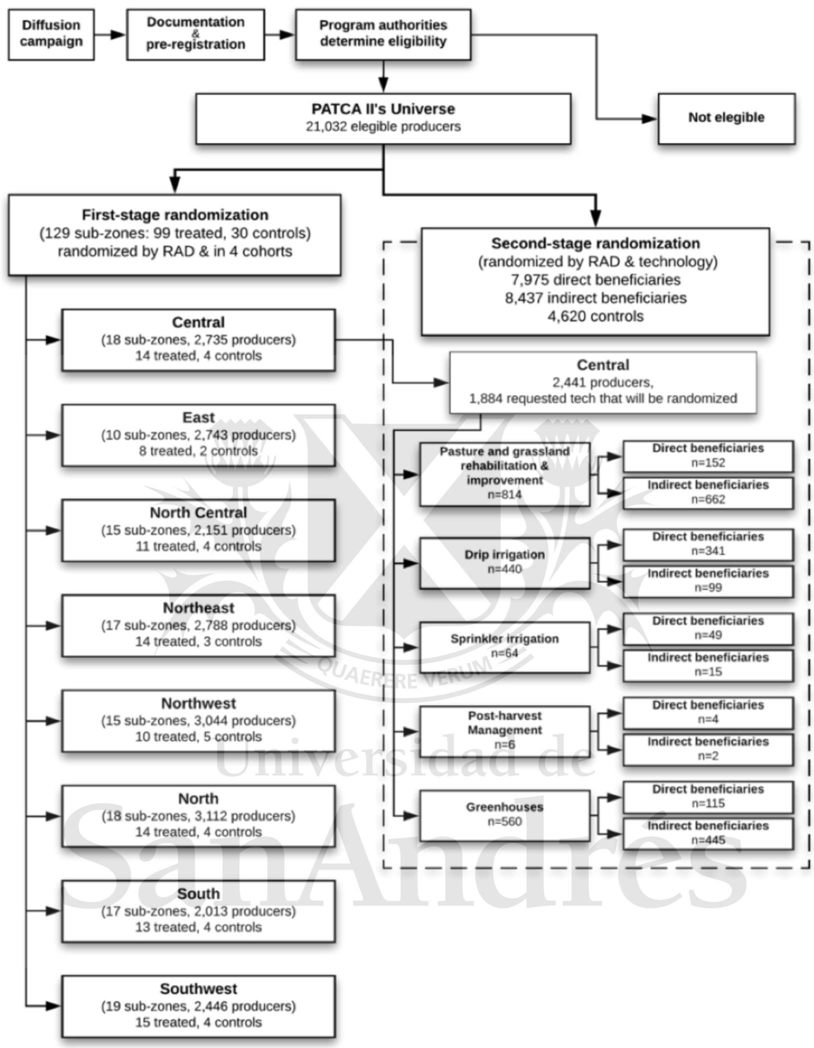

Figure 1: Program's flowchart: Diffusion, Eligibility & Cluster Sampling

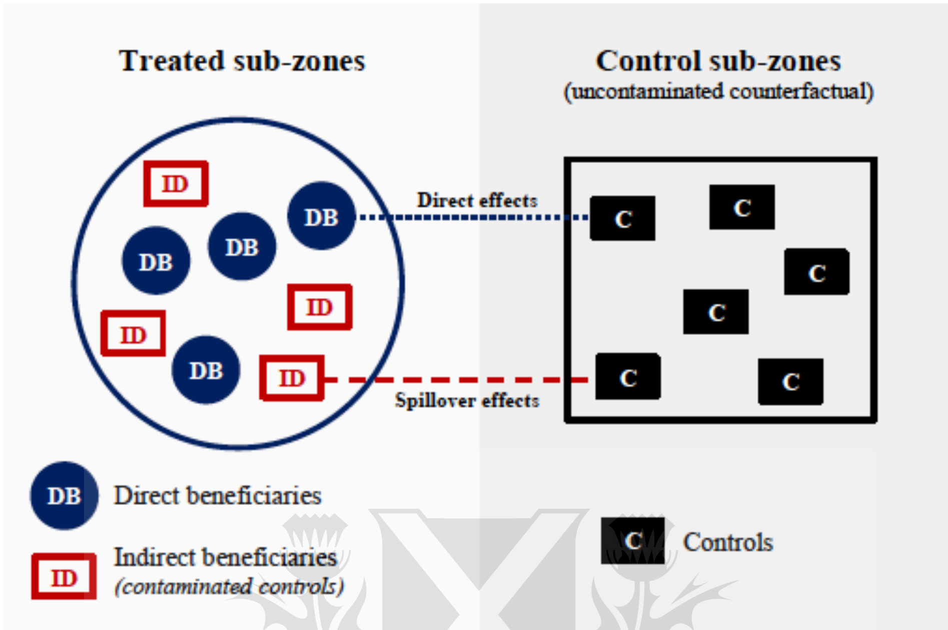

Figure 2: Direct and Spillover Effects

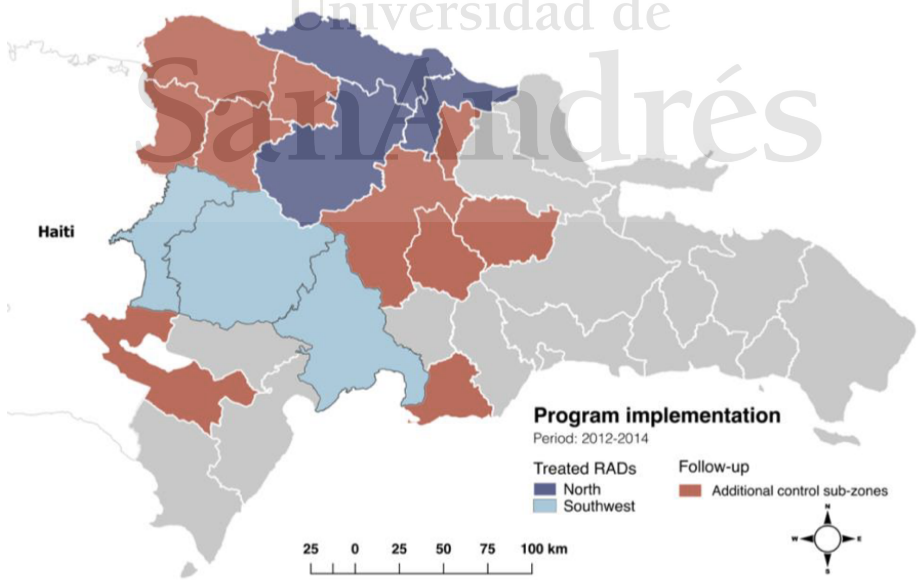

Figure 3: Treatment Regions

Table 1. Program Demand by Technology

Groups	1	2	3	4	5	6	7	8	Total
	Technologies								
DB	598	801	1,431	1,746	2,363	39	746	251	**7,975**
ID	0	212	0	444	5,995	0	1,735	51	**8,437**
Controls	0	350	0	1,206	2,331	0	514	219	**4,620**
Total	**598**	**1,363**	**1,431**	**3,396**	**10,689**	**39**	**2,995**	**521**	**21,032**

Technologies: 1. Land leveling; 2.Sprinklers; 3. Micro-sprinklers; 4. Drip irrigation; 5.Grassland improvements; 6. Mulching; 7. Greenhouses; 8. Post-harvest

Table 2. PATCA Implementation Universe (Regions North and Southwest)

Group	1	2	3	4	5	6	7	8	Total
	Technology								
DB-ET	0	25	56	244	447	3	23	25	823
DB-IT	2	52	103	301	347	16	175	17	1,013
IB	0	16	0	138	1,966	0	289	19	2,428
Controls	0	14	0	442	638	0	195	5	1,294
Total	2	107	159	1,125	3,398	19	682	66	5,558

Technologies: 1. Land leveling; 2.Sprinklers; 3. Micro-sprinklers; 4. Drip irrigation; 5.Grassland improvements; 6. Mulching; 7. Greenhouses; 8. Post-harvest

Table 3. Universe of Analysis (irrigation and livestock technologies)

	Irrigation		**Livestock**		**Total**	
Group	**Sub-zones**	**Producers**	**Sub-zones**	**Producers**	**Sub-zones**	**Producers**
DB – ET	19	211	19	330	**22**	**541**
DB – IT	24	389	18	164	**24**	**545**
IB	16	134	20	1234	**20**	**1368**
Control	18	1531	20	1097	**20**	**973**
Total	**37**	**2265**	**39**	**2825**	**42**	**5090**

Table 4. Descriptive Statistics (all regions included)

		Treatment	Control	Difference
Household	HH size	3.914	3.796	0.118
	Own housing (0,1)	0.861	0.860	0.001
Head of Household	Gender (=1 if male)	0.876	0.900	-0.024
	Age	51.727	52.040	-0.313
Education of the Head of the Household	Illiterate (0,1)	0.123	0.110	0.013*
	Primary Complete (0,1)	0.531	0.527	0.004
	Secondary Complete (0,1)	0.162	0.165	-0.003
	Tertiary Complete (0,1)	0.143	0.149	-0.006
	University Complete (0,1)	0.035	0.022	0.013
Plots	Own Plots (% of total)	0.869	0.850	0.019
	Hectares worked	10.621	10.475	0.146
Economic Status	Savings (0,1)	0.467	0.476	-0.009
	Formal Credit (0,1)	0.263	0.287	-0.024*
	Remittances (0,1)	0.046	0.051	-0.005
Livestock Outcomes	Natural Grass (Has.)	8.514	9.214	-0.700
	Fortified Pasture (Has.)	4.821	5.014	-0.193
	TLU	16.574	15.367	1.207
	Livestock Sales Income (US$)	963.412	909.254	54.158
	Products Sales Income (US$)	1205.369	1302.254	-96.885
	Improved Breed Livestock (0,1)	0.625	0.671	-0.046
	Improved Breed Livestock (%)	0.357	0.314	0.043
Irrigation Outcomes	Value of Production (US$)	3987.250	3821.320	165.930*
	Value of Production (US$/sown has)	2874.210	2973.201	-98.991
	Value of Production (US$/phis. has)	2793.589	2934.146	-140.557
	Land Use Intensity (sown/phis. has)	0.987	0.935	0.052
	Agricultural Cycles (#)	1.126	1.097	0.029
	Agricultural Cycles (=1 if more than 1)	0.069	0.092	-0.023
	Labor Expenditures (US$)	635.698	621.058	14.640
	Input Expenditures (US$)	120.214	129.361	-9.147
	Gross Margins (US$/has)	1853.247	1985.675	-132.428
Program Outcomes	HH Agricultural Income (US$)	1896.287	1935.256	-38.969
	Food Insecurity (0,1)	0.483	0.472	0.011
	Observations	***1,174***	***693***	

Notes: Difference in means significant at * 10 percent level.

Table 5. Descriptive Statistics Treated Regions (North and Southwest)

		Treatment	Control	Difference
Household	HH size	3.914	3.796	0.118
	Own housing (0,1)	0.861	0.860	0.001
Head of Household	Gender (=1 if male)	0.876	0.900	-0.024
	Age	51.727	52.040	-0.313
Education of the Head of the Household	Illiterate (0,1)	0.123	0.110	0.013*
	Primary Complete (0,1)	0.531	0.527	0.004
	Secondary Complete (0,1)	0.162	0.165	-0.003
	Tertiary Complete (0,1)	0.143	0.149	-0.006
	University Complete (0,1)	0.035	0.022	0.013
Plots	Own Plots (% of total)	0.869	0.850	0.019
	Hectares worked	10.621	10.475	0.146
Economic Status	Savings (0,1)	0.467	0.476	-0.009
	Formal Credit (0,1)	0.263	0.287	-0.024*
	Remittances (0,1)	0.046	0.051	-0.005
Livestock Outcomes	Natural Grass (Has.)	8.514	9.214	-0.700
	Fortified Pasture (Has.)	4.821	5.014	-0.193
	TLU	13.160	14.619	-1.459
	Livestock Sales Income (US$)	1267.082	1158.226	108.856
	Products Sales Income (US$)	1306.515	935.114	371.401
	Improved Breed Livestock (0,1)	0.625	0.671	-0.046
	Improved Breed Livestock (%)	0.357	0.314	0.043
Irrigation Outcomes	Value of Production (US$)	6542.878	7488.800	-945.922*
	Value of Production (US$/sown has)	3906.102	4223.260	-317.158
	Value of Production (US$/phis. has)	3793.589	3934.146	-140.557
	Land Use Intensity (sown/phis. has)	0.987	0.935	0.052
	Agricultural Cycles (#)	1.126	1.097	0.029
	Agricultural Cycles (=1 if more than 1)	0.069	0.092	-0.023
	Labor Expenditures (US$)	882.934	925.887	-42.953
	Input Expenditures (US$)	797.781	933.674	-135.893
	Gross Margins (US$/has)	1853.247	1985.675	-132.428
Program Outcomes	HH Agricultural Income (US$)	7064.021	6384.875	679.146
	Food Insecurity (0,1)	0.291	0.331	-0.040
	Observations	***351***	***212***	

Notes: Difference in means significant at * 10 percent level.

Table 6. Distribution of the final sample sizes, by technology and beneficiary group.

Groups	Irrigation	Grassland	Total
DB-ET	211	330	541
DB-IT	267	164	431
IB	134	380	514
Controls	344	384	728
Total	**956**	**1258**	**2214**

Table 7. First Stage Estimations

	TOTAL	GRASSLAND	IRRIGATION
PATCA (0,1)	0.574	0.688	0.452
	(0.017)***	(0.021)***	(0.025)***
	[0.071]***	[0.086]***	[0.070]***
F Stat	16.03	14.82	11.04
	[0.000]	[0.000]	[0.000]
Covariates	Yes	Yes	Yes
N	1,700	878	822

Notes: Standard errors are in parenthesis. Clustered standard errors at the Subzone level are in brackets. Significant at *** 1 percent level.

Table 8. Impacts of PATCA on Income and Food Security

Dependent Variables (unit)	**(1) OLS-ITT**	**(2) OLS-ITT**	**(3) 2SLS-LATE**	**(4) 2SLS-LATE**
Agricultural Income (log-US$)	0.007	0.053	0.014	0.022
	(0.185)	(0.182)	(0.324)	(0.316)
	[0.752]	[0.681]	[1.324]	[1.189]
Food Insecurity (0,1)	-0.124	-0.115	-0.216	-0.199
	(0.025)***	(0.024)***	(0.044)***	(0.042)***
	[0.107]	[0.093]	[0.189]	[0.163]
Covariates	No	Yes	No	Yes
Observations	1,700	1,700	1,700	1,700

Notes: Standard errors are in parenthesis. Clustered standard errors at the Subzone level are in brackets. Significant at ***1, **5, *10 percent level using the Bonferroni correction.

Table 9. Impacts of Grassland Technology in Productivity

Dependent Variables (unit)	(1) OLS-ITT	(2) OLS-ITT	(3) 2SLS-LATE	(4) 2SLS-LATE
Natural Grass (Has.)	-2.283	-2.483	-3.360	-3.611
	(0.980)*	(1.005)*	(1.453)*	(1.471)**
	[2.631]	[2.547]	[3.931]	[3.734]
Fortified Pasture (Has.)	1.481	1.741	2.180	2.531
	(0.516)**	(0.518)***	(0.745)**	(0.738)***
	[1.389]	[1.251]	[1.896]	[1.655]
TLU	3.187	4.045	4.113	5.169
	(1.764)	(1.685)**	(2.250)	(2.124)**
	[6.610]	[5.454]	[7.659]	[6.847]
Livestock Sales Income (log-US$)	0.623	0.670	0.804	0.855
	(0.336)	(0.332)*	(0.429)	(0.420)*
	[0.914]	[0.856]	[1.159]	[1.037]
Livestock Products-Sales Income (log-US$)	0.664	0.710	0.775	0.813
	(0.375)	(0.382)*	(0.435)	(0.435)*
	[0.934]	[0.854]	[1.087]	[0.976]
Improved Breed Livestock (0,1)	0.120	0.132	0.155	0.168
	(0.041)**	(0.041)***	(0.052)**	(0.051)***
	[0.146]	[0.144]	[0.189]	[0.182]
Improved Breed Livestock (%)	0.171	0.181	0.220	0.231
	(0.030)***	(0.029)***	(0.037)***	(0.036)***
	[0.101]	[0.089]	[0.118]	[0.109]
Food Insecurity (0,1)	-0.210	-0.204	-0.309	-0.298
	(0.034)***	(0.032)***	(0.051)***	(0.048)***
	[0.127]	[0.102]	[0.199]	[0.157]
Covariates	No	Yes	No	Yes
Observations.	878	878	878	878

Notes: Standard errors are in parenthesis. Clustered standard errors at the Subzone level are in brackets. Significant at *** 1, ** 5, * 10 percent level using the Bonferroni correction.

Table 10. Impacts of Irrigation Technology in Productivity

Dependent Variables (unit)	(1) OLS-ITT	(2) OLS-ITT	(3) 2SLS-LATE	(4) 2SLS-LATE
Value of Production (log- US$/sown has)	0.244	0.221	0.534	0.489
	(0.251)	(0.252)	(0.548)	(0.556)
	[0.605]	[0.589]	[1.335]	[1.329]
Gross Margins (log-US$/has)	-0.051	-0.037	-0.105	-0.077
	(0.027)	(0.024)	(0.056)	(0.051)
	[0.083]	[0.070]	[0.174]	[0.149]
Labor Expenditures (log-US$)	0.398	0.368	0.872	0.814
	(0.216)	(0.209)	(0.478)	(0.467)
	[0.555]	[0.481]	[1.249]	[1.095]
Input Expenditures (log-US$)	0.491	0.471	1.078	1.049
	(0.216)	(0.192)*	(0.419)*	(0.429)*
	[0.445]	[0.441]	[1.024]	[1.018]*
Hectares sown	0.113	0.096	0.249	0.214
	(0.181)	(0.199)	(0.397)	(0.439)
	[0.227]	[0.229]	[0.501]	[0.509]
Food Insecurity (0,1)	-0.029	-0.034	-0.063	-0.076
	(0.036)	(0.035)	(0.079)	(0.077)
	[0.124]	[0.102]	[0.272]	[0.224]
Covariates	No	Yes	No	Yes
Observations	822	822	822	822

Notes: Standard errors are in parenthesis. Clustered standard errors at the Subzone level are in brackets. Significant at *** 1, ** 5, * 10 percent level using the Bonferroni correction.

Table 11. Probit for Technology Adoption – Indirect Beneficiaries

		(1) Total	(2) Grassland	(3) Irrigation
Randomization	Indirect Beneficiary (0,1)	0.192	0.262	0.401
		(0.143)	(0.237)	(0.215)
		[0.249]	[0.397]	[0.265]
Head of Household	Gender (=1 if Male)	0.136	0.281	0.116
		(0.267)	(0.463)	(0.369)
		[0.238]	[0.385]	[0.280]
	Age	-0.035	-0.015	-0.055
		(0.033)	(0.056)	(0.047)
		[0.042]	[0.036]	[0.063]
	Age Sq.	0.001	0.001	0.001
		(0.000)	(0.001)	(0.000)
		[0.000]	[0.000]	[0.001]
Household	HH size	-0.008	-0.115	0.0519
		(0.040)	(0.075)	(0.054)
		[0.051]	[0.064]	[0.065]
Education of the Head of the Household	Illiterate (0,1)	-0.525	0.001	-0.341
		(0.402)	-0.125	(0.514)
		[0.274]	[0.328]	[0.328]
	Primary Complete (0,1)	0.122	-0.276	0.214
		(0.199)	(0.384)	(0.266)
		[0.245]	[0.336]	[0.274]
	Secondary Complete (0,1)	-0.0213	0.155	-0.422
		(0.235)	(0.346)	(0.376)
		[0.226]	[0.256]	[0.410]
	Tertiary Complete (0,1)	0.504	-0.204	0.803
		(0.363)	(0.641)	(0.530)
		[0.304]	[0.472]	[0.345]
	University Complete (0,1)	0.229	0.272	0.0273
		(0.217)	(0.323)	(0.315)
		[0.182]	[0.295]	[0.244]
Economic Status	Savings (0,1)	0.282	0.733	0.147
		(0.155)*	(0.317)**	(0.215)
		[0.141]**	[0.148]***	[0.232]
	Formal Credit (0,1)	0.278	0.661	0.0990
		(0.152)*	(0.242)***	(0.229)
		[0.148]**	[0.173]***	[0.183]
	Remittances (0,1)	0.575	0.906	0.482
		(0.236)**	(0.355)**	(0.351)
		[0.259]**	[0.417]**	[0.230]**
	Constant	-1.412	-2.353	-0.809
		(0.894)	(1.504)	(1.305)
		[1.193]	[1.097]**	[1.883]
	Observations	1,242	764	478

Notes: Standard errors are in parenthesis. Clustered standard errors at the Subzone level are in brackets. Significant at *** 1 percent level, ** 5 percent level, * 10 percent level.

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