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

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Direct and spillover effects of agricultural technology adoption programs: Experimental evidence from the Dominican Republic

Julián Aramburu,[*] Lucas Figal Garone,[†] Alessandro Maffioli,[‡]
Lina Salazar,[§] Cesar Augusto Lopez[**]

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Abstract

This paper estimates the impact of an agricultural technology adoption program on agricultural production and income using an experimental approach. The context of analysis is the Program for the Support of Innovation in Agricultural Technology (*PATCA II*) implemented in the Dominican Republic. The program aimed to increase the agricultural productivity and income of smallholder farmers by encouraging the adoption of a technology. We exploit a two-stage randomized experiment conducted at the geographic- and farmer-level to evaluate the effects of adopting improved pasture and irrigation technologies using an instrumental variable (IV) analysis to recover the local average treatment effect (LATE). To measure the effectiveness of the program, we combined rich microeconomic data obtained from a comprehensive household survey with administrative data to measure both direct and spillover effects. The sample includes 2,499 farmers, including direct beneficiaries, indirect beneficiaries, controls, and farmers within the social network of direct beneficiaries. We find different patterns of adoption and significant impacts on production-related outcomes for both of the technologies analyzed. The results show adoption of improved pastures increased agricultural income and that the effects intensify over time. In the case of irrigation, treatment had adverse effects on total household income and agricultural production; however, there is evidence of a change in the production portfolio of program beneficiaries from temporary to permanent crops as a function of time of exposure to the technology. Whereas irrigation can be implemented immediately after treatment, income benefits take time to materialize, for instance, as permanent crops reach the initial point of harvest or maturity. These results imply the existence of a dynamic *learning-by-doing* process. Also, the assessment of indirect or spillover effects validate the hypotheses that knowledge spillovers might take place among farmers in close proximity to program beneficiaries, especially through social networks. The results present evidence that liquidity constraints are critical determinants of technology adoption for smallholder farmers in the Dominican Republic.

JEL Codes: C26, C93, D13, D24, O13, O33, Q12, Q16
Keywords: technology adoption; agriculture; spillover effects; productivity; policy evaluation

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[*] Department of Economics, Yale University. E-mail: julian.aramburu@yale.edu.
[†] Strategy, Development Effectiveness, and Programming Department, Inter-American Development Bank. E-mail: lfigal@iadb.org.
[‡] Strategy, Development Effectiveness, and Programming Department, Inter-American Development Bank. E-mail: alessandrom@iadb.org.
[§] Environment, Rural Development and Disaster Risk Management Division, Inter-American Development Bank. E-mail: lsalazar@iadb.org.
[**] Environment, Rural Development and Disaster Risk Management Division, Inter-American Development Bank. E-mail: clopezrivas@iadb.org.

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1. Introduction

There is an emerging consensus among macro-economists that differences in total factor productivity (TFP) across countries account for meaningful differences in per capita GDP (Caselli and Coleman, 2001; Comin and Hobijn, 2004; Pages, 2010; Rosenzweig, 2010; Foster and Rosenzweig, 2010; Crespi et al., 2014). In particular, for developing countries, productivity growth in the agricultural sector often explains a significant portion of aggregate productivity growth and, therefore, is recognized as a relevant driver of structural transformation and economic growth (Gollin et al., 2002). However, agricultural productivity in these economies remains low and is considered one of the main obstacles to poverty alleviation in rural areas. In Latin America, for instance, the agricultural productivity gap with OECD countries reaches almost 50 percent (Nin-Pratt et al., 2015).

Improvements in agriculture productivity through the adoption of new technologies have been one of the fundamental triggers of economic growth in agriculture-intensive economies, leading to structural transformation, industrial development, and welfare improvements (White, 1967; Andersen et al., 2014). The agricultural sector has significant direct and indirect contributions to both income growth and poverty reduction, including on the poorest segments of society—by raising income and generating employment in rural areas and diminishing food prices in urban areas (Christiaensen et al., 2012; Christiaensen and Martin, 2018; de Janvry and Sadoulet, 2002, 2009; Dethier and Effenberger, 2012).

Nevertheless, in developing countries, agricultural productivity growth has been obstructed by the lack of access to modern inputs and adoption of improved agricultural practices (Emerick et al., 2016). Several explanations for constraints on technology adoption and inputs, mainly due to market and coordination failures, have arisen in the literature. Among them, we find lack of technologies well suited to local conditions (Emerick et al., 2016); subjective preferences for characteristics of technology (Adesina and Baidu-Forson, 1994); high transaction costs due to poor infrastructure (Suri, 2011); asymmetric and/or incomplete information and difficulties in learning (Munshi, 2004; Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Ashraf et al., 2009; Conley and Udry, 2010; Hanna et al., 2014); limited size or absence of market opportunities (thin markets) and scarcity of human capital (Feder et al., 1985); liquidity or credit constraints (Miyata and Sawada, 2007; Gine and Klonner, 2008); and, insurance market failures (Dercon and Christiaensen, 2007; Foster and Rosenzweig, 2009; Karlan et al., 2014).

The presence of market and coordination failures rationalize public interventions in the form of productive programs aimed at increasing agricultural productivity and rural income by promoting the adoption of agricultural innovations. Three questions are particularly relevant in the context of Technology Adoption Programs (TAP): (1) What are the direct causal effects of TAP on technology adoption and subsequent performance and welfare on participant farmers? (2) Does TAP generate spillovers effects on non-participant farmers?[1] (3) What are the main factors hindering the adoption of agricultural technologies among smallholder farmers? To date, however, little empirical evidence has been produced to answer these questions together, and few studies have adequately dealt with the methodological challenges related to the identification of these effects. The evidence is particularly scarce in the case of Latin American and the Caribbean countries (LAC).

In particular, as pointed out by Syverson (2011), any attempt to identify spillovers has to deal with two fundamental challenges. The first one is the so-called “reflection problem” (Manski, 1993);[2] correlated behaviors among specific groups of farmers can be a sign of knowledge spillovers, but they can also reflect the effects of unobserved third factors. For this reason, the estimation of knowledge spillovers would require the identification of an exogenous source of variation for a subset of farmers and a clear understanding of how these farmers’ behavior may respond to such variation. The second challenge is related to the precise tracking of this behavioral response. Relationships between farmers are not always easy to identify, more so those implying some level of knowledge sharing. Various proxies have been used to identify potential knowledge-sharing relationships among farmers. These include geographical proximity (Besley and Case, 1993; Foster and Rosenzweig, 1995; Holloway et al., 2002; Munchi, 2006), “information neighbors”[3] (Conley and Udry, 2010), network of kinship and friends (Bandiera and Rasul, 2006; Duflo et al., 2004; Van den Broeck and Dercon, 2011), cooperative members (Abebaw and Haile, 2012), informed parties such as company representatives and input dealers (Maertens, 2010),

[1] In the economic literature, the concept of knowledge spillovers is associated to that of a nonpecuniary externality. Scholars have also referred to this concept as technological and Research & Development (R&D) externalities: “the impact of the discovered ideas or compounds (not embodied in a particular service or product) on the productivity of the research endeavors of others” (Griliches, 1992).

[2] In Manski (1993)'s words: “the ‘reflection’ problem that arises when a researcher observing the distribution of behavior in a population tries to infer whether the average behavior in some group influences the behavior of the individuals that comprise the group. The term reflection is appropriate because the problem is similar to that of interpreting the almost simultaneous movements of a person and his reflection in a mirror. Does the mirror image cause the person's movements or reflect them? An observer who does not understand something of optics and human behavior would not be able to tell”.

[3] The set of individuals from whom an individual neighbor may learn about agriculture.

social pressure (Moser and Barrett, 2006; Maertens, 2010), ethnically based and participatory social affiliations (Isham, 2002), among others.[4]

To answer the questions mentioned above and to address the associated empirical challenges, we exploit a two-stage randomized control trial (RCT) conducted at the geographic and farmer levels to estimate the causal direct and spillover effects of adopting improved pastures and irrigation technologies. The context of analysis is the second phase of the Program for the Support of Innovation in Agricultural Technology (*PATCA II*)[5] implemented in the Dominican Republic in 2012. The program aimed to increase agricultural productivity and income among smallholder farmers by encouraging technological adoption. In particular, *PATCA* II provided non-reimbursable vouchers to finance a percentage (between 33-59 percent) of the total cost of a technology chosen by the farmer from a fixed menu of agricultural technologies.

The program was designed based on two main hypotheses. First, the presence of liquidity constraints, such as access to formal credit, is a factor that directly affects technology adoption among small- and medium-size farmers. These are not only due to the typical market failures such as asymmetric information, and non-convexities and indivisibilities. But also due to specific constraints inherent to agriculture: seasonality and gestation periods (IFC, 2011), covariant and systemic risks (IFC, 2014), high transaction costs due to low population densities, low infrastructure quality, distant locations that limit the viability of agribusiness financial services (Gallardo et al., 2006; BID, 2016). Moreover, the problem of absence or scarceness of collaterals in the form of physical assets usually makes access to credit more difficult for small- and medium-size farmers. Second, the lack of information or knowledge could be a significant barrier to technology adoption. In this context, knowledge spillovers are expected to occur. That is, non-participant farmers with close geographical or social proximity to program beneficiaries are expected to benefit from information sharing and, therefore, technology uptake.

Using an instrumental variable (IV) approach to estimate the impact on program compliers, we find strong evidence of a positive treatment effect on technology adoption.[6] We find different patterns of treatment effects on production-related outcomes for both technologies under analysis, and in general, the results imply the existence of a learning curve or *learning-by-doing* process. For farmers who benefited from the improved pastures technology, participation has statistically

[4] There is a substantial body of evidence in the theoretical and empirical economics literature showing that a significant share of knowledge spillovers tends to be geographically bounded (Marshall, 1920; Jaffe 1989; Jaffe et al., 1993; Audretsch and Feldman, 1996; Baptista, 2000; Acts and Varga, 2002).

[5] *Programa de Apoyos a la Innovación Tecnológica Agropecuaria.*

[6] We define technology adoption as using the technology during the 2014 agricultural cycle.

significant positive direct and time effects on agricultural income. Moreover, these effects intensify over time. On the other hand, the benefits of access to irrigation have not yet materialized. as participating farmers experienced negative effects on production-related outcomes. However, we find evidence of changes in their production from temporary to permanent crops (e.g., fruit trees), suggesting that a plausible explanation of the negative impacts on production may be related to the lack of time for these crops to reach the stage of harvest. Lastly, the assessment of indirect or spillover effects did not validate the hypotheses that knowledge spillovers might influence technology uptake among farmers in close geographical and social proximity to program beneficiaries. The absence of spillover effects reinforces the hypothesis that liquidity constraints are critical determinants of technology adoption for smallholder farmers in the Dominican Republic.

The paper is structured as follows. Section 2 reviews the empirical literature on agricultural technology adoption programs. Section 3 explains the program and the experimental design. Section 4 describes the data. Section 5 presents the econometric methodology used to estimate treatment effects. Section 6 contains the main results, and Section 7 concludes.

2. Literature review: Effectiveness of technology adoption programs in agriculture

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).[7]

[7] "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).

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). 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 high-yielding 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. 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 non-reimbursable 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.[8] 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.[9] 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 &

[8] Each farmer was able to choose only one technology.
[9] See Table A1 in Appendix A for a brief description of the technologies offered by the program, and Table A2 for a breakdown of the cost of the technologies.

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.

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;[10] (iii) have agricultural or livestock production as the main economic activity; (iv) be a smallholder producer;[11] (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).[12] The excess demand encouraged government officials from the MA to implement a randomized controlled trial (RCT) to ensure transparency in the allocation of resources.

3.1 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 non-treated 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

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

[11] 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.

[12] 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.

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.[13] 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).[14] 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.[15] The 21,032 producers in the universe of *PATCA II* are located across 129 sub-zones (approximately 96 percent of all sub-zones) across the RADs.[16]

In 2012, authorities from the MA conducted lotteries nationwide through each of the RADs to select the beneficiaries from *PATCA* II.[17] 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 designated farmer to witness the process. Also, public notaries were present to register and legalize the selection process.

[13] 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).

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

[15] See Table A3 in Appendix A for a breakdown of administrative provinces by RADs.

[16] See Tables A4 and A5 in Appendix A for a distribution of producers and requested technologies in the universe across RADs.

[17] 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.

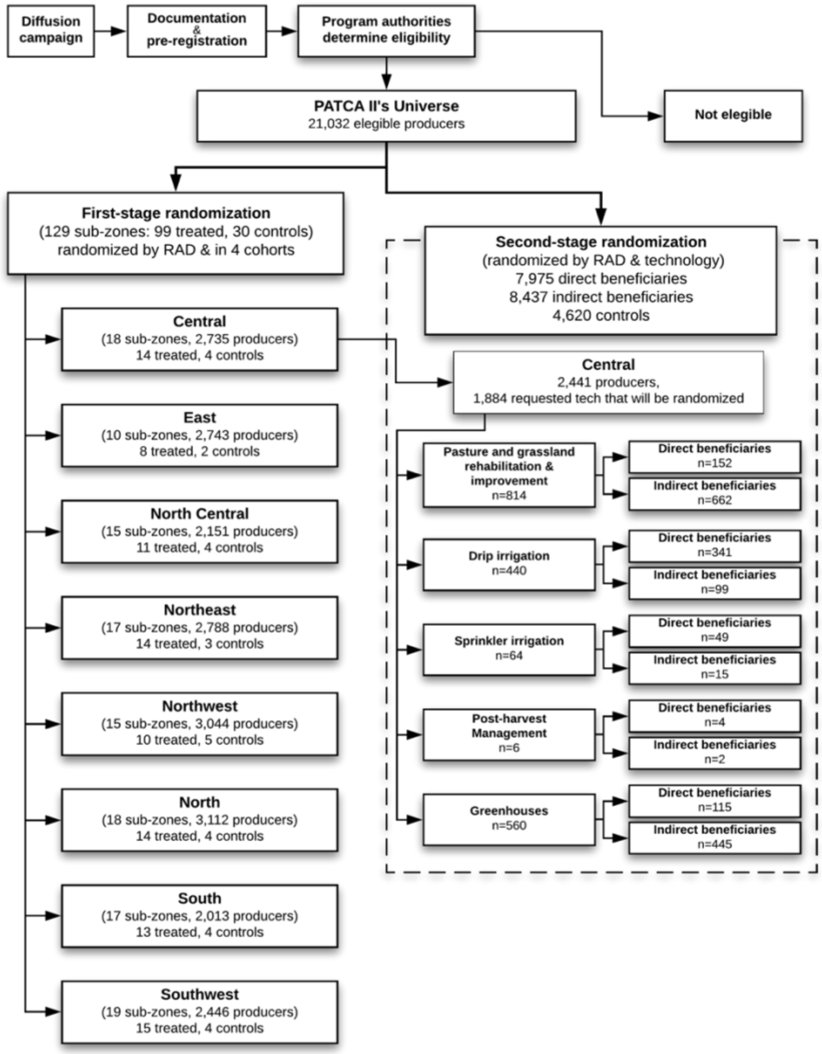

Figure 1. Program's flowchart: Diffusion, eligibility & cluster sampling

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.[18] 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 sub-zones were randomly drawn from the *tombola* in the first-stage, of which the first set of four balls

[18] 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).

(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).[19]

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.

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 sub-zones (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).[20] 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.

[19] See Table A6 in Appendix A for a distribution of the number of sub-zones per treatment cohort and RADs.
[20] See Table A7 in Appendix A for a distribution of producers randomly assigned to treatment, per stage and RADs.

Table 1. Program universe: Requested technologies by treatment group

Requested technologies	Randomized	Treatment groups: Direct beneficiaries	Treatment groups: Indirect beneficiaries	Treatment groups: Controls	Pooled
1. Pasture and grassland rehabilitation & improvement	✓	2,363	5,995	2,331	10,689
2. Drip irrigation	✓	1,746	444	1,206	3,396
3. Sprinkler irrigation	✓	801	212	350	1,363
4. Greenhouses	✓	746	1,735	514	2,995
5. Post-harvest management	✓	251	51	219	521
		5,907	8,437	4,620	18,964
6. Land leveling		598	-	-	598
7. Mulching		39	-	-	39
8. Micro-sprinkler irrigation		1,431	-	-	1,431
Total		7,975	8,437	4,620	21,032

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). Also, be described in more detail in Section 4.2B, social network data from program beneficiaries were collected at follow-up to estimate social spillovers.

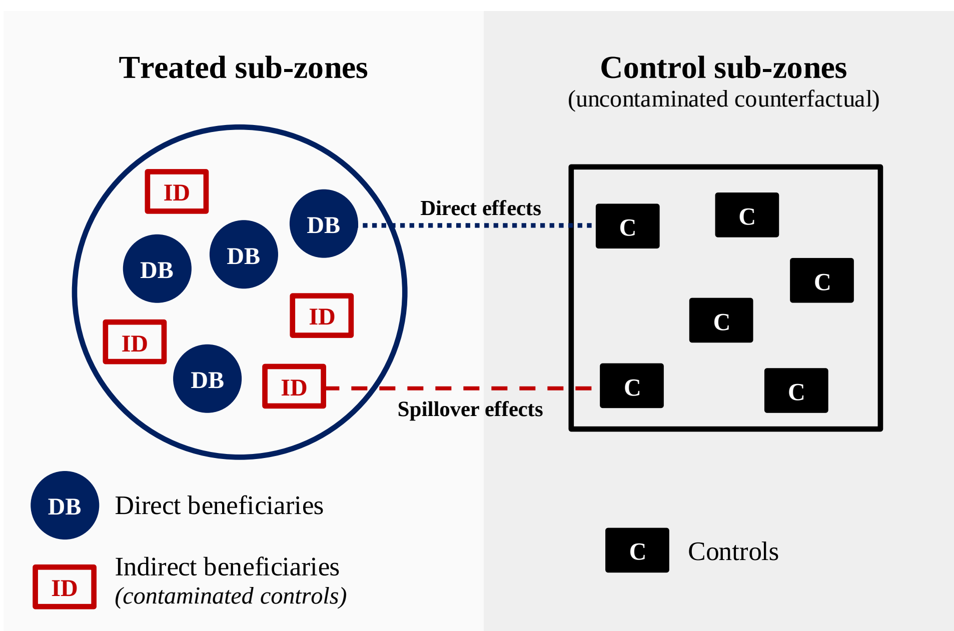

Figure 2. Direct and spillovers effects

4. Data

This section describes the datasets used for the estimation of treatment effects. First, we assess the validity of the randomization strategy by testing the comparability between the treatment and control groups using baseline data. Then, we discuss issues in the implementation phase and its consequences on the estimation of treatment effects. Both rounds of data were collected using a comprehensive agricultural household survey with detailed information regarding agricultural and livestock production, land allocation, inputs use, household socio-economic characteristics, income sources, food security, social capital, migration, among others.[21]

4.1 Baseline data

The data collection for the baseline was implemented between November and December 2012, referencing the 2011 agricultural cycle (January to December).[22] The sample selected for the baseline survey includes 4,126 producers which were representative by RADs, technology, and treatment group. Overall, the sample was composed of 2,053 direct beneficiaries, 924 indirect beneficiaries, and 1,149 *pure* controls.[23] The final baseline sample for the analysis is composed of 3,735 households (1,879 direct beneficiaries, 842 indirect beneficiaries, and 1,014 pure controls).[24] The baseline balance test results are available in Appendix A (Tables A13 and A14). Overall, the balance tests are not statistically significant, therefore, we fail to reject the null-hypothesis of no baseline imbalance—that is, that treatment assignment is independent of pre-treatment data—suggesting the randomization was successful.

4.2 Program implementation and follow-up survey

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).[25] 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

[21] Social network data were collected during the follow-up round only.

[22] The survey instrument was first piloted between April 13-15, 2012 across 4 RADs and to a sample of 80 producers. The final questionnaire is composed of 531 questions organized into 12 modules. A total of 84 enumerators received training in two phases: the first phase included six sessions of eight hours (October 16-21), followed by two days of reinforcement in the second phase (October 31 to November 3rd).

[23] The sample size calculation for the baseline survey was determined using the first two treatment cohorts, and proportional sampling by cohort and technology. These two cohorts include 55 of the 99 treated sub-zones selected in the first-stage of the randomization. This strategy indirectly increased the number of producers that had to be surveyed within the treated sub-zones and therefore for each of the RADs. In the case of the control group, the sampling strategy considered all the non-treated sub-zones (30).

[24] The data collection process started on November 8th, and by December 21st most of the interviews had been completed; however, the process extended until January 2013 in an attempt to locate the subset of producers not reached in the previous months. While 3,811 (92.4 percent) of the expected set of producers completed the baseline survey, there were 76 households in the sample where more than one member registered in the program. Of the 315 producers not interviewed (7.6 percent of the sample), 39 rejected the interview, 239 could not be reached, and the remaining 37 were not agricultural producers. The survey firm was not provided with information on the treatment status of producers to avoid enumeration bias.

[25] 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.

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.[26]

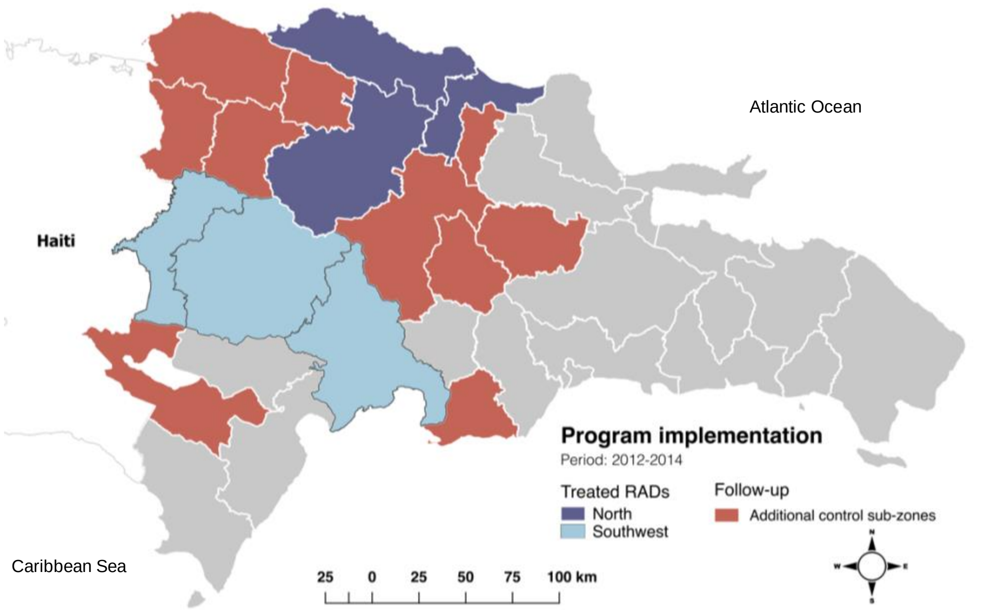

Figure 3. Program implementation

By the end of 2014, the number of *effectively treated* beneficiaries was 1,014, including 666 with improved pastures and 317 with irrigation (drip, sprinkler, or micro-sprinkler).[27] By *effectively treated*, we refer to those farmers who were selected as direct beneficiaries and received the technologies as of December 31, 2014.[28] 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).[29] 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

[26] 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).

[27] 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.

[28] See Table B1 in Appendix B for a tabulation of the technologies implemented as of December 31, 2014. Table B2 provides a breakdown by month and year.

[29] 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.

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.[30]

Given the similarity between the irrigation technologies (drip, sprinkler, and micro-sprinkler) 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".[31] The follow-up sample was representative of the three treatment groups (direct beneficiaries, indirect beneficiaries, and controls) and both technologies (improved pastures and irrigation) in the North and Southwest regions.[32] 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).

[30] 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.

[31] Only a limited set of those producers randomly assigned to receive greenhouses and post-harvest management technologies were *effectively treated* as of December 2014 (n=1 and n=27, respectively); therefore, greenhouses and post-harvest management technologies were not considered in sample size and power calculations for the follow-up, and will not be part of the analysis.

[32] See Annex C for a summary of the power and sample size calculation. Table C5 presents a distribution of the universe for the follow-up survey, including effectively treated (541), intended to be treated (545), indirect beneficiaries (1,368), and control (2,548) farmers.

Follow-up data was successfully collected for 94 percent (n=2,089) of the expected sample, and 76 percent (n=410) of the social network nodes.[33] However, a subset of these observations were excluded from the analysis for various reasons, including outliers, farmers who reported not planting any crops during the 2014 agricultural cycle, and farmers associated with the micro-sprinkler irrigation technology.[34] The final sample comprises 2,146 farmers (Table 2).

Table 2. Follow-up data: Final sample

	Follow-up sample		
Treatment groups	Pooled	Improved pastures	Irrigation
DB	765 (220)	465 (105)	300 (115)
DB-ET	447 (139)	316 (80)	131 (59)
DF-IT	318 (81)	149 (25)	169 (56)
IB	463 (107)	361 (70)	102 (37)
Controls	583 (280)	354 (95)	229 (185)
sub-total	1,811 (607)	1,180 (270)	631 (337)
Social network nodes	335	255	80
Total	2,146	1,435	711

Notes: Direct beneficiaries-*effectively treated* (DB-ET), direct beneficiaries-intended to be treated (DB-IT), indirect beneficiaries (IB). Number of producers with baseline data in parenthesis.

5. Econometric methodology

Randomized controlled trials (RCTs) are deemed the gold standard method for evaluating the effectiveness or causal effects of social interventions when the assumptions of the test are met (Cartwright, 2007). Formally, when treatment, T_i, is randomly assigned (1 if farmer i is a direct beneficiary, 0 otherwise), the expected outcome of the treatment group, $E(Y_{1i}|\ T_i = 1)$, is equal to the expected outcome of the control group had they not received the treatment, $E(Y_{1i}|\ T_i = 0)$, and vice-versa, $E(Y_{0i}|\ T_i = 1) = E(Y_{0i}|\ T_i = 0)$. Hence, any observed difference in the outcome of interest between the treatment and the control groups captures the average causal effect of the treatment (Angrist and Pischke, 2014).

In the case of random assignment with perfect compliance (i.e., all farmers assigned as direct beneficiaries participate in the program, and those assigned to the control group do not), an

[33] Among the subset of DB-IT in the follow-up sample, 38 percent (n=138) reported not receiving the program's voucher, nine percent (n=34) reports not having the financial resources to cover the remaining cost of the technology, 44 percent did not provide a reason, and the rest states multiple reasons for not taking up the program.

[34] The excluded observations include 60 households that reported not having any land (i.e., owned, leased or rented) during the 2014 agricultural cycle (two DT-ET, 22 DB-IT, 9 IB, 24 controls, and three network nodes), 21 DB-ET that received a technology different from improved pastures or irrigation (drip, sprinkler or micro-sprinkler), 116 observations of the irrigation technology group that reported not planting any crops (five DB-ET, 16 DB-IT, 12 IB, and 83 controls) in 2014—these 116 observations reported not planting any crops (temporary or permanent) during the 2014 cycle and not having any permanent crops (e.g., fruit trees, pastures, etc.) on their land; there is no data in the agricultural module for these farmers. Also, 88 producers associated with the micro-sprinkler irrigation technology were excluded because this technology was not randomized (40 DB-IT, 44 DB-ET, and 4 network nodes), and another 22 network nodes were excluded because they were not part of the social network of DB-ET farmers.

unbiased estimate of the *average treatment effect* (ATE) can be calculated using a conventional *ordinary least squares* (OLS) regression model as follows:

$$Y_i = \alpha + \beta PATCA_i + e_i, \qquad i = 1, 2, \dots, n. \tag{1}$$

where Y_i represent an outcome of interest and $PATCA_i$ is the *treatment variable*, in this case, a dummy that takes the value of 1 if farmer *i* is randomly assigned as a direct beneficiary of $PATCA$ II, and 0 otherwise.

However, not all direct beneficiaries participated in the program (*never-takers*), and some controls observations did (*always-takers*). Under this scenario, participant farmers might have unobservable characteristics (e.g., better ability or higher motivation) correlated with the outcome of interest. Hence, program participation is endogenous, and the β in Eq. (1) corresponds to the *intention-to-treat* (ITT) or *reduced form* estimate – the direct effect of being randomly assigned to treatment regardless of treatment status.[35] To circumvent the problem of partial compliance and endogeneity, an *instrumental variable* (IV) methodology, using *two-stage least squares* (2SLS), will be implemented to estimate the *local average treatment effect* (LATE) (Anderson, 2005; Imbens and Angrist, 1994).[36] We combine the microdata obtained from households surveys with administrative records to measure direct effects, time effects, and spillover effects using different models.[37]

5.1 Direct effects

First, to measure direct effects, program participation (an endogenous binary variable) will be instrumented in the first-stage using a binary treatment indicator representing random assignment to the treatment group, as follows:

$$PATCA\_TREATED_i = \theta + \lambda RAND_i + \boldsymbol{X}_i\gamma + \mu_i \tag{2}$$

where $PATCA\_TREATED_i$ is a dummy variable equal to 1 if the direct beneficiary was *effectively treated* with the technology (i.e., improved pastures or irrigation), and 0 otherwise; $RAND_i$ is a dummy variable equal to 1 if the farmer was selected as a direct beneficiary in the lottery, and 0 otherwise; the coefficient λ represents the probability of treatment given that the farmer was

[35] The ITT is relevant in situations where compliance rates are expected to be similar to those observed in the study (Angrist, 2006).

[36] Imbens and Angrist (1994) define the LATE (ratio of reduced form to firs-stage) as the average treatment effect "for individuals whose treatment status is influenced by changing an exogenous regressor that satisfies an exclusion restriction"; that is, the LATE is the average causal effect of *PATCA II* for the set of farmers (compliers) whose technology adoption is determined solely by the program's randomization (*monotonicity* assumption). However, IV methods are uninformative about the program's effects on *always-* or *never-takers* since the lottery is unrelated to treatment status (Angrist and Pischke, 2014, pg. 112-113).

[37] The 2SLS analysis has been done using the user-written Stata command –*ivreg2*– (Baum et al., 2010). Standard errors for all models are clustered at the sub-zone level given the program's experimental design (Abadie et al., 2017). All analysis has been done using Stata 15.

selected as a direct beneficiary; $\boldsymbol{X}_i$ is a vector of exogenous individual-level covariates;[38] and μ_i is the error term.

The second-stage equation corresponds to estimating the impact of *PATCA II* on adopting an agricultural technology and other outcomes of interest, as follows:

$$y_i = \alpha + \beta \widehat{PATCA\_TREATED}_i + \boldsymbol{X}_i \gamma + e_i \quad (3)$$

where y_i is an outcome of interest (e.g., value of production, household income, and technology adoption); β is the unbiased estimate of participating in *PATCA*; $\widehat{PATCA\_TREATED_i}$ is the instrumented variable for participation decision; and e_i is the error term.

Also, as a robustness check, we use an alternative specification to examine the sensitivity of our treatment effect estimates to the choice of control variables. Specifically, we ran the OLS and 2SLS models described above but without covariates, except for regional dummies. As noted in Athey and Imbens (2017), covariates in randomized experiments have two principal roles: (1) making the analysis more informative (e.g., Fisher's exact test, gains in precision), and (2) removing biases in a situation in which the randomization was compromised. With PATCA *II*, given that the program was implemented in only two of the eight regions, and since sub-zones were randomized to treatment groups by region and in cohorts in the first-stage of the randomized experiment, we believe it is relevant to incorporate regional control variables. This alternative specification essentially gives the same results and are presented in Appendix E.

5.2 Time effects: Exposure to treatment

Second, it is well established in the literature that technology adoption is a dynamic process that requires time and training to enhance productivity and ultimately, income. Thus, exposure to treatment plays a crucial role for obtaining impacts. To further deepen our understanding of *PATCA*'s treatment effects, we use 2SLS applied to a model with variable treatment intensity to estimate the average causal effect on compliers (Angrist and Imbens, 1995). Following the two-step procedure described in Wooldridge (2002), we first obtain fitted values using a Poisson regression model with a discrete count dependent variable (number of months using the technology),[39] the set of control variables included in the specification above, and two dummy

[38] Covariates included are head of household characteristics (age, age-squared, gender, educational level dummies), household size, dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.

[39] For the group of DB-ET, the dependent variable was constructed using the implementation date included in the administrative records. Among other things, the survey instrument asks, "When did you start using the technology on your farm?" we used this question to construct the dependent variable for the rest of the observations that reported adopting the technology outside of the program. Since the program implementation started in December 2002 and the available data covers up to December 2014, the dates were converted to months for a maximum of 25 months. Observations without improved pastures or irrigation technologies were assigned a 0.

variables representing the randomized treatment cohorts from the experimental design.[40] Then, we use 2SLS to estimate the impact of time or *learning-by-doing* with the fitted values obtained from the Poisson regression as the excluded instrument, as follows:

First: Poisson regression to obtain fitted values

$$E[MONTHS_i \mid \boldsymbol{X_i} + cohorts1_{2_i} + cohorts3_{4_i}] = \exp(\boldsymbol{X}_i\gamma + cohorts1\_2_i + cohorts3\_4_i) \tag{4}$$

Second: 2SLS using the fitted values from the Poisson estimation

First-stage: $$MONTHS_i = \theta + \lambda FITTED\_VALUES_i + \boldsymbol{X}_i\gamma + \mu_i \tag{5}$$

Second-stage: $$y_i = \alpha + \beta\widehat{MONTHS_\iota} + \boldsymbol{X}_i\gamma + e_i \tag{6}$$

where $MONTHS_i$, the endogenous regressor in the first-stage, is a discrete count variable that takes on values $\{0, 1, 2, 3, 4, \dots 25\}$ for the number months farmer *i* has been exposed to the technology; $cohorts1\_2_i$ and $cohorts3\_4_i$ are dummy variables that take the value of 1 if the farmer belongs to a subzone that was randomly assigned to treatment cohorts 1 or 2 or to treatment cohorts 3 or 4, respectively, and 0 otherwise; $FITTED\_VALUES_i$, the excluded instrument in the first-stage, are the predicted fitted values from the Poisson regression model; and $\widehat{MONTHS_i}$ in the second-stage is the instrumented variable. The control variables, $\boldsymbol{X}_i$, are included in the Poisson regression model, as well as in both the first and second stages of the 2SLS.[41]

5.3 Geographical and social spillovers

Third, we examine the presence of indirect or spillover effects that might have taken place among farmers who did not directly receive the benefits of the program but whose close geographical and social proximity to DB-ET farmers may have influenced technology adoption. We use probit regression models to investigate the influence of household characteristics and indirect exposure to treatment on technology adoption. The probit model takes the form:

$$\Pr(y_i = 1 \mid \mathbf{x}_i) = \Phi(\mathbf{x}_i\boldsymbol{\beta}) \tag{7}$$

where Pr denotes probability; y_i is a binary choice variable (=1 if the producer reported using the technology during the 2014 agricultural cycle, 0 otherwise);[42] $\Phi(\cdot)$ denotes the standard normal

[40] Recall from the section describing the program's experimental design that the treatment group was sub-divided into four treatment cohorts based on the random drawing of the balls from the *tombola,* where treatment cohort determined the order of the treatment, with the first cohort receiving the treatment first. Two dummy variables were created based on these four treatment cohorts: the first dummy takes the value of 1 for treatment cohorts 1 and 2, and 0 otherwise; the second dummy takes the value of 1 for treatment cohorts 3 and 4, and 0 otherwise. Since treatment cohorts were randomly selected (exogenous) and determine the order of the treatment (relevant), we use these cohort dummies as instruments for the number of months using the technology.

[41] Wooldridge (2002, pg. 939) point out that the 2SLS standard errors and test statistics are asymptotically valid under this IV procedure. In addition, the procedure has an important robustness property: since the fitted values from the Poisson regression model are used as instrument for the endogenous variable, the model does not have to be correctly specified.

[42] The latent variable y^*can be specified as $y_i^* = \beta_0 + \sum_{n=1}^{N}\beta_n x_{ni} + e_i,\ e_i \sim N(0, \sigma^2)$.

c.d.f.; $\mathbf{x}_i$ is a $1 \times (k+1)$ vector of k explanatory variables; and $\boldsymbol{\beta}$ is a $(k+1) \times 1$ vector of unknown coefficients to be estimated.

We do the analysis for the pooled sample and by technologies separately. For each analysis, we run four model specifications that include household demographic and economic characteristics, head of household characteristics, and regional dummies as explanatory variables.[43] Hence, by comparing the adoption rates between control farmers and untreated households located in treated sub-zones or within the social network of , we attempt to measure program's spillovers at the geographical and social levels.

6. Empirical results

6.1 Direct effects: Program take-up and technology adoption

Table 3 includes the results of the 2SLS estimations on program take-up and its impact on technology adoption. The first-stage relationship between being randomly selected to participate in the program and technology take-up (effectively treated by *PATCA II*) is positive and statistically significant at the 0.01 level for the pooled sample (column 4, panel A), as well as for farmers enrolled for the improved pastures (column 5) and irrigation (column 6) technologies; in other words, we have strong evidence of a positive treatment effect: farmers randomly assigned as direct beneficiaries of *PATCA II* are more likely to be *effectively treated* as a result of winning the lottery.[44]

The results from the first-stage regressions confirm the instrument is relevant as evidenced by the F statistics. In the case of randomization inference in instrumental variables settings, the 2SLS produces unbiased estimates of treatment effects when the instrument is exogenous and relevant; however, when the instrument is weak, the 2SLS estimators are asymptotically biased (Imbens 2014). Stock and Yogo (2005) proposed testing for weak instruments in linear IV regression with i.i.d errors using the first-stage F statistic, which tests the null hypothesis that a given group of instruments does not enter the first-stage regression. The estimated nonrobust first-stage F statistic is 49.59, 43.42, and 23.17 for the pooled, improved pastures, and irrigation sample, respectively.[45] More recently, Montiel Olea and Pflueger (2013) introduced the "effective F statistic," a test for weak instruments in linear IV regression that is robust to heteroscedasticity,

[43] The set of explanatory variables included in the probit model are similar to those in the previous models, but with slight modifications. First, we replaced the levels of education of the household's head with a single continuous variable representing years of educational attainment. Second, we control for whether the household reports having access to formal credit, savings, and a member of a Producers Association. The choice of variables in our models is based on the literature (de Janvry et al., 2016) and intuition.

[44] See Table D4 in Appendix D for a complete output of the first-stage regressions, including the estimated coefficients for the control variables.

[45] The critical values are obtained from Stock and Yogo (2005), which assumes i.i.d disturbances. However, since the standard errors in this study were calculated using the cluster-robust option, the relevant F statistic is the Kleibergen-Paap *rk* Wald statistic; a "rule of thumb" is for the first-stage F statistic to be larger than 10.27 to ensure that the maximum bias to be less than 10 percent, otherwise it indicates the instruments are weak (Staiger and Stock, 1997; Baum et al., 2007).

autocorrelation, and clustering. The values of the effective F statistics are greater than the Montiel-Pflueger critical values for the pooled, improved pastures, and irrigation samples, thus rejecting the null hypothesis for a weak instrument threshold of $\tau = 10$ percent.[46]

Table 3. Direct effects: Program take-up & impact of *PATCA* on technology adoption

	OLS			IV-2SLS		
	Pooled (1)	Improved pastures (2)	Irrigation (3)	Pooled (4)	Improved pastures (5)	Irrigation (6)
Panel A				*First-stage regressions*		
Dependent variable: Effectively treated by *PATCA* (0,1)						
Instrument: Randomized to *PATCA* (0,1)				0.577*** (0.082) [0.42, 0.74]	0.643*** (0.098) [0.45, 0.84]	0.439*** (0.091) [0.26, 0.62]
Kleibergen-Paap *rk* Wald *F* statistic				49.59	43.42	23.17
Effective *F* statistic [a]				50.71	44.43	23.70
Shea's partial R^2				0.356	0.319	0.373
Panel B				*Second-stage regressions*		
Dependent variable: Technology was used in 2014 (0,1) [b]						
$\widehat{PATCA}$ (0,1)				0.652*** (0.065) [0.53, 0.78]	0.682*** (0.065) [0.55, 0.81]	0.615*** (0.090) [0.44, 0.79]
Randomized to *PATCA* (0,1)	0.377*** (0.066) [0.24, 0.51]	0.438*** (0.082) [0.27, 0.61]	0.270*** (0.060) [0.15, 0.39]			
Observations	1,348	819	529	1,348	819	529
Covariates [c]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (4)-(6) in panel A correspond to OLS estimates for the first-stage specification of the 2SLS analysis on technology adoption. Columns (1)-(3) in panel B correspond to OLS estimates of the ITT, and columns (4)-(6) correspond to the second-stage of the 2SLS analysis on technology adoption. Robust standard errors clustered at the sub-zone level in parenthesis, and 95% confidence intervals are shown in brackets.
[a] Montiel-Pflueger robust weak instrument test; Stata command –*weakivtest*– (Pflueger and Wang, 2015).
[b] Takes the value of 1 if the producers reported using the technology (irrigation or livestock) during the 2014 agricultural cycle, 0 otherwise
[c] Covariates included are head of household characteristics (age, age^2, gender, educational level), household size, a dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

The program aimed to improve agricultural productivity and income by facilitating the adoption of technologies, and thus technology adoption is one of the primary outcomes of interest. The second-stage estimates indicate *PATCA* had a significant positive effect on adoption: compared to the control group, farmers treated by the program are 65 percentage points (pp) more likely to use the technology during the 2014 agricultural cycle. Similarly, farmers enrolled for the improved pastures and irrigation technologies and treated by the program are 68 pp and 62 pp, respectively, more likely to use the technology. The ITT estimates are also positive and significant, albeit smaller in magnitude which is a typical consequence of RCTs with non-compliance (Angrist, 2006). These results provide strong statistical evidence of a non-zero treatment effect of *PATCA* on technology adoption.

[46] According Montiel Olea and Pflueger (2013), an asymptotically valid rule of thumb (with a single endogenous regressor) is to reject the null hypothesis for weak instruments when the effective *F* statistic is greater than 23.1. See the Stock-Yogo and Montiel-Pflueger critical values in Table D5 of Appendix D.

6.2 Direct effects: Agricultural production and income

Regarding agricultural production measures, first we examine the direct effects of the program on income, and then we use technology-specific outcomes to analyze the impacts of improved pastures and irrigation technologies separately. For the pooled sample, we find no effects on agricultural income and total household income (Table 4). When we carry out the analysis by technology, we observe a positive treatment effect of improved pastures technology on agricultural income (627 percent), but no effects of the irrigation technology on income; However, the impact of improved pastures on agricultural income is only significant at a 10 percent level.[47]

Table 4. Direct effects: Impact of *PATCA* on income

	OLS			IV-2SLS		
Outcomes	Pooled (1)	Improved pastures (2)	Irrigation (3)	Pooled (4)	Improved pastures (5)	Irrigation (6)
Agricultural income (US$) (log) [a]	1.020 (0.743)	1.276* (0.745)	-0.489 (0.411)	1.766 (1.322)	1.984* (1.134)	-1.113 (0.881)
Total household income (US$) (log) [b]	-0.125 (0.223)	-0.191 (0.267)	-0.475 (0.307)	-0.216 (0.368)	-0.298 (0.386)	-1.082 (0.663)
Total household income per capita (US$/pc) (log)	-0.108 (0.212)	-0.168 (0.250)	-0.452 (0.294)	-0.188 (0.350)	-0.261 (0.362)	-1.029 (0.637)
Observations	1,348	819	529	1,348	819	529
Covariates [c]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes value of crop production and livestock products (i.e., milk, meat, eggs, honey, and other products), including losses.
[b] Includes income derived from land leased and sold, crop production (excluding losses), livestock products, off-farm income (cash and in-kind), small-business sales, non-agricultural self-employment, remittances, and transfers from the Government and NGOs.
[c] Covariates included are head of household characteristics (age, age-squared, gender, educational level), household size, dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Regarding agricultural production, beneficiaries of *PATCA*'s improved pastures technology are more likely of subdividing their pastures into paddocks (20 pp), use a higher number of paddocks (3 additional paddocks), and increased the productive land dedicated to rotational grazing by about one hectare (54 percent) (table 5, column 2).[48] On average, the results confirm that *PATCA* increased the probability of having improved pastures (28 pp), and the number of hectares cultivated with improved pastures by 2.4 (64 percent). However, while the program had a significant positive impact on the probability of producing livestock products (17 pp), it did not impact the total value of milk and meat production or the proxy measures of productivity.

[47] The mean value of agricultural income and total household income for the control group is US$9,373.85 and US$18,874.81, respectively, in the pooled sample (n=583), US$6,326.73 and US$13,631.78 for improved pastures technology (n=354), US$14,084.25 and US$26,979.76 for irrigation technology (n=229).

[48] Rotational grazing refers to the management practice of subdividing pastures into paddocks (smaller areas) for livestock grazing. Livestock is moved from one paddock to another so that only a portion of pasture is grazed at a time, while the remainder is left to rest for forage plants to achieve long-term maximum production capacity (e.g., renew energy reserves, rebuild vigor, deepen their root system) (Undersander et al., 2002).

Table 5. Direct effects: Impact of *PATCA*'s improved pastures on agricultural production

Outcomes	OLS (1)	IV-2SLS (2)
Land divided into paddocks (0,1)	0.128** (0.058)	0.199* (0.104)
Number of paddocks (#)	1.968** (0.860)	3.060** (1.402)
Paddocks (ha) (log)	0.276** (0.135)	0.429* (0.238)
Pastures (natural + improved) (ha) (log)	0.623* (0.334)	0.969* (0.554)
Natural pasture (0,1)	0.181 (0.169)	0.282 (0.275)
Natural pasture (ha) (log)	0.454 (0.382)	0.706 (0.621)
Improved pasture (0,1)	0.180** (0.081)	0.280*** (0.108)
Improved pasture (ha) (log)	0.318* (0.176)	0.494** (0.245)
Produces livestock products (0,1) [a]	0.107* (0.056)	0.167** (0.078)
Meat and milk production		
Value of milk and meat production (US$) (log)	0.735 (0.591)	1.143 (0.869)
Value of milk and meat production (US$/ha pastures) (log)	0.392 (0.455)	0.609 (0.682)
Value of milk and meat production (US$/TLU) (log)	0.316 (0.390)	0.491 (0.581)
TLU in 2014	2.967 (2.805)	4.614 (4.197)
Observations	819	819
Covariates	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes production of meat, milk, eggs, honey, and other unspecified products.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

In the case of beneficiaries of the irrigation technology, although *PATCA* had a significant positive effect on the likelihood of having modern irrigation (137 percent), it had no impact on the number of hectares equipped with modern or traditional irrigation (Table 6, column 2). According to Lipton et al. (2003), in the short-run, irrigation can increase total farm output, and therefore, farm incomes, through at least three channels: improvements in yields, cropping intensity, and by extending production to areas where rainfed production was not possible. The results suggest having access to the technology had a substantial adverse impact on the probability of harvesting (-22 pp), but no effects on the number of hectares harvested or cropping intensity. Consequently, program beneficiaries have a significantly lower value of production per hectare (86 percent), lower expenditures on labor (87 percent) and variable inputs of production (79 percent).

Table 6. Direct effects: Impact of *PATCA*'s irrigation on agricultural production

Outcomes	OLS (1)	IV-2SLS (2)
Panel A: Land variables		
Has irrigation (0,1) – own land	0.178 (0.142)	0.406 (0.282)
Land equipped with irrigation (ha) (log)	0.117 (0.229)	0.266 (0.491)
Modern irrigation (0,1)	0.148* (0.082)	0.336** (0.160)
Land equipped with modern irrigation (ha) (log)	0.103 (0.116)	0.233 (0.246)
Panel B: Production variables		
Total area planted (ha) (log) [a]	0.038 (0.186)	0.087 (0.410)
Permanent crops (% total area planted)	0.027 (0.073)	0.062 (0.161)
Harvested crops (0,1) [b]	-0.097* (0.055)	-0.221** (0.109)
Land area cultivated and harvested (ha) (log)	-0.243 (0.160)	-0.553 (0.338)
Cropping intensity [c]	-12.92 (12.02)	-29.41 (25.52)
Value of crop production (US$) (log)	-1.082** (0.469)	-2.464*** (0.871)
Value of crop production per hectare (US$/ha) (log)	-0.853* (0.453)	-1.941** (0.890)
Labor expenditures (US$/ha) (log)	-0.886*** (0.265)	-2.016*** (0.679)
Input expenditures (US$/ha) (log) [d]	-0.688* (0.375)	-1.566* (0.844)
Sells (0,1)	-0.064 (0.057)	-0.145 (0.116)
Observations	529	529
Covariates [e]	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes land area covered with crops, temporary and permanent, including fruit trees, pastures, and forest. For example, if the producer has two plots of land with 2 hectares per plot and reported cultivating 6 crops, each crop in 1 hectare, then this variable takes the value of 6.
[b] Takes the value of '1' if the producer reported harvesting any (temporary or permanent) crop in 2014.
[c] Cropping intensity = [(gross cropped area/net sown area) x 100], where gross cropped area is the total area (in hectares) sown once as well as more than once in the agricultural cycle, and net sown area is the area sown with crops but is counted only once.
[d] Includes expenditures on seeds, organic and chemical fertilizer, fungicides, insecticides, and herbicides.
[e] Covariates included are head of household characteristics (age, age-squared, gender, educational level), household size, a dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

So far, the effects of the program's improved pastures technology support the hypothesis that underpins the theory of change; However, the estimated impacts of the irrigation technology are quite puzzling. These results give rise to several questions. Why does having access to irrigation through *PATCA* negatively affects agricultural production, including input expenditures, the likelihood of harvesting and selling, and on the value of production? Is the lack of an impact on the total value of agricultural and livestock production indicative of technical inefficacies following an outward shift in the production frontier, and if so, is productivity likely to improve over time? In the next section, we exploit the features of the program's experimental design and data from administrative records to try to answer these questions.

6.3 Time effects: Months of exposure to the technology

Tables 7-9 show LATE estimates derived from the 2SLS setup described in Eq. (4) and (5). In this specification, we aim to capture the impact of *learning-by-doing* using a model with variable treatment intensity based on the number of months of exposure to the technology. As mentioned before, the instrument corresponds to the randomized assignment to different treatment cohorts that resulted from the lottery process.

The results from the first-stage show a highly significant positive relationship between the instrument (Poisson fitted values) and the number of months of exposure to the technology (Table 7, panel A, columns 1-3).[49] The Stock and Yogo (2005) first-stage *F* statistic for the excluded instruments is greater than the conventional weak instrument threshold value of 10, and the Montiel Olea and Pflueger (2013) robust and effective *F* statistic exceeds the 5 percent critical value, so we reject the null hypothesis of a weak instrument. This implies that random assignment to treatment predicts the number of months exposed to treatment.

Table 7. Time effects: *PATCA*'s impact on income

	IV-2SLS					
	Pooled	Improved pastures	Irrigation	Pooled	Improved pastures	Irrigation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A—First-stage regressions	Months using technology (#)					
Instrument: Fitted values (Poisson regression)	0.945***	1.031***	0.690***			
	(0.102)	(0.140)	(0.105)			
	[0.74, 1.15]	[0.76, 1.31]	[0.48, 0.90]			
Kleibergen-Paap Wald rk *F* statistic	85.23	54.18	43.47			
Effective *F* statistic [a]	87.14	55.43	44.47			
Panel B—Second-stage regressions	Agricultural income (US$) (log)			Total household income (US$) (log)		
Months $\widehat{\text{using technology}}$ (#)	0.047	0.115*	-0.037	-0.023	-0.020	-0.016
	(0.072)	(0.068)	(0.061)	(0.026)	(0.032)	(0.043)
	Total household income per capita (US$/pc) (log)					
Months $\widehat{\text{using technology}}$ (#)	-0.019	-0.017	-0.009			
	(0.025)	(0.030)	(0.041)			
Observations	1,348	819	529	1,348	819	529
Covariates [b]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis, and 95% confidence intervals are shown in brackets.
[a] Montiel-Pflueger robust weak instrument test; Stata command –*weakivtest*– (Pflueger and Wang, 2015).
[b] Covariates included are head of household characteristics (age, age-squared, gender, educational level), household size, dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control zub-zones' for regional characteristics.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

[49] See Table D6 in Appendix D for a complete output of the Poisson regression analysis. The response or dependent variable is the number of months of exposure to the technology; we explore its relationship with the randomly assigned treatment cohorts, and a set of other control variables. We assume each farmer has the same length of observation time. Both coefficients for the treatment cohorts' dummies are statistically different from zero: the logs of the expected counts are expected to be 1.920 (0.989) units higher for farmers randomly assigned to treatment cohorts 1 or 2 (3 or 4) compared to farmers randomly assigned to the control group, other things equal.

The estimated effects of exposure to *PATCA* II confirm that time of exposure to the improved pastures technology had a statistically significant impact on agricultural income; each month of exposure to the technology increased agricultural income by about 12 percent (Table 7, panel b, column 2). Similarly, we find significant effects of exposure to improved pastures technology on agricultural production outcomes, namely on the likelihood of subdividing pastures into paddocks, number of paddocks, the probability of having improved pastures, and the area of productive land with improved pastures. Contrary to the binary treatment model, we find evidence of a positive impact of time on livestock accumulation measured as the number of TLUs (0.613 TLUs per month of exposure or 7 TLUs per year of exposure to the technology) (Table 8).

Table 8. Time effects: Impact of PATCA's improved pastures on agricultural production

	IV-2SLS (Instrument: Poisson fitted values)						
Second-stage regressions	Land divided into paddocks (0,1)	Number of paddocks (#)	Paddocks (ha) (log)	Pastures (natural + improved) (ha) (log)	Natural pasture (0,1)	Natural pasture (ha) (log)	Improved pasture (0,1)
$\widehat{\text{Months using technology}}$ (#)	0.011* (0.006)	0.151* (0.086)	0.017 (0.011)	0.055** (0.022)	0.009 (0.016)	0.023 (0.037)	0.023** (0.010)
	Improved pasture (ha) (log)	Produces livestock products (0,1)	Value of milk and meat production (US$) (log)	Value of milk and meat production (US$/ha pastures) (log)	Value of milk and meat production (US$/TLU) (log)	TLU in 2014	
$\widehat{\text{Months using technology}}$ (#)	0.055*** (0.021)	0.014** (0.006)	0.092 (0.092)	0.047 (0.072)	0.039 (0.061)	0.613* (0.359)	
Observations	819	819	819	819	819	819	819
Covariates [a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Covariates included are head of household characteristics (age, age-squared, gender, educational level), household size, dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

In the case of irrigation, the results from the exposure model reveal interesting trends that allow us to unravel some of the ambiguous impacts obtained from the binary treatment model in the previous section. First, exposure to the technology has a significant effect on the likelihood of having irrigation, causing the extension of land equipped with irrigation (modern) to increase, on average, by about 8 percent (3 percent) per month (Table 9). The results show that every month of treatment increases the proportion of permanent crops by 2 pp, representing about 2.8 hectares of land per agricultural year. Since the program's implementation started in December 2012, and the data under analysis covers the 2014 agricultural cycle, it means that beneficiaries of the irrigation technologies have at most 25 months of exposure to the technology. Therefore, a plausible explanation of the observed negative effects of the irrigation technology on production (i.e., harvesting, selling, and value of crop production) might be related to a gradual change in the crop portfolios of program beneficiaries—switching from temporary to permanent crops—and the lack of time for these crops to reach the harvesting stage. Since the agricultural cycle of permanent crops, relative to temporary crops, is longer, one might infer from these results that a share of the crop portfolios of irrigation beneficiaries are still in the growing stage of the production cycle, hence the negative impacts on the value of crop production and sales. Further, the negative but insignificant effect of irrigation on cropping intensity supports the notion of a switch in the crop portfolio of program beneficiaries; that is, if there is a switch toward the production of permanent crops, we should not observe an increase in the proportion of the net area being cropped more than once during the 2014 agricultural cycle.

Table 9. Time effects: Impact of *PATCA*'s irrigation on agricultural production

	IV-2SLS (Instrument: Poisson fitted values)						
Second-stage regressions	Has irrigation (0,1) – own land	Land equipped with irrigation (ha) (log)	Modern irrigation (0,1)	Land equipped with modern irrigation (ha) (log)	Total area planted (ha) (log)	Permanent crops (% total area planted)	Harvested crops (0,1)
$\widehat{\text{Months using technology}}$ (#)	0.059***	0.078***	0.016	0.027***	0.021	0.022*	-0.028***
	(0.016)	(0.021)	(0.011)	(0.010)	(0.022)	(0.011)	(0.009)
	Land area cultivated and harvested (ha) (log)	Cropping intensity	Value of crop production (US$) (log)	Value of crop production per hectare (US$/ha) (log)	Labor expenditures (US$/ha) (log)	Input expenditures (US$/ha) (log)	Sells (0,1)
$\widehat{\text{Months using technology}}$ (#)	-0.036**	-2.458	-0.231***	-0.207***	-0.114	-0.102	-0.024**
	(0.016)	(1.570)	(0.083)	(0.075)	(0.070)	(0.070)	(0.011)
Observations	529	529	529	529	529	529	529
Covariates [a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Covariates included are head of household characteristics (age, age-squared, gender, educational level), household size, dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Overall, the 2SLS estimates are indicative of the complex dynamics underlying the adoption process of improved pastures and modern irrigation technologies among beneficiaries of the program. The results suggest that *learning-by-doing* is an important determinant of the effectiveness the program programs, and time of exposure to the technology plays a crucial role.

6.4 Indirect or spillover effects: Geographic and social proximity

The focus of this sub-section is to measure geographical and social spillover effects, as defined by the probit regression models in Section 5.3. Since the assignment of farmers to the indirect beneficiaries (IB) group derives from the program's experimental design, it is possible to divide the set of IB between improved pastures and irrigation technologies. On the other hand, farmers in the social network are divided between improved pastures and irrigation technologies according to the technology selection of the DB-ET farmer directly linked to each node.

The results from the spillover analysis suggests that geographical proximity to program beneficiaries does not increase the probability of technology adoption (Table 10). On the other hand, marginal effects from the probit models suggest that social proximity has a negative impact on the adoption of irrigation technologies. Specifically, being part of a social network from a direct beneficiary reduces the probability of adopting irrigation by about 9 percentage points (pp).

Table 10. Geographical and social proximity: Marginal effects on probability of adoption

	Pooled		Improved pastures		Irrigation	
	(1)	(2)	(3)	(4)	(5)	(6)
Social network (SN) nodes (0,1)	-0.042** (0.018)	-0.040** (0.017)	-0.002 (0.001)	-0.002 (0.001)	-0.090** (0.040)	-0.089** (0.041)
Indirect beneficiaries (IB) (0,1)	-0.010 (0.016)		-0.001 (0.001)		0.002 (0.028)	
IB in treatment cohorts 1 or 2		-0.021 (0.018)		-0.001 (0.001)		-0.028 (0.038)
IB in treatment cohorts 3 or 4		0.006 (0.016)		-0.0003 (0.001)		0.016 (0.028)
Head of household characteristics						
Age (years)	0.0004 (0.002)	0.0004 (0.001)	2.52e-05 (0.0001)	2.19e-05 (9.87e-05)	-0.003 (0.004)	-0.003 (0.004)
Age (years) – squared	-4.94e-06 (1.32e-05)	-4.95e-06 (1.29e-05)	-3.35e-07 (9.65e-07)	-3.19e-07 (9.35e-07)	2.77e-05 (3.45e-05)	2.66e-05 (3.41e-05)
Male (0,1)	0.003 (0.011)	0.005 (0.011)	0.001 (0.001)	0.001 (0.001)	-0.022 (0.032)	-0.020 (0.030)
Years of education (#)	0.001 (0.001)	0.001 (0.001)	7.37e-05 (4.73e-05)	7.14e-05 (4.76e-05)	-0.0009 (0.001)	-0.001 (0.001)
HH demographic and economic characteristics						
Land title (on or before2012) (0,1)	-0.005 (0.008)	-0.004 (0.007)	0.001 (0.001)	0.001 (0.001)	-0.017 (0.013)	-0.016 (0.014)
Receives remittances (0,1)	0.020 (0.014)	0.022 (0.014)	0.001 (0.001)	0.001 (0.001)	0.043** (0.019)	0.043** (0.019)
Household size (number)	-0.001 (0.003)	-0.001 (0.003)	-0.0003 (0.0003)	-0.0003 (0.0003)	0.004 (0.006)	0.004 (0.006)
Access to formal credit (bank or coop) (0,1)	0.008 (0.008)	0.008 (0.008)	0.001 (0.001)	0.001 (0.001)	-0.001 (0.018)	-0.001 (0.018)
Savings (0,1)	0.007 (0.007)	0.007 (0.007)	0.001** (0.0003)	0.001** (0.0003)	0.007 (0.024)	0.009 (0.024)
Member of a Producers Association (0,1)	0.001 (0.009)	0.002 (0.009)	-0.001 (0.001)	-0.001 (0.0008)	0.033 (0.021)	0.035 (0.022)
Regions						
North (0,1)	0.038* (0.020)	0.037** (0.019)	0.011 (0.007)	0.011 (0.007)	0.067* (0.038)	0.067* (0.038)
Southwest (0,1)	0.006 (0.021)	0.006 (0.019)	0.010 (0.006)	0.010 (0.006)	0.010 (0.040)	0.014 (0.039)
Observations	1,381	1,381	970	970	411	411

Notes: The dependent variable is a dummy for whether the farmer reported using the technology during the 2014 agricultural cycle as a proxy measure for technology adoption. The results shown are average marginal effects at the means of covariates on a probit regression; therefore, the coefficients represent the change in the probability that a farmer used the technology in 2014 based on geographical and social proximity to DB-ET farmers.
The sample includes n=583 controls (354 improved pastures and 229 irrigation), n=463 IB (361 improved pastures and 102 irrigation), and n=335 social network nodes (255 improved pastures and 80 irrigation).
Robust standard errors clustered at the sub-zone level in parenthesis.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Moreover, the results suggest that liquidity constraints are factors associated with lack of adoption among farmers in close proximity to program beneficiaries. This finding is well-recognized in the literature as a problem inhibiting agricultural productivity and growth (de Janvry et al., 2016; de Janvry et al., 2017a). The estimations confirm that the most significant variables that determine technology adoption by farmers, located in close proximity to DB-ET farmers, are access to savings and remittances. Specifically, in the case of improved pastures technology, having access to savings increases the likelihood of adoption by 0.1 pp. On the other hand, in the case of irrigation technology, having a stream of remittances increases the probability of adoption by 4 pp. This result confirms that removing liquidity constraints is fundamental to increasing technology adoption, supporting the initial motivation that led to the implementation of this program. This also explains the lack of results in the spillover analysis as liquidity constraints might be stronger than indirect effects due to social or geographical proximity. Therefore, programs that aim at dealing with this market failure can generate incentives for technological change.

7. Discussion and conclusion

This paper evaluates the effects of the second phase of the Program for the Support of Innovation in Agricultural Technology (*PATCA* II)—an agricultural technology transfer program—implemented in the Dominican Republic in 2012. The program offered non-reimbursable vouchers that partially financed the cost of a technology chosen by the farmer. The focus of this paper is on two of the technologies offered by the program: improved pasture and modern irrigation. To provide a source of exogenous variation to program participation, and to account for the presence of non-compliance, we use the program's random treatment assignment as an instrumental variable for treatment and implement a two-stage least squares (2SLS) regression analysis to estimate both direct effects and time effects of program participation on different outcomes of interest. Further, the experimental design (two stage random assignment at the subregion and farmer levels) allows us to analyze the existence of spillover effects among farmers in close geographical proximity to program beneficiaries. Also, social network data is collected to estimate social network spillovers.

Using a rich household survey microdata combined with administrative records, we estimated that technology adoption, proxied by the use of the technology during the 2014 agricultural cycle, increased by 65 percentage points (pp) for the pooled sample of compliers, and by 68 and 62 percentage points for beneficiaries of improved pastures and irrigation technologies, respectively.

The results for the improved pasture technology show that participating farmers are better equipped to benefit from the advantages of rotational grazing. *PATCA* not only caused positive impacts on the number and size of paddocks but also fostered a switch from natural to improved pasture. Nonetheless, even though we find significant impacts on agricultural income, we find no effects on the production of meat or milk.

PATCA's irrigation had unexpected effects on production. Beneficiary farmers experienced significantly lower agricultural expenditures (i.e., labor), lower value of production, and are less likely to harvest and sell crops from the 2014 agricultural cycle. When analyzing the impacts of the intervention based on the number of months of exposure to irrigation, we find evidence of changes to their crop portfolios—switching from the production of temporary to permanent crops, such as fruit trees. Further, since program implementation began in December 2012, it is plausible that these permanent crops have not reached the optimum stage of harvesting, which might explain the negative effects on output and income.

Lastly, we find negative social network spillover effects of *PATCA*. Being within the social network of beneficiary farmers significantly decreases the probability of technology adoption, particularly for irrigation. Moreover, in line with the economic development literature, the results suggest that liquidity constraints, such as access to savings and cash from remittances, are important determinants of adoption.

Taken together, we find different patterns of treatment effects on production-related outcomes for both technologies under analysis, and in general, the results imply the existence of a dynamic *learning-by-doing* process, as well as a change towards the production of more valuable crops. Whether the program had an effect on technical efficiency remains an open question that requires further analysis beyond the scope of this paper. Also, further research is needed to measure the long-term impacts of this initial transformations.

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Appendix A

Table A1. Menu of agricultural technologies financed by *PATCA* II

Technology	Description	Objectives	Impacts on production	Environmental impacts and climate change adaptation
1. Pasture and grassland rehabilitation & improvement *(Extensive systems for beef and milk production)*	It consists in the improvement of pastures already implanted through intercalation of forage species, fertilization, and the installation of wire and electric fences.	Increase the availability, composition, and nutritional quality of the forage provided to livestock, and improve pasture management to increase their useful life, maintain their quality, and reduce erosion.	Increase in livestock yields expressed as higher production of meat and/or milk.	Reduce the risk of soil erosion. Indirect risk of increased use of herbicides.
2. Drip irrigation *(Fruit trees, vegetables, berries)*	It consists of the distribution of water through pipes at low pressure (0.3 to 2 atm) and its application in the form of drops, applied close to plants so that only part of the soil in which the roots grow is wetted	Provide a more efficient and timely use of water for irrigation, optimizing water consumption according to the needs of crops.	Increase crop yields and greater efficiency in the use of water. Less use of herbicides.	Improvement in the efficiency of water use (saving up to 96%). Solid waste generation (plastic from pipes and tapes). Reduction of the risk of soil erosion.
3. Sprinkler irrigation *(Fruit trees, vegetables, berries, pastures)*	It consists in distributing water through pipes at medium pressure (2.5 to 4 atm) and applying thought sprinklers in the form of rain.	Provide a more efficient and timely use of water for irrigation by optimizing water bodies according to the needs of the crops.	Increase crop yields and greater efficiency in the use of water.	Improvement in the efficiency of water use (savings up to 38%). Waste generation (plastic from pipes and tapes).
4. Greenhouses *(Vegetables, berries, ornamental flowers, and other crops)*	It consists of the installation of a rustic structure up to 4 meters high in the lower part of the structure and up to 7.5 meters high in the ridge, with wooden poles, including ventilation and pressurized irrigation systems.	Extend the period of production and improve control over the harvest season. Reduce damage and cost from rain, pests, and diseases, and enhance the use of water.	Increase the quality of yields (in limited space) and sales prices. Greater possibilities of crop diversification and production periods.	Improvement in water-use efficiency (saving up to 96%). Better control of climatic variables that cause crop losses. Solid waste generation (plastics). Reduce the risk of soil erosion.
5. Post-harvest management *(Fruit trees, vegetables, berries)*	It consists of the provision of instruments, equipment, and knowledge to improve the harvest and the activities of selection, washing and stockpiling on the farm, including training in good agricultural practices (GAPs) and manufacturing.	Improve the quality and selection of agricultural products and its storage conditions on the farm to obtain better prices and sales opportunities.	Increase in quality and therefore in its sales prices. Better access to markets.	--
6. Land leveling *(Rice, banana)*	It consists of earth movements through the use of fleet or laser to eliminate the highest areas and fill the lowest areas of an agricultural site.	Allow a more efficient use of the soil (less losses due to localized waterlogging), machinery, and water.	Increase in crop yields, and better chance of harvest time.	More efficient use of water (saving up to 35%) and soil. Minor soil erosion risks during the implementation of the technology.
7. Mulching *(Vegetables, berries)*	It consists of the application of a plastic film to ridges of soil and the installation of the tapes for pressurized irrigation.	Cover the surface of the soil to increase the temperature, to retain moisture, and to prevent the appearance of weeds and protect the fruits from direct contact with the soil.	Increase yield quantity and quality. Greater water-use efficiency and reduce the application of agrochemicals.	Improvement in water-use efficiency (saving up to 96%). Solid waste generation (plastics). Reduce the risk of soil erosion.
8. Micro-sprinkler irrigation *(Fruit trees, vegetables, berries)*	It consists of the distribution of water through pipes at low pressure (2 to 2.5 atm) and applying it through diffusers or micro-sprinklers.	Provide a more efficient and timely use of water for irrigation, optimizing water consumption according to the needs of crops.	Increase crop yields and greater efficiency in the use of water. Less use of herbicides.	Improvement in the efficiency of water use (saving up to 85%). Waste generation (plastic from pipes and tapes). Reduction of the risk of soil erosion.

Note: atm = standard atmosphere.

Appendix A

Table A2. Cost of the technologies and *PATCA II*'s financial support

Technology	Cost of technology (USD)	Maximum area (*tareas*)	Cost per *tarea* (USD)	Program's financial support (% of cost of technology)	Amount of financial support per *tarea* (USD)	Maximum total financial support to producers (USD)
1. Pasture and grassland rehabilitation & improvement	6,153	200	31	59	18.25	3,650
2. Drip irrigation	9,152	30	305	38	116.67	3,500
3. Sprinkler irrigation	9,872	30	329	33	110	3,300
4. Greenhouses	14,842	1.59	9,895	34	3,144.65	5,000
5. Post-harvest management	6,333	16	396	46	181	2,900
6. Land leveling	2,253	50	45	38	17	850
7. Mulching	7,237	30	241	36	86.67	2,600
8. Micro-sprinkler irrigation	6,918	30	231	38	86.67	2,600

Note: 1 *tarea* = 0.06 hectare

Table A3. Breakdown of administrative provinces, by administrative regions and RADs

Administrative macro regions	Administrative regions	Administrative provinces	RADs
North	North Cibao	Santiago	North
		Puerto Plata	North
		Espaillat	North
	South Cibao	La Vega	North Central
		Monseñor Nouel	North Central
		Sánchez Ramírez	Northeast
	Northeast Cibao	Duarte	Northeast
		Salcedo (Hermanas Mirabal)	North Central
		María Trinidad Sánchez	Northeast
		Samaná	Northeast
	Northwest Cibao	Valverde	Northwest
		Monte Cristi	Northwest
		Dajabón	Northwest
		Santiago Rodríguez	Northwest
Southwest	Valdesia	San Cristóbal	Central
		Azua	Southwest
		Peravia	Central
		San José de Ocoa	Central
	Enriquillo	Barahona	South
		Baoruco	South
		Pedernales	South
		Independencia	South
	El Valle	San Juan	Southwest
		Elías Piña	Southwest
Southeast	Yuma	La Romana	East
		La Altagracia	East
		El Seibo	East
	Higuamo	San Pedro de Macorís	East
		Hato Mayor	East
		Monte Plata	Central
	Ozama or Metropolitan	Distrito Nacional	-
		Santo Domingo	Central

Note: The classification of administrative provinces into Regional Agricultural Directorates (RADs) was determined based on the information available in universe of eligible producers.

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Table A4. Program universe: Producers by RAD

Regional Agricultural Directorates (RADs) (administrative regions)	Num. of pre-registered producers	Percent of total	Cumulative percentage
Central (Higuamo & Ozama or Metropolitana)	2,735	13	13
East (Yuma)	2,743	13.04	26.05
North Central (South Cibao)	2,151	10.23	36.27
Northeast (Northeast Cibao)	2,788	13.26	49.53
Northwest (Northwest Cibao)	3,044	14.47	64
North (North Cibao)	3,112	14.8	78.8
South (Enriquillo)	2,013	9.57	88.37
Southwest (Valdesia & El Valley)	2,446	11.63	100
Total	21,032	100.00	

Table A5. Program universe: Distribution of the technologies by RADs

	RADs								
Requested technologies	Central	East	North Central	Northeast	Northwest	North	South	Southwest	Total
Pasture and grassland rehabilitation & improvement*	896	2,077	571	2,322	754	1,817	671	1,581	10,689
Drip irrigation*	540	104	315	14	229	702	1,069	423	3,396
Sprinkler irrigation*	82	40	31	5	1,038	77	60	30	1,363
Greenhouses*	623	369	533	273	343	405	172	277	2,995
Post-harvest management*	37	9	94	5	305	64	5	2	521
Total	2,178	2,599	1,544	2,619	2,669	3,065	1,977	2,313	18,964
Land leveling	34	119	144	167	113	2	19	0	598
Mulching	2	11	0	0	6	5	1	14	39
Micro-sprinkler irrigation	521	14	463	2	256	40	16	119	1,431
Total	2,735	2,743	2,151	2,788	3,044	3,112	2,013	2,446	21,032

Note: * Randomized technology.

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Table A6. Treatment cohorts in the first-stage

Regional Agricultural Directorates (RADs) (administrative regions)	Sub-zones		Treatment cohorts (first-stage)				Controls
	Universe	First-stage randomization	Cohort 1	Cohort 2	Cohort 3	Cohort 4	
Central (Higuamo & Ozama or Metropolitana)	18	14	4	4	3	3	4
East (Yuma)	10	8	2	2	2	2	2
North Central (Cibao Sur)	15	11	3	3	3	2	4
Northeast (Cibao Nordeste)	17	14	4	4	3	3	3
Northwest (Cibao Noroeste)	15	10	3	3	2	2	5
North (Cibao Norte)	18	14	4	4	3	3	4
South (Enriquillo)	17	13	4	3	3	3	4
Southwest (Valdesia & El Valley)	19	15	4	4	4	3	4
Total	129	99	28	27	23	21	
Controls		30					30

Table A7. Randomized treatment, by RADs and stages

Regional Agricultural Directorates (RADs) (administrative regions)	Universe		First-stage		Second-stage		Controls
	Sub-zones	Producers	Sub-zones	Producers* (tech to be randomized)	Direct beneficiaries* (randomized)	Indirect beneficiaries	
Central (Higuamo & Ozama or Metropolitana)	18	2,735	14	2,441 (1,884)	1,218 (661)	1,223	294
East (Yuma)	10	2,743	8	2,047 (1,903)	736 (592)	1,311	696
North Central (Cibao Sur)	15	2,151	11	1,722 (1,115)	1,084 (477)	638	429
Northeast (Cibao Nordeste)	17	2,788	14	2,391 (2,222)	833 (664)	1,558	397
Northwest (Cibao Noroeste)	15	3,044	10	2,034 (1,659)	1,405 (1,030)	629	1,010
North (Cibao Norte)	18	3,112	14	2,382 (2,335)	981 (934)	1,401	730
South (Enriquillo)	17	2,013	13	1,513 (1,477)	863 (827)	650	500
Southwest (Valdesia & El Valley)	19	2,446	15	1,882 (1,749)	855 (722)	1,027	564
Total	129	21,032	99	16,412 (14,344)	7,975 (5,907)	8,437	4,620
Controls			30	4,620			

Note: * Producers that requested land leveling, mulching, and micro-sprinkler irrigation technologies were automatically treated.

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Table A8. Distribution of producers in the subset of the universe considered for the sample size calculation of the baseline

Requested technologies	Treatment groups: Direct beneficiaries	Treatment groups: Indirect beneficiaries	Total	Controls
Pasture and grassland rehabilitation & improvement*	1,241	3,126	4,367	2,331
Drip irrigation*	659	161	820	1,206
Sprinkler irrigation*	494	119	613	350
Greenhouses*	381	860	1,241	514
Post-harvest management*	183	35	218	219
Land leveling	307	-	307	-
Mulching	16	-	16	-
Micro-sprinkler irrigation	586	-	586	-
Total	3,867	4,301	8,168	4,620

Note: * Randomized technology.

Table A9. Baseline sampling percentage, by cohort and technology

Technologies	Cohort 1		Cohort 2		Indirect beneficiaries		Controls
	Direct beneficiaries	Indirect beneficiaries	Direct beneficiaries	Indirect beneficiaries	Cohort 3	Cohort 4	
Pasture and grassland rehabilitation & improvement	48.3%	16%	21%	7%	-	-	10%
Drip irrigation	73%	100%	47%	100%	-	-	20%
Sprinkler irrigation	100%	100%	60%	100%	-	-	70%
Greenhouses	100%	60%	83%	25%	-	-	48%
Post-harvest management	100%	100%	100%	100%	-	-	100%
Land leveling	60%	-	-	-	30%	100%	-
Mulching	-	-	-	-	-	-	-
Micro-sprinkler irrigation	50%	-	-	-	-	68%	-

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Table A10. Sample of producers to survey at baseline, by treatment cohorts

	Technologies								
Treatment group	1	2	3	4	5	6	7	8	Total
Cohort 1									
Direct beneficiaries	133	82	136	195	202	-	138	130	1,016
Indirect beneficiaries	-	17	-	82	161	-	169	21	450
Total	133	99	136	277	363	-	307	151	1,466
Cohort 2									
Direct beneficiaries	-	242	-	169	161	-	191	53	816
Indirect beneficiaries	-	102	-	79	140	-	139	14	474
Total	-	344	-	248	301	-	330	67	1,290
Cohorts 3 and 4									
Direct beneficiaries	109	-	112	-	-	-	-	-	221
Total	109	-	112	-	-	-	-	-	221
Baseline sample (treatment cohorts 1-4 and controls)									
Direct beneficiaries	242	324	248	364	363	-	329	183	2,053
Indirect beneficiaries	-	119	-	161	301	-	308	35	924
Controls	-	239	-	229	225	-	237	219	1,149
Total	242	682	248	754	889	-	874	437	4,126

Notes: (1) Land leveling, (2) sprinkler irrigation, (3) micro-sprinkler irrigation, (4) drop irrigation, (5) pasture and grassland rehabilitati improvement, (6) mulching, (7) greenhouses, and (8) post-harvest management.

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Table A11. Sample of producers to survey at baseline, by RADs and administrative provinces

RADs	Administrative provinces	Number of producers
Central	Monte Plata	121
	Peravía	224
	San José de Ocoa	158
	Santo Domingo	72
	San Cristóbal	72
East	San Pedro de Macorís	140
	Hato Mayor	61
	La Altagracia	147
	Seybo	20
North Central	Monseñor Noel	179
	Hermanas Mirabal	14
	La Vega	432
Northeast	Duarte	53
	María Trinidad Sánchez	55
	Samaná	96
	Sánchez Ramírez	112
Northwest	Dajabón	195
	Montecristi	288
	Santiago Rodríguez	174
	Valverde	441
North	Espaillat	181
	Puerto Plata	146
	Santiago	148
South	Independencia	97
	Bahoruco	17
	Barahona	106
	Pedernales	21
Southwest	San Juan	139
	Azua	194
	Elías piña	23
Total		4,126

Table A12. Sample of producers to survey at baseline, by RADs and technologies

Requested technologies	RADs								Total
	Central	East	North Central	Northeast	Northwest	North	South	Southwest	
Pasture and grassland rehabilitation & improvement	65	171	69	174	75	122	77	136	889
Drip irrigation	207	29	115	7	48	132	103	113	754
Sprinkler irrigation	33	12	27	3	531	45	17	14	682
Greenhouses	126	100	186	83	141	122	27	89	874
Post-harvest management	34	4	88	1	264	43	1	2	437
Land leveling	20	49	80	47	31	1	14	0	242
Mulching	-	-	-	-	-	-	-	-	-
Micro-sprinkler irrigation	162	3	60	1	8	10	2	2	248
Total	647	368	625	316	1,098	475	241	356	4,126

Appendix A

Baseline balance testing

In this section of the analysis we will focus only on the set of technologies that were randomized (in the second-stage of the two-stage randomization process) to test for baseline balance. After excluding producers with technologies that were not randomized (n=460), the sample of treated and non-treated producers with baseline data includes 3,275 observations: 1,419 direct beneficiaries, 842 indirect beneficiaries, and 1,014 controls (Table A13).

Table A13. Baseline sample: distribution of technologies by treatment group

Requested technologies	Direct beneficiaries	Indirect beneficiaries	Controls	Pooled
Pasture and grassland rehabilitation & improvement	350	277	207	834
Drip irrigation	339	150	214	703
Sprinkler irrigation	264	98	206	568
Greenhouses	300	285	198	783
Post-harvest management	166	32	189	387
Total	1,419	842	1,014	3,275

We test whether the two-stage randomization process led to treatment groups with balance characteristics, including time-invariant indicators and retrospective responses on key outcome indicators, at baseline. That is, we are testing the degree to which the distribution of these characteristics is near its expectation across treatment groups. The results from the hypothesis test of differences in means between treatment groups, with standard errors clustered at the sub-zone level, show no statistically significant differences across any of the variables, confirming the validity of the randomization process (Table A14).

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Table A14. Balance statistics: Baseline characteristics

	Control		Pooled		Direct beneficiaries			Indirect Beneficiaries		
	N	Mean	N	Mean	N	Mean	*p*-value	N	Mean	*p*-value
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Demographic characteristics										
Household size (number)	1,014	3.90	2,433	3.84	1,419	3.80	0.42	842	3.94	0.76
Dependency ratio (%)	1,014	0.23	2,433	0.23	1,419	0.22	0.58	842	0.25	0.23
Non-agricultural work (% members)	1,014	0.64	2,433	0.64	1,419	0.64	0.99	842	0.74	0.21
Household with members < 18 years (0,1)	1,014	0.58	2,433	0.56	1,419	0.55	0.41	842	0.61	0.34
Head of household characteristics										
Age (years)	1,014	52.29	2,433	52.02	1,419	51.82	0.55	842	51.96	0.68
Male (0,1)	1,014	0.89	2,433	0.88	1,419	0.87	0.19	842	0.91	0.59
Education (years)	1,014	8.18	2,432	8.08	1,418	8.01	0.72	842	8.50	0.54
No education (0,1)	1,014	0.09	2,432	0.11	1,418	0.12	0.18	842	0.10	0.63
Primary incomplete (0,1)	1,014	0.35	2,432	0.34	1,418	0.33	0.51	842	0.31	0.25
Primary completed (0,1)	1,014	0.12	2,432	0.11	1,418	0.10	0.38	842	0.11	0.66
Secondary incomplete (0,1)	1,014	0.08	2,432	0.08	1,418	0.08	0.50	842	0.08	0.96
Secondary completed (0,1)	1,014	0.11	2,432	0.11	1,418	0.11	0.79	842	0.11	0.97
More than secondary (0,1)	1,014	0.04	2,432	0.04	1,418	0.04	0.93	842	0.03	0.73
Dwelling and other household characteristics										
Electricity (0,1)	1,014	0.92	2,433	0.94	1,419	0.94	0.31	842	0.95	0.19
Own housing (0,1)	1,014	0.85	2,433	0.86	1,419	0.86	0.49	842	0.87	0.15
Access to credit (0,1) – formal or informal	1,014	0.36	2,433	0.34	1,419	0.33	0.38	842	0.36	0.96
Access to formal credit (0,1)	1,014	0.31	2,433	0.29	1,419	0.27	0.27	842	0.33	0.52
Savings (0,1)	1,014	0.48	2,433	0.47	1,419	0.46	0.57	842	0.49	0.88
Baseline agricultural characteristics										
Agri/productive association member (0,1)	1,014	0.46	2,433	0.41	1,419	0.38	0.28	842	0.33	0.10
Receives technical assistance (0,1)	1,014	0.17	2,433	0.15	1,419	0.14	0.54	842	0.15	0.66
Own agricultural plots (number)	1,014	1.29	2,433	1.29	1,419	1.28	1.00	842	1.30	0.89
Own agricultural plot (% number of plots)	1,014	0.83	2,433	0.85	1,419	0.87	0.42	842	0.87	0.42
Mora than one agricultural plot (0,1)	1,014	0.25	2,433	0.24	1,419	0.23	0.69	842	0.24	0.76
Plots worked (number)	1,014	1.55	2,433	1.51	1,419	1.49	0.60	842	1.49	0.62
Land area (ha)	1,014	8.39	2,433	8.38	1,419	8.38	1.00	842	8.35	0.98
Land worked (ha)	1,014	9.21	2,433	9.31	1,419	9.38	0.93	842	9.24	0.99
Household has at least one crop (0,1)	1,014	0.83	2,433	0.83	1,419	0.83	0.94	842	0.80	0.61
Harvests (0,1)	1,014	0.63	2,433	0.61	1,419	0.59	0.60	842	0.54	0.22
Uses chemical fertilizer (0,1)	1,014	0.53	2,433	0.53	1,419	0.53	0.98	842	0.53	0.93
Has a permanent crop (0,1)	1,014	0.68	2,433	0.67	1,419	0.67	0.90	842	0.63	0.55
Land with permanent crops (% total)	843	0.77	2,028	0.75	1,185	0.74	0.69	675	0.72	0.56
Livestock producer (0,1)	1,014	0.49	2,433	0.48	1,419	0.47	0.82	842	0.50	0.91
Pastures (ha)	449	16.46	1,126	15.37	677	14.65	0.22	424	14.81	0.27
TLUs	1,014	8.53	2,433	7.16	1,419	6.18	0.38	842	6.31	0.40
Has irrigation (0,1)	1,014	0.22	2,433	0.24	1,419	0.25	0.65	842	0.21	0.80
Modern irrigation (0,1)	843	0.07	2,028	0.08	1,185	0.08	0.92	675	0.07	0.89
Baseline economic characteristics										
Income from livestock sales (US$)	1,014	996.87	2,433	762.33	1,419	594.73	0.23	842	592.07	0.24
Income from animals (US$)	1,014	856.34	2,433	661.19	1,419	521.73	0.23	842	522.00	0.24
Livestock expenditures (US$)	1,014	1,199.46	2,433	947.58	1,419	767.59	0.32	842	838.83	0.42
Livestock products – sales (US$)	1,014	360.96	2,433	315.10	1,419	282.33	0.60	842	304.87	0.70
Livestock products – production costs (US$)	1,014	23.48	2,433	18.00	1,419	14.08	0.64	842	13.96	0.64
Livestock products – net income (US$)	1,014	303.36	2,433	282.88	1,419	268.25	0.80	842	290.91	0.93
Agricultural income (US$)	1,014	4,067.63	2,433	4,186.76	1,419	4,271.89	0.82	842	3,848.00	0.81
Value of production (US$/ha)	1,014	2,201.02	2,433	2,193.33	1,419	2,187.83	0.98	842	1,981.79	0.63
Value of production (US$/ha) (log)	1,014	4.56	2,433	4.51	1,419	4.47	0.87	842	4.05	0.40
Total household income (US$)	1,014	8,411.24	2,433	8,581.43	1,419	8,703.05	0.72	842	9,472.87	0.26
Total household Income (US$) (log)	1,014	10.45	2,433	10.44	1,419	10.44	0.64	842	10.46	0.50
Food insecurity (0,1)	1,014	0.48	2,433	0.46	1,419	0.44	0.63	842	0.47	0.92

Notes: This table describes the demographic, and baseline agricultural and economic characteristics of farmers in *PATCA II* for the set of technologies that were randomized. Columns (1), (3), (5), (8) show the number of farmers for the treatment groups specified by the column heading. Column (2) shows the average for the control group, and column (4) shows the average for the pooled sample (controls and direct beneficiaries). Columns (7) and (10) compare averages in the direct and indirect beneficiary groups with the average in column (2); P-values are based on a simple (2-tailed) t-test). Standard errors clustered at the sub-zone level.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Appendix B

Table B1. Technologies implemented as of December 31, 2014
(North and Southwest regions)

Technologies	Requested in the universe			Implemented (as of 12/31/2014)		
	Freq.	Percent	Cum.	Freq.	Percent	Cum.
Mulching	3	0.3	0.3	3	0.3	0.3
Greenhouses	27	2.66	2.96	1	0.1	0.39
Post-harvest management	25	2.47	5.42	27	2.66	3.06
Pasture and grassland rehabilitation & improvement	629	62.03	67.46	666	65.68	68.74
Sprinkler irrigation	25	2.47	69.92	28	2.76	71.5
Drip irrigation	249	24.56	94.48	222	21.89	93.39
Micro-sprinkler irrigation	56	5.52	100	67	6.61	100
(Improved pastures + drip & sprinkler irrigation)	903	89.05		916	90.34	
Total	1,014	100		1,014	100	

Table B2. Program implementation, by month, year, and technology, as of December 31, 2014

Program implementation (month & year)	Freq.	Percent	Cum.	Lottery		Technologies Implemented [a]		DB of randomly assigned technologies [b]	
				1st	2nd	Improved pastures	Irrigation [c]	Improved pastures	Irrigation [c]
December 2012	19	1.87	1.87	19	-	17	2	17	1
April 2013	9	0.89	2.76	9	-	7	2	7	1
May 2013	62	6.11	8.88	62	-	49	13	48	11
June 2013	126	12.43	21.3	126	-	111	15	110	15
July 2013	11	1.08	22.39	11	-	6	5	6	0
August 2013	29	2.86	25.25	29	-	16	5	16	5
September 2013	60	5.92	31.16	60	-	50	10	50	8
October 2013	47	4.64	35.8	47	-	25	6	24	3
November 2013	27	2.66	38.46	27	-	14	12	13	4
December 2013	24	2.37	40.83	24	-	6	17	6	16
January 2014	13	1.28	42.11	13	-	6	7	6	6
February 2014	46	4.54	46.65	46	-	23	22	14	10
March 2014	66	6.51	53.16	66	-	31	34	19	23
April 2014	37	3.65	56.8	37	-	6	31	3	24
May 2014	29	2.86	59.66	29	-	1	28	1	20
August 2014	6	0.59	60.26	6	-	2	4	2	1
September 2014	6	0.59	60.85	6	-	0	6	0	5
October 2014	20	1.97	62.82	20	-	6	12	6	11
November 2014	101	9.96	72.78	39	62	84	17	81	17
December 2014	276	27.22	100	51	225	206	69	198	67
Total	1,014	100		727	287	666	317	627	248

Notes: Out of the 1,014 observations in the administrative dataset, 287 (28.3 percent) obtained the benefits of the program as a result of a second lottery that took place on June 2014 in the Southwest region. The objective of this second lottery was to reach the MA's goal of delivering 400 technologies by December 2014. A total of 531 producers were randomized in this second lottery, some of which were either indirect beneficiaries (n=243) or controls (n=84) from the first lottery; those observations classified as indirect beneficiaries or controls in the first lottery but treated as a result of the second lottery (n=327) were excluded from the analysis.

[a] Includes the number of technologies implemented as of December 2014, regardless of the technology chosen by the farmer in the program's universe.

[b] Includes the number of technologies implemented as of December 2014, but only for those farmers randomly assigned to receive either improved pastures, drip or sprinkler irrigation. Also, excludes farmers that requested improved pastures but received a different technology, and farmers that requested either drip or sprinkler irrigation but did not receive an irrigation technology (drip, sprinkler or micro-sprinkler).

[c] Drip, sprinkler, or micro-sprinkler irrigation.

Appendix C

Power and sample size calculation

The sample size for a randomized control trial (RCT) usually follows one of two possible paths: (i) for fixed values of α and β, the sample size of the study is increased until an effect of meaningful size can be detected with power β by a test with level of significance α or (ii) having fixed the minimum size of the effect that the study wants to detect and the level of significance α, the sample size of the study is increased until the desired level of power for the test is achieved. If the randomization is performed at the cluster level, a suitable combination between the number of clusters to be selected and the number of observations per cluster is determined. However, in the case of *PATCA II*, it is not possible to follow these standard paths. A selection of clusters is not advised given the small size of the universe. Regarding the number of observations to select per cluster, given the high variability among the sizes of the clusters that constitute the universe for the follow-up survey, an ad-hoc approach is necessary.

The sample size for the impact evaluation of *PATCA II* was determined as follows. After setting the desired α and β for each technology, the power under different values of the true effect in the population was simulated using the following mixed-effects model:

$$Y_{ij} = \gamma_{00} + \gamma_{01}W_j + \gamma_{02}X_j + u_{0j} + e_{ij} \qquad (1)$$

where j indexes the clusters, i indexes the units within the clusters, W_j is a constant variable that takes the value $\frac{1}{2}$ if the cluster was randomly assigned to treatment and $-\frac{1}{2}$ otherwise, and X_j is a covariate at the cluster level, with correlation coefficient r^2 with the outcome variable (chapter 7, Spybrook et al., 2011). The potential impact of clustering in the randomization is considered by including the random effect u_{0j}, assumed to be coming from a normal distribution with mean 0 and variance $\tau_{|X}$. The notation for the variance of the random effect emphasizes that u_{0j} corresponds to unexplained heterogeneity between clusters, once controlled by the cluster-level covariate X. Lastly, the error term associated with unit i in cluster j is represented by e_{ij}, assumed as coming from a normal distribution with mean 0 and variance σ^2.

The effect of the program is measured by the parameter γ_{01}.[55] Instead of specifying the values of the true population effect in their real scale, we used the standardized effect size, defined as:

$$\delta = \gamma_{01}/\sqrt{\tilde{\sigma}^2}$$

where $\tilde{\sigma}^2 = \tau_{|X} + \sigma^2$ is the variance of the outcome variable for the program's universe. The use of a standardized effect size is preferable as it is not necessary to have an estimate for $\tilde{\sigma}^2$ in order to perform the simulation; however, a suitable estimate is required to bring the expected standardized effect sizes to their true scale. The simulations considered a grid of values of δ between 0.2 and 0.8.

Table C1. Main parameters of the simulation

Parameter	Source	Irrigation	Improved pastures	Households
Y	*PATCA*'s Baseline	Value of Production per Hectare (US$/ha) (log)	TLU Index per Hectare of improved pastures (TLU/ha) (log)	Household Income (US) (log)
ICC	*PATCA*'s Baseline	0.1537	0.1455	0.0913
r^2	CRIAR IE Study	0.32	0.3	0.29
α	Standard approach	0.05	0.05	0.05

Table C1 shows the main parameters of the simulations. The parameters γ_{00} and σ^2 are irrelevant for the evaluation and are therefore set to 0 and 1, respectively.

[55] Notice that the expected values for a unit in the treated and control groups are, respectively, $\gamma_{00} + (1/2)\gamma_{01}$ and $\gamma_{00} - (1/2)\gamma_{01}$. The difference between the means of a treated and a control unit is hence γ_{01}. In practice, this indicates that testing the existence of an effect is equivalent to testing the hypothesis Ho: $\gamma_{01} = 0$.

Appendix C

For each value of δ, 5,000 datasets were randomly generated; for each one of them, the mixed random effects model (1) is fitted and the significance of γ_{01} is evaluated using the ANOVA function of the *lmerTest* package in the statistical package R. The proportion of times that the test manages to reject the null hypothesis of no effect is used as an approximation to the power of the test. The chosen scenario for the sample size is presented in Table C2. The minimum standardized effects that are expected to be detectable at a power of 0.8 with this sample size are presented in Table C3. The following rules determine the sample:

1. The whole universe of DB-ET is selected
2. For all other comparison groups (DB-IT, IB, Controls): if the universe for a given group and technology is:
   a. Smaller than the universe of DB-ET: all of the producers are selected
   b. Bigger than the universe of DB-ET: a sampling fraction f is calculated for each technology-comparison group, such that the sample size coincides with the one for DB-ET. This fraction is amplified by a 15 percent, as a protection against non-response. The sampling fraction f is applied to each subzone-technology-comparison group with the following adjustments:
      i. A minimum of 3 households if possible
      ii. If the initial sample size is smaller than the number of observations available in the baseline, the size is increased up to the size of the baseline, if it is smaller than 30 units, or 30 units.
3. Units selected in the baseline will have priority to take part in the sample

Table C2. Sample sizes for the chosen scenario

Group	Pooled	Irrigation	Improved pastures
DB-ET	541	211	330
DB-IT	412	248	164
IB	514	134	380
Controls	676	292	384
Total	2143	885	1258

Table C3. Minimum standardized effects to be detected with a power of 0.8 under the chosen scenario

Comparison	Irrigation	Improved pastures	Households
DB-ET vs Control	0.42	0.37	0.28
IB vs Control	0.46	0.35	0.28

Sensitivity analysis due to non-response

Given that in cluster randomized trials the impact of losing clusters due to non-response is more significant than the effect of losing units within clusters and since some of the clusters in *PATCA II* have a small number of observations, we conducted a sensitivity analysis to estimate the minimum standardized effects under certain non-response scenarios. For illustration purposes, the structure of the sample at the cluster level is presented in Figures C1 and C2. The main conclusion for both technologies is that the loss of around 5 percent of the units in the smallest clusters has a similar or even bigger impact on the loss of power than the loss of 25 percent of the observations if the non-response is randomly distributed. As additional protection, the size of the sample for all clusters was increased to a minimum of 10 when possible, which gives the final sample depicted in Table C4.

Appendix C

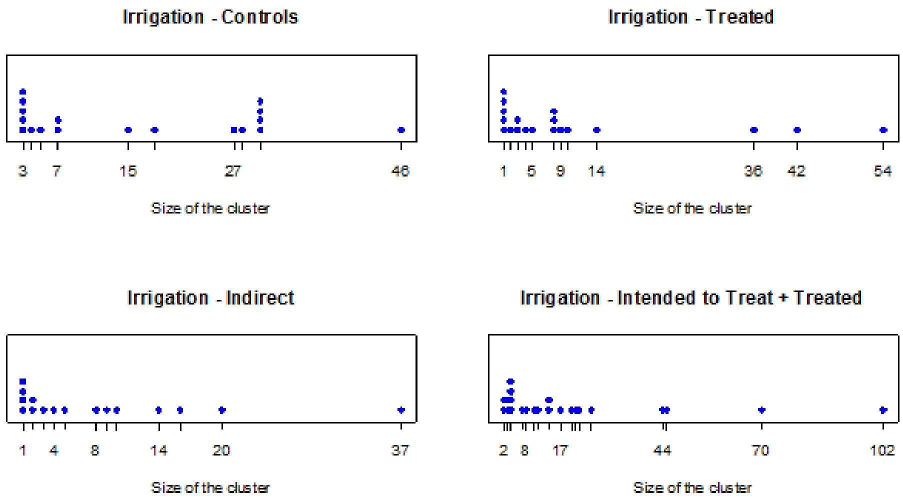

Figure C1. Irrigation: structure of the sample at the cluster level

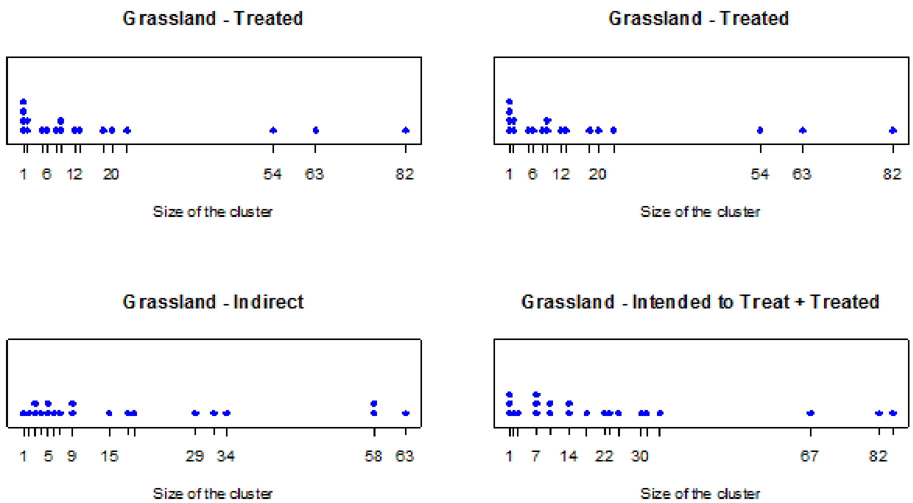

Figure C2. Improved pastures: structure of the sample at the cluster level

Table C4. Distribution of the final sample sizes, by technology and beneficiary group

	Technologies		
Treatment Groups	Irrigation	Improved pastures	Pooled
DB	478	494	972
DB-ET	211	330	541
DF-IT	267	164	431
IB	134	380	514
Controls	344	384	728
Total	956	1,258	2,214

Notes: Direct beneficiaries-effectively treated (DB-ET), direct beneficiaries-intended to be treated (DB-IT), indirect beneficiaries (IB).

Appendix C

Table C5. Distribution of the universe for the follow-up survey
(North & Southwest regions and additional control sub-zones)

	Technologies					
	Irrigation technologies [a]		Improved pastures [b]		Pooled	
Treatment groups	Sub-zones	Producers	Sub-zones	Producers	Sub-zones	Producers
DB-ET	19	211	19	330	22	541
DB-IT	24	381	18	164	24	545
IB	16	134	20	1,234	21	1,368
Controls	18	1,451	20	1,097	20	2,548
Total	41	2,177	42	2,825	44	5,002

Notes: Direct beneficiaries-effectively treated (DB-ET), direct beneficiaries-intended to be treated (DB-IT), indirect beneficiaries (IB).
[a] Includes drip irrigation, sprinkler irrigation, and micro-sprinkler irrigation.
[b] Pasture and grassland rehabilitation & improvement.

Table C6. Follow-up sample, by technology and treatment groups

	Number of farmers to interview					
	Expected			Collected		
Treatment groups	Pooled	Improved pastures	Irrigation technologies	Pooled	Improved pastures	Irrigation technologies
DB	972 (250)	494 107	478 (143)	915 (241)	475 (106)	440 (135)
DB-ET	541 (154)	330 (81)	211 (73)	519 (149)	320 (80)	199 (69)
DF-IT	431 (96)	164 (26)	267 (70)	396 (92)	155 (26)	241 (66)
IB	514 (116)	380 (70)	134 (46)	484 (113)	363 (70)	121 (43)
Controls	728 (367)	384 (98)	344 (269)	690 (358)	361 (95)	329 (263)
sub-total	2,214 (733)	1,258 (275)	956 [a] (458)	2,089 (712)	1,199 (271)	890 [b] (441)
Social network nodes	541			410		
Total	2,755	1,588	1,167	2,499		

Notes: Direct beneficiaries-effectively treated (DB-ET), direct beneficiaries-intended to be treated (DB-IT), indirect beneficiaries (IB). Number of producers with baseline data in parenthesis.
[a] n=100 producers associated with the micro-sprinkler technology (n=46 DB-ET, n=54 DB-IT).
[b] n=92 producers associated with the micro-sprinkler technology (n=44 DB-ET, n=48 DB-IT).

Appendix E

Table D1. Summary statistics: Income outcomes

	Control group		
Outcomes	Pooled (1)	Improved pastures (2)	Irrigation (3)
Technology was used in 2014 (0,1)	0.038 (0.191)	0.020 (0.139)	0.066 (0.248)
Agricultural income (US$) (log)	6.089 (4.032)	4.987 (4.202)	7.791 (3.063)
Total household income (US$) (log)	8.517 (2.294)	8.176 (2.375)	9.044 (2.060)
Total household income per capita (US$/pc) (log)	7.338 (2.127)	7.036 (2.210)	7.806 (1.905)
Observations	583	354	229

Notes: Columns (1)-(3) reports mean values for the control group at follow-up, with standard deviations in parenthesis.

Appendix D

Table D2. Summary statistics: Improved pastures technology

Outcomes	Control group (1)
Land divided into paddocks (0,1)	0.381 (0.486)
Number of paddocks (#)	2.463 (4.663)
Paddocks (ha)	1.825 (3.406)
Paddocks (ha) (log)	0.641 (0.811)
Pastures (natural + improved) (ha)	14.876 (39.66)
Pastures (natural + improved) (ha) (log)	1.742 (1.456)
Natural pasture (0,1)	0.551 (0.498)
Natural pasture (ha)	11.204 (37.88)
Natural pasture (ha) (log)	1.371 (1.433)
Improved pasture (0,1)	0.362 (0.481)
Improved pasture (ha)	3.672 (11.60)
Improved pasture (ha) (log)	0.669 (1.069)
Produces livestock products (0,1) [a]	0.418 (0.494)
Produces milk and meat (0,1)	0.370 (0.484)
Value of milk and meat production (US$) (log)	3.169 (4.264)
Value of milk and meat production (US$/ha pastures) (log)	2.186 (3.035)
Value of milk and meat production (US$/TLU) (log)	2.093 (2.881)
TLU in 2014	13.920 (21.22)
Observations	354

Notes: Column (1) reports mean values for the control group at follow-up, with standard deviations in parenthesis.
[a] Includes production of meat, milk, eggs, honey, and other unspecified products.

Appendix D

Table D3. Summary statistics: Irrigation technology

Outcomes	Control group (1)
Panel A: Land variables	
Has irrigation (0,1) – own land	0.507 (0.501)
Land equipped with irrigation (ha) (log)	0.614 (0.768)
Modern irrigation (0,1)	0.245 (0.431)
Land equipped with modern irrigation (ha) (log)	0.260 (0.539)
Panel B: Production variables	
Total area planted (ha) (log) [a]	1.719 (1.067)
Total area planted (ha)	12.118 (34.05)
Permanent crops (% total area planted)	0.636 (0.453)
Harvested crops (0,1) [b]	0.655 (0.476)
Land area cultivated and harvested (ha) (log)	0.812 (0.784)
Cropping intensity [c]	74.76 (61.76)
Value of production (US$) (log)	5.492 (4.169)
Value of production per hectare (US$/ha) (log)	4.985 (3.779)
Labor expenditures (US$/ha) (log)	3.573 (3.008)
Input expenditures (US$/ha) (log) [d]	3.416 (2.897)
Sells (0,1)	0.638 (0.482)
Observations	229

Notes: Column (1) reports mean values for the control group at follow-up, with standard deviations in parenthesis.

[a] Includes land area covered with crops, temporary and permanent, including fruit trees, pastures, and forest. For example, if the producer has two plots of land with 2 hectares per plot and reported cultivating 6 crops, each crop in 1 hectare, then this variable takes the value of 6.

[b] Takes the value of '1' if the producer reported harvesting any (temporary or permanent) crop in 2014.

[c] Cropping intensity = [(gross cropped area/net sown area) x 100], where gross cropped area is the total area (in hectares) sown once as well as more than once in the agricultural cycle, and net sown area is the area sown with crops but is counted only once.

[d] Includes expenditures on seeds, organic and chemical fertilizer, fungicides, insecticides, and herbicides.

Covariates included are head of household characteristics (age, age-squared, gender, educational level), household size, a dummy for whether the household receives remittances, a dummy for whether the household had a land title on or before 2012, and dummies for the North and Southwest regions. Reference group is 'no formal education, but not illiterate' for head of household educational level, and 'surrounding control sub-zones' for regional characteristics.

Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Appendix D

Table D4. OLS and First-stage regressions: complete output

Variables	OLS			IV-2SLS		
	Pooled (1)	Improved pastures (2)	Irrigation (3)	Pooled (4)	Improved pastures (5)	Irrigation (6)
Instrument: Randomized to *PATCA* (0,1)				0.577***	0.643***	0.439***
				(0.082)	(0.098)	(0.091)
				[0.42, 0.74]	[0.45, 0.84]	[0.26, 0.62]
Randomized to *PATCA* (0,1)	0.377***	0.438***	0.270***			
	(0.066)	(0.082)	(0.060)			
	[0.24, 0.51]	[0.27, 0.61]	[0.15, 0.39]			
Socio-economic characteristics						
Land title (on or before2012) (0,1)	0.036*	0.056**	0.006	0.041	0.031	0.022
	(0.020)	(0.026)	(0.032)	(0.029)	(0.031)	(0.037)
Receives remittances (0,1)	0.040	0.034	0.029	0.005	0.022	-0.007
	(0.035)	(0.051)	(0.068)	(0.041)	(0.051)	(0.032)
Household size (number)	-0.009	-0.016*	0.005	-0.011*	-0.011	-0.006
	(0.008)	(0.008)	(0.013)	(0.006)	(0.009)	(0.007)
Head of household characteristics						
Age (years)	-0.004	-0.004	-0.006	0.008	0.003	0.013
	(0.004)	(0.004)	(0.010)	(0.005)	(0.004)	(0.008)
Age (years) – squared	2.15e-05	2.46e-05	3.11e-05	-7.54e-05	-2.46e-05	-0.0001*
	(3.80e-05)	(3.32e-05)	(9.15e-05)	(4.88e-05)	(3.35e-05)	(7.35e-05)
Male (0,1)	-0.001	-0.007	0.023	0.034	0.021	0.066
	(0.045)	(0.061)	(0.061)	(0.039)	(0.048)	(0.048)
Illiterate (0,1)	0.051	0.061	0.032	0.026	0.011	0.078
	(0.036)	(0.045)	(0.072)	(0.026)	(0.031)	(0.052)
Primary school completed (0,1)	-0.038	-0.007	-0.060	-0.039	-0.001	-0.050
	(0.032)	(0.034)	(0.043)	(0.032)	(0.031)	(0.058)
Secondary school completed (0,1)	-0.014	0.073	-0.098**	-0.008	0.039	-0.026
	(0.029)	(0.043)	(0.038)	(0.035)	(0.040)	(0.058)
Technical school completed (0,1)	0.125**	0.153**	0.159	0.171**	0.181***	0.248*
	(0.057)	(0.073)	(0.103)	(0.073)	(0.061)	(0.140)
Post-secondary education (0,1)	-0.012	0.064	-0.050	-0.047	0.045	-0.054
	(0.028)	(0.045)	(0.034)	(0.034)	(0.042)	(0.040)
Regions						
North (0,1)	0.227***	0.265***	0.169**	0.133*	0.207**	0.018
	(0.070)	(0.089)	(0.063)	(0.075)	(0.096)	(0.063)
Southwest (0,1)	-0.109*	-0.080	-0.106*	-0.099	-0.115	-0.020
	(0.057)	(0.064)	(0.058)	(0.068)	(0.080)	(0.082)
Constant (0,1)	0.194	0.121	0.266	-0.202	-0.103	-0.352
	(0.130)	(0.136)	(0.242)	(0.160)	(0.126)	(0.222)
Kleibergen-Paap rk Wald *F* statistic				49.59	43.42	23.17
Effective *F* statistic [a]				50.71	44.43	23.70
Shea's partial R^2				0.356	0.319	0.373
Observations	1,348	819	529	1,348	819	529

Notes: Robust standard errors clustered at the sub-zone level in parenthesis, and 95% confidence intervals are shown in brackets.
The dependent variable is a dummy variable that takes the value of 1 if the producers reported using the technology (irrigation or livestock) during the 2014 agricultural cycle, 0 otherwise.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Appendix D

Table D5. Weak identification test critical values with single endogenous regressor

	Pooled (1)	Improved pastures (2)	Irrigation (3)
Stock and Yogo (2005) critical values			
Kleibergen-Paap rk Wald *F* statistic	49.59	43.42	23.17
Critical values for a single endogenous regressor			
10% maximal IV size – 16.38	20% maximal IV size – 6.66		
15% maximal IV size – 8.96	25% maximal IV size – 5.53		
Montiel-Pflueger critical values (2SLS) – (Pflueger and Wang, 2015)			
Effective *F* statistic	50.71	44.43	23.70
Critical values (% of worst-case bias)			
tau = 5% – 37.418	tau = 20% – 15.062		
tau = 10% – 23.109	tau = 30% – 12.039		

Table D6. Poisson regression

Variables	Coefficient
Randomized treatment cohorts	
Cohorts 1 and 2	1.913*** (0.477)
Cohorts 3 and 4	0.848 (0.532)
Socio-economic characteristics	
Land title (on or before 2012) (0,1)	0.117 (0.106)
Receives remittances (0,1)	-0.050 (0.111)
Household size (number)	-0.054** (0.024)
Head of household characteristics	
Age (years)	-0.014 (0.014)
Age (years) – squared	7.27e-05 (0.0001)
Male (0,1)	0.060 (0.148)
Illiterate (0,1)	0.216** (0.103)
Primary school completed (0,1)	-0.076 (0.135)
Secondary school completed (0,1)	-0.146 (0.121)
Technical school completed (0,1)	0.330* (0.190)
Post-secondary education (0,1)	-0.062 (0.110)
Regions	
North (0,1)	2.191*** (0.790)
Southwest (0,1)	0.945 (0.791)
Constant	-0.969 (0.682)
Observations	1,348

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
Dependent variable: Number of months with the technology.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Appendix E

Table E1. Direct effects: Program take-up & impact of PATCA on technology adoption

	OLS			IV-2SLS		
	Pooled (1)	Improved pastures (2)	Irrigation (3)	Pooled (4)	Improved pastures (5)	Irrigation (6)
Panel A				*First-stage regressions*		
Dependent variable: Effectively treated by *PATCA* (0,1)						
Instrument: Randomized to *PATCA* (0,1)				0.578*** (0.082) [0.42, 0.74]	0.641*** (0.099) [0.45, 0.83]	0.440*** (0.095) [0.25, 0.63]
Kleibergen-Paap *rk* Wald *F* statistic				49.61	42.28	21.32
Effective *F* statistic [a]				50.73	43.25	21.82
Shea's partial R^2				0.358	0.320	0.375
Panel B				*Second-stage regressions*		
Dependent variable: Technology was used in 2014 (0,1) [b]						
$\widehat{PATCA}$ (0,1)				0.651*** (0.066) [0.52, 0.78]	0.674*** (0.068) [0.54, 0.81]	0.621*** (0.103) [0.42, 0.82]
Randomized to *PATCA* (0,1)	0.377*** (0.067) [0.24, 0.51]	0.432*** (0.085) [0.26, 0.60]	0.273*** (0.063) [0.15, 0.40]			
Observations	1,348	819	529	1,348	819	529
Covariates	No	No	No	No	No	No
Regional dummies [c]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Columns (4)-(6) in panel A correspond to OLS estimates for the first-stage specification of the 2SLS analysis on technology adoption. Columns (1)-(3) in panel B correspond to OLS estimates of the ITT, and columns (4)-(6) correspond to the second-stage of the 2SLS analysis on technology adoption. Robust standard errors clustered at the sub-zone level in parenthesis, and 95% confidence intervals are shown in brackets.
[a] Montiel-Pflueger robust weak instrument test; Stata command –*weakivtest*– (Pflueger and Wang, 2015).
[b] Takes the value of '1' if the producers reported using the technology (irrigation or livestock) during the 2014 agricultural cycle.
[c] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Table E2. OLS and First-stage regressions: complete output

	OLS			IV-2SLS		
Variables	Pooled (1)	Improved pastures (2)	Irrigation (3)	Pooled (4)	Improved pastures (5)	Irrigation (6)
Instrument: Randomized to *PATCA* (0,1)				0.578*** (0.082) [0.42, 0.74]	0.641*** (0.099) [0.45, 0.83]	0.440*** (0.095) [0.25, 0.63]
Randomized to *PATCA* (0,1)	0.377*** (0.067) [0.24, 0.51]	0.432*** (0.085) [0.26, 0.60]	0.273*** (0.063) [0.15, 0.40]			
Regions						
North (0,1)	0.228*** (0.071)	0.272*** (0.092)	0.166*** (0.057)	0.128* (0.076)	0.209** (0.096)	0.008 (0.058)
Southwest (0,1)	-0.112* (0.060)	-0.101 (0.069)	-0.096 (0.064)	-0.105 (0.069)	-0.132 (0.081)	-0.012 (0.091)
Kleibergen-Paap rk Wald *F* statistic				49.61	42.28	21.32
Effective *F* statistic [a]				50.73	43.25	21.82
Shea's partial R^2				0.358	0.320	0.375
Observations	1,348	819	529	1,348	819	529
Covariates	No	No	No	No	No	No
Regional dummies [c]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis, and 95% confidence intervals are shown in brackets.
The dependent variable is a dummy variable that takes the value of 1 if the producers reported using the technology (irrigation or livestock) during the 2014 agricultural cycle, 0 otherwise.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Appendix E

Table E3. Direct effects: Impact of PATCA on income

Outcomes	OLS Pooled (1)	OLS Improved pastures (2)	OLS Irrigation (3)	IV-2SLS Pooled (4)	IV-2SLS Improved pastures (5)	IV-2SLS Irrigation (6)
Agricultural income (US$) (log) [a]	1.051	1.372*	-0.532	1.817	2.141*	-1.209
	(0.767)	(0.775)	(0.391)	(1.373)	(1.212)	(0.848)
Total household income (US$) (log) [b]	-0.156	-0.197	-0.579*	-0.269	-0.307	-1.315**
	(0.218)	(0.247)	(0.291)	(0.357)	(0.363)	(0.659)
Total household income per capita (US$/pc) (log)	-0.0969	-0.146	-0.456	-0.168	-0.228	-1.035*
	(0.231)	(0.254)	(0.276)	(0.386)	(0.378)	(0.609)
Observations	1,348	819	529	1,348	819	529
Covariates	No	No	No	No	No	No
Regional dummies [c]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes value of crop production and livestock products (i.e., milk, meat, eggs, honey, and other products), including losses.
[b] Includes income derived from land leased and sold, crop production (excluding losses), livestock products, off-farm income (cash and in-kind), small-business sales, non-agricultural self-employment, remittances, and transfers from the Government and NGOs.
[c] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Appendix E

Table E4. Direct effects: Impact of PATCA's improved pastures on agricultural production

Outcomes	OLS (3)	IV-2SLS (4)
Land divided into paddocks (0,1)	0.131**	0.205*
	(0.061)	(0.108)
Number of paddocks (#)	2.134**	3.330**
	(0.967)	(1.568)
Paddocks (ha) (log)	0.281*	0.439*
	(0.141)	(0.250)
Pastures (natural + improved) (ha) (log)	0.658*	1.027*
	(0.362)	(0.607)
Natural pasture (0,1)	0.198	0.309
	(0.177)	(0.292)
Natural pasture (ha) (log)	0.505	0.788
	(0.406)	(0.673)
Improved pasture (0,1)	0.181**	0.283**
	(0.084)	(0.112)
Improved pasture (ha) (log)	0.309*	0.483*
	(0.183)	(0.256)
Produces livestock products (0,1) [a]	0.116*	0.180**
	(0.061)	(0.086)
Milk and meat production		
Value of milk and meat production (US$) (log)	0.782	1.220
	(0.663)	(0.985)
Value of milk and meat production (US$/ha pastures) (log)	0.424	0.662
	(0.499)	(0.754)
Value of milk and meat production (US$/TLU) (log)	0.350	0.547
	(0.434)	(0.653)
TLU in 2014	3.350	5.228
	(3.321)	(5.031)
Observations	819	819
Covariates	No	No
Regional dummies [b]	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes production of meat, milk, eggs, honey, and other unspecified products.
[b] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

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Table E5. Direct effects: Impact of PATCA's irrigation on agricultural production

Outcomes	OLS (3)	IV-2SLS (4)
Panel A: Land variables		
Has irrigation (0,1) – own land	0.211 (0.166)	0.479 (0.339)
Land equipped with irrigation (ha) (log)	0.159 (0.274)	0.362 (0.590)
Modern irrigation (0,1)	0.156** (0.0732)	0.355** (0.149)
Land equipped with modern irrigation (ha) (log)	0.123 (0.106)	0.280 (0.229)
Panel B: Production variables		
Total area planted (ha) (log) [a]	0.042 (0.181)	0.094 (0.400)
Permanent crops (% total area planted)	0.031 (0.075)	0.070 (0.164)
Harvested crops (0,1) [b]	-0.116* (0.062)	-0.265** (0.121)
Land area cultivated and harvested (ha) (log)	-0.253 (0.162)	-0.575* (0.348)
Cropping intensity [c]	-14.73 (14.44)	-33.45 (30.98)
Value of crop production (US$) (log)	-1.245** (0.517)	-2.828*** (0.910)
Value of crop production per hectare (US$/ha) (log)	-1.022** (0.486)	-2.322*** (0.884)
Labor expenditures (US$/ha) (log)	-0.947*** (0.276)	-2.150*** (0.615)
Input expenditures (US$/ha) (log) [c]	-0.813** (0.371)	-1.846** (0.788)
Sells (0,1)	-0.087 (0.063)	-0.197 (0.125)
Observations	529	529
Covariates	No	No
Regional dummies [d]	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.

[a] Includes land area covered with crops, temporary and permanent, including fruit trees, pastures, and forest. For example, if the producer has two plots of land with 2 hectares per plot and reported cultivating 6 crops, each crop in 1 hectare, then this variable takes the value of 6.

[b] Takes the value of '1' if the producer reported harvesting any (temporary or permanent) crop in 2014.

[c] Cropping intensity = [(gross cropped area/net sown area) x 100], where gross cropped area is the total area (in hectares) sown once as well as more than once in the agricultural cycle, and net sown area is the area sown with crops but is counted only once.

[c] Includes expenditures on seeds, organic and chemical fertilizer, fungicides, insecticides, and herbicides.

[d] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.

Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

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Table E6. Time effects: PATCA's impact on income

	IV-2SLS					
	Pooled (1)	Improved pastures (2)	Irrigation (3)	Pooled (4)	Improved pastures (5)	Irrigation (6)
Panel A—First-stage regressions	Months using technology (#)					
Instrument: Fitted values (Poisson regression)	0.958*** (0.109) [0.75, 1.17]	1.071*** (0.151) [0.78, 1.37]	0.654*** (0.104) [0.45, 0.86]			
Kleibergen-Paap Wald rk F statistic	77.96	50.27	39.40			
Effective F statistic [a]	79.71	51.43	40.31			
Panel B—Second-stage regressions	Agricultural income (US$) (log)			Total household income (US$) (log)		
$\widehat{\text{Months using technology (\#)}}$	0.046 (0.077)	0.122* (0.072)	-0.042 (0.056)	-0.034 (0.028)	-0.024 (0.031)	-0.033 (0.037)
	Total household income per capita (US$/pc) (log)					
$\widehat{\text{Months using technology (\#)}}$	-0.021 (0.028)	-0.013 (0.032)	-0.014 (0.037)			
Observations	1,348	819	529	1,348	819	529
Covariates	No	No	No	No	No	No
Regional dummies [b]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis, and 95% confidence intervals are shown in brackets.
[a] Montiel-Pflueger robust weak instrument test; Stata command –*weakivtest*– (Pflueger and Wang, 2015).
[b] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Table E7. Poisson regression

Variables	Coefficient
Randomized treatment cohorts	
Cohorts 1 and 2	1.930*** (0.477)
Cohorts 3 and 4	0.861 (0.529)
Regions	
North (0,1)	2.172*** (0.789)
Southwest (0,1)	0.926 (0.793)
Constant	-1.585** (0.627)
Observations	1,348
Covariates	No
Regional dummies	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
Dependent variable: Number of months with the technology.

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Table E8. Time effects: Impact of PATCA'S improved pastures on agricultural production

	IV-2SLS (Instrument: Poisson fitted values)						
Second-stage regressions	Land divided into paddocks (0,1)	Number of paddocks (#)	Paddocks (ha) (log)	Pastures (natural + improved) (ha) (log)	Natural pasture (0,1)	Natural pasture (ha) (log)	Improved pasture (0,1)
Months using technology (#)	0.012*	0.139*	0.018	0.059**	0.011	0.027	0.024**
	(0.007)	(0.084)	(0.012)	(0.023)	(0.018)	(0.039)	(0.010)
	Improved pasture (ha) (log)	Produces livestock products (0,1)	Value of milk and meat production (US$) (log)	Value of milk and meat production (US$/ha pastures) (log)	Value of milk and meat production (US$/TLU) (log)	TLU in 2014	
Months using technology (#)	0.053**	0.016**	0.124	0.071	0.059	0.717*	
	(0.023)	(0.007)	(0.098)	(0.077)	(0.065)	(0.368)	
Observations	819	819	819	819	819	819	819
Covariates	No	No	No	No	No	No	No
Regional dummies [a]	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.

Table E9. Time effects: Impact of PATCA's irrigation on agricultural production

	IV-2SLS (Instrument: Poisson fitted values)						
Second-stage regressions	Has irrigation (0,1) – own land	Land equipped with irrigation (ha) (log)	Modern irrigation (0,1)	Land equipped with modern irrigation (ha) (log)	Total area planted (ha) (log)	Permanent crops (% total area planted)	Harvested crops (0,1)
Months using technology (#)	0.074***	0.102***	0.020*	0.035***	0.036	0.030**	-0.034***
	(0.020)	(0.026)	(0.012)	(0.010)	(0.029)	(0.014)	(0.011)
	Land area cultivated and harvested (ha) (log)	Cropping intensity	Value of crop production (US$) (log)	Value of crop production per hectare (US$/ha) (log)	Labor expenditures (US$/ha) (log)	Input expenditures (US$/ha) (log)	Sells (0,1)
Months using technology (#)	-0.043**	-3.090	-0.301***	-0.274***	-0.163**	-0.162**	-0.031***
	(0.017)	(1.977)	(0.095)	(0.090)	(0.075)	(0.076)	(0.011)
Observations	529	529	529	529	529	529	529
Covariates	No	No	No	No	No	No	No
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the sub-zone level in parenthesis.
[a] Includes dummies for the North and Southwest regions; Reference group is 'surrounding control sub-zones'.
Asterisks indicate coefficient statistical significance level (2-tailed): *** p<0.01; ** p<0.05; * p<0.1.