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## Working Paper

# The impact of smart subsidies on agricultural production: Innovative evidence from Argentina using survey and remote sensing data

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

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# **The Impact of Smart Subsidies on Agricultural Production: Innovative Evidence from Argentina Using Survey and Remote Sensing Data**

Maja Schling, Nicolás Pazos

2022

## **Abstract**

This study assesses the impact of the Program for Rural Development and Family Agriculture (PRODAF), a smart subsidies project that benefited the family farming stratum in northeastern Argentina. The evaluation draws on two complementary data sources. The first is a survey of agricultural households with a sample of 898 farmers (534 treated and 364 control) conducted after the end of the project. The second uses plot georeferencing to measure agricultural yields with satellite data for a subsample of 195 farmers over a 10-year period. Using the inverse probability weighting methodology, we find that PRODAF increased the technology adoption rate by 21 percentage points, and increased access to credit by 47 percentage points. Overcoming these barriers enabled the beneficiary farmers to increase the value of their sales and net income, although impacts varied among the four prioritized chains. In contrast, the analysis only detected a significant impact on yields for the citrus chain, which may be due to the type of technology adopted in this chain. Finally, we construct the Normalized Difference Vegetation Index (NDVI) to estimate productivity in the cotton and citrus chains. Applying the event study method, we confirm that technology adoption is a complex process whose full impact on yields only materializes between the second and third year post-treatment. We additionally confirm that the use of satellite data is an effective tool that accurately estimates yield changes and can be used to monitor and assess this type of intervention in real time and at a low cost.

**JEL classifications:** H43, O12, O13, Q12, Q16

**Keywords:** Technology Adoption, Productivity, Remote Sensing, Impact Evaluation, Argentina

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## 1 Introduction

Over the last 30 years, the agricultural sector in Latin America and the Caribbean (LAC) has grown at an unprecedented rate. The region accounts for a larger share of global agricultural production than the European Union or the United States and Canada and today leads the world as its largest net food exporter (Morris et al., 2020). In 20 countries in the region, the agricultural sector accounts for over 5% of GDP and employs over 14% of the region's workforce (OECD & FAO, 2019). Even so, the population of LAC is expected to grow from roughly 625 million in 2010 to about 720 million in 2030, which will mean a considerable increase in the demand for food, especially animal products (United Nations, 2015). Today, agriculture already uses more than one third of the land area and consumes almost 75% of the region's freshwater resources (Morris et al., 2020). At the same time, the consequences of climate change put additional pressure on critical resources such as water, reducing agricultural yields and livestock productivity and jeopardizing food security. To meet the growing demand for food with increasingly limited natural resources, agriculture in the region must increase production without expanding the agricultural frontier and in an environmentally sustainable manner.

Although commercial agriculture in the region dominates a significant share of production, more than 50% of food in LAC is produced by family farmers (Duff & Padilla, 2015). Estimates vary, but the region has between 15 and 21 million family farmers, whose production is characterized by intensive labor use because the area under cultivation is limited and often subsistence oriented (Morris et al., 2020). Smallholder farmers also face significant socioeconomic challenges: 48% of the region's rural population experienced poverty or extreme poverty in 2016, and 39% were food insecure in 2021 (CEPAL, 2018; Salazar, 2021a). Therefore, to achieve the objective of supplying future food demand and ensuring food security for the poorest in the region, it is essential that agricultural productivity in this population of farmers be increased.

In this context, one of the keys to increasing yields and reducing poverty among small farmers is the adoption of more efficient and sustainable agricultural technologies. However, family farmers often face significant barriers that hinder access to and successful incorporation of new technologies and practices. These barriers include lack of information and access to technical assistance, which limits knowledge about the suitability and effectiveness of technologies, and limited access to financial resources (Carletto et al., 2007; Foster & Rosenzweig, 2011). Since the presence of such market failures results in a suboptimal rate of adoption of modern technologies, the provision of agricultural extension services and financial support is considered a public good that plays an important role in the sector's productive growth (Fuglie & Rada, 2013; Ragasa et al., 2012).

In recent years, smart subsidies have emerged as a relevant public policy instrument to address the dual challenge of limited access to knowledge and liquidity (IDB, 2019; Rehman et al., 2017). Broadly speaking, a smart subsidy combines the provision of a financial credit conditional on the purchase of certain agricultural inputs or equipment with the technical assistance needed to facilitate the adoption of a new technology by the beneficiary farmer. Evidence from several studies conducted in LAC confirms that this tool significantly increases technology adoption rates and also supports increased productivity and income (Cerdán-Infantes et al., 2008; Bravo-Ureta et al., 2011; Salazar & Lopez, 2017). Most of these studies detect significant effects on yields only in the medium to long term—that is, several years after the intervention—which highlights the complex process of reshaping the social and technical components of a production system (Glover et al., 2019).

To better understand the dynamic impact of smart subsidies on smallholder production systems in the region, both policy makers and researchers highlight the need to rigorously monitor and evaluate the performance of these interventions. While the conventional strategy is to conduct field surveys, remote sensing using satellite imagery is an innovative and increasingly cost-effective tool for evaluating agricultural projects. Although satellite imagery presents a low-cost option for measuring changes in land use and crop health at high spatial and temporal resolution, the literature that draws on this data source in the context of impact evaluations remains limited (Kubitza et al., 2020).

This study aims to contribute to the literature in two ways: first, it presents a rigorous impact evaluation that uses a quasi-experimental methodology to analyze the impacts of a smart subsidies project on the family farming sector in Argentina. The “Program for Rural Development and Family Agriculture” (PRODAF) was implemented in northeastern Argentina between 2013 and 2019, and benefited over 2,000 family farmers by providing a non-reimbursable financial contribution and technical assistance for the adoption of technologies considered efficient and environmentally sustainable. Given that this combination of benefits was regarded as a pilot project in the country, it is vitally important to carry out a rigorous evaluation that identifies the productive and economic impacts of the program. Based on a survey of agricultural households collected in 2021 from 534 beneficiary farmer and 364 comparable non-beneficiary farmer, the analysis uses the inverse probability weighting (IPW) methodology to estimate the impact of PRODAF on the rate of adoption and access to credit, expenditures on production inputs, productivity, and income. Although the impacts vary by production chain, the effects are generally positive, showing significant improvements in sales, income, and productivity.

Second, our study presents a complementary analysis that utilizes a longitudinal panel of satellite data to measure agricultural yield using the Normalized Difference Vegetation Index (NDVI) for two of the four chains prioritized by PRODAF. To our knowledge, this analysis is one of the first to use remote sensing data to estimate the impact of an agricultural project on productive yields, complementing the work of Ortiz-Monasterio and Lobell (2007), Bellora et al. (2017), and Salazar et al. (2021b). Through the event study methodology, we can use this data to examine the temporal dynamics between the provision of the technology and the productive impacts. The results confirm that the full effects on productivity only become apparent two to three years after the intervention. The parallel application of the two analyses also makes it possible to confirm that satellite images can be used to accurately estimate yield changes, since the estimates made using the IPW and event study methodologies are highly comparable in terms of significance and direction.

The remainder of the paper is organized as follows: Section 2 reviews the empirical evidence. Section 3 provides information on the PRODAF program and the state of family farming in Argentina. Section 4 describes the identification strategy. Section 5 describes the data used and how they were obtained. Section 6 details both empirical strategies, and Section 7 presents the results. The conclusions are found in Section 8.

## **2 Empirical Evidence**

In Argentina, as in other countries of the region and the world, family farming faces significant barriers that hinder the adoption of more efficient technologies that could enhance productivity and income. These include the lack of information and access to technical assistance, which limits knowledge about the suitability and efficacy of more effective and environmentally sustainable

technologies, and limited access to financial resources that keeps farmers from investing in the adoption of more efficient farming practices.

A large number of studies have examined the economic, social, and environmental impacts of agricultural extension services. In general, the public provision of agricultural extension services is driven by market failures such as asymmetric information, limited access to credit, and inadequate or incomplete market infrastructure, among other factors (Feder et al., 1985). The evidence shows that, in many rural contexts, family farmers have more limited access to extension services and technology dissemination, although they are also the ones who could derive the greatest benefits (Ragasa et al., 2012). If this is the case and there is a gap between the technology currently used and the best farming technology for a given region, extension services can close this gap and accelerate the dissemination of improved technology, leading to faster growth in yields and rural incomes while protecting natural resources from degradation (Birkhaeuser et al., 1990).

Existing data support the hypothesis that innovation and adoption of more efficient agricultural technologies can effectively improve farmer productivity and income. In a comprehensive review, Fuglie and Rada (2013) evaluate the technological improvements introduced in sub-Saharan Africa by the Consultative Group on International Agricultural Research (CGIAR) and estimate that for the 34 million hectares where these technologies had been applied (representing 21% of the region's cropland), production increased by 65%. Through this mechanism, agricultural extension services providing more efficient and environmentally sustainable technologies play a significant role in increasing food security (Rosegrant and Cline, 2003; Aramburu et al., 2014) and improving climate change adaptation (Lybbert & Summer, 2012).

Given the twin barriers of limited access to both the information and the financial resources needed to adopt new technologies, the provision of smart subsidies has been a relevant and generally successful policy (IDB, 2019). This instrument serves two objectives: first, it gives the farmer the necessary financial resources (in the form of coupons or vouchers) as well as the technical assistance so that the beneficiaries can not only acquire inputs or machinery identified as more efficient, but also have the technical support needed to use them appropriately. Because this is a one-time financial support, it is expected that any possible distortion that a direct subsidy might have on input prices or private investment will be avoided (World Bank, 2013).

There is ample empirical evidence to show that providing smart subsidies has significant and positive impacts on agricultural productivity and incomes. In Bolivia, the "Direct Support Program for the Creation of Rural Agrifood Initiatives" (CRIAR), implemented in 2011 and co-financed by the IDB, offered financial support for the cost of adopting and implementing new agricultural technologies among small rural farmers. In an evaluation of the program using the instrumental variable method, Salazar et al. (2015) found that, on average, productivity increased by 92%, household net farm income increased by 36%, and the likelihood of being food secure increased from 20% to 30%. Rossi (2013) evaluated the "Project to Integrate Small Producers into the Wine Production Chain" (PROVIAR) carried out in the Argentine provinces of San Juan and Mendoza, which promoted the integration of wine value chains through the implementation of business plans that also provided co-financing and technical assistance for the adoption of new technologies. Using the quasi-experimental double-difference methodology, the study found significant impacts on increased production (7.8%) and productivity (7.9%). Other impact studies conducted in the region, including by Lema et al. (2015), Durán et al. (2018), and Bravo-Ureta et al. (2011), confirm



a close causal link between smart subsidies and significant increases in farmers' production, productivity, and incomes.

Other extension programs that focus on supplying inputs and improved crop varieties have also obtained positive results. In the case of an extension program targeting grape growers in Mendoza, Argentina, Cerdán-Infantes et al. (2008) used a 5-year panel with a fixed effects model and found that yields increased by 40%, but only for those farmers whose output had reflected low productivity before the program. Using the Propensity Score Matching (PSM) method to account for unobservable differences between adopters and non-adopters of an extension program in the Dominican Republic, González et al. (2009) detected significant positive effects on the productivity of rice and livestock farmers, but no other type of producer, suggesting that the effectiveness of different technologies may vary in the short run. In this context, numerous empirical studies have indicated that productivity impacts tend to take several agricultural cycles after the adoption of a new technology. For example, Aramburu et al. (2019) assessed the impact of an extension program in the Dominican Republic, and while they found that the adoption of new technologies increased significantly, they did not detect positive impacts on productivity in the short term. A subsequent evaluation by Salazar et al. (2021) found that yields did not experience significant increases until three years after technology adoption occurred. Other rigorous evaluations of similar IDB-funded projects, including Lopez and Maffioli (2008), Salazar and Lopez (2017), and Corral and Zane (2020), also find that the effective and sustainable adoption of a new technology takes time, and that adjustments to the entire farm production system only show their full impact on yields in the medium to long term.

To understand the temporal dynamics between technology adoption and productivity changes, remote sensing using satellite imagery is an increasingly relevant and cost-effective tool. Access to and availability of satellite data has increased rapidly in recent decades, driven by recent milestones such as the Sentinel satellite launches, as well as the falling costs of space transportation and the development of microsattelites (Lal et al., 2017). Remote sensing data make it possible to detect pattern variations in crop organic matter, thus capturing their growth from the time of planting to harvest, as well as any other changes that occur over the years and seasons. The accuracy of estimates of agricultural yields and other agronomic and environmental indicators, and their consistency with field measurement, have been confirmed by several studies (see Bégué et al. (2018) and Chivasa et al. (2017) for systematic reviews of this literature).

Measuring agricultural yields using remote sensing tools has several advantages over traditional measurement using farm household surveys. Today, several satellites, including the Sentinel 2 satellite, provide remote images of the earth with high spatial resolution (up to 10 m resolution) and high temporal frequency (up to daily revisit cycles). They are also a valuable source of longitudinal observations, providing historical data going back a decade or more. Given that a wealth of satellite data is now available at low or no cost, it is also a highly cost-efficient method of monitoring and evaluating productivity performance.

In comparison, the conventional strategy for monitoring and evaluating agricultural projects is still based on field surveys. This measurement requires substantial human and financial resources, and only allows for a temporary impression of the productive conditions of the farm. Agricultural yield estimation based on self-reported data can also be subject to significant measurement errors that affect its accuracy and reliability (Burke & Lobell, 2017; Carletto et al., 2013).

Despite these advantages, the use of satellite data for evaluating the productive impacts of agro-technological interventions is still limited. In a systematic review of the literature, Kubitzka et al.

(2020) evaluate 54 studies using satellite data to estimate the adoption of agricultural practices and their impact in developing countries. The authors find that remote sensing has been successfully applied to detect changes in agricultural practices and technologies and to estimate crop yields in various contexts. For example, Lobell et al. (2020) use Sentinel-2 imagery to assess the accuracy of maize yield estimation from satellite data with field measurements in an application in Uganda, and Hoffman et al. (2018) test the validity of various vegetation indices for monitoring crop yields in Ukraine. Despite these advances, Kubitzka and colleagues highlight that there are only few studies that analyze how the adoption of new technologies impacts agricultural yields.

In this context, some exceptions should be noted. For wheat production in Mexico, Ortiz-Monasterio and Lobell (2007) assess the impact of planting dates and weed infestation during the fallow period on yield, using vegetation indices derived from Landsat-7 satellite images, among other data sources. Bellora et al. (2017) also employ a vegetation index to quantify the biomass of crops produced in South Africa to analyze the causal relationship between crop diversity and its survival (resilience) and productivity. In a more recent contribution, Salazar et al. (2021b) combine three rounds of household surveys with the measurement of yields by two vegetation indices based on satellite images to estimate the long-term impact of irrigation adoption on the yields of family farmers in the Dominican Republic.

The literature provides ample evidence that smart subsidies, meaning the provision of co-financing and technical assistance for the implementation of new agricultural technologies, help to increase the productivity and income of family farmers. However, it is important to consider the timing between the moment of adoption and the resulting productivity gains. In this context, an impact evaluation combining household survey data with satellite observations makes it possible to analyze the accuracy of yield estimates, and to examine the dynamic impacts of such an intervention with high robustness.

### **3 The Program for Rural Development and Family Agriculture (PRODAF)**

#### *3.1 Family Farming in Argentina*

The agricultural sector in Argentina accounts for 8% of the gross domestic product (GDP) and is the main source of foreign exchange with exports totaling US\$ 36.17 billion (OECD, 2019). Between 1999 and 2014, total factor productivity (TFP) in Argentine agriculture grew at an annual average rate of 1.4% (Lema, 2015). However, this positive dynamic seen in the sector hides important differences within the country: farm production is dominated by extensive agriculture and the use of mechanization and modern technologies in the Pampas region in the western part of the country. Argentina's strong presence in the world food market is based on the strength of its business sector, which has leveraged the comparative advantages of production in the Humid Pampas (oilseeds and cereals, beef), through an intensive process of technological modernization and capital investment (ECLAC, 2010). In 2016, agricultural exports accounted for 64% of the country's total exports (OECD, 2019). By contrast, the family farming stratum,<sup>1</sup> distributed throughout the country in multiple productive enclaves, continues to face restrictions

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<sup>1</sup> Family farming consists of small farms, where the producer works directly on the farm and employs up to two paid non-family workers.

derived mainly from the scarcity of associated public infrastructure, along with low levels of private investment focused on optimizing farm activity. It is thus characterized by significant disparities.

Family farming is limited by the fact that it consists of smaller-scale and less efficient production units, mostly located outside the most favorable areas of the country. According to the 2002 National Agricultural Census, family farming represents 75% of the country's farms (more than 210,000) and occupies only 18% of the land under cultivation (30.9 million ha), with an average area of 142 ha, compared to the 1,839 ha of commercial farms in corporate agriculture (FAO, 2009). It accounts for 27% of the sector's gross value of production (GVP), generates 64% of agricultural employment at the national level, and is found mainly in regions outside the Pampas (70% of family farmers) (MAGyP, 2009). Important production sub-sectors for family farming, such as fruits and vegetables, livestock, dairy, and cotton, have seen opportunities for growth and expansion in recent years due to the increase in domestic consumption, as well as the increase in international prices.

However, family farming faces several important barriers that have resulted in low productivity and income levels: (i) *Lack of information and/or asymmetric information*: A study conducted by MAGyP found that 35% of the most capitalized family farmers lack access to technical assistance (ACEE, 2009), which hinders the adoption of technologies that conform to the productive and climatic characteristics of the production unit; (ii) *Limited access to financial resources*: Only 18% of the most capitalized family farmers in the provinces of Entre Ríos and Chaco had access to formal credit in 2009, compared to 30% of commercial farmers (ibid). Over 60% of family farmers reported that formal banking requirements were a barrier to accessing credit (ibid); (iii) *Small scale and low participation in associations*: On average, the most capitalized family farmers cultivate an area of 250 ha, compared to 1,550 ha for commercial farmers, which has consequences for the cost-effectiveness of technologies that require a certain scale of production. In addition, over 70% of these farmers were not part of any productive association that could facilitate production processes or market insertion (ibid).

Because of these barriers faced by the family farming stratum, the adoption of sustainable and efficient technologies is low, resulting in low levels of productivity and income. For example, for the chains prioritized by the PRODAF program, production gaps of between 14% and 50% were found in relation to experimental yields (Moscardi, 2011).

### 3.2 The PRODAF Program

The "*Program for Rural Development and Family Agriculture (PRODAF)*" was implemented by the Ministry of Agriculture, Livestock, and Fisheries (MAGYP) of Argentina for a total cost of US\$ 41 million, with partial financing from the Inter-American Development Bank. The program was implemented between 2013 and late 2019, with the objective of increasing agricultural income by boosting the productivity of family farmers in the provinces of Chaco and Entre Ríos in northeastern Argentina. To this end, the program supported the incorporation of new technologies and provided technical assistance and training to more than 2,000 farmers in both regions. In this context, PRODAF promoted the development of business plans at the individual farmer level, covering the following investment areas: (i) appropriate production technologies; (ii) facilitation of access to additional financing for technology adoption; and (iii) provision of technical assistance for business management. These investments were implemented through direct transfers to the beneficiaries in the form of non-reimbursable contributions (NRC). These NRC were intended to

partially cover the costs of implementing the business plans, and were limited to 35% or up to US\$ 12,000 of the expected costs. The Program additionally financed training activities for more than 100 private technicians to support the development of business plans and to facilitate the provision of effective technical assistance to the beneficiary farmers. This assistance was extended in each case for a maximum duration of one year, including three months for the preparation of the business plan, three months for its effective execution, and six months for post-implementation follow-up.

The program's target population consisted of the stratum of the most capitalized family farmers in the provinces of Chaco and Entre Ríos in northeastern Argentina. This stratum is defined as producers with farms of up to 1,000 ha in total area, up to 500 ha in production, and/or between 100 and 500 livestock units, and with up to two permanent paid workers. To define the geographic scope of the program, the following criteria were taken into account during the design of the intervention: (i) high concentration of family farmers in the target population; (ii) adequate public infrastructure for the activities of the target population in these territories; and (iii) relative economic importance and existence of technological gaps in the chains in which the potential beneficiaries are involved. Four production chains were selected, two in the Province of Chaco (cotton and livestock) and two in the Province of Entre Ríos (citrus and dairy products). Family farming has a strong presence in these chains in terms of gross value of production, export volume, and employment, as well as potential productivity.

The program offered a broad menu of technologies to farmers in these four chains, in order to address the various technological gaps observed in this stratum of family farmers based on individual producer demand and need. The menu of available technologies was selected according to economic and technical-environmental criteria that took into account: (i) the positive impact on the beneficiaries' net income; (ii) applicability to the agro-ecological conditions where its use is promoted; (iii) the promotion of sustainable agricultural practices; and (iv) the feasibility of objectively verifying their adoption. For cotton, the subsidies were used to improve production inputs, including improved seeds, planting, agrochemical use, and integrated pest control. In the livestock chain, business plans were oriented towards investments in watering areas, forage resources, fencing, machinery, and general infrastructure, taking into account the feeding, reproduction, and sanitary issues that dominate the sector. In the case of the dairy chain in Entre Ríos, investments were concentrated on herd feeding and dairy equipment, while the citrus segment invested mainly in plant replacement, fertilization, integrated pest control, crop quality, and post-harvest management. Table A in **Appendix A** presents the most relevant program-financed technologies in greater detail. Both the selection of the most appropriate technologies for each prioritized production chain and the training plans for technicians were developed in close coordination with the National Institute of Agricultural Technology (INTA) to ensure the greatest technical effectiveness.

The design of the program also envisaged the creation of a guarantee fund to overcome restrictions on access to credit for the co-financing of business plans. Although this fund was set up in 2014, it did not create enough demand among farmers due to several factors. In terms of the sector, there was little knowledge of the fund and a limited field presence to help make the service operational. In addition, macroeconomic conditions in the country led to high real interest rates, which played a part in farmers' aversion to debt. In this context, the promotion of access to financing during the program's implementation was not successful. However, a significant proportion of the beneficiary farmers were not registered taxpayers when they entered the

PRODAF program. In this context, the absence of a business management structure for the type of farmers in the four selected chains required an additional effort to incorporate them into the formal system, especially by regularizing their tax obligations and registering them in the National Sanitary Registry of Agricultural and Livestock Producers (RENSPA).<sup>2</sup> This regularization process had the additional effect of allowing the producer to access the official banking system by having the necessary formal documents once the tax requirements had been met. This mechanism may have had a positive impact on access to credit among beneficiary producers.

By the end of the program, 2,005 farmers had implemented a business plan with support from NRC and were provided with technical assistance for the adoption of new technologies. Seven hundred and ninety-five business plans were executed in the cotton chain, 565 in the livestock chain, 333 in the dairy chain, and 317 in the citrus chain. According to the theory of change presented in this section, PRODAF is expected to have contributed to the following objectives: In the short term, the provision of smart subsidies should have increased both the rate of new technology adoption and the rate of access to credit. As a direct result of these impacts, beneficiary farmers should experience significant improvements in the medium to long term in their production system, making it more efficient and effective in its input use and yield levels. This includes spending on production inputs, production and sales levels, and, finally, yields and income from production.

#### **4 Identification Strategy**

To determine the impact of the PRODAF program on the productivity and income of the beneficiary farmers, the evaluation must identify a counterfactual to answer the following question: “How would farmer productivity and income have developed if the program had not been implemented?” Of course, this is a hypothetical question that can only be answered by identifying a group of producers similar to the beneficiary farmers in terms of the characteristics that determine the relevant impact indicators. The main challenge in identifying the causal impact of the program is to select a control group that can plausibly satisfy the identifying assumption of difference-in-differences, i.e., for which the changes in the impact variables would likely be the same as those in the treatment group in the absence of treatment (parallel trends assumption).

When the program was approved, it was proposed that an impact evaluation be carried out to evaluate whether PRODAF succeeded in increasing the agricultural income of family farmers in the provinces of Chaco and Entre Ríos by improving their productivity (IDB, 2011). The methodological design was based on the difference-in-differences method, comparing the productive performance of two groups—a treatment group and a control group—before and after program implementation. Although a baseline survey was conducted in the fall of 2015, it failed to meet the methodological requirements needed to carry out the evaluation as initially conceived. The main problem was the failure to identify a sufficiently large control group to be able to successfully apply either the difference-in-differences methodology or propensity score matching, meaning that it was not possible to create a valid counterfactual to assess the program rigorously. In Chaco, only 67 farmers were identified and interviewed for the control group. In Entre Ríos, no non-beneficiary farmers were interviewed. In addition, the information collected from the

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<sup>2</sup> RENSPA is a mandatory registry for all primary production activities in the agricultural sector. It keeps production data up to date, strengthens sanitary controls, preserving animal and plant health and the quality, hygiene, and safety of agricultural products, inputs, and foodstuffs.

interviewed farmers was relatively limited, which did not allow for the reliable construction of key indicators regarding income, production, and productivity.

Because of these identified problems, the identification strategy for the PRODAF evaluation was revised in 2018. The identified strategy had a two-pronged approach. First, a new round of surveys was proposed among the farmers interviewed in 2015, complementing the original sample with a number of additional farmers in Entre Ríos and Chaco. This survey with a larger sample size would then make it possible to assess the program using a simple ex post difference combined with matching treatment and control group using retrospective information. Second, to measure the program’s impact on agricultural productivity despite the problems encountered during the baseline, a complementary line of research was also proposed that would take advantage of satellite data. Specifically, the endline of the evaluation compiled the georeferencing of cotton and citrus growers’ plots to measure the productivity of these crops through remote sensing.

The sample of treated farmers was randomly selected from the list of 1,078 farmers who participated in PRODAF between 2014 and 2017, that is, during the first four years of the program’s implementation. This decision was made to allow the productive changes implemented to develop over sufficient time to become an observable impact. To ensure comparability of farmers, 35 beneficiaries producing under a limited liability company (LLC) legal structure were expressly excluded from the sample, as their profile diverged in terms of the scale of production of a family farmer.

**Table 1. Sample distribution**

<b>Group</b> <b>Chain</b>	<b>Treatment group</b>	<b>Control group</b>	<b>Total</b>
<b>Cotton</b>	119	78	<b>197</b>
<b>Livestock</b>	197	142	<b>339</b>
<b>Citrus</b>	70	60	<b>130</b>
<b>Milk</b>	148	84	<b>232</b>
	<b>534</b>	<b>364</b>	<b>898</b>

The control group was made up from a list of farmers who produced within the same four chains in the provinces of Chaco and Entre Ríos, and who met the PRODAF eligibility criteria, but had not received (or applied for) funds from the program. As mentioned in the previous section, farmers in both provinces were eligible for the program if they had farms of up to 1,000 ha in total area, up to 500 ha in production, and/or between 100 and 500 livestock units, and with up to two permanent paid workers. A list of 601 farmers who met those criteria was obtained by working with the provincial MAGyP offices in Chaco and Entre Ríos. In the case of Chaco, this information came from the 2019 provincial cotton survey, and from an administrative list of livestock producers kept at the provincial level. In the case of Entre Ríos, the list of citrus farmers was obtained from the official registry of the Entre Ríos Citrus Federation,<sup>3</sup> and for the dairy chain it was obtained from INTA’s Dairy Sector Survey (ESL). Notably, in the case of the dairy chain, PRODAF was able to cover the entire provincial population of eligible farmers (approximately 330 farmers), so

<sup>3</sup> Since the list provided by the province was not long enough to reach the desired sample size, some 40 additional farmers were identified during the fieldwork using the snowball methodology.

the control group was selected from among farmers with the same characteristics in the provinces of Córdoba, Santa Fe, and Buenos Aires.<sup>4</sup>

The endline survey was carried out between March and June 2021. Initially, a total sample of 1,197 farmers from the four chains prioritized by PRODAF was planned; however, logistical and time constraints imposed by the COVID-19 pandemic meant that the sample was reduced to 982 farmers.<sup>5</sup> In addition, the fieldwork was met with a relatively high non-response rate related to the safety measures taken by the consulting firm in charge of the survey (e.g., initial contact by phone call and impossibility of meeting inside the home due to social distancing), besides other macroeconomic factors that affected farmers' willingness to participate in the survey (e.g., total meat export ban imposed by the national government during June 2021). The sampled farmers were geographically distributed across nine departments in the province of Chaco and five departments in the province of Entre Ríos. As shown in Table 1, the final survey sample totaled 898 surveys, with 534 treated farmers and 364 untreated farmers interviewed, and with some proportional variation by production chain.

## 5 Description of the Data

### 5.1 Survey of Agricultural Households

The questionnaire given to the selected agricultural households in the sample gathered detailed information on agricultural production and land characteristics, and consisted of the following modules: characterization of the production unit (PU) and plots, labor, agricultural production (temporary and permanent crops), livestock production (cattle and dairy), investments and technical assistance, problems in the production unit, equipment, credit and savings, organization and membership in associations, household and housing characteristics, and non-farm economic activities. The survey was based on the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) and was adjusted to take into account the local production context. For the dairy chain, the structure of the Dairy Sector Survey (ESL) developed by INTA was incorporated. In the case of the dairy control group, a limited version of the survey was used to update the information collected by the ESL annually by telephone. This action was due to the inability to mobilize field teams to locations outside the provinces of Chaco and Entre Ríos, again due to travel restrictions imposed by the national government of Argentina during the COVID-19 pandemic.

The production questions covered the 2019-2020 season, the timing of which varied slightly by production chain. With cotton, the last agricultural period covered the crop cycle planted in October 2019 and harvested between April and May 2020. For citrus, the agricultural cycle covered the period from March to December 2020. For livestock and dairy farming, the production cycle is July 2019 to June 2020. However, data were taken from the period of the last vaccination, which took place in October 2020 but was extended to January 2021 due to the pandemic. Some retrospective questions were also included for the 2014-2015 season.

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<sup>4</sup> The ESL (*Encuesta Sectorial Lechera*) was completed in 2019, and the productive indicators were updated by phone during the first quarter of 2021.

<sup>5</sup> Sampling was restricted due to the impossibility of interprovincial and interdepartmental travel because of travel restrictions in line with the health measures implemented by the national government of Argentina.

The following tables present variables describing the main productive and sociodemographic characteristics of the farmers, both for the control group and the treated group. Table 2 shows the descriptive statistics for the sociodemographic characteristics of the farmers, differentiating between the treatment group and the control group. It also includes productive characteristics derived from retrospective questions about the situation in 2015 (i.e., before treatment), including an equipment index, plot area, number of plots, and participation in associations. These variables are the same ones that will be used later for matching between treated and control groups, so here we also present the pre-matching balance between these variables for both groups.

It is worth clarifying how some of these variables were constructed. The dependency ratio is calculated as the ratio of household members outside working age (under 16 and over 65) to household members of working age (between 16 and 65), multiplied by one hundred. As for the proportion of households where at least one household member works outside the PU, this is calculated taking into account whether any household member reported working outside the PU as an employee for an employer, company, or organization, worked outside the PU independently, or had a company or microenterprise with at least one hired employee. The telecommunications services access index is calculated as the weighted sum of internet access and telephone signal access. The housing quality index is calculated as the weighted sum of the dichotomous variables of housing with good quality flooring, good quality roofing, good quality interior ceiling cladding, and housing with access to a paved road. The overcrowding index is calculated as the number of people living in the dwelling divided by the number of rooms in the dwelling. The variable on participation in associations refers to whether any member of the household belonged to a farmers' association, agricultural-livestock cooperative, federation, or similar organization during 2015. Finally, the equipment index was constructed as the proportion of equipment that the farmer reported owning in 2015, from a closed list of farm equipment. The list is the same for all chains and includes equipment such as tractors, mechanical shovel, pickup truck, light truck, harrow, harvester, and others.

Table 2 shows these statistics for the full sample, including and excluding dairy farms. In the specific case of the dairy chain, the questionnaire for the control group was a shorter and simplified version of the one used for the other chains and for the treatment group. The survey for the control group was also conducted by telephone. Therefore, many of the control variables, especially the sociodemographic variables, are not available for this subsample of the control group. Thus, although excluding the dairy sample decreases the total number of observations, it also allows us to include a larger number of variables for matching (see next section), including variables that characterize the farmer and his or her household, as well as the quality of housing and the household's access to various public services. Because the sampling for the two groups was conducted in different ways, there may be differences in the responses for the production variables section. Excluding this chain not only allows us to match a larger number of variables, but could also solve potential biases arising from differences between the control and treatment questionnaires. Therefore, part of our future analysis will be carried out excluding the dairy chain.



**Table 2: Productive and sociodemographic characteristics, full sample**

	<i>Full sample</i>			<i>Sample excluding dairy</i>		
	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>
<b>Sociodemographic variables</b>						
Farmer's age in 2020	53.52 (13.44)	53.23 (12.47)	-0.283	52.80 (13.77)	52.65 (12.89)	-0.150
Years of education of the farmer in 2020	11.99 (4.36)	11.69 (3.70)	-0.29	11.30 (3.95)	12.17 (3.94)	<b>0.874***</b>
Number of household members in 2020	2.94 (1.45)	3.10 (1.38)	0.16	2.94 (1.45)	2.95 (1.30)	0.015
Dependency ratio in 2020	32.99 (50.92)	31.08 (49.35)	-1.913	33.23 (51.02)	32.03 (50.54)	-1.193
Proportion of farmers who are women	0.09 (0.28)	0.08 (0.28)	-0.006	0.09 (0.29)	0.09 (0.29)	0.004
Proportion of farmers who are married	0.67 (0.47)	0.79 (0.41)	<b>0.112***</b>	0.67 (0.47)	0.76 (0.43)	<b>0.090**</b>
Proportion of households where at least one household member works outside the PU	0.35 (0.48)	0.39 (0.49)	0.043	0.35 (0.48)	0.45 (0.50)	<b>0.103***</b>
Distance from the house to the road in km	7.48 (3.60)	7.29 (3.58)	-0.182	7.51 (3.59)	7.06 (3.65)	-0.452
Proportion of households with internet access at home	0.65 (0.48)	0.82 (0.38)	<b>0.171***</b>	0.65 (0.48)	0.78 (0.41)	<b>0.136***</b>
Proportion of households with access to a good quality telephone signal at home	0.33 (0.47)	0.52 (0.50)	<b>0.191***</b>	0.33 (0.47)	0.54 (0.50)	<b>0.212***</b>
Telecommunications services access index	0.49 (0.38)	0.67 (0.35)	<b>0.181***</b>	0.49 (0.38)	0.66 (0.37)	<b>0.174***</b>
Proportion of dwellings with good quality flooring	0.22 (0.41)	0.14 (0.35)	<b>-0.077***</b>	0.22 (0.41)	0.17 (0.37)	<b>-0.052*</b>
Proportion of dwellings with good quality roofing	0.18 (0.39)	0.18 (0.38)	-0.002	0.18 (0.39)	0.23 (0.42)	0.051
Proportion of dwellings with good quality interior ceiling cladding	0.90 (0.30)	0.97 (0.18)	<b>0.069***</b>	0.90 (0.31)	0.96 (0.21)	<b>0.06***</b>
Proportion of households with access to a paved road	0.22 (0.42)	0.38 (0.48)	<b>0.153***</b>	0.23 (0.42)	0.42 (0.49)	<b>0.197***</b>
Housing quality index	0.38 (0.18)	0.41 (0.19)	<b>0.036**</b>	0.38 (0.18)	0.44 (0.20)	<b>0.064***</b>
Overcrowding index	1.11 (0.54)	1.08 (0.50)	-0.024	1.10 (0.54)	1.05 (0.49)	-0.050

**Table 2 (continued).** Productive and sociodemographic characteristics, full sample

	<i>Full sample</i>			<i>Sample excluding dairy</i>		
	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>
<b>2015 Production variables</b>						
2015 equipment index	0.14 (0.16)	0.25 (0.19)	<b>0.107***</b>	0.14 (0.16)	0.19 (0.17)	<b>0.050***</b>
Total land area (ha) in 2015	185.73 (251.00)	226.51 (336.08)	<b>40.777*</b>	197.01 (280.15)	279.16 (380.55)	<b>82.150***</b>
Number of plots into which the PU is divided in 2015	1.06 (1.44)	2.50 (3.11)	<b>1.438***</b>	1.05 (1.42)	1.75 (2.50)	<b>0.700***</b>
Belonged to any farmers' association/organization during 2015	0.09 (0.29)	0.14 (0.35)	<b>0.049**</b>	0.09 (0.29)	0.14 (0.34)	<b>0.044*</b>
Livestock proportion	0.39 (0.49)	0.37 (0.48)	-0.018	0.51 (0.50)	0.51 (0.50)	0.003
Dairy proportion	0.23 (0.42)	0.27 (0.45)	0.039	-	-	-
Cotton proportion	0.21 (0.41)	0.22 (0.42)	0.011	0.28 (0.45)	0.31 (0.46)	0.030
Citrus proportion	0.39 (0.49)	0.37 (0.48)	-0.018	0.51 (0.50)	0.51 (0.50)	0.003
<b>Observations</b>	<b>366</b>	<b>532</b>		<b>280</b>	<b>386</b>	
Note: Standard deviation in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***), 95(**) or 90 (*).						

As shown in Table 2, there are several significant differences between the treatment group and the control group. At the sociodemographic level, it is noted that the beneficiary farmers tend to live in better conditions in terms of access to certain services and the quality of their housing. However, the farmers themselves do not differ in their personal characteristics. At the production level in the base year, the production units in the treatment group tend to be larger, have more plots of land, and have more equipment than the control group. Regarding certain farmer characteristics, it is interesting to note that a higher proportion of farmers in the treatment group belonged to an association in 2015. Because of these significant differences, it is important to use econometric methodologies to address potential biases resulting from these divergences, as described in the following section.

In **Appendix B**, Tables B1 and B2 present the same results, but for the four chains separately. The differences between treatment and control groups, when observed by chain, are similar to those found in the full sample, with some exceptions.

## 5.2 Normalized Difference Vegetation Index (NDVI)

As a complementary data source, the evaluation takes advantage of the availability of satellite data to measure cotton and citrus crop yields through remote sensing. When the survey was conducted among the sample of farmers in 2021, georeferenced information was collected for all the parcels owned or worked by the farmer. At the beginning of each interview, the interviewer asked the farmer to identify the location of each plot on a digital map of the area, thus marking the polygon of the plot based on the identification of the extreme corners marking its boundaries.

Due to the logistical constraints posed by the COVID-19 pandemic, it was impossible to physically survey each plot, as the interviewers had to maintain physical distance and not share a vehicle with the interviewee. Therefore, there may be some inaccuracies in the identification of the polygons. However, the polygons were processed thoroughly, using plot visualization to correct any remotely detected inaccuracies (e.g., visual examination of the georeferenced polygons allowed plot boundaries to be adjusted if planting areas diverged slightly from the measured area). In all, this process resulted in 262 georeferenced plots in the cotton chain and 190 georeferenced plots in the citrus chain, for a total of 195 and 126 farmers, respectively.

The georeferencing of this subsample was used to measure agricultural yields remotely. A common measurement indicator in this context is the Normalized Difference Vegetation Index (NDVI). The NDVI is a remote sensing index that measures the level of vegetation in a given area. First, this level of greenness indicates the density of biomass present in the evaluated area, that is, the presence or absence of crops. The NDVI also functions as a measure of the health of the plants observed. This is because healthy vegetation absorbs most of the visible light from the sun (RED), and reflects more near-infrared light (NIR) during photosynthesis (Kinyanjui, 2011; Lillesand & Keifer, 2002). Where there are no plants or stressed plants (e.g., dehydrated plants), plants do not photosynthesize efficiently and therefore do not absorb as much RED or reflect as much NIR as healthy vegetation. Plant health is also a good indicator of productivity, since a greater capacity to photosynthesize means more energy to produce seeds (Bégué et al., 2018). NDVI is calculated as the difference between NIR and RED, divided by the sum of the two ( $NDVI = (NIR - RED)/(NIR + RED)$ ). Numerous studies have confirmed the validity of NDVI for accurately estimating the level of and changes in yields (see Bégué et al., 2018; Chivasa et al., 2017).

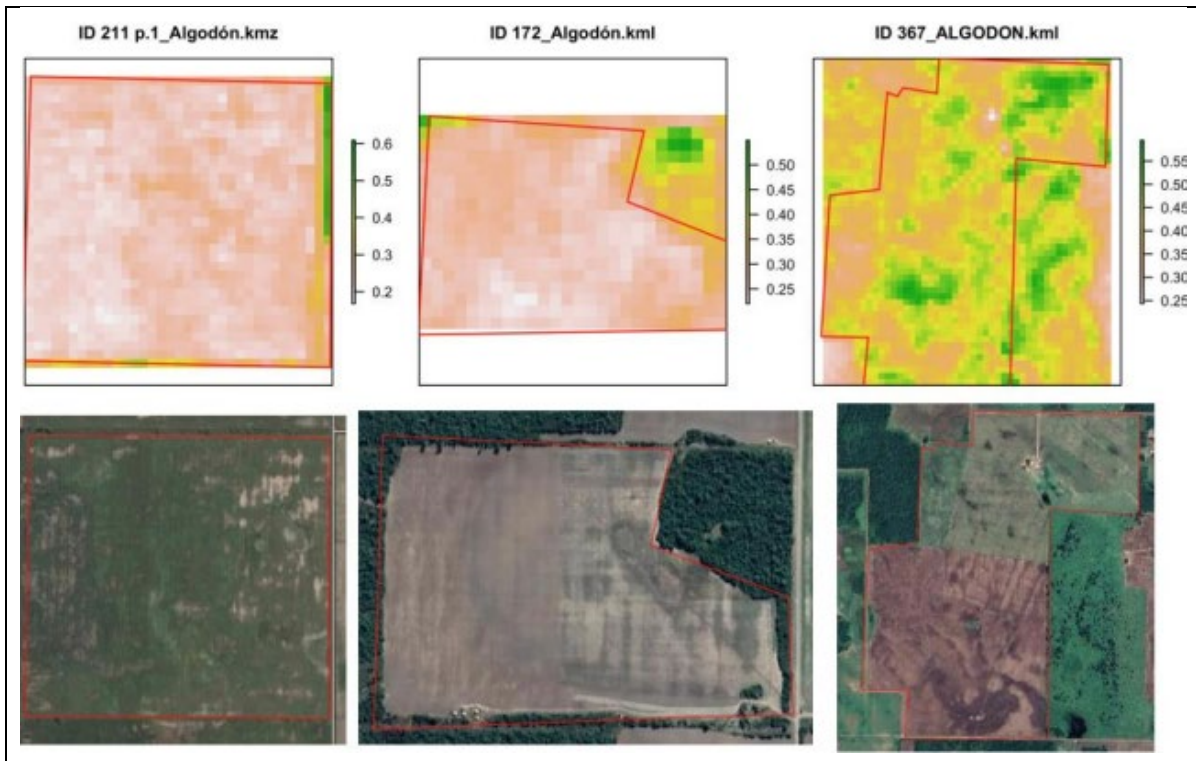
To construct the NDVI, we used NASA satellite images (Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced, Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI)) for the period between January 2010 and December 2020.<sup>6</sup> Using the georeferenced information from the cotton and citrus plots, we were able to collect satellite imagery of the study plots and calculate the NDVI for each one using pixel data, following a methodology similar to Huang et al. (2019). Figure 1 provides a visual example of this NDVI data for some cotton plots. Figure 2 shows the same for citrus plots.

Satellite images are collected every 16 days. An average monthly NDVI variable was constructed for each plot between January 2010 and December 2020 using these data. Throughout this study, the analysis will be carried out at the PU level rather than at the plot level. Thus, we construct information at the production unit level from the pixel-weighted sum of all the plots within the production unit.

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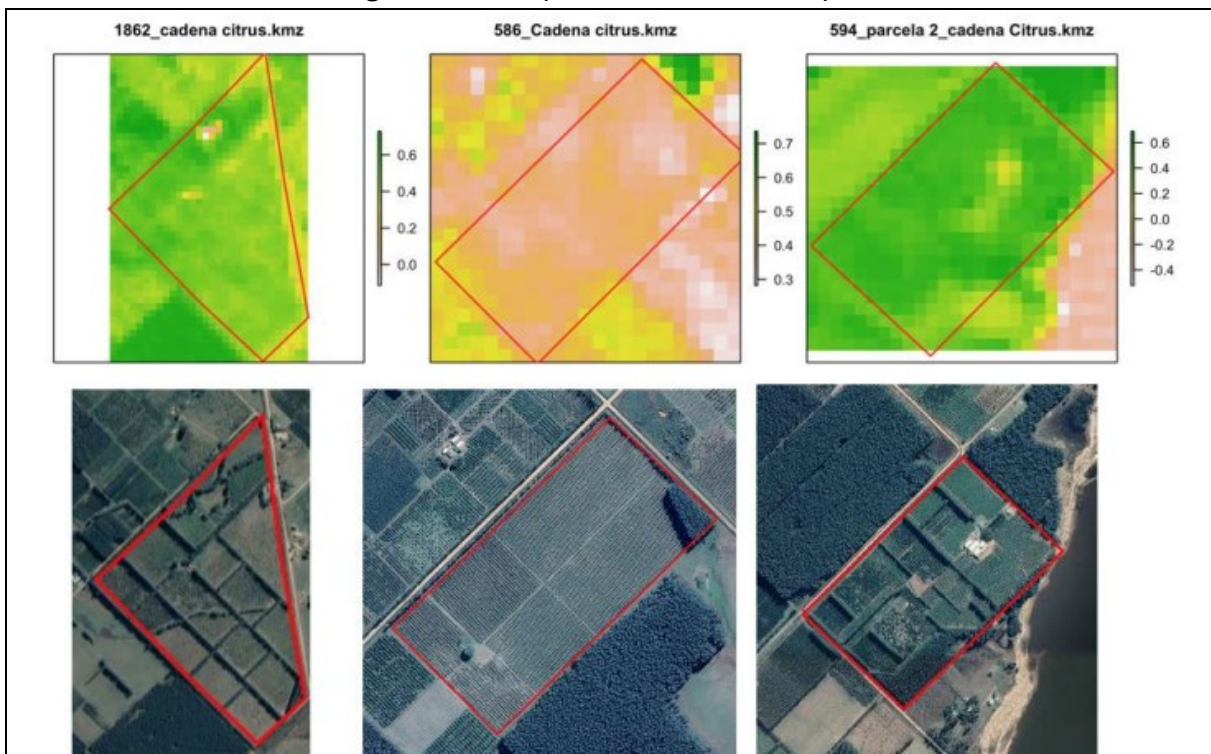
<sup>6</sup> The geospatial data were collected and processed by Applied Geosolutions (2021).

**Figure 1.** Example of NDVI for cotton plots



Source: Applied Geosolutions (2021).

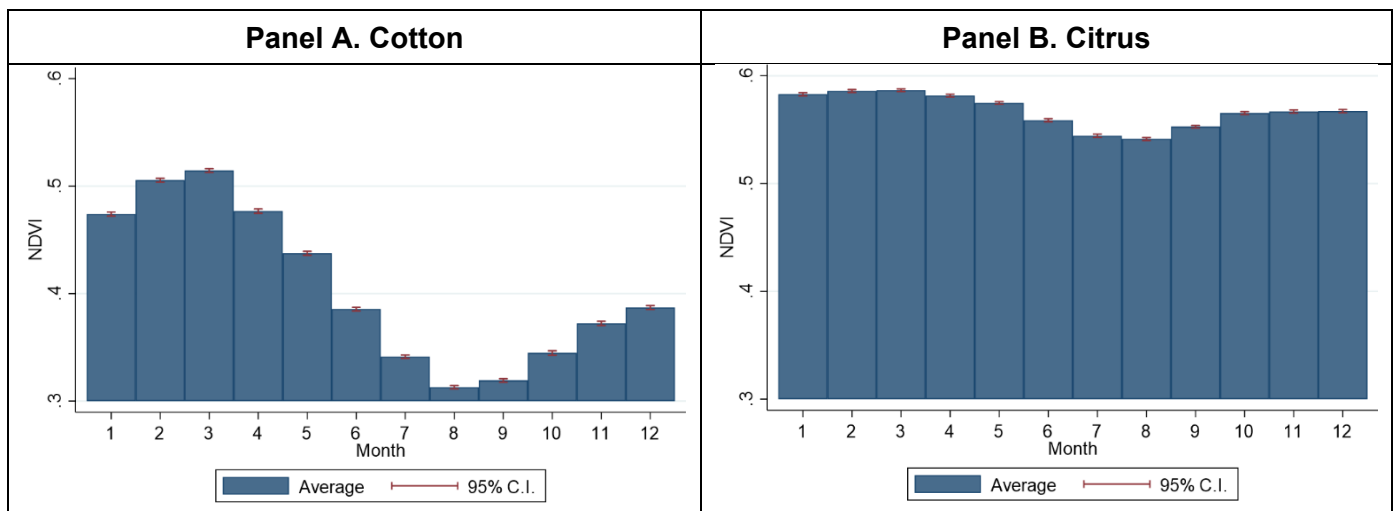
**Figure 2.** Example of NDVI for citrus plots



Source: Applied Geosolutions (2021).

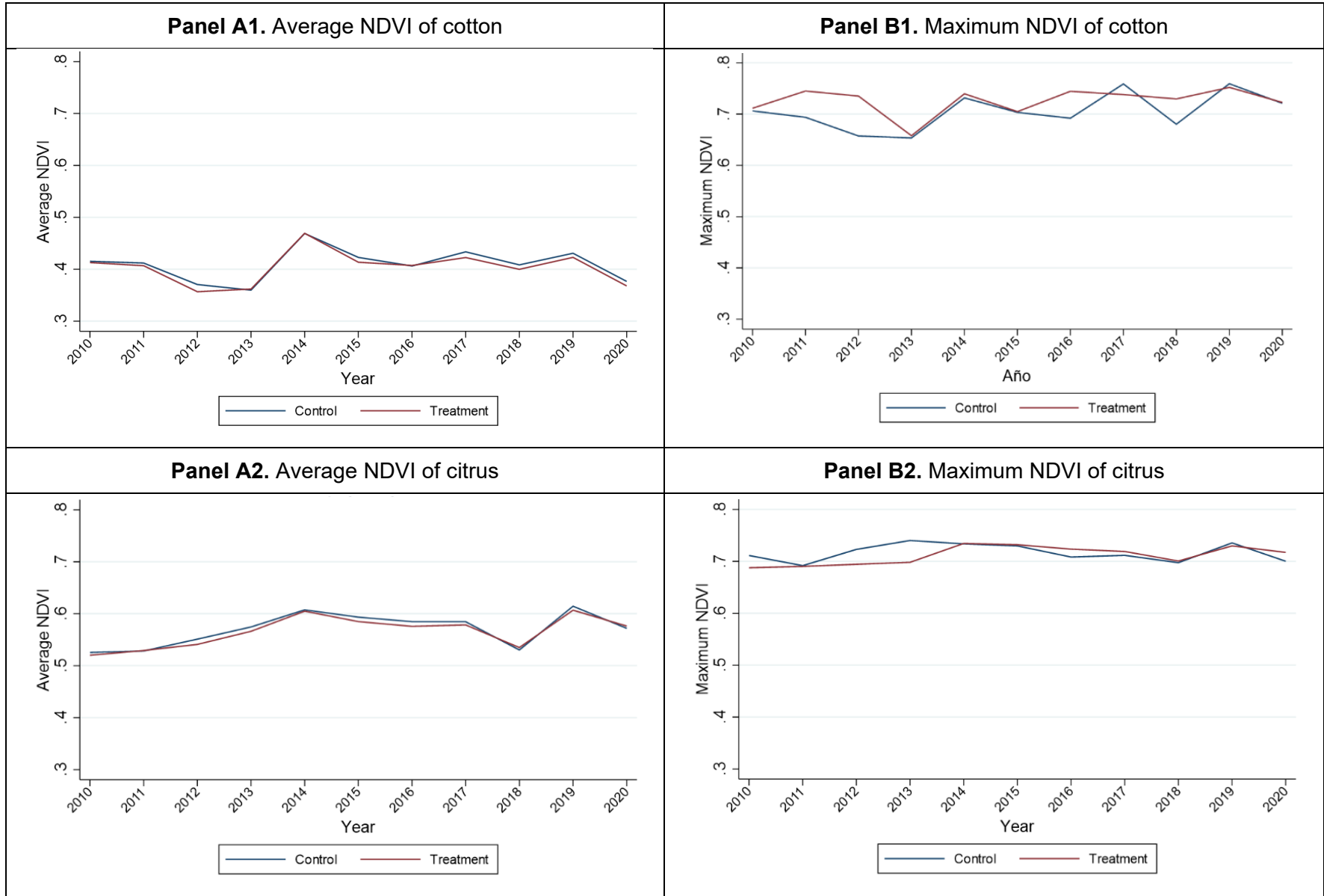
As we know, the NDVI indicates the biomass density present in the evaluated area. In the case of cotton, the NDVI shows the different stages of the agricultural cycle, so we should observe significant changes in the NDVI between periods. In contrast, in the case of citrus as a perennial crop, the NDVI should detect smaller changes in the health of the tree leaves, so we expect less monthly variability. Graph 1 shows the average monthly NDVI for the cotton and citrus chains, respectively, including a 95% confidence interval. As seen in the graphs, the NDVI data for cotton show a large month-to-month variation, while those for citrus remain relatively constant. As discussed above, this difference in distributions is due to the differences in cotton and citrus production. While cotton is a seasonal crop that is usually planted in September, citrus crops are permanent and are not cyclical like cotton. We also note that the average monthly NDVI is higher for citrus crops in all months, due to the number of leaves found on citrus trees.

**Graph 1. Monthly NDVI averages by chain**



For longitudinal analysis purposes, two NDVI-based measurements were constructed. First, the average annual NDVI value was constructed, assuming that a significant change in crop health and harvest potential is reflected in a higher level of average annual NDVI. Second, the maximum annual NDVI value was constructed to more directly capture the highest greenness value in each agricultural cycle, which should reflect the time of harvest and therefore an appropriate measurement of yield. Graph 2 shows both measures of NDVI, the average annual NDVI (Panel A) and the maximum annual NDVI (Panel B), for cotton and citrus, for both the control and treated groups.

**Graph 2. Average and maximum NDVI by year and group**



As shown in the first graph, the average NDVI is very similar for both groups, with the average NDVI of the control group being slightly higher in most periods. When we look at the annual maximums, we see an inverse situation for most periods, with a few exceptions. However, both groups seem to follow a similar trend, most clearly observable in the case of the average NDVI. With the citrus chain, the average NDVI is again similar for both groups. In observing the maximum NDVI, we can see that the groups follow a similar, albeit less marked, trajectory.

Although the above graphs allow us to observe annual changes in NDVI for the control and treatment group, it is impossible to draw a clear line that temporarily separates “before PRODAF” and “after PRODAF,” since farmers benefitted from the program in different years. Most of the farmers participated in the program between 2014 and 2018. Therefore, the analysis was based on calculating the number of years that had passed since the intervention was carried out. Farmers were treated in different months, so a farmer was considered to have received treatment during the year if it was received before July, in order to closely align the allocation with the agricultural cycles of both chains. If the farmer received treatment after July, then it was considered to have been received the following year.

## 6 Empirical Strategy

### 6.1 *Inverse Probability Weighting (IPW)*

Because PRODAF was not randomly distributed, the control group may not be a good counterfactual for the beneficiary group, since there is a risk of self-selection for the treatment group. If this is the case, the simple comparison between control and treatment groups could introduce endogeneity and lead to biased results. Econometric strategies must therefore be used to perform an analysis that leads to unbiased results. The first strategy we will employ, based on the agricultural household survey data, will be *Inverse Probability Weighting (IPW)*. IPW uses observable characteristics to adjust the distribution of treatment and control to ensure similarity. In this context, IPW as a matching method has been widely used to address concerns of self-selection bias (Titus, 2007; Ye & Kaskutas, 2009; Schling & Winters, 2018).

IPW, initially proposed by Rosenbaum (1987) and by Hirano and Imbens (2001), uses the inverse of the estimated propensity scores to generate regression weights. The aim is to synthetically construct a counterfactual from a control group selected to create a sample similar to that resulting from a randomized experiment. Since propensity scores are estimated on the basis of observable characteristics, the method is based on the assumption of conditional independence, which means that there are no unobservable differences between groups in terms of the characteristics that affect program outcome (Rosenbaum & Rubin, 1983).

It is important to note that propensity score matching (PSM), first introduced by Rosenbaum and Rubin (1983), is a viable alternative approach for addressing sources of endogeneity. However, we believe that the IPW approach has several advantages. As Todd et al. (2010) point out, IPW achieves a synthetic counterfactual and does not restrict the sample to the common area of support and thus uses all available data. In addition, a key advantage over PSM is that its parametric specification allows for the estimation of ordinary standard errors in a regression framework, simplifying further analysis (Cavatassi et al., 2011).

The inverse propensity weights  $\omega_i$  for observation  $i$  were obtained using the following model, where  $Treatment_i$  is a dichotomous variable that takes the value of 1 if the individual is treated and 0 otherwise, and  $p(Treatment_i)$  is the estimated propensity score, which defines the probability of being treated:

$$\omega_i = \left( \frac{Treatment_i}{p(Treatment_i)} + \frac{1-Treatment_i}{1-p(Treatment_i)} \right) \quad (1)$$

Thus, the IPW assigns greater weight to farmers in the treated group with lower propensity scores, and greater weight to non-beneficiary farmers who are more likely to participate in the program. This process adjusts the kurtosis of the distribution of both groups to an area of greater overlap and eliminates the bias of the observable characteristics of the sample (Cavatassi et al., 2011).

Six IPW estimates were made. The first estimate includes the entire sample, i.e., the set of the four chains. Although this estimation has the advantage of having the largest number of observations, it has limitations. The main limitation is that certain key sociodemographic variables of the dairy chain are not available for the control group, which reduces the number of variables available to calculate the propensity score. In total, only seven variables can be included to estimate the propensity score in this case: productive hectares, years of education of the farmer, age of the farmer, and four dichotomous variables denoting the chain to which the farmer belongs. This limitation also affects the possibility of eliminating sources of bias among the full sample.

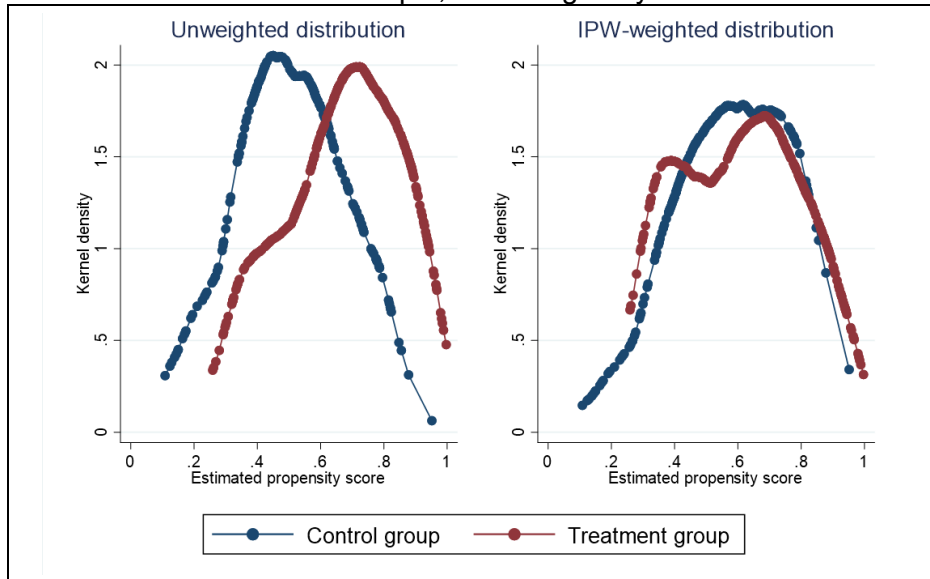
To remedy this deficiency, the second estimate includes only the livestock, cotton, and citrus chains, excluding the dairy chain. Although it reduces the sample size, this definition allows us to use a larger number of variables to calculate the propensity score. In all, 27 variables are used for this matching. Besides the variables used in the previous case, this estimation includes the 2015 equipment index, the number of plots in 2015, a dichotomous variable that determines whether the farmer belonged to an association during 2015, and sociodemographic variables: household size, dependency ratio, sex of the farmer, marital status of the farmer, overcrowding index, distance to the road, whether the household has internet access, and housing quality, among others. The third, fourth, fifth, and sixth estimates are made separately for the livestock, dairy, cotton, and citrus chains, respectively. This analysis makes it possible to examine the differential impact on each prioritized chain. Once again, the estimate for the dairy chain has fewer variables than the others, which leads to the same problems described above.

Graph 3 presents the distribution of propensity scores for the treatment and control groups, before and after weighting, for the full sample excluding dairy. We note that IPW makes it possible to achieve a high degree of overlap between the distributions of the treated and control groups. **Appendix C** presents the same figures, but for the sample that includes dairy, and the subsamples for each of the four chains.

Table 3 presents the productive and sociodemographic characteristics, as reported in Table 2, but this time after weighting by IPW. Again, results are shown for the full sample and the sample excluding dairy. In **Appendix B**, Tables B3 and B4 show the same analysis for the chains separately.



**Graph 3.** Distribution of propensity scores with and without IPW, full sample, excluding dairy



The analysis in Table 3 shows that the IPW had varying degrees of success in achieving balance in observable variables. For the full sample, which includes the dairy chain, the balance of observable variables is quite similar to what it was before weighting. In fact, we now find significant differences in variables such as the number of household members and the likelihood that at least one household member works outside the PU. However, a better balance was achieved in terms of total PU area and a decrease in the preexisting bias in the equipment index and the number of plots. By contrast, the IPW was very successful in reducing existing biases in the full sample that excluded the dairy chain, to the point that the control and treatment groups are completely balanced with respect to both sociodemographic and production variables. Since a considerably higher success rate is achieved for the sample that excludes dairy farms and therefore allows matching on a larger number of covariates, we consider that only this specification will allow us to identify the causal impact of PRODAF. For this reason, our results that aggregate the chains will present only the version that excludes the dairy chain.

The tables in **Appendix B** evaluating chains separately show that the IPW weighting achieved a perfect balance for the livestock, cotton, and citrus chains. In the case of the dairy chain, weighting by IPW poses problems in achieving a balance in the number of household members, but corrects the imbalance in hectares and years of education that existed prior to weighting. In general, the absence of key variables for the control group in this chain creates problems for evaluating effects using the IPW technique. However, the results for the dairy chain will be presented as illustrative, albeit with the methodological caveats mentioned above.

**Table 3.** IPW-weighted productive and sociodemographic characteristics, full sample

	<i>Full sample</i>			<i>Sample excluding dairy</i>		
	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>
<b>Sociodemographic variables</b>						
Farmer's age in 2020	53.36 (13.08)	53.37 (12.50)	0.010	53.11 (13.13)	52.98 (13.15)	-0.128
Years of education of the farmer in 2020	11.83 (4.38)	11.84 (3.76)	0.015	11.85 (4.01)	11.91 (4.02)	0.058
Number of household members in 2020	2.92 (1.40)	3.11 (1.40)	<b>0.195*</b>	2.93 (1.38)	2.95 (1.32)	0.026
Dependency ratio in 2020	35.09 (51.51)	30.75 (48.38)	-4.342	33.27 (51.01)	33.94 (51.80)	0.675
Proportion of farmers who are women	0.09 (0.28)	0.10 (0.29)	0.008	0.09 (0.29)	0.10 (0.30)	0.003
Proportion of farmers who are married	0.74 (0.44)	0.82 (0.38)	<b>0.081**</b>	0.76 (0.43)	0.78 (0.41)	0.023
Proportion of households where at least one household member works outside the PU	0.34 (0.48)	0.41 (0.49)	<b>0.066*</b>	0.43 (0.50)	0.43 (0.50)	-0.001
Distance from the house to the road in km	7.37 (3.64)	7.30 (3.63)	-0.071	7.29 (3.55)	7.18 (3.69)	-0.115
Proportion of households with internet access at home	0.66 (0.47)	0.82 (0.38)	<b>0.159***</b>	0.72 (0.45)	0.74 (0.44)	0.015
Proportion of households with access to a good quality telephone signal at home	0.29 (0.46)	0.53 (0.50)	<b>0.238***</b>	0.41 (0.49)	0.44 (0.50)	0.029
Telecommunications services access index	0.48 (0.37)	0.68 (0.35)	<b>0.198***</b>	0.57 (0.38)	0.59 (0.38)	0.022
Proportion of dwellings with good quality flooring	0.21 (0.41)	0.13 (0.34)	<b>-0.086***</b>	0.17 (0.38)	0.17 (0.37)	-0.006
Proportion of dwellings with good quality roofing	0.16 (0.37)	0.17 (0.37)	0.005	0.17 (0.38)	0.18 (0.39)	0.013
Proportion of dwellings with good quality interior ceiling cladding	0.90 (0.30)	0.96 (0.18)	<b>0.065***</b>	0.93 (0.25)	0.95 (0.23)	0.014
Proportion of households with access to a paved road	0.23 (0.42)	0.38 (0.49)	<b>0.155***</b>	0.35 (0.48)	0.36 (0.48)	0.004
Housing quality index	0.38 (0.18)	0.41 (0.19)	<b>0.035**</b>	0.41 (0.18)	0.41 (0.20)	0.006
Overcrowding index	1.12 (0.56)	1.09 (0.50)	-0.035	1.08 (0.53)	1.08 (0.51)	-0.003

**Table 3 (continued).** Productive and sociodemographic characteristics, full sample

	<i>Full sample</i>			<i>Sample excluding dairy</i>		
	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>	<b>Control group</b>	<b>Treatment group</b>	<b>Difference</b>
<b>2015 Production variables</b>						
2015 equipment index	0.14 (0.15)	0.24 (0.19)	<b>0.094***</b>	0.18 (0.19)	0.17 (0.16)	-0.008
Total land area (ha) in 2015	205.52 (254.03)	212.08 (307.17)	6.556	209.22 (278.54)	241.13 (345.17)	31.913
Number of plots into which the PU is divided in 2015	1.16 (1.43)	2.47 (3.01)	<b>1.310***</b>	1.62 (2.07)	1.62 (2.25)	0.002
Belonged to any farmers' association/organization during 2015	0.09 (0.29)	0.15 (0.36)	<b>0.060**</b>	0.11 (0.32)	0.12 (0.32)	0.005
Livestock proportion	0.40 (0.49)	0.40 (0.49)	-0.002	0.56 (0.50)	0.54 (0.50)	-0.015
Dairy proportion	0.24 (0.43)	0.24 (0.43)	0.003	-	-	-
Cotton proportion	0.18 (0.39)	0.19 (0.39)	0.001	0.23 (0.42)	0.25 (0.43)	0.014
Citrus proportion	0.17 (0.38)	0.17 (0.38)	-0.001	0.21 (0.41)	0.21 (0.41)	0.001
<b>Observations</b>	<b>366</b>	<b>532</b>		<b>280</b>	<b>386</b>	
Note: Standard deviation in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***), 95(**) or 90 (*).						

## 6.2 Longitudinal Analysis

Using the longitudinal data collected through remote sensing, our study incorporates a second empirical strategy to analyze the impact of PRODAF on productivity, estimated by NDVI. The longitudinal NDVI data obtained from remote sensing allow us to include pre-intervention data for the cotton and citrus chains and complement the survey data. Therefore, our strategy consists of observing the changes in average and maximum annual NDVI in the treated production units compared to the control production units, both before and after the PRODAF intervention.

To perform this analysis, we use two strategies. First, we apply the *Difference-in-Differences* (DID) methodology. In general, this methodology makes it possible to control for observable and unobservable differences over time, thus addressing the potential self-selection bias that was highlighted as a possible threat to the robust estimation of PRODAF's impact. The DID model uses the following formula:

$$NDVI_{it} = \alpha + \beta_1(Treatment \times YearPost) + \beta_2Tratamiento + \beta_3YearPost + \delta_i + \varepsilon_{it}, \quad (2)$$

where  $NDVI_{it}$  is the NDVI measure to be used, either average annual or maximum annual NDVI, of year  $t$ , for UP  $i$ . The model includes fixed effects  $\delta_i$  at the PU level, which allow us to control for the characteristics of each PU that remain constant over time. It should be noted that the addition of fixed effects at the PU level as controls is possible thanks to the temporal nature of NDVI data, which allows the same PU to be observed over a 10-year period. The main advantage of using fixed effects at the PU level compared to the inclusion of survey covariates is that it

makes it possible to control for unobservables that remain constant over time. The *Treatment* variable takes the value of 1 if the PU belongs to the treated group and 0 otherwise. The dichotomous variable *YearPost* takes the value of 1 if the year  $t$  is after treatment, or the year of treatment itself, and 0 otherwise. This description does not apply to the control group, which never receives treatment. For the control group, however, we considered the average year in which treatment was received by the beneficiaries and assigned that year to the farmers in the control group. This year was 2015 for the cotton sample and 2017 for the citrus sample. The interaction between this variable and the treatment variable will take the value of 1 only in the case of a PU in the treated group in a later year or in a year equivalent to the year of treatment. In this model, the coefficient of interest,  $\beta_1$ , provides us with the average impact of PRODAF on NDVI for the post-treatment period.

The main assumption for the validity of this estimate is that the parallel trends assumption is met; that is, in the absence of treatment, both the control group and the treatment group would have followed the same trend in terms of NDVI. Both groups need not have the same NDVI level before treatment, but the trends should be similar. As observed in Graph 2 in the previous section and discussed earlier, both groups follow a very similar trend over time, for both the cotton and citrus chains. This seems to suggest that the assumption holds for pre-treatment periods. However, not all beneficiaries were treated simultaneously, so this graph only establishes an approximate impression. The second strategy used, which will be discussed in greater detail in the following paragraphs, more rigorously confirms that this assumption has been met.

While this model serves to find average effects, it does not consider differences in years of program receipt. As highlighted in Section 2, temporal dynamics can be key to the materialization of productive impacts. In this context, it is particularly relevant that PRODAF did not provide the smart subsidies to all farmers at the same time, but rather that the implementation was rolled out over several years. This temporal distribution of treatment may affect the average impact on yields, thus obscuring potentially significant impacts among those farmers who received treatment in the first years of execution. To incorporate this feature of the program's application and take full advantage of the longitudinal nature of the data, our second strategy consists of an event study model. This model not only facilitates a better understanding of the temporal dynamics between program implementation and productivity effects, but also allows us to corroborate the parallel trends assumption.

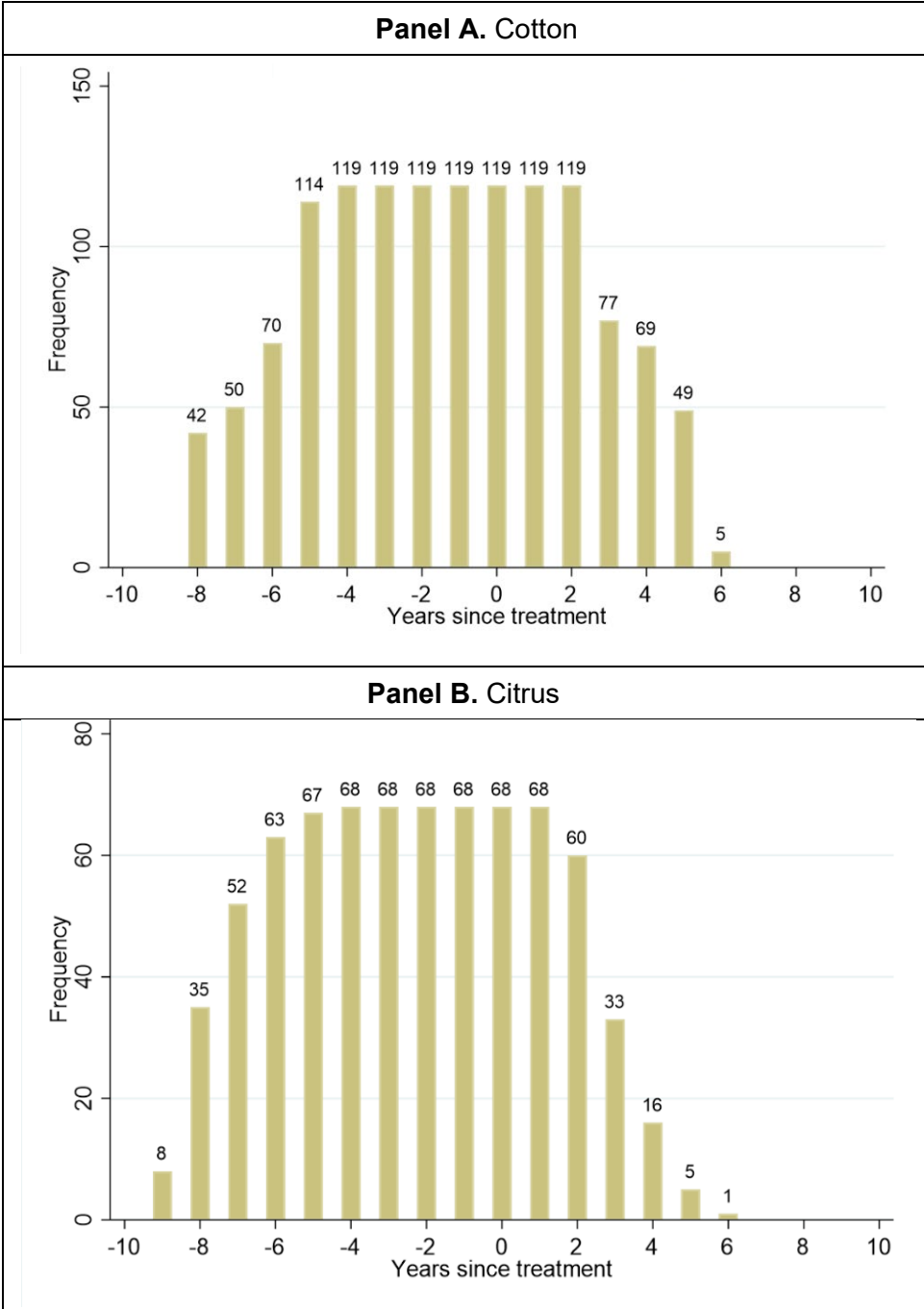
To perform this analysis, we use the following model (following Miller's model, 2021):

$$NDVI_{it} = \alpha + Treatment_i \times \sum_{y=-8, y \neq -1}^{y=6} \beta_y I(t - t_i^* = y) + \theta_t + \delta_i + \varepsilon_{it}, \quad (3)$$

where  $NDVI_{it}$  is the maximum or average NDVI in year  $t$ , for PU  $i$ ;  $Treatment_i$  is a dichotomous variable that takes the value of 1 if the PU is part of the treatment group and 0 otherwise,  $\theta_t$  are fixed effects of the year and  $\delta_i$  are fixed effects at the PU level. The expression  $\sum \beta_y I(t - t_i^* = y)$  represents the sum of a set of dichotomous variables indicating years before treatment ( $y < 0$ ), the year of treatment ( $y = 0$ ), and years after treatment ( $y > 0$ ). Given that the database is at the PU level, the dichotomous variable for each year relative to treatment ( $y$ ) will take the value of 1 if the observation year ( $t$ ) coincides with the year of treatment. Since the PU in the control group are not treated in any period, the dichotomous variables  $I(t - t_i^* = y)$  take the value of 0 for all years. The year immediately before treatment ( $y = -1$ ) is an omitted variable. Therefore, the coefficients  $\beta_y$  should be interpreted as the difference generated by being in the treatment group

for the year  $y$ , compared to the year immediately before treatment ( $y = -1$ ). Thus, our coefficients of interest are all of the  $\beta_y$ , for  $y \geq 0$ , as these represent the differences between treatment and control groups after the treatment period. The coefficients  $\beta_y$  for pre-treatment years serve as a test of the pre-treatment parallel trends assumption and should be significantly indifferent from zero. The error term is represented by  $\varepsilon_{it}$ . Estimates were made with ordinary least squares (OLS) and robust standard errors.

**Graph 4.** Distribution of years relative to treatment



Graph 4 shows the distribution of years relative to treatment (variable  $y$ ) for both the cotton chain (Panel A) and the citrus chain (Panel B). This distribution reflects the pace of implementation of the PRODAF program, where beneficiary farmers began participating in the program after a provincial approval committee (PAC) reviewed and approved their respective business plans. The PAC met several times a year to review the business plans of a variable number of farmers who had prepared their business plans in coordination with the program's technical assistants. The time of treatment reflects the date of approval of the business plan by the PAC, as this was the most reliable and consistently recorded date for all beneficiary farmers.

The graphs then show the total number of farmers in the treatment group for whom we have NDVI data for each year before, during, and after treatment. No information is shown for the PU in the control groups, since they never received treatment. The intervention year is defined as year zero (0). The years after year zero show the number of years that have passed since the intervention. The years before zero (defined as negative years) are the periods before the treatment period, with year -1 being the year immediately preceding PRODAF.

Considering that the cotton treatment group has 119 observations, we know that we have information for the entire sample for four years before the intervention and up to two years after the intervention. In the citrus chain, where the total number of treated observations is 68, we know that we have information for the entire sample for the period between four years before and one year after the intervention. In both cases we have few observations with information beyond six years after the intervention. Due to the low variability of that variable, we will exclude from the sample the few PU that received treatment during 2013 and that show results for six years after treatment. For citrus, we will also exclude cases treated in 2014 due to the small number of observations.

## **7 Results**

### *7.1 Results Derived from the Survey*

The results of the inverse probability weighting for the medium- and long-term impact indicators are shown in Table 5. We find that PRODAF succeeded in achieving its objectives in the short term, given that there are positive and statistically significant impacts on the likelihood of accessing credit and the rate of technology adoption. For the total sample (excluding dairy), estimates indicate that the likelihood of accessing credit increased by 47 percentage points, while the likelihood of adopting a technology increased by 21 percentage points, among the treatment group compared to the control group. These results confirm that the smart subsidies instrument was successful in reducing the information and liquidity barriers that hinder the adoption of effective technologies, thus limiting productive improvements. Therefore, they can be considered direct and short-term results of the program. However, although these results are observed for most of the chains, the increase in the likelihood of adopting new technologies in the cotton chain is positive but not significant. This absence of effects on technological adoption may be due to the fact that, for this chain, in many occasions the program granted improved seeds, fertilizers, and so on, as a production input, rather than encouraging the purchase of modern equipment or the implementation of more sustainable practices. In this case, the question remains as to whether the provision of this subsidy resulted in systematic and sustainable changes in the production system in the longer term.

In terms of the expected medium- to long-term impacts, the estimates do not show significant effects on expenditure levels for the full sample. However, we do observe a significant decrease in agricultural inputs and labor costs for the dairy chain. While this is an interesting result that suggests dairy farmers were able to lower their expenditure levels because of the program, we interpret the dairy results with some caution due to the methodological limitations encountered in this chain. A slight impact on the reduction of labor costs in the livestock chain is also observed, which suggests some efficiency gains in this substratum.

**Table 5. Results with IPW**

	Full sample, excluding dairy	Divided by chain			
		Livestock	Dairy	Cotton	Citrus
<b>Effects of PRODAF on:</b>					
Access to credit	<b>0.470***</b> (0.04)	<b>0.501***</b> (0.07)	<b>0.317***</b> (0.09)	<b>0.419***</b> (0.11)	<b>0.314**</b> (0.13)
Technology adoption	<b>0.211***</b> (0.04)	<b>0.197***</b> (0.06)	<b>0.689***</b> (0.08)	0.133 (0.11)	<b>0.293***</b> (0.07)
Spending on agricultural inputs (US\$)	282.2 (318.20)	-58.73 (361.50)	<b>-33,854***</b> (6,865)	976.4 (855.60)	-475.0 (593.4)
Labor costs (US\$)	-920.2 (1,033)	<b>-3,137*</b> (1,686)	<b>-11,507***</b> (1,773)	1,514 (1,172)	-1,444 (2,326)
Total production (US\$)	3,395 (4,639)	-1,827 (4,631)	<b>-32,101**</b> (16,004)	<b>21,214*</b> (11,975)	64,007 (39,713)
Total sales (US\$)	<b>13,064*</b> (7,802)	-2,709 (4,478)	<b>-32,101**</b> (16,004)	<b>30,980***</b> (6,288)	<b>110,473***</b> (41,391)
Net income (US\$)	<b>12,928**</b> (6,090)	-1,127 (3,511)	19,598 (14,653)	<b>27,227***</b> (5,919)	52,346 (33,991)
Net income per hectare (US\$)	<b>372.7*</b> (201.90)	21.01 (28.69)	<b>261.9***</b> (92.42)	<b>182.2**</b> (73.70)	<b>1,504*</b> (912.7)
Productivity (production per hectare in US\$)	95.17 (122.90)	-31.39 (34.64)	-194.6 (127.4)	61.27 (149.00)	<b>1,161**</b> (551.4)
<b>Observations<sup>7</sup></b>	<b>549</b>	<b>296</b>	<b>190</b>	<b>139</b>	<b>107</b>
Note: Robust standard error in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***) , 95 (**) or 90 (*).					

In terms of impacts on production volume, we observe impacts that vary by chain. The estimated impact for all the chains suggests a positive change in the level of production, although this increase is not statistically significant. When analyzed by chain, the results show that there was

<sup>7</sup> The total number of observations presented here represents the number of observations on access to credit and technology adoption. For the rest of the outcome indicators, we lost some observations due to lack of response. In the worst case, we have a total of 488, 250, 189, 112, and 74 observations, respectively. In most cases, these numbers refer to the income variable.

a significantly positive impact only for the cotton chain. On the other hand, the impact for dairy farming appears to be significant and negative (although, again, we must interpret these results with caution).

In terms of medium- to long-term economic outcomes, the results show that the values of sales, income, and income per hectare tended to increase due to PRODAF. Focusing on the total non-dairy sample, we find that the value of sales increased by more than US\$ 13,000, which translates into similar increases in net income (gross income minus input expenses). Positive effects on income per hectare are observed for all chains except livestock.

Finally, at the productivity level, the results appear to be consistent throughout the chains. In general, there was no significant increase in yields, with the sole exception of the citrus chain, where the value of production per hectare increased by US\$ 1,161. Considering that the average productivity of the citrus chain is around US\$ 3,000 per hectare, this would represent an impact on productivity of around 37% as of 2020.

## 7.2 Results Derived from Remote Sensing

Having identified limited impacts on yield, we now turn to longitudinal analysis. Table 6 shows the effects of PRODAF on average and maximum annual NDVI for the cotton and citrus chains. The table includes the results according to the difference-in-differences estimation in Panel A and those of the event study in Panel B. Columns 1 and 2 show results for cotton and columns 3 and 4 for citrus, for effects on average annual NDVI and maximum annual NDVI, respectively. As detailed in Section 6, all estimates include fixed effects for the PU and the treatment year. The table also reports the adjusted  $R^2$  for each estimate, as well as the number of observations.

First, it is important to note that for both cotton and citrus we find no significant difference between treated and untreated farmers in years prior to treatment, which is consistent with the parallel trends assumption and ensures the validity of the estimated impacts. The results in Panel A show that the average effects on average NDVI appear to be negative for the cotton sample, but positive for the citrus sample. However, we find no effects for either chain when we look at the maximum NDVI. In the case of cotton production, the maximum NDVI should be less susceptible to differences in periods where the crop is newly planted. Here, the analysis is collecting differences during the period of maximum NDVI, that is, the period before the March harvest (see Graph 1).

Panel B shows the main results according to the event study model. In this case, the results for average NDVI and maximum NDVI are considerably similar in both chains. For cotton, the differences between the treatment and control groups in terms of average NDVI are negative, although statistically insignificant, for all periods. Therefore, we detect no significant effect of PRODAF on the average NDVI for this chain. The results for maximum NDVI are similar, so the results seem to indicate that the program had no significant impact on yields in the cotton chain.

In the case of the citrus chain, however, we do find positive and significant effects after a few years of intervention. Effects on average NDVI appear immediately after one year of treatment. The effects continue to increase in magnitude in years 2 and 3 after treatment, although no impact is detected in the fourth year after the delivery of the smart subsidy. Similarly, we find positive effects of similar magnitude on maximum NDVI for the second and third year after treatment. These results suggest that citrus growers require several years since adopting a new technology to see significant and consistent impacts on their yield levels.

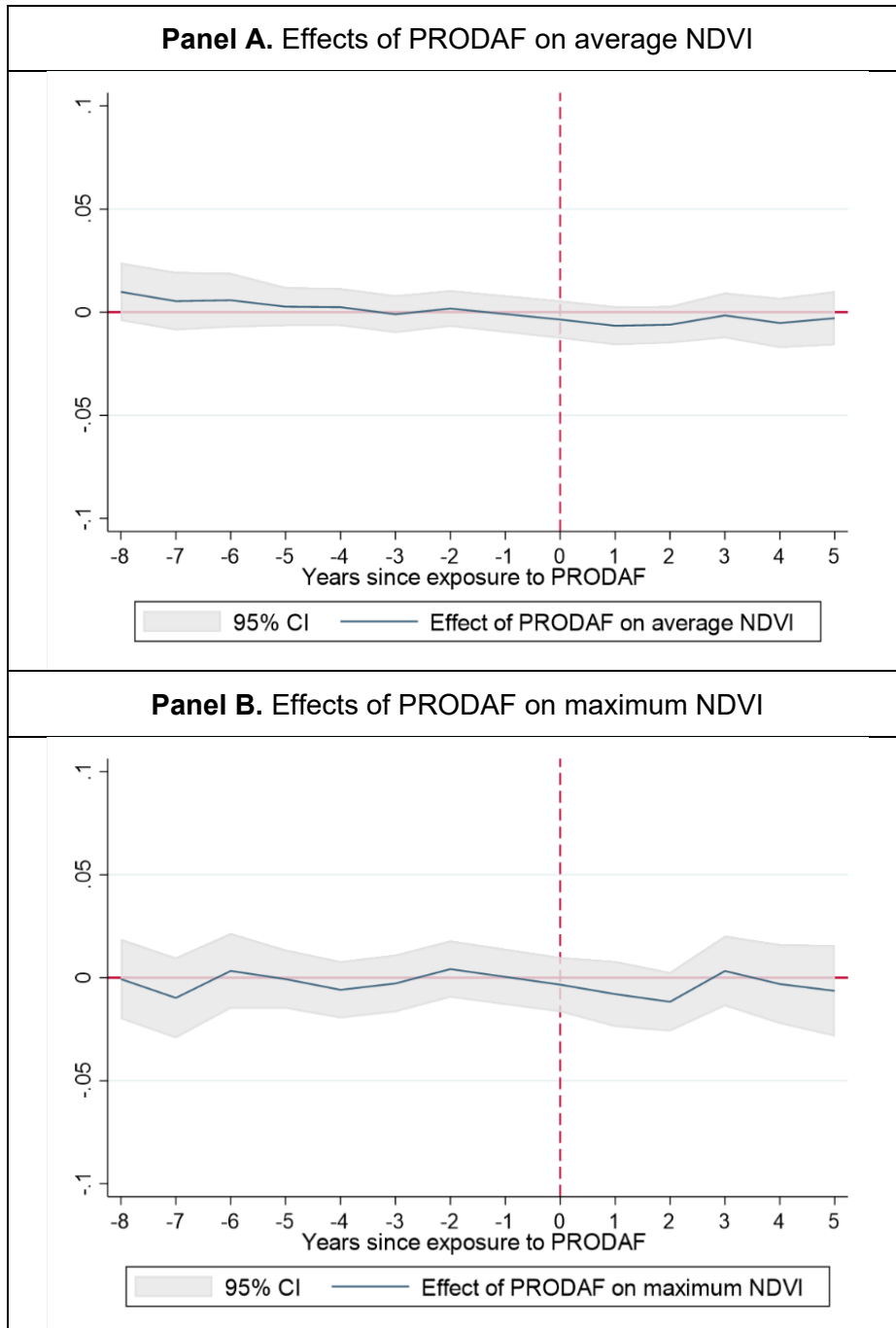


**Table 6:** Effects on average and maximum annual NDVI

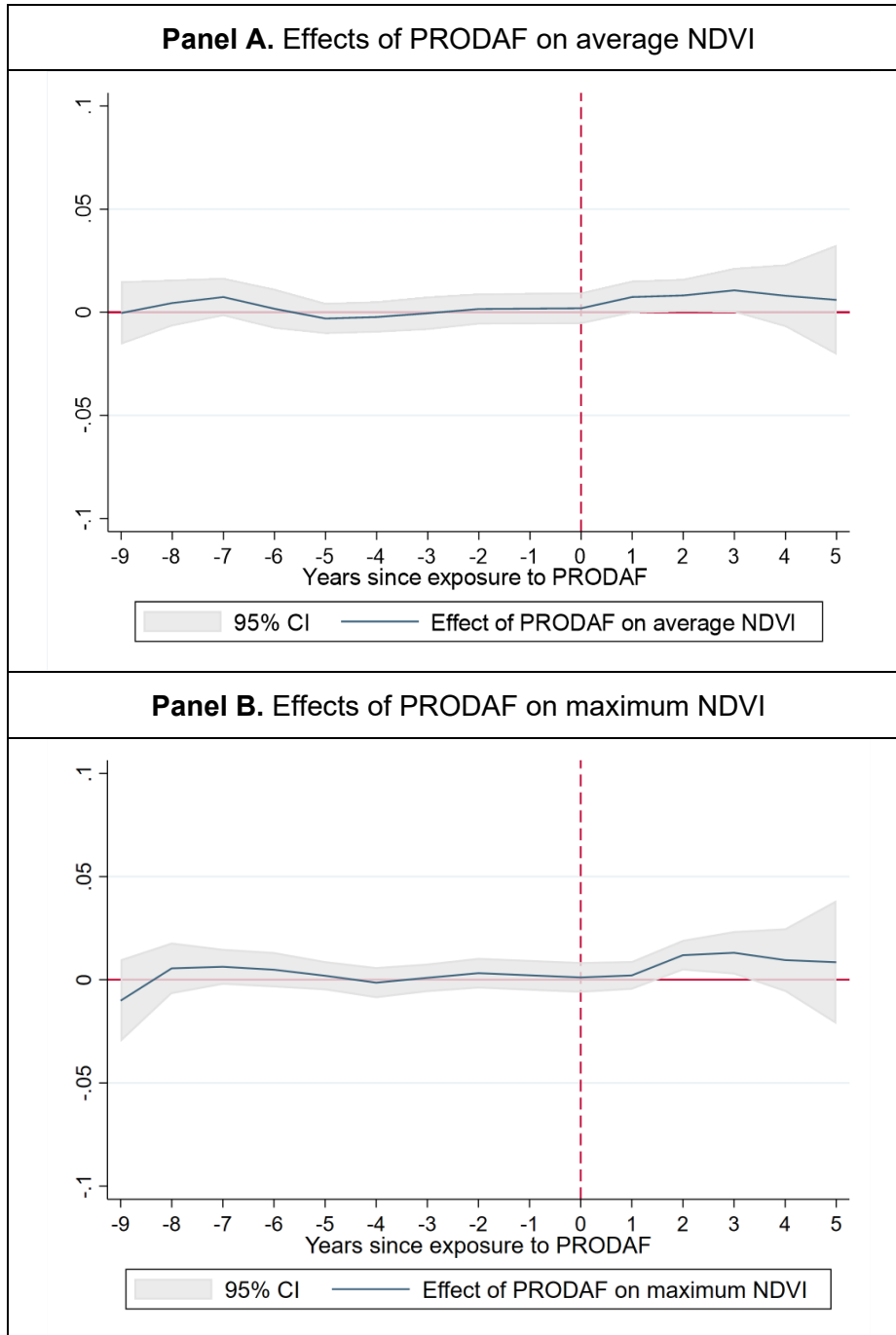
	<b>Cotton</b>		<b>Citrus</b>	
	<i>Average NDVI</i> <b>(1)</b>	<i>Maximum NDVI</i> <b>(2)</b>	<i>Average NDVI</i> <b>(3)</b>	<i>Maximum NDVI</i> <b>(4)</b>
<b>PANEL A: Difference-in-differences</b>				
Average effect	<b>-0.008**</b> (0.003)	-0.003 (0.005)	<b>0.006**</b> (0.002)	0.003 (0.002)
Adjusted R <sup>2</sup>	0.692	0.531	0.813	0.768
<b>PANEL B: Event study</b>				
Year 5 post-treatment	-0.003 (0.007)	-0.006 (0.011)	0.006 (0.014)	0.009 (0.015)
Year 4 post-treatment	-0.005 (0.006)	-0.003 (0.010)	0.008 (0.008)	0.010 (0.008)
Year 3 post-treatment	-0.002 (0.006)	0.003 (0.009)	<b>0.011*</b> (0.006)	<b>0.013**</b> (0.005)
Year 2 post-treatment	-0.006 (0.005)	-0.012 (0.007)	<b>0.008**</b> (0.004)	<b>0.012***</b> (0.004)
Year 1 post-treatment	-0.007 (0.005)	-0.008 (0.008)	<b>0.007*</b> (0.004)	0.002 (0.004)
Year of treatment	-0.004 (0.005)	-0.003 (0.007)	0.002 (0.004)	0.001 (0.004)
1 year pre-treatment (omitted)				
2 years pre-treatment	0.002 (0.005)	0.004 (0.007)	0.002 (0.004)	0.003 (0.004)
3 years pre-treatment	-0.001 (0.005)	-0.003 (0.007)	-0.000 (0.004)	0.001 (0.004)
4 years pre-treatment	0.002 (0.005)	-0.006 (0.007)	-0.002 (0.004)	-0.001 (0.004)
5 years pre-treatment	0.003 (0.005)	-0.001 (0.007)	-0.003 (0.004)	0.002 (0.004)
6 years pre-treatment	0.006 (0.007)	0.003 (0.009)	0.002 (0.005)	0.005 (0.004)
7 years pre-treatment	0.005 (0.007)	-0.010 (0.010)	0.007 (0.005)	0.006 (0.004)
8 years pre-treatment	0.010 (0.007)	-0.001 (0.010)	0.004 (0.006)	0.006 (0.006)
9 years pre-treatment	-	-	-0.000 (0.008)	-0.010 (0.010)
Adjusted R <sup>2</sup>	0.694	0.532	0.813	0.768
<b>Number of observations</b>	<b>2,090</b>	<b>2,090</b>	<b>1,364</b>	<b>1,364</b>
Note: All models control for year and production unit fixed effects. Robust standard error in parentheses. Coefficients are non-zero if the p-value is significant at confidence levels of 99(***), 95 (**), or 90 (*).				

For ease of reading, **Graph 5** provides a visual display of the same results as Table 4. Panel A shows the estimated coefficients of the effect of PRODAF on the average NDVI of cotton, Panel B shows those coefficients for the maximum NDVI of cotton. Graph 6 presents the same for citrus. In all graphs the 95% confidence intervals are presented as the gray area and the time of treatment (year zero) as a dashed vertical line. These graphs readily show that there is no significant difference for any of the estimates in the pre-treatment stages, thus ensuring that the parallel trends assumption is met.

**Graph 5.** Effects on average and maximum NDVI, for cotton



**Graph 6. Effects on average and maximum NDVI, for citrus**



These graphs also show some standard error increases in the results after the third year for the citrus variable. This could be due to a smaller sample size for these periods. As observed in Graph 4, the sample of citrus beneficiaries drops considerably after the third year following treatment, as most of them were treated in later years.

### 7.3 *Comparison of Estimates*

In this study, we have used two different strategies to measure the effects of the PRODAF program. The first strategy used cross-sectional data obtained from a survey conducted in 2021, while the second strategy used longitudinal data obtained by remote sensing. Although the second strategy allows us to better control for unobservables and pre-treatment trends, it only allows us to measure effects on NDVI as a proxy for productivity and not effects on other productive or economic indicators. NDVI also only serves to measure yield in agricultural chains and does not allow us to analyze the livestock impacts observed in the cattle and dairy chains. In contrast, the survey does provide direct information on productivity in the last observation period (2020) for all chains, including livestock and dairy. However, since the data were collected in a single period of time, they do not allow us to observe the productivity of farmers in earlier periods and the comparison is made only using data observable during 2020, although some retrospective variables are included for the 2015 period.

Therefore, although both strategies aim to evaluate the impact of PRODAF on the productivity of treated PU, they are not equivalent. The results of both models should be considered complementary rather than redundant. First, the IPW strategy allows us to assess the program's impact from an overall perspective, that is, across all chains, and to examine both the mechanisms through which farmers improved their production, such as the effective adoption of new technologies and practices and increased access to credit, and the various dimensions of impact, including the use of inputs, increased production, commercialization, and the resulting income.

Our analysis also confirms that the use of satellite data is an extremely valuable and cost-effective measure to assess the productive impact of this smart subsidies intervention, allowing for a comprehensive examination of the temporal dynamics of impact. The effects on cotton and citrus yields estimated by survey and satellites are highly consistent, both in terms of statistical significance and in terms of magnitude and direction. In both cases, we find insufficient evidence of effects on productivity for the cotton chain, but we do find evidence of significant effects on productivity in the citrus chain. This finding confirms that NDVI is an appropriate indicator to monitor and evaluate the yield of these two crops, despite the fact that they are very different plants in terms of their phenological characteristics. In addition, the availability of two sources of information to measure the effects on yield allows us to assert with high confidence that the differential impacts between the citrus and cotton chains should not be due to the evaluation methodology, since the results are consistent in both methodologies and use the same sample of farmers.

Instead, it is more likely that the difference in effects is due to differences in the type of treatment received. While the beneficiary farmers in the citrus chain mostly received irrigation equipment and technical assistance related to the implementation of good agricultural practices (soil management, crop management), the cotton chain mainly received variable inputs such as certified seeds, herbicides, insecticides, and adjuvants, among others. The provision of inputs alone may not be a sustainable strategy for increasing productivity in the long term, while the provision of more efficient machinery and practices may support a systematic change in production techniques.

## 8 Conclusion

In the agricultural sector in Latin America and the Caribbean, the provision of smart subsidies has been a key public policy tool to overcome asymmetries in access to credit and knowledge about more efficient production technologies. Although the evidence confirms that smart subsidies contribute to higher rates of technology adoption, the literature indicates that it has been difficult to quantify impacts on yields due to the dynamic and complex process that leads from the adoption of a technology to its sustainable and effective incorporation into the production system.

This study adds to the policy dialogue in two ways. First, we conduct an impact evaluation using robust quantitative methodologies to estimate the impact of a smart subsidies agricultural program in northeastern Argentina. It is important to underscore that the “Program for Rural Development and Family Agriculture” (PRODAF) was a pilot program when it was designed and implemented between 2013 and 2019, so special attention must be paid to assessing the impact of this intervention. In total, more than 2,000 farmers in the livestock, dairy, cotton, and citrus production chains in the provinces of Chaco and Entre Ríos received a non-reimbursable financial contribution and technical assistance for the adoption of efficient and environmentally sustainable technologies. Based on a survey of farm households and using the quasi-experimental inverse propensity weighting (IPW) methodology, we estimate the impacts for a sample of 534 beneficiary farmers and 364 non-beneficiary farmers. We find that PRODAF contributed significantly to increasing the likelihood of adopting a new technology by 21 percentage points, and increased the likelihood of accessing credit by 47 percentage points. This finding confirms that smart subsidies are effective in overcoming market failures in terms of information and financial resources.

In the long term, we find that PRODAF had a positive impact on the economic performance of the production units. Significant positive effects are observed on the level of sales and net income, and these effects are more pronounced for the cotton and citrus chains. Regarding productivity, we detect uneven effects in the different production chains. Although positive effects are observed in all chains except for the dairy chain (which seems to be due to methodological limitations), only the impact on citrus productivity is significant. However, the survey does not allow us to measure long-term impacts, nor to differentiate between the impacts experienced by early and late adopters in this chain.

The evaluation based on survey data faced important limitations. First, due to the low quality of the baseline, it was not possible to apply a more rigorous difference-in-differences methodology that could have controlled for unobservable differences between treated and untreated farmers. The challenges of the COVID-19 pandemic also limited the collection of data from the dairy control group subsample, which prevented the inclusion of this chain in the estimation of the program’s average impact. However, a prudent identification strategy and the application of IPW succeeded in estimating the impacts for the other chains in such a way that they are considered attributable to the program.

Another important point is the limited impact found for the cotton chain. This seems to be because farmers in this chain preferred to invest in the purchase of direct production inputs, in the form of seeds and fertilizers. This choice contrasts, for example, with the demand of citrus growers, most of whom invested in the purchase of irrigation equipment and the implementation of good agricultural practices. The literature on smart subsidies highlights the importance of providing inputs that allow the production system to change over the long term, that is, to be sustainable after the completion of the intervention (Dorward et al., 2008; Sims & Kienzle, 2017; Jayne et al.,

2018). In this regard, it seems important for the smart subsidies instrument to be part of a longer-term strategy, with the explicit objective of improving the farmer's production system systematically and sustainably, rather than to provide subsidies that facilitate access to certain inputs in the short term, but do not offer a way to incorporate these inputs on a regular basis.

Our second relevant contribution to the literature is a complementary analysis using satellite data to estimate the impact on yields using the Normalized Difference Vegetation Index (NDVI) for agricultural and citrus chains. Remote sensing is an increasingly effective and cost-efficient tool for monitoring and evaluating agroecological conditions, but as highlighted by Kubitzka et al. (2020), it has only been used to a very limited extent in agricultural project evaluations. A key advantage of this tool is that it provides a panel base of over 10 years of data, which allows for the detection of trends over time, both before the intervention (to confirm the key parallel trends assumption) and after the intervention. Estimating the impact of PRODAF on NDVI based on a fixed effects regression and the event study model, we can confirm that beneficiary farmers only experienced the full impact on yields between the second and third year post-treatment. The consistency between the results obtained from survey data and remote sensing data also confirms that using satellite data is a valid and accurate tool for detecting changes in yield levels. As obtaining such geospatial data becomes increasingly easier and cheaper, we recommend using these data in future evaluations of agricultural projects, either where a field survey is not feasible or to supplement conventional estimation with an additional dimension of data, including environmentally and ecologically relevant variables.

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## Appendices

### Appendix A: Menu of technologies promoted by PRODAF

**Table A1. Main technologies financed by PRODAF**

Type of technology	Dairy chain	Citrus chain	Cotton chain	Livestock chain
Process technologies	Feeding Milk quality Reproductive management Sanitary management	Integrated Production Management (INTA PIC Protocol): - <i>Thinning and pruning</i> - <i>Weed and insect control</i> - <i>Fertilization and irrigation</i>	Integrated Production Management (INTA Procalgodón Protocol): - <i>Fallowing</i> - <i>Planting</i> - <i>Weed and insect control</i> - <i>Stubble treatment</i>	Pasture management Reproductive management Sanitary management
Input technologies, investments	Milking systems Genetic improvements Water supply Feeding systems Milk preservation	Irrigation equipment Certified plants Sprayers Harvesting and processing equipment Fertilizer equipment Handling equipment (weed cutters) Inputs for fertilization and phytosanitary control	Improved seeds Insecticides Herbicides Growth regulators	Wire fencing Water supply Fodder resources Breeding

**Appendix B: Additional tables**

**Table B1:** Productive and sociodemographic characteristics, livestock and dairy

	Livestock			Dairy		
	Control	Treatment	Difference	Control	Treatment	Difference
<b>Sociodemographic variables</b>						
Farmer's age in 2020	53.62 (13.41)	54.86 (13.12)	1.244	55.68 (12.20)	54.77 (11.19)	-0.915
Years of education of the farmer in 2020	11.88 (4.40)	13.22 (4.16)	<b>1.348***</b>	13.98 (4.88)	10.44 (2.60)	<b>-3.534***</b>
Number of household members in 2020	2.79 (1.39)	2.87 (1.23)	0.079	4.00 (1.41)	3.51 (1.52)	-0.493
Dependency ratio in 2020	33.04 (51.26)	30.92 (53.36)	-2.118	-	28.55 (46.14)	-
Proportion of farmers who are women	0.11 (0.31)	0.12 (0.33)	0.016	-	0.05 (0.23)	-
Proportion of farmers who are married	0.62 (0.49)	0.71 (0.45)	<b>0.091*</b>	-	0.85 (0.36)	-
Proportion of households where at least one household member works outside the PU	0.44 (0.50)	0.51 (0.50)	0.071	-	0.23 (0.42)	-
Distance from the house to the road in km	7.42 (3.56)	6.73 (3.55)	<b>-0.69*</b>	-	7.91 (3.31)	-
Proportion of households with internet access at home	0.58 (0.50)	0.76 (0.43)	<b>0.179***</b>	-	0.92 (0.28)	-
Proportion of households with access to a good quality telephone signal at home	0.37 (0.49)	0.61 (0.49)	<b>0.241***</b>	-	0.47 (0.50)	-
Telecommunications services access index	0.48 (0.41)	0.69 (0.38)	<b>0.21***</b>	-	0.70 (0.27)	-
Proportion of dwellings with good quality flooring	0.31 (0.46)	0.19 (0.39)	<b>-0.122***</b>	-	0.07 (0.25)	-
Proportion of dwellings with good quality roofing	0.20 (0.40)	0.24 (0.43)	0.041	-	0.03 (0.18)	-
Proportion of dwellings with good quality interior ceiling cladding	0.83 (0.38)	0.92 (0.27)	<b>0.093***</b>	-	0.99 (0.08)	-
Proportion of households with access to a paved road	0.27 (0.44)	0.49 (0.50)	<b>0.225***</b>	-	0.25 (0.44)	-
Housing quality index	0.40 (0.20)	0.46 (0.21)	<b>0.059**</b>	-	0.34 (0.14)	-
Overcrowding index	1.07 (0.59)	1.05 (0.50)	-0.02	-	1.16 (0.52)	-

**Table B1 (continued):** Productive and sociodemographic characteristics, livestock and dairy

	Livestock			Dairy		
	Control	Treatment	Difference	Control	Treatment	Difference
<b>2015 Production variables</b>						
2015 equipment index	0.17 (0.17)	0.22 (0.17)	<b>0.053***</b>	-	0.41 (0.15)	-
Total land area (ha) in 2015	313.58 (332.16)	445.39 (443.60)	<b>131.808***</b>	151.90 (123.99)	98.12 (110.96)	<b>-53.772***</b>
Number of plots into which the PU is divided in 2015	1.19 (1.83)	2.29 (3.24)	<b>1.104***</b>	-	4.48 (3.65)	-
Belonged to any farmers' association/organization during 2015	0.04 (0.20)	0.09 (0.28)	0.044	-	0.15 (0.36)	-
<b>Observations</b>	<b>142</b>	<b>197</b>		<b>86</b>	<b>146</b>	
Note: Standard deviation in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***), 95 (**), or 90 (*).						

**Table B2: Productive and sociodemographic characteristics, cotton and citrus**

	<b>Cotton</b>			<b>Citrus</b>		
	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>
<b>Sociodemographic variables</b>						
Farmer's age in 2020	51.32 (14.54)	49.18 (12.60)	-2.141	52.83 (13.68)	52.45 (11.56)	-0.381
Years of education of the farmer in 2020	12.20 (3.07)	11.79 (3.32)	-0.409	9.05 (3.01)	10.00 (3.32)	<b>0.949*</b>
Number of household members in 2020	2.46 (1.02)	2.82 (1.27)	<b>0.362**</b>	3.90 (1.63)	3.40 (1.43)	<b>-0.5*</b>
Dependency ratio in 2020	19.66 (34.37)	28.01 (44.95)	8.353	51.31 (62.55)	42.00 (50.75)	-9.306
Proportion of farmers who are women	0.09 (0.29)	0.07 (0.25)	-0.023	0.05 (0.22)	0.06 (0.23)	0.007
Proportion of farmers who are married	0.64 (0.48)	0.78 (0.41)	<b>0.14**</b>	0.83 (0.38)	0.87 (0.34)	0.038
Proportion of households where at least one household member works outside the PU	0.27 (0.45)	0.45 (0.50)	<b>0.176**</b>	0.25 (0.44)	0.31 (0.47)	0.064
Distance from the house to the road in km	7.75 (3.72)	6.78 (3.52)	<b>-0.976*</b>	7.39 (3.55)	8.44 (3.87)	1.041
Proportion of households with internet access at home	0.59 (0.50)	0.75 (0.44)	<b>0.158**</b>	0.88 (0.32)	0.91 (0.28)	0.031
Proportion of households with access to a good quality telephone signal at home	0.27 (0.45)	0.47 (0.50)	<b>0.201***</b>	0.32 (0.47)	0.47 (0.50)	<b>0.155*</b>
Telecommunications services access index	0.43 (0.37)	0.61 (0.40)	<b>0.18***</b>	0.60 (0.29)	0.69 (0.30)	<b>0.093*</b>
Proportion of dwellings with good quality flooring	0.22 (0.42)	0.23 (0.42)	0.009	0.00 (0.00)	0.00 (0.00)	0
Proportion of dwellings with good quality roofing	0.28 (0.45)	0.34 (0.47)	0.054	0.02 (0.13)	0.04 (0.20)	0.026
Proportion of dwellings with good quality interior ceiling cladding	0.94 (0.25)	0.98 (0.13)	<b>0.047*</b>	1.00 (0.00)	1.00 (0.00)	0
Proportion of households with access to a paved road	0.17 (0.38)	0.37 (0.48)	<b>0.203***</b>	0.20 (0.40)	0.31 (0.47)	0.114
Housing quality index	0.40 (0.17)	0.48 (0.20)	<b>0.078***</b>	0.30 (0.10)	0.34 (0.13)	<b>0.035*</b>
Overcrowding index	1.03 (0.40)	1.08 (0.51)	0.058	1.32 (0.51)	1.01 (0.40)	<b>-0.302***</b>



**Table B2 (continued):** Productive and sociodemographic characteristics, cotton and citrus

	<b>Cotton</b>			<b>Citrus</b>		
	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>
<b>2015 Production variables</b>						
2015 equipment index	0.21 (0.11)	0.26 (0.12)	<b>0.054***</b>	0.00 (0.00)	0.00 (0.00)	0
Total land area (ha) in 2015	87.55 (58.63)	104.98 (65.71)	17.424	23.28 (15.07)	32.80 (31.24)	<b>9.52**</b>
Number of plots into which the PU is divided in 2015	0.88 (0.74)	1.18 (1.19)	<b>0.292*</b>	0.95 (0.85)	1.21 (0.98)	0.264
Belonged to any farmers' association/organization during 2015	0.17 (0.38)	0.08 (0.28)	<b>-0.083*</b>	0.12 (0.32)	0.37 (0.49)	<b>0.255***</b>
<b>Observations</b>	<b>78</b>	<b>119</b>		<b>60</b>	<b>70</b>	
Note: Standard deviation in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***), 95 (**), or 90 (*).						

**Table B3: IPW-weighted productive and sociodemographic characteristics, livestock and dairy**

	Livestock			Dairy		
	Control	Treatment	Difference	Control	Treatment	Difference
<b>Sociodemographic variables</b>						
Farmer's age in 2020	54.12 (12.79)	54.37 (13.06)	0.251	54.83 (9.60)	54.66 (10.62)	-0.172
Years of education of the farmer in 2020	12.87 (4.19)	12.85 (4.21)	-0.02	11.95 (4.05)	11.21 (3.13)	-0.739
Number of household members in 2020	2.78 (1.26)	2.81 (1.23)	0.033	5.00 .	3.60 (1.56)	<b>-1.404***</b>
Dependency ratio in 2020	30.05 (48.96)	32.00 (53.07)	1.948	-	30.73 (48.50)	-
Proportion of farmers who are women	0.12 (0.33)	0.13 (0.34)	0.014	-	0.06 (0.24)	-
Proportion of farmers who are married	0.69 (0.47)	0.73 (0.44)	0.044	-	0.87 (0.34)	-
Proportion of households where at least one household member works outside the PU	0.55 (0.50)	0.52 (0.50)	-0.029	-	0.25 (0.44)	-
Distance from the house to the road in km	7.39 (3.49)	7.04 (3.60)	-0.357	-	7.92 (3.32)	-
Proportion of households with internet access at home	0.69 (0.46)	0.69 (0.46)	-0.002	-	0.94 (0.24)	-
Proportion of households with access to a good quality telephone signal at home	0.50 (0.50)	0.51 (0.50)	0.015	-	0.49 (0.50)	-
Telecommunications services access index	0.59 (0.41)	0.60 (0.40)	0.007	-	0.71 (0.26)	-
Proportion of dwellings with good quality flooring	0.19 (0.40)	0.20 (0.40)	0.006	-	0.06 (0.24)	-
Proportion of dwellings with good quality roofing	0.19 (0.39)	0.21 (0.41)	0.022	-	0.03 (0.18)	-
Proportion of dwellings with good quality interior ceiling cladding	0.90 (0.30)	0.92 (0.28)	0.018	-	0.99 (0.08)	-
Proportion of households with access to a paved road	0.42 (0.50)	0.42 (0.49)	0.001	-	0.29 (0.46)	-
Housing quality index	0.43 (0.20)	0.44 (0.21)	0.012	-	0.34 (0.14)	-
Overcrowding index	1.05 (0.57)	1.06 (0.53)	0.005	-	1.17 (0.52)	-

**Table B3 (continued):** IPW-weighted productive and sociodemographic characteristics, livestock and dairy

	Livestock			Dairy		
	Control	Treatment	Difference	Control	Treatment	Difference
<b>2015 Production variables</b>						
2015 equipment index	0.24 (0.22)	0.21 (0.17)	-0.025	-	0.42 (0.15)	-
Total land area (ha) in 2015	314.38 (314.35)	389.55 (410.47)	75.168	138.68 (100.83)	126.09 (108.72)	-12.594
Number of plots into which the PU is divided in 2015	2.10 (2.68)	1.92 (2.96)	-0.188	-	4.90 (3.87)	-
Belonged to any farmers' association/organization during 2015	0.09 (0.29)	0.07 (0.26)	-0.015	-	0.17 (0.37)	-
<b>Observations</b>	<b>142</b>	<b>197</b>		<b>86</b>	<b>146</b>	
Note: Standard deviation in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***), 95 (**), or 90 (*).						

**Table B4:** IPW-weighted productive and sociodemographic characteristics, cotton and citrus

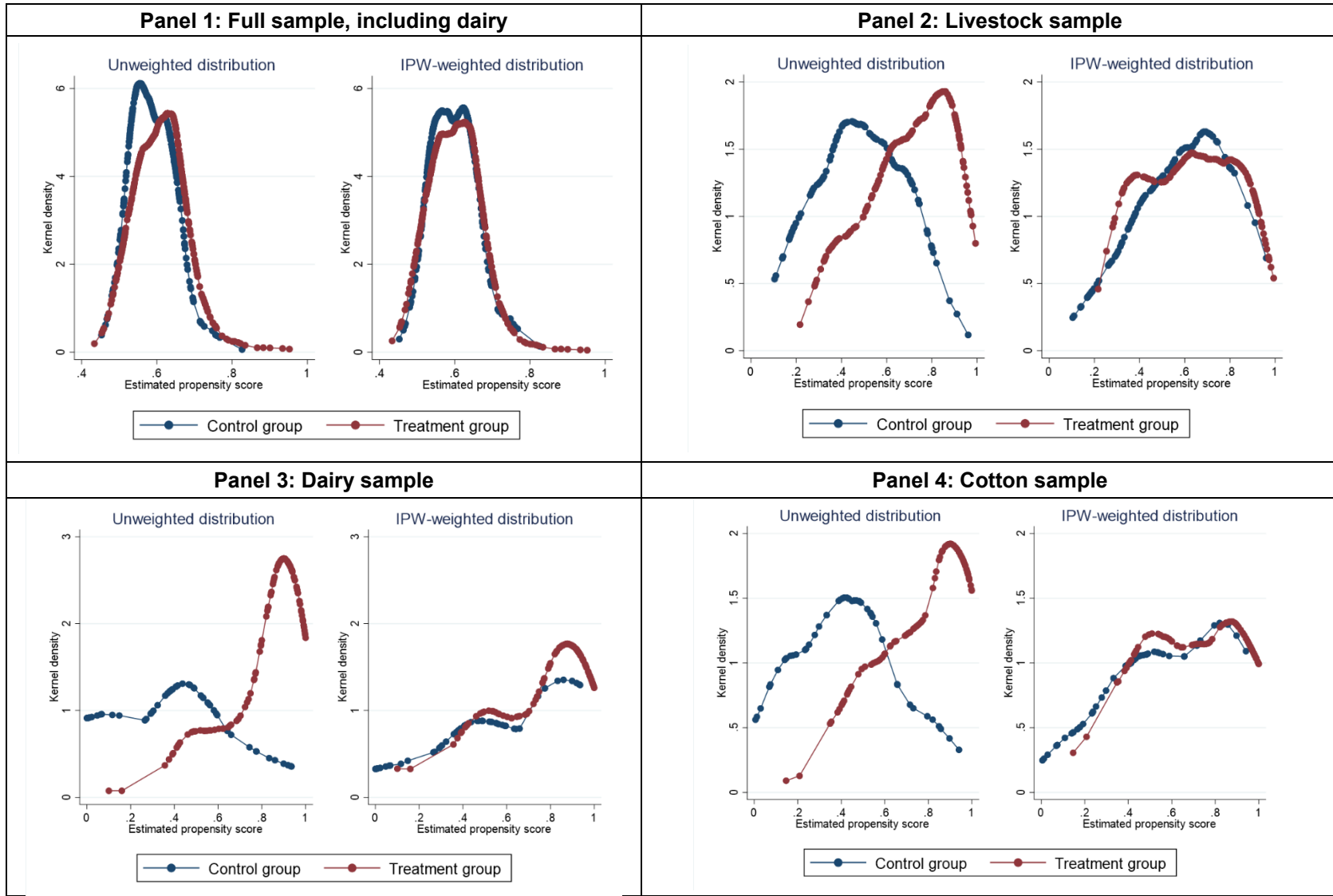
	<b>Cotton</b>			<b>Citrus</b>		
	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>
<b>Sociodemographic variables</b>						
Farmer's age in 2020	51.41 (13.57)	50.02 (12.88)	-1.394	53.78 (13.55)	53.12 (11.16)	-0.664
Years of education of the farmer in 2020	11.61 (3.04)	11.82 (3.30)	0.21	8.90 (2.83)	9.50 (3.17)	0.599
Number of household members in 2020	2.75 (1.02)	2.76 (1.31)	0.014	3.42 (1.58)	3.48 (1.40)	0.064
Dependency ratio in 2020	36.41 (44.34)	27.22 (43.86)	-9.185	43.88 (65.03)	44.04 (47.47)	0.16
Proportion of farmers who are women	0.06 (0.23)	0.07 (0.26)	0.013	0.06 (0.24)	0.06 (0.24)	0.002
Proportion of farmers who are married	0.84 (0.37)	0.84 (0.37)	-0.006	0.90 (0.30)	0.88 (0.32)	-0.016
Proportion of households where at least one household member works outside the PU	0.40 (0.50)	0.38 (0.49)	-0.02	0.32 (0.47)	0.35 (0.48)	0.028
Distance from the house to the road in km	6.19 (3.74)	6.58 (3.49)	0.387	8.30 (3.75)	8.04 (3.99)	-0.265
Proportion of households with internet access at home	0.69 (0.47)	0.71 (0.45)	0.019	0.93 (0.26)	0.93 (0.26)	0.000
Proportion of households with access to a good quality telephone signal at home	0.34 (0.48)	0.35 (0.48)	0.01	0.37 (0.49)	0.41 (0.50)	0.043
Telecommunications services access index	0.52 (0.38)	0.53 (0.39)	0.015	0.65 (0.27)	0.67 (0.28)	0.022
Proportion of dwellings with good quality flooring	0.20 (0.41)	0.24 (0.43)	0.04	0.00 (0.00)	0.00 (0.00)	0.000
Proportion of dwellings with good quality roofing	0.20 (0.40)	0.24 (0.43)	0.047	0.00 (0.00)	0.00 (0.00)	0.000
Proportion of dwellings with good quality interior ceiling cladding	0.96 (0.19)	0.97 (0.17)	0.004	1.00 (0.00)	1.00 (0.00)	0.000
Proportion of households with access to a paved road	0.19 (0.40)	0.30 (0.46)	0.107	0.28 (0.45)	0.31 (0.47)	0.033
Housing quality index	0.39 (0.14)	0.44 (0.19)	0.05	0.32 (0.11)	0.33 (0.12)	0.008
Overcrowding index	1.13 (0.49)	1.10 (0.50)	-0.035	1.13 (0.50)	1.12 (0.40)	-0.007

**Table B4 (continued):** IPW-weighted productive and sociodemographic characteristics, cotton and citrus

	<b>Cotton</b>			<b>Citrus</b>		
	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>	<b>Control</b>	<b>Treatment</b>	<b>Difference</b>
<b>2015 Production variables</b>						
2015 equipment index	0.25 (0.11)	0.25 (0.13)	0.001	0.00 (0.00)	0.00 (0.00)	0.000
Total land area (ha) in 2015	91.72 (57.38)	97.05 (59.86)	5.327	24.48 (14.30)	28.38 (27.28)	3.899
Number of plots into which the PU is divided in 2015	1.22 (0.75)	1.41 (1.01)	0.194	1.12 (0.85)	1.06 (0.95)	-0.059
Belonged to any farmers' association/organization during 2015	0.11 (0.31)	0.08 (0.27)	-0.032	0.002E28 (0.45)	0.26 (0.44)	-0.020
<b>Observations</b>	<b>78</b>	<b>119</b>		<b>60</b>	<b>70</b>	
Note: Standard deviation in parentheses. Differences are non-zero if the p-value is significant at confidence levels of 99(***), 95 (**), or 90 (*).						

**Appendix C: Additional graphs**

**Graph C1: Distribution of propensity score with and without IPW**



**Panel 5: Citrus sample**

