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The Impact of Agricultural Technical Assistance: Evidence from Guyana

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Abstract:

This paper provides one of the first quasi-experimental evaluations of a climate-resilient agricultural intervention in Guyana and the wider Caribbean. We isolate and examine the empirical impact of the targeted technical assistance (TA) component delivered under the Sustainable Agricultural Development Program (SADP) on smallholder productivity and resource management. Using a balanced panel of 802 agricultural households surveyed in 2022 and 2025 and employing a Difference-in-Differences (DiD) approach combined with Inverse Probability Weighting (IPW), the study estimates the program's effects on agricultural outcomes and sustainable practices. The results show no measurable effect on the adoption of sustainable agricultural practices or environmental sustainability indicators, nor on the gross value of overall crop or livestock production during the evaluation period. We find some evidence of higher cassava yields, although this result is based on a small subsample and is not reflected in increased production values. Overall, the evidence suggests limited program impacts during the evaluation period. These findings contribute to the limited evidence base on agricultural technology adoption and rural extension services in the Caribbean. The study highlights the distinction between crop-specific productivity gains and broader changes in production systems and resource management, which may require longer time horizons to become observable.

Keywords: technology adoption, agricultural extension, difference-in-differences, smallholder productivity, climate resilience, Guyana, Caribbean

JEL Codes: O13, Q12, Q16

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1. Introduction

Guyana's rural agricultural sector occupies a key position in the country's economy. With approximately 90 percent of households dependent on agriculture, forestry, and fishing located in rural areas (Food and Agriculture Organization [FAO], 2023), the sector is characterized by persistently low productivity and limited modernization. Rice and sugar, the country's traditional export crops, produce yields below those of regional competitors (FAOSTAT, 2026), while most smallholders engaged in diversified crop and livestock production operate largely outside the reach of formal extension services or structured research support, compounded by limited access to credit and secure land tenure (FAO, 2023).

Despite rapid economic growth in Guyana, persistent poverty and food insecurity remain significant challenges, particularly for rural and smallholder farming households. According to the CARICOM–World Food Program Food Security and Livelihoods Survey, 54 percent of respondents in Guyana reported worrying about their ability to meet food and other essential needs, while 58 percent were classified as moderately or severely food insecure; the survey also found that rising food prices and climate-related shocks continue to disproportionately affect low-income and agriculture-dependent households (World Food Program [WFP], 2023).

Additionally, Guyana's agriculture is highly vulnerable to climate change because its primary farming lands sit 0.5 to 1 meter below sea level, leaving them exposed to accelerated sea-level rise of over 10 mm per year and shrinking drainage windows (FAO, 2002; World Bank, 2012). This exposure manifests in catastrophic coastal flooding—such as the 2005 flood that caused $465 million in economic losses—alongside worsening saltwater intrusion and severe interior droughts that devastate staple crops like rice and cassava (Bovolo et al., 2014; Small, 2023). An empirical analysis of rice-producing countries, including Guyana, finds that higher average temperatures are associated with lower rice production, underscoring the crop's exposure to climate variability (Joseph et al., 2023).

In this context, the agricultural sector faces a dual challenge: raising farm-level productivity to support rural livelihoods and food security, while simultaneously adapting to the increasingly severe climate risks that threaten production. The combination of low baseline productivity and high climate exposure makes the design and delivery of effective rural extension services a first-order policy challenge.

The Sustainable Agricultural Development Program (SADP), financed by the Inter-American Development Bank (Sovereign Guaranteed Loan GY-L1060) and implemented by the Ministry of Agriculture (MoA), seeks to address the dual challenges of low productivity and limited capacity for climate-resilient agriculture in Guyana. Approved in 2016 with a total budget of US$15 million and a planned duration of five and a half years, the program sought to raise agricultural productivity and promote sustainable, climate-resilient natural resource management.

Its central pillar, and the focus of this evaluation, was a technical assistance and extension component. This intervention delivered training, transferred technology, and provided co-financed incentives directly to farmers to encourage adoption. While the wider program also included complementary components to strengthen agricultural data systems and enhance compliance with sanitary and phytosanitary (SPS) standards, these sit outside the scope of this evaluation.

Ultimately, the SADP represents one of the first large-scale, structured extension interventions in Guyana's agricultural sector, offering valuable lessons for similar initiatives across the Caribbean.

This paper estimates the causal effects of the SADP's extension component using a quasi-experimental design. We exploit a treatment group drawn from the program's beneficiary population and a comparison group identified ex ante from administrative data, together with a two-round farmer household panel (baseline 2022, endline 2025) to estimate a Difference-in-Differences (DiD) model with Inverse Probability Weighting (IPW) as the identification strategy. To our knowledge, this is the first impact evaluation of an agricultural extension program in Guyana to utilize panel data and causal inference methods. This places the study at the frontier of evidence on technology adoption and extension effectiveness in Guyana and the wider Caribbean, aligning with the limited regional evidence base documented in the Inter-American Development Bank's literature synthesis on agricultural productivity (Salazar et al., 2025).

Our main findings document no measurable impact on the adoption of sustainable agricultural practices, efficient irrigation techniques, or ecosystem-pressure-reducing behaviors, or on the gross value of overall crop or livestock production. While we find a large, marginally significant effect on cassava yields among treated farmers, this result is based on a small subsample and is not reflected in higher cassava production values. Therefore, we treat it cautiously rather than as a central finding. These null results on practice adoption and production value contribute to the limited evidence base on agricultural technology adoption and rural extension services in the Caribbean.

The remainder of the paper is organized as follows. Section 2 describes the SADP's institutional context. Section 3 reviews the conceptual framework and relevant literature. Section 4 presents the data and descriptive statistics. Section 5 details the empirical strategy. Section 6 discusses the main results and their implications. Section 7 concludes.

2. Institutional Context: The Sustainable Agricultural Development Program

The SADP was a government-led initiative implemented by the MoA and financed by the IDB (Loan GY-L1060). It combined institutional strengthening with direct support to farmers to enhance productivity and competitiveness in the context of a rapidly changing national economy driven by petroleum revenues.

2.1. Program Components and Target Population

The program targeted primarily small and medium-sized farmers engaged in crop and livestock production. Eligible beneficiaries were required to meet a set of criteria related to their landholding size, production scale, and willingness to participate in co-financing and registration schemes with the MoA. Specifically, eligibility required (i) residence in the target regions, (ii) a farm size not exceeding 5 hectares for smallholders and 10 hectares for medium-sized farmers, (iii) agreement to be registered with the MoA, and (iv) consent to a co-financing scheme that included monetary incentives for technology implementation.

While the program focused primarily on smallholders, medium-sized farmers with larger holdings (above 5 ha) were also allowed to participate in technical assistance and training activities, though they did not qualify for financial incentives. Based on the agricultural household survey, approximately 4% of farmers operated medium-size farms (5–10 ha), and 7% operated large farms (more than 10 ha). In total, about 5,000 farmers were expected to participate, of which roughly 11% (550 farmers) were medium or large producers. Among the eligible smallholders, a randomly selected subgroup of 2,000 farmers was initially expected to receive a monetary incentive of US$500 to support technology adoption.

For participating farmers, the extension component was organized around three technology packages prioritized by the Ministry, each corresponding to a distinct production system: Cash Crops, Cattle, and Small Ruminants. Technical support combined the transfer of knowledge with the delivery of physical inputs and equipment: through an extension program, participating farmers received hands-on training and a technology package, while demonstration farms established in several regions served as a practical, on-site channel for building farmer capacity and raising awareness of the promoted technologies. The technologies were intended to raise crop-specific productivity, particularly for non-traditional crops such as cassava and bora bean, and to promote more sustainable agricultural and livestock practices, including improved pasture management and more efficient irrigation. Specifically, cassava is the second most important food crop in Guyana, and a key food security and income-generating crop for smallholder farmers across the country. National production is estimated at around 3,000 hectares, yielding approximately 57,000 tons of fresh tubers annually. The crop is typically harvested 10 to 12 months after planting, or 6 to 7 months for short-duration varieties (NAREI, 2023) and is grown by smallholder farmers across varying soil types in all regions of the country, with the two main production and supply chains centered in Regions 3 and 4 (FAO, 2018).

The evaluated technology packages encompassed nearly 50 distinct measures tailored to crop and livestock management, as well as ecosystem protection. For crop production, the promoted technologies included sustainable techniques like intercropping, composting, integrated pest management, and water harvesting systems. On the livestock side, the program applied advanced health and management practices such as artificial insemination, vaccination, supplemental feeding, and improved grazing and housing conditions. Furthermore, cross-cutting practices aimed at reducing ecosystem pressure, such as physical soil conservation works, mulching, and planting cover crops, to ensure long-term environmental sustainability.

To lower the financial barriers to technology adoption documented in the target regions, the program incorporated a co-financing scheme through which eligible smallholders received a monetary incentive, in effect a voucher, toward the cost of the technology package and associated inputs and equipment. By pairing technical assistance and training with a targeted adoption incentive, the SADP followed a subsidy design intended to address simultaneously the information and liquidity constraints that limit technology adoption among smallholders.

The program was originally designed to enroll beneficiaries in successive annual cohorts across Regions 5, 9, and 10. This phased structure was intended to support a prospective evaluation based on a randomized roll-out, under which the order of entry of eligible farmers would be randomly assigned, allowing later cohorts to serve as a credible counterfactual for earlier ones.

2.2. Implementation Challenges and Program Modifications

It was not possible to identify the annual cohorts of beneficiaries ex ante, as general program delays and implementation challenges resulted in significant adjustments to the geographic focus of the program and its timelines, thereby making the randomized roll-out infeasible. As a result, the Ministry opted to select beneficiaries year-by-year (without fixing cohorts ex ante). The geographic focus also shifted, excluding Region 9 and adding Regions 2, 3, and 4 to the original geographical scope that included Regions 5 and 10. Given these constraints and the tight timeline before fieldwork was set to begin, the evaluation constructed a counterfactual group using administrative data. Specifically, we utilized the 2021 National Flood Assessment Database – which contains farmer contact details, production types, and basic asset information – to identify a pool of non-beneficiary farmers comparable to the first cohort of Ministry-identified beneficiaries. Recognizing that listed farmers likely suffered flood-related losses which could possibly lead to an upward bias on impact estimations, we leveraged baseline data on recent exposure to extreme weather events to match treated and control farmers, allowing us to control for these shocks in our estimation.

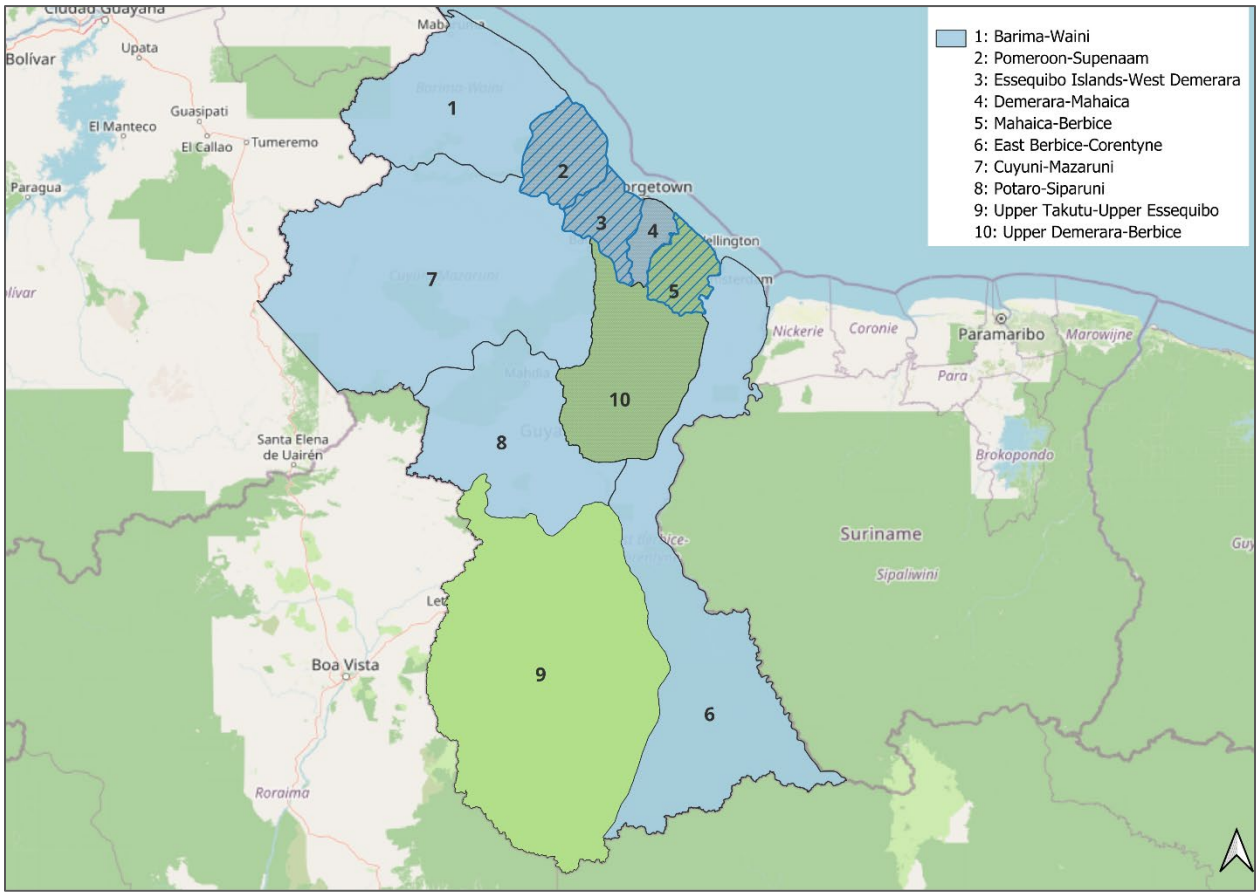
To ensure statistical power and regional representativeness, the analysis focuses on Regions 2, 3, and 5 and evaluates three technology packages prioritized by the Ministry: Cash Crops, Cattle, and Small Ruminants (see Figure 1). From the National Flood Assessment Database, we included the universe of livestock farmers across the three target regions – noting that the data does not disaggregate between cattle and small ruminants – and drew a random 50% sample of cash-crop farmers, retaining a reserve sample to mitigate potential tracking or attrition issues. The treatment group was sampled from the March 2022 MoA master registry for the SADP. For the cattle and small ruminants packages, the final sample constituted a near census of the available list. Conversely, the cash-crops registry yielded approximately 400 to 500 registrants per region, facilitating stratified random selection.

3. Conceptual Framework and Literature Review

3.1. SADP Extension Component: Theory of Change

The SADP's extension component follows a causal chain that links program inputs directly to intermediate and final outcomes. The inputs were the services and goods delivered to farmers: technology transfer, hands-on training, demonstration farms, and a co-financed adoption incentive. According to the SADP’s Project Completion Report, the project succeeded in implementing 10 research programs as well as 4 agricultural extension programs, provided training to 5,519 farmers, and offered incentives for agricultural technology adoption to 4,629 farmers, with more than 90% of the distribution of technologies and incentives occurring during 2023 and 2024 (IDB, 2026). These inputs were designed to generate an initial set of intermediate outcomes, namely gains in farmers' technical knowledge and the adoption of improved production and sustainable management practices. This adoption, in turn, translates into the program's final outcomes: higher crop- and livestock-specific productivity, increased agricultural income, and reduced pressure on natural ecosystems.

Figure 1: Geographic Distribution of the Study Regions



Regions 5, 9, and 10 (green regions) were originally planned to be intervened and included in the evaluation. After modification, regions 2, 3, 4, 5, and 10 (dotted regions) were intervened. Regions 2, 3, and 5 (hashed regions) were evaluated.

Each link in this chain is conditional. Knowledge gains materialize only if extension services are effectively delivered; adoption follows knowledge only when complementary inputs, credit, and incentives are available and the technologies are well matched to local conditions; and productivity and income gains follow adoption only if the practices are sustained across production cycles (Avila et al., 2010; Heisey, 2001). A review of impact evaluations of agricultural programs across Latin American countries conducted by the World Bank (2011) lends empirical grounding to this causal chain, and the Latin American experience further shows that productivity and income gains for small farmers are strengthened when technical assistance is combined with incentives for technology adoption (Salazar et al., 2015; Maffioli and Mullally, 2014).

Concretely, the SADP operationalizes this theory through its agricultural innovation and extension component. This component – the sole focus of the present evaluation –financed technology transfer, demonstration plots, and training services, paired with co-financed incentives to drive technology adoption. It was complemented by two supporting components: the generation of agricultural information for evidence-based policy, and compliance support for sanitary and phytosanitary standards. While these supporting initiatives are not evaluated here, they were designed to reinforce the program's overarching productivity objectives.

3.2. The Economics of Technology Adoption and Agricultural Extension

The extension activities financed through SADP follow the vertical logic established in the literature on agricultural development in Latin America and the Caribbean. The theoretical justification for public investment in agricultural extension services rests on the presence of market failures that prevent the efficient diffusion of technology in rural economies. Feder et al. (1985) provides the foundational economic framework, identifying asymmetric information, limited access to credit, and inadequate market infrastructure as the primary market imperfections that inhibit technology adoption among smallholders. In the absence of corrective public intervention, these failures generate a persistent wedge between the technologies available at the frontier and those employed on farms, with consequences for both productivity and rural welfare.

Birkhaeuser et al. (1991) confirm that agricultural extension has generally generated positive returns by accelerating technology diffusion and closing the gap of yields and rural income. The scale of potential returns is substantial: a meta-analysis of rigorous studies on the effects of agricultural research and development by Alston et al. (2000) estimates a median rate of return on investment of 58 percent to agricultural R&D. Additionally, Fuglie and Rada (2013) evaluate the technological improvements introduced in Sub-Saharan Africa and estimate that for the 34 million hectares on which these technologies had been implemented (representing 21% of cropland in the region), output increased by 65%. Other important effects of agricultural extension services include increased food security (Rosegrant & Cline, 2003; Aramburu et al., 2014), and improved climate change adaptation (Lybbert & Summer, 2012).

Within this framework, the SADP's extension component can be understood as an intervention designed to correct the specific market failures that characterize Guyana's agricultural sector. Pre-program survey data revealed that only 3% of farmers in the target regions reported having received some kind of technical assistance, only 8% of farmers had obtained loans from a formal credit institution, and 60% reported that financial constraints prevented them from adopting more productive farming techniques (IDB, 2016). These credit constraints are consistent with Miyata and Sawada (2007) and Foster and Rosenzweig (2010), who document that credit constraints are a leading cause of slow technology diffusion among poor rural households.

3.3. Barriers to Technology Adoption Among Smallholders

The literature has examined why smallholder farmers often fail to adopt technologies that appear profitable at prevailing prices, even when extension services successfully transmit knowledge of those technologies, identifying several mechanisms beyond credit constraints. First, in the presence of incomplete insurance markets, risk aversion leads farmers to underinvest in new technologies with uncertain returns, particularly when existing consumption levels are close to subsistence thresholds (Foster & Rosenzweig, 2010). Second, social learning dynamics mean that adoption spreads gradually through networks as farmers observe neighbors' experiences, generating adoption curves that are concave in time (Conley & Udry, 2010). Novice adopters are substantially more responsive to information from their network than experienced farmers, suggesting that learning effects concentrate among recent adopters and attenuate with experience. Third, the complexity of sustainable practices, which often require coordinated changes across multiple dimensions of farm management, imposes higher adoption barriers than single-technology interventions (Waddington et al., 2014).

In the case of the SADP, its extension component aimed to achieve two objectives: improving crop-specific productivity through technology transfer and increasing production sustainability through the promotion of sustainable agricultural and livestock practices. Crop-specific productivity responses to targeted extension inputs, improved varieties, and fertilization techniques can materialize within a single production cycle, as the technology is applied and the yield is observed within the intervention period. By contrast, the adoption of complex, multi-behavior sustainable practices faces greater challenges, as evidence indicates that practices perceived as too complex to implement, combined with limited access to inputs and capital, act as key barriers to adoption (Waddington et al., 2014).

3.4. Evidence on Extension Program Effectiveness

The empirical record on agricultural extension programs in Latin America and the Caribbean is positive but uneven, and the pattern of results in the literature is instructive for interpreting the SADP's findings.

Evidence from farmer field schools shows consistent positive effects on intermediate outcomes such as knowledge acquisition and adoption of beneficial practices, but more variable impacts on agricultural production and income (Waddington et al., 2014). Godtland et al. (2004) finds that potato farmers who participated in farmer schools achieved significantly higher scores in an exam about farming practices, though the translation of knowledge gains into productivity outcomes depends critically on access to complementary inputs. Similarly, Bentley et al. (2011) document that Bolivian farmers who visited plant clinics improved pesticide use and harvest quality and consequently saw increases in their income.

For programs involving direct input distribution and variety improvement, a closer analog to the SADP's technology packages, the evidence shows crop-specific and context-specific responses. Cerdán-Infantes, Maffioli, and Ubfal (2011) evaluate an extension program targeting grape farmers in Mendoza, Argentina, and find yield increases of 40 percent, but only among farmers whose pre-treatment productivity was below average. This finding anticipates one of the SADP's central results: technology transfer programs may generate concentrated gains in specific crops or production contexts, while leaving aggregate value outcomes unchanged if the treated population is heterogeneous.

For livestock programs, Maffioli and Mullally (2014) evaluate a publicly funded, privately delivered extension program for cattle breeders in Uruguay and find significant impacts on calf production, between 11.36 and 15.3 additional calves per beneficiary on average, and a positive though less precisely estimated effect on net calf sales of 4.35 calves annually. The authors note that the internal rate of return of the program is sensitive to the time horizon over which benefits are assumed to persist, suggesting that the economic case for the program depends heavily on the durability of the management changes induced by the intervention.

In the broader Latin American context, Aramburu et al. (2014) evaluate a technology adoption program for smallholders in Bolivia and find positive short- and medium-term effects on crop diversification, sales, and agricultural income. Gonzalez et al. (2009) evaluate a technology adoption program in the Dominican Republic and detect significant productivity effects for rice producers but not for other crop types, suggesting that the effectiveness of technology transfer

varies across product. Finally, Schling and Pazos (2022) evaluate a smart-subsidy program in Argentina that combined technical assistance with co-financed input vouchers. They find that the intervention effectively mitigated rural credit constraints, driving immediate technology adoption and ultimately enabling beneficiary farmers to increase both their total value of sales and net income. Crucially, their analysis reveals that the type of provided inputs played a decisive role in determining these outcomes, suggesting that the composition of the technology package heavily influences overall program effectiveness.

4. Data and Descriptive Statistics

4.1. Treatment and Control Group Identification

The shift away from the originally planned randomized rollout necessitated the construction of an administrative-data counterfactual. The treatment group was drawn from the MoA's March 2022 registry of farmers who had formally signed up for the program and selected one of six available technology packages. The evaluation prioritizes three of these packages – Cash Crops, Cattle, and Small Ruminants – which were selected based on their dominant share of farmer demand to ensure the study is representative of the program's primary beneficiary population.

For the control group, the 2021 National Flood Assessment Database provided the most operationally feasible source of comparable, non-beneficiary farmers. This database contained contact information, basic productive asset profiles, and production types for farmers across Regions 2, 3, 4, 5, 6, and 10 who had experienced flood-related losses. In consultation with the MoA and the IDB, the evaluation team focused on Regions 2, 3, and 5, where the geographic overlap between program beneficiaries and the database population was highest, ensuring sufficient sample sizes across all three priority technology packages.

While this sampling strategy introduces potential threats to internal validity, specifically, (i) comparability risks between beneficiaries and non-beneficiaries, and (ii) selection bias stemming from voluntary program enrollment, the evaluation design incorporates several measures to mitigate these risks. Specifically, the empirical strategy combines Inverse Probability Weighting (IPW) with Differences-in-Differences (DiD) estimation, exploiting the panel structure of the baseline and endline data to compare changes in outcomes over time between treatment and control farmers. IPW is used to improve covariate balance between the two groups, with balance diagnostics conducted before and after weighting, while the DiD framework helps account for time-invariant unobserved differences between beneficiaries and non-beneficiaries. Region fixed effects are included to account for time-invariant geographic heterogeneity, and standard errors are clustered at the community level to address spatial correlation concerns. Although this approach cannot fully eliminate the possibility of bias arising from unobserved factors affecting program participation, it substantially strengthens the credibility of the counterfactual and represents the most rigorous evaluation strategy feasible under the operational constraints of the 2022 program rollout. Consequently, the estimates should be interpreted as providing credible evidence of program impacts under a combination of selection-on-observables assumptions (for the IPW component) and the parallel trends assumption underlying the DiD specifications.

4.2. Working sample: Survey Data and Panel Construction

The study combines information from both the baseline and follow-up surveys, which collected detailed data on household demographics, agricultural practices and production outcomes across three regions of Guyana: Region 2 (Pomeroon-Supenaam), Region 3 (Essequibo Islands–West Demerara), and Region 5 (Mahaica-Berbice). The baseline survey, conducted between July and September of 2022, covered 1,220 farmers (633 treated and 587 control). The follow-up survey, implemented between November 2024 and February 2025, successfully re-interviewed 819 farmers (422 treated and 397 control), representing an overall attrition rate of 32.9 percent. Appendix 9.1 reports attrition tests assessing whether attrition is systematically correlated with baseline characteristics, with results suggesting no evidence of selective attrition by observable farmer characteristics. Table 1 presents the number of samples collected.

Table 1: Collected samples, by group and survey

Group	Baseline	Follow-up	Total
Treatment	633	422	1,055
Control	587	397	984
Total	1,220	819	2,039

Note: The samples excludes farmers who refused to participate.

The survey instrument comprised a series of modules structured to reflect the household production system. It first collected information on household demographics as well as dwelling and farm characteristics. It then captured data on productive assets, including land, machinery, and livestock holdings. The survey proceeded to detail information on agricultural production, including crop activities, input use, and farm management practices. It also gathered data on access to agricultural support services and training. Finally, it included modules on household economic activities, covering labor allocation, income generation, and off-farm employment. (Appendix 9.2 presents the structure of the SADP survey instrument)[1] Given the study design and the availability of two survey rounds, the working sample is restricted to a balanced panel in order to more reliably estimate program effects over time. This implies that baseline observations for farmers not successfully re-interviewed in the follow-up are excluded from the analytical sample. Table 2 presents the resulting reduced working sample.

Table 2 - Working balanced sample, by group and survey

Group	Baseline	Follow-up	Total
Control	388	388	776
Treatment	414	414	828
Total	**802**	**802**	**1,604**

[1] Production values of crops are winsorized at the 90th percentile. The winsorization is applied separately by survey round, that is, once for the baseline observations and once for the endline observations.

4.3. Key Variable Construction

The primary productivity outcome for cash crop farmers is crop yield, defined as production per unit of cultivated area (kg/ha), for the two main crops targeted by the program: cassava and bean/bora. These crops correspond to the principal technology packages promoted under the SADP in the intervention regions. Yields are constructed using farmer-reported production quantities and cultivated areas for each crop, with the reference period aligned to the July-June agricultural year in both baseline and endline survey rounds.

Agricultural value outcomes are measured as the gross value of crop production and the gross value of livestock production (both expressed in 2022 USD per farm). Land-use intensity in livestock production is measured in hectares and used as a proxy for ecosystem pressure.

Sustainable practice adoption is captured through a set of indices that measure: (i) the number of sustainable crop practices adopted from a list of practices promoted under the program; (ii) the number of sustainable livestock practices adopted; (iii) the adoption of efficient irrigation technologies; and (iv) the number of ecosystem-pressure-reducing practices implemented. These indices are constructed by aggregating individual binary indicators into count variables, consistent with the measurement approach used in the baseline survey. The construction of all remaining outcome indicators is presented in Table A3. A detailed list of included practices is presented in Table A4.

4.4. Descriptive statistics

Table 3 presents descriptive statistics of baseline household characteristics, together with t-tests of difference in means between the treatment and control groups. These comparisons provide an initial assessment of covariate balance and the plausibility of the control group as a counterfactual. The table reports statistics for the 802 households included in the balanced panel used for the main analysis, for which complete information is available in both survey rounds. While full descriptive statistics are reported, the discussion focuses on differences between groups rather than levels, in order to assess baseline comparability and the quality of the constructed counterfactual.

The average treated farmer in our sample is 51 years old, male-headed in 85% of cases, 64% of them are married, and has completed secondary school in 28% of cases. The average treated household has 3.4 members, of whom 1.64 are female (46%), with a dependency ratio of 0.24. The majority identify as East Indian (73%) and treated households are evenly distributed across Region 2 (36%), Region 3 (31%), and Region 5 (33%). In terms of living conditions, 85% own their dwelling, 50% have water piped into the dwelling, 91% are connected to the public electricity network, 92% cook with gas, and 25% have a telephone; households live an average of 1.42 miles from the nearest highway and 1.54 miles from the nearest food market. The average treated farmer operates a smallholding of approximately 3.24 hectares across 1.38 parcels, of which 45% hold formal title, and has been farming for an average of 23 years. Finally, crop farming is the dominant activity (60% of treated households), followed by livestock (39%).

Table 3 - Balance Test: Treated vs Controls (Baseline)

	Treated	Control	Difference
Panel A – Sociodemographic characteristics:			
HH head (female = 1)	0.15	0.28	**-0.13*** **
HH head age	51.03	52.7	**-1.67***
HH Secondary school completed	0.28	0.23	**0.06***
HH head married	0.64	0.62	0.02
N. HH members	3.4	3.25	0.16
N. HH female members	1.64	1.6	0.04
% HH female members	0.46	0.48	-0.02
Dependency ratio (<18, >65)	0.24	0.29	**-0.06*** **
Ethnicity: East Indian	0.73	0.55	**0.18*** **
Ethnicity: African	0.12	0.19	**-0.07*** **
Ethnicity: Other	0.15	0.26	**-0.11*** **
Region 2	0.36	0.36	0.01
Region 3	0.31	0.34	-0.03
Region 5	0.33	0.31	0.02
Panel B – Dwelling characteristics:			
Agricultural assets index	3.04	2.71	**0.33*** **
Nonagricultural assets index	3.03	2.71	**0.32*** **
Wall: Wood & concrete	0.4	0.3	**0.09*** **
Water: Public - piped into dwelling	0.5	0.41	**0.09** **
Electricity: Public network	0.91	0.79	**0.12*** **
Cooking energy: Gas	0.92	0.82	**0.09*** **
Has telephone	0.25	0.18	**0.07** **
Owns dwelling	0.85	0.86	-0.01
Distance to nearest highway (miles)	1.42	1.44	-0.02
Distance to nearest food market (miles)	1.54	3.13	**-1.59*** **
Panel C – Parcels characteristics:			
N. parcels	1.38	1.23	**0.15***
Farm size (Ha)	3.24	2.43	**0.81** **
% parcels with title	0.45	0.43	0.02
Parcel cultivated last year (Ha)	0.95	0.82	**0.13***
Years producing	23.00	23.03	-0.03
Panel D – Main agricultural activity:			
Crop farming	0.6	0.57	0.04
Livestock	0.39	0.43	-0.04
Cash crops	0.68	0.60	**0.07** **
Cattle	0.32	0.20	**0.12*** **
Small ruminants	0.33	0.42	**-0.09*** **

Note: Statistical significance is denoted as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 3 (continued) - Balance Test: Treated vs Controls (Baseline)

	Treated	Control	Difference
Panel E – Production loss by primary cause:			
Any conflicts	0.05	0.04	0.01
Drought	0.05	0.03	**0.03****
Pest	0.37	0.33	0.04
Livestock disease	0.19	0.2	-0.01
Flooding	0.82	0.86	**-0.04***
Theft	0.11	0.1	0.02
Panel F – Technical Assistance			
Was offered assistance last year	0.28	0.39	**-0.1*****
Received assistance for: Crops	0.78	0.57	**0.21*****
Received assistance for: Livestock	0.17	0.42	**-0.24*****
Received assistance for: General farming practices	0.02	0.02	0
One member of HH received a loan	0.12	0.09	**0.04***
Observations	**414**	**388**	

Note: Statistical significance is denoted as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

Nevertheless, Table 3 shows that treatment and control households differ significantly across several variables. Treated households are more likely to be male-headed, younger, and of East Indian ethnicity, and report a lower dependency ratio; they also score higher on both asset indices and are more likely to have piped water, public electricity, and cooking gas, and to live closer to food markets. Treated farms are considerably larger on average than control farms, and treated households are more oriented toward cattle rather than small ruminant production. Patterns of technical assistance also differ: treated households are more likely to have received assistance for crops but less likely to report assistance for livestock or in general, which likely reflects the presence of other technical assistance schemes operating among control farmers. Because this imbalance spans sociodemographic, asset, and productive characteristics rather than a single domain, an unweighted comparison of outcome levels would not support a credible counterfactual. This is precisely what motivates our main strategy of IPW, as shown later, the resulting covariate balance improves substantially once the IPW weights are applied.

5. Methodology

To explicitly address potential estimation biases posed by challenges in the identification strategy and group differences identified in Section 4, each element of the empirical strategy is designed to resolve a specific problem regarding the comparability of the treatment and control groups. First, because the treatment group voluntarily enrolled in the program (introducing potential self-selection bias) and the control group was drawn from a flood assessment database, there are significant baseline imbalances in observable characteristics, such as farm size, assets, and prior exposure to shocks. We address this specific comparability problem using Propensity Score Estimation and Inverse Probability Weighting (IPW). By modeling the probability of program participation and reweighting the sample, IPW directly corrects these observable imbalances to construct a more credible counterfactual. Second, to address the problem of selection bias

stemming from unobservable characteristics, such as the intrinsic motivation or unobserved ability of farmers who proactively signed up for the program, we employ a Difference-in-Differences (DiD) framework. The DiD approach mitigates this issue by controlling for any time-invariant unobserved heterogeneity between the treated and control groups. By combining these two methods, the IPW-DiD approach ensures that we are comparing groups with similar baseline characteristics and trajectories, thereby strengthening the validity of the parallel trends assumption necessary for causal inference.

The following sections describe the construction of the comparison group, the estimation of propensity scores, and the empirical strategy used to identify program impacts.

5.1. Difference in Differences

The primary impact estimates reported in this study are obtained using the IPW-DiD specification. The DiD method accounts for unobserved, time-invariant differences between treatment and control groups by comparing changes in outcomes between beneficiaries and non-beneficiaries before and after the intervention.

The validity of the DiD strategy rests on two key assumptions. First, the parallel trends assumption requires that, in the absence of the intervention, outcomes for beneficiary and comparison farmers would have evolved similarly over time (Blundell and Dias, 2000). While this assumption cannot be tested directly because only a single pre-intervention observation is available, its plausibility is strengthened by the fact that treatment and comparison farmers operate in the same regions and are exposed to similar agroecological, market, and institutional conditions. In addition, the propensity-score weighting procedure substantially improves the comparability of beneficiaries and non-beneficiaries in observed baseline characteristics, reducing concerns that differential outcome trends are driven by systematic differences between the two groups. It is important to note that our identification strategy relies on observable baseline characteristics and cannot rule out the possibility that unobserved factors may have led treatment and control farmers to follow different trajectories in the absence of the program. With only a single pre-intervention observation, we are unable to conduct standard tests of the parallel trends assumption, such as event-study analyses or pre-trend tests, that could provide additional support for the validity of the DiD design. Second, the comparison group must provide a credible counterfactual for the treatment group. This requires that observable differences between treated and untreated farmers are adequately controlled for and that any remaining unobserved differences remain stable over time. To support this assumption, we implement an Inverse Probability Weighting based on a rich set of baseline covariates related to both program participation and agricultural outcomes. The balance diagnostics indicate a substantial reduction in observable differences between treated and control farmers after weighting, the mean absolute standardized bias declined from 16.1 to 9.7 percent after applying the IPW weights, and the share of covariates satisfying the conventional 10 percent balance threshold rose from 40 percent (18 of 45) to 71 percent (32 of 45), suggesting that the resulting comparison group provides a credible counterfactual for the estimation of program impacts. Under these assumptions, differences in outcome trajectories between the treatment and comparison groups can be attributed to the intervention (Gertler et al., 2011).

The DiD model is estimated using the following regression specification:

$$Y_{it} = \beta_0 + \beta_1 \times Treated_i + \beta_2 \times Time_t + \beta_3 \times (Treated_i * Time_t) + \beta_4 \times \boldsymbol{X}_{it} + \alpha_r + \epsilon_{it} \qquad (1)$$

where Y_{it}: outcome variable of interest for household i during time t. $Treated_i$ is a binary variable that equals 1 for the treatment group and 0 for the control group; $Time_t$ is a binary variable for time that equals 1 for follow-up data and 0 for baseline data; $\boldsymbol{X}_{it}$ is a vector of farm (household)-level covariates, α_r represents region fixed effects and, ε_{it} error represents an error term that satisfies the standard orthogonality conditions.

While the coefficient β_1 captures baseline differences, both observable and unobservable, as long as they remain constant over time, between the treatment and control groups, the coefficient β_2 reflects overall time trends that affect both groups equally. The coefficient β_3, therefore, isolates the change in the treatment group that goes beyond these common trends, allowing us to identify the causal impact of the intervention.

5.2. Propensity Score Estimation

Because participation in the program was not randomly assigned, beneficiary and non-beneficiary farmers may differ systematically in characteristics that influence both participation and outcomes. To address this issue, we estimate the propensity scores following the approach proposed by Rosenbaum and Rubin (1983). Propensity score methods are used to reduce selection bias when estimating treatment effects with observational data. In the absence of random assignment, a comparison group is constructed by identifying non-beneficiary units that are observationally similar to beneficiary units based on pre-treatment characteristics. Specifically, a probit model is estimated using baseline covariates to predict the probability of program participation (Table 4).[2] The resulting propensity score summarizes the likelihood of treatment conditional on observed characteristics and serves as a balancing score that facilitates comparison between treated and untreated farms with similar observable attributes.

These propensity scores are subsequently used to construct the IPW weights for beneficiary and non-beneficiary farmers in the working sample. Under the assumption of selection on observables, this approach reduces systematic differences between groups and improves the credibility of the estimated treatment effects. The propensity score is defined as follows:

$$p(x) = Pr[W = 1|X = x]$$

Where W is the treatment status ($W = 1$ if treated, $W = 0$ otherwise), and X is a vector of observable characteristics. Thus, the propensity score indicates the conditional probability of treatment participation, given a set of characteristics.

[2] The selection of covariates for the Propensity Score follows the methodology described in Corral *et al.* (2024). The variables were chosen based on their theoretical association with treatment status and iteratively added to the model according to improvements in the likelihood ratio statistic.

Table 4 - Variables used for the selection of the comparison group

Variable	Codification
HH head female	1 = Yes, 0 = No
HH Secondary school complete	1 = Yes, 0 = No
Ethnicity: East Indian	1 = Yes, 0 = No
N. HH members	Sum of members
Dependency ratio	%
Cooking energy: Gas	1 = Yes, 0 = No
Agricultural assets index	1-5
Owns dwelling	1 = Yes, 0 = No
Water: Public - piped into dwelling	1 = Yes, 0 = No

The propensity score model includes a set of baseline covariates selected based on both theory and prior evidence regarding the determinants of program participation and agricultural outcomes. Conditioning on these variables aims to satisfy the conditional independence assumption, whereby treatment assignment is assumed to be independent of potential outcomes given observed characteristics. The complete list of covariates used in the estimation is reported in Table 4, while Table 5 presents the results of the probit model.

5.3. Inverse Probability Weighting (IPW)

After estimating the propensity score, the study constructs Inverse Probability Weights (IPW) to address self-selection bias while retaining the full sample each observation is reweighted by the inverse of its estimated propensity score. Specifically, for observation *i*, the weight is defined as:

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

This approach assigns greater weight to treated observations with lower propensity scores and control observations with higher scores, thereby constructing a weighted sample that more closely resembles a randomized allocation of treatment. An additional advantage of IPW is that it retains all observations, preserving statistical power and allowing standard errors to be estimated within a regression framework (Rosenbaum, 1987; Hirano and Imbens, 2001).

Table 5 - Probit: Propensity Score

	(1) Treatment
HH head (female = 1)	**-0.37***** (0.12)
HH Secondary school completed	**0.23**** (0.11)
Ethnicity: East Indian	**0.42***** (0.10)
N. HH members	0.03 (0.03)
Dependency ratio (<18, >65)	**-0.47***** (0.17)
Cooking energy: Gas	**0.41***** (0.14)
Agricultural assets index	0.05 (0.03)
Water: Public - piped into dwelling	**0.16*** (0.10)
Owns dwelling	**-0.17** (0.13)
Constant	**-0.66***** (0.23)
Observations	**802**

Note: Statistical significance is denoted as follows:
* p < 0.10, ** p < 0.05, *** p < 0.01.

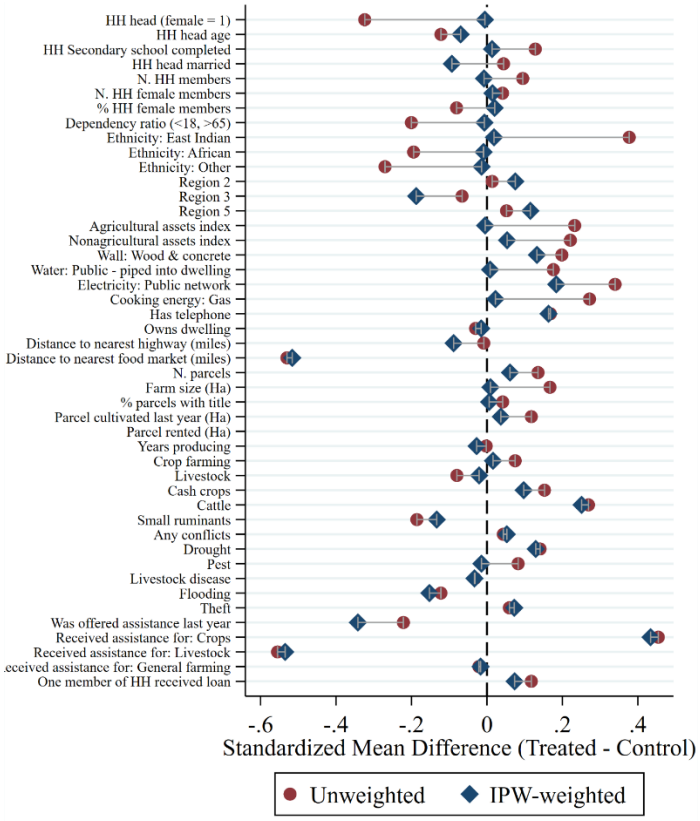
In Table 6, we replicate the balance test using the IPW weights to assess how covariate balance changes once households are reweighted. Compared to Table 3, most of the significant differences in sociodemographic characteristics, ethnicity, and asset holdings are no longer significant, suggesting that the weights bring the treatment and control groups closer to observational equivalence. Some imbalances persist, however, particularly regarding dwelling and parcel characteristics, exposure to shocks, and prior access to technical assistance. Similarly, Figure 2 presents these results graphically for each covariate, plotting the standardized mean difference between treated and control households before (red) and after (blue) applying the IPW weights, with the dashed vertical line marking exact balance. Most covariates move visibly closer to the zero-difference line once weighted, consistent with the reduction in significant differences reported above.

Table 6 - Weighted Balance Test: Treated vs Controls (Baseline)

	Treated	Control	Difference
Panel A – Sociodemographic characteristics:			
HH head (female = 1)	0.21	0.21	0.00
HH head age	51.28	52.23	-0.95
HH Secondary school completed	0.25	0.25	0.01
HH head married	0.60	0.65	-0.05
N. HH members	3.32	3.33	-0.01
N. HH female members	1.63	1.61	0.02
% HH female members	0.47	0.47	0.01
Dependency ratio (<18, >65)	0.27	0.27	0.00
Ethnicity: East Indian	0.66	0.66	0.01
Ethnicity: African	0.15	0.15	0.00
Ethnicity: Other	0.19	0.20	-0.01
Region 2	0.36	0.33	0.04
Region 3	0.30	0.39	**-0.09****
Region 5	0.34	0.28	0.05
Panel B – Dwelling characteristics:			
Agricultural assets index	2.89	2.90	-0.01
Nonagricultural assets index	2.94	2.86	0.08
Wall: Wood & concrete	0.39	0.32	**0.06***
Water: Public - piped into dwelling	0.47	0.47	0.00
Electricity: Public network	0.90	0.84	**0.06****
Cooking energy: Gas	0.88	0.87	0.01
Has telephone	0.25	0.18	**0.07****
Owns dwelling	0.85	0.86	-0.01
Distance to nearest highway (miles)	1.39	1.61	-0.22
Distance to nearest food market (miles)	2.89	2.90	-0.01
Panel C – Parcels characteristics:			
N. parcels	1.57	3.24	**-1.67****
Farm size (Ha)	1.37	1.29	0.08
% parcels with title	2.90	2.86	0.05
Parcel cultivated last year (Ha)	0.45	0.45	0.00
Parcel rented (Ha)	0.94	0.90	0.05
Years producing	0.00	0.00	0.00
Panel D – Main agricultural activity:			
Crop farming	0.57	0.56	0.01
Livestock	0.43	0.44	-0.01
Cash crops	0.65	0.60	0.05
Cattle	0.33	0.22	**0.11*****
Small ruminants	0.36	0.42	**-0.07***
Panel E – Production loss by primary cause:			
Any conflicts	0.05	0.04	0.01
Drought	0.05	0.03	**0.03***
Pest	0.35	0.35	-0.01
Livestock disease	0.19	0.21	-0.01
Flooding	0.81	0.87	**-0.06*****
Theft	0.12	0.10	0.02
Panel F – Technical Assistance			
Was offered assistance last year	0.26	0.42	-0.16*****
Received assistance for: Crops	0.79	0.59	0.20*****
Received assistance for: Livestock	0.17	0.40	-0.23*****
Received assistance for: General farming practices	0.02	0.02	0.00
One member of HH received a loan	0.12	0.09	0.02
Observations	**414**	**388**	

Note: Statistical significance is denoted as follows: * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure 2: Pre and Post Weighting Bias across Covariates



6. Results

This section presents the estimated impacts of the SADP's extension component using the IPW-DiD approach. Following the causal sequence set out in the theory of change in Section 3, the analysis first examines the intermediate outcome of adopting improved and sustainable agricultural practices. It then assesses the program's final outcomes: agricultural production and sales values, crop productivity, and pressure on natural ecosystems.

6.1. Adoption of sustainable agricultural practices

Table 7 presents the estimation results for the adoption of sustainable agricultural practices. Column (1) reports results for use of sustainable crop practices, column (2) for livestock practices, and (3) for practices that specifically reduce pressures on ecosystems. At baseline, treated households displayed a higher average number of adopted practices compared to control households. However, the program did not lead to statistically significant changes in adoption of sustainable crop practices over time. The interaction term is statistically indistinguishable from zero across all specifications. In relative terms, the imprecisely estimated impacts are negative, ranging between -17% for crop practices and -35.5% for ecosystem-pressure reducing practices, but positive by 0.6% for use of sustainable livestock practices, relative to the baseline control mean. However, it should be noted that the large percentage change reflects the very low baseline prevalence of these eco-friendly practices rather than a substantively large absolute change.

These null results on sustainable practice adoption echo the findings of the systematic review by Waddington et al. (2014), who find that while farmer training interventions reliably improve farmers' knowledge of beneficial practices, effects on actual adoption are substantially more heterogeneous and context-dependent, with several scaled-up and long-term programs showing null or negative adoption effects.

Table 7: Adoption of sustainable practices by farmers (count)

	(1)	(2)	(3)
	Use of sustainable crop practices	**Use of sustainable livestock practices**	**Use of ecosystem-pressure reducing practices**
Treatment	0.30 (0.19)	0.32 (0.21)	0.07 (0.07)
Time	-0.23 (0.29)	**-0.38**** (0.08)	0.20 (0.08)
Time * Treatment	-0.30 (0.24)	0.01 (0.13)	-0.14 (0.09)
Relative effect (% of baseline control mean)	-17.0%	0.6%	-35.5%
Baseline Weighted Mean:			
Treated	2.06	1.59	0.46
Control	1.75	1.26	0.38
Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
N	1,604	1,604	1,604
R^2	0.08	0.04	0.04

Controls: Gender, ethnic and education level of household head, number of household members, dependency ratio, farm size, cooking energy, quantiles of agricultural assets index. Clustered standard errors by region in parentheses. Statistical significance denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2. Agricultural production and sales values

Table 8 reports the gross value of production for primary cash crops, cassava, bora as well as for livestock. The estimated effects on the agricultural production value show no statistically significant impact for these crops. The coefficient of the interaction term between treatment and time is positive but not significant for all four outcomes, suggesting that program participation did not lead to measurable changes in the total value of harvested crops over the evaluation period.

In relative terms, the estimated impacts on the value of production are relatively small when compared to baseline levels. For cassava, the estimated DiD coefficient is equivalent to 35.6% of the weighted baseline mean for the control group. The corresponding relative effects are much smaller for bora (3.3%) and livestock (3.1%). Although the point estimate for cassava is sizable, it is not statistically significant, so these magnitudes do not allow us to conclude that the program generated measurable short-term effects on the gross value of crop production during the evaluation period.

The absence of short-term effects on crop production is consistent with the pattern observed in other extension programs in the region. Cerdán-Infantes, Maffioli, and Ubfal (2008) evaluate an agricultural extension program for grape farmers in Mendoza, Argentina, and find that the overall effect on yields was negative in the short run, with quality improvements only emerging two to three years after participation. González et al. (2009) similarly find, in their evaluation of a technology adoption program in the Dominican Republic, that significant productivity effects materialized for rice producers but not for other commodity types, suggesting that the tractability of extension impacts varies substantially across crops and production systems within the same program. In both cases, aggregate value outcomes showed limited short-term response even where physical productivity gains were detectable, a pattern consistent with the results, where the significant gain in cassava yield is not matched by a statistically significant gain in the value of production.

Table 8: Gross Value of Agricultural Production (in USD)

	(1) All Cash Crops	(2) Cassava	(3) Bora	(4) Livestock
Treatment	389.94	106.84	301.80	7013.58*
	(270.96)	(488.16)	(549.40)	(2109.51)
Time	153.27	57.34	-60.71	6045.70
	(470.02)	(643.61)	(688.98)	(2851.71)
Time * Treatment	175.14	426.20	53.74	361.68
	(347.36)	(789.66)	(612.73)	(4383.73)
Relative effect (% of baseline control mean)	12.0	35.6	3.3	3.1
Baseline Weighted Mean:				
Treated	1,528.76	2,067.51	1,336.04	16,652.92
Control	1,456.90	1,197.30	1,606.46	11,549.52
Controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	217	86	139	360
R^2	0.21	0.37	0.19	0.30

Controls: Gender, ethnic and education level of household head, number of household members, dependency ratio, farm size, cooking energy, quantiles of agricultural assets index. Clustered standard errors by region in parentheses. Statistical significance denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9 reports estimated impacts on the gross value of agricultural sales. As with the production-value outcomes, none of the estimated DiD coefficients is statistically significant. Relative to the weighted baseline control mean, the estimated effects are 14.6% for all cash crops, -6.4% for bora, and 9.9% for livestock. For cassava, the estimated effect is approximately US$879, equivalent to 79.2% of the weighted baseline control mean. Although this is the largest relative estimate among the sales outcomes and its positive sign is consistent with the cassava yield effect reported in Table 10, it is based on a small subsample and is not statistically significant.

Table 9: Gross Value of Agricultural Sales (in USD)

	(1) All Cash Crops	(2) Cassava	(3) Bora	(4) Livestock
Treatment	357.18	-93.71	551.68	394.53
	(616.44)	(403.46)	(557.87)	(366.32)
Time	155.14	43.95	240.96	461.36
	(643.24)	(774.92)	(891.28)	(728.38)
Time * Treatment	195.97	878.83	-86.36	277.36
	(774.72)	(413.84)	(755.63)	(536.08)
Relative effect (% of baseline control mean)	14.6	79.2	-6.4	9.9
Baseline Weighted Mean:				
Treated	1,550.37	1,688.94	1,483.86	3,170.21
Control	1,339.21	1,109.28	1,344.91	2,811.44
Controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
N	176	64	117	176
R^2	0.20	0.47	0.18	0.20

Controls: Gender, ethnic and education level of household head, number of household members, dependency ratio, farm size, cooking energy, quantiles of agricultural assets index. Clustered standard errors by region in parentheses. Statistical significance denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.3. Crop productivity

Regarding land productivity at the farm level, results show a positive and statistically significant impact for cassava yields. On average, cassava yields among treated farmers increased by approximately 3,692 kg/ha relative to the control group (Table 10), suggesting that program support for technology adoption and extension services may have contributed to yield improvements. The effect for bora is negative but not statistically significant.

Table 10: Crop yields (in kg/ha)

	(4) Cassava	(5) Bora	(6) All Cash Crops
Treatment	1,895.19	-2,803.92	808.17
	(676.44)	(2,924.80)	(1,599.42)
Time	491.62	-6,092.51	-2,983.63
	(879.16)	(8,682.15)	(2,318.28)
Time * Treatment	**3,692.08*** **	-1,454.99	1,425.66
	(137.29)	(2545.30)	(2,,364.69)
Relative effect (% of baseline control mean)	385.9	-13.0	27.7
Baseline Weighted Mean:			
Treated	1,486.19	13,756.42	6,330.98
Control	956.86	11,149.69	5,154.19
Controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
N	95	101	188
R^2	0.34	0.31	0.16

Controls: Gender, ethnic and education level of household head, number of household members, dependency ratio, farm size, cooking energy, quantiles of agricultural assets index. Clustered standard errors by region in parentheses. Statistical significance denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

When expressed in relative terms, this impact is economically large. The estimated increase in cassava productivity corresponds to approximately a 385.9% increase relative to the weighted baseline mean for the control group and is more than twice the baseline mean for treated farmers.. However, both the statistical significance and magnitude of this estimate should be interpreted with caution for three reasons. First, the estimate is based on a small subsample of farmers reporting cassava production in both survey rounds. Second, yield is calculated as the ratio of self-reported production to self-reported cultivated area and is therefore particularly sensitive to measurement error in the denominator, especially among smallholders cultivating small or irregularly measured plots. Third, the estimated productivity effect is not accompanied by a statistically significant increase in the gross value of cassava production (Table 8). Thus, while the result provides suggestive evidence of improved physical productivity among cassava producers, it does not indicate a corresponding short-term improvement in production value. This divergence across outcomes is consistent with the broader literature showing that the effects of agricultural extension programs may vary by outcome and may take time to translate into economic gains. For example, Aramburu et al. (2014), evaluating of a technology adoption program for smallholders in Bolivia, find positive short- and medium-term effects on crop diversification, input use, and income from sales, but no significant effects on productivity measures such as the value of production or gross margins within a single agricultural cycle.

6.4. Pressure on natural ecosystems

Table 11 reports the estimated impact on hectares used for livestock production, which serves as a proxy for land-use intensity and associated pressure on fragile ecosystems. The estimated DiD coefficient indicates a reduction of approximately 0.1 hectares among treated farmers relative to the control group, equivalent to 4% of the weighted baseline control mean. However, the estimate is small and not statistically significant, providing no evidence that the program reduced livestock-related land-use intensity during the study period.

Table 11: Livestock pressure on ecosystems (in Ha)

	(1) **Area for livestock production (Ha)**
Treatment	-0.07
	(0.13)
Time (1=2025)	-0.40
	(0.44)
Time * Treatment	-0.10
	(0.51)
Relative effect (% of baseline control mean)	-4.0%
Baseline Weighted Mean:	
Treated	2.56
Control	2.47
Controls	Yes
Region FE	Yes
N	590
R^2	0.89

Controls: Gender, ethnic and education level of household head, number of household members, dependency ratio, farm size, cooking energy, quantiles of agricultural assets index. Clustered standard errors by region in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7. Conclusions

This paper provides the first rigorous quasi-experimental evidence on the effects of a comprehensive agricultural development program in Guyana. Using a balanced panel of 802 households and an IPW-DiD strategy, the analysis finds no measurable impacts on the adoption of sustainable agricultural practices, aggregate crop or livestock production value, or livestock-related land-use intensity during the evaluation period. The results provide some evidence of higher cassava yields, but this estimate is based on a small subsample, may be sensitive to measurement error in self-reported production and cultivated area, and is not accompanied by a significant increase in the gross value of cassava production. It is therefore interpreted as a finding warranting further research rather than as a demonstrated program achievement. Overall, the findings indicate limited program impacts over the evaluation period.

The pattern of results highlights the time required for agricultural interventions to affect different types of outcomes. While extension services can effectively transfer information and technologies, the adoption of more complex practices often requires sustained engagement, complementary investments, and favorable market and institutional conditions. Crop-specific yield improvements can plausibly materialize within the program period, whereas the adoption of complex, multi-behavior sustainable practices require sustained engagement over multiple seasons, supporting institutional infrastructure (input markets, credit, price incentives), and program durations that extend well beyond a single intervention cycle. A growing body of evidence from Latin America and the Caribbean shows that the impacts of agricultural extension and technology adoption programs often emerge gradually, as farmers move along learning curves, adapt technologies to local conditions, and adjust their production systems over multiple production cycles. Several long-term evaluations have found that productivity gains only became visible two or three years after exposure to an intervention, while others documented impacts that strengthened over time (Aramburu et al., 2019; Salazar et al., 2021; Schling and Pazos, 2022b; Salazar et al., 2023; Schling et al., 2025b). The results presented here should therefore be interpreted within the relatively short observation window available for the evaluation. Accordingly, the absence of broader measurable effects during the evaluation period does not rule out the possibility of longer-term changes, but neither does the available evidence establish that such changes will occur.

The cassava result merits particular attention. Its magnitude and positive sign suggest that the combination of technical assistance, technology transfer, and adoption incentives successfully improved performance in a priority crop. However, with the absence of a statistically significant effect on the value of cassava production, we do not consider this result strong enough to support a claim of a genuine productivity gain. Additional research using a larger crop-specific sample and more precise measures of production and cultivated area would be needed to determine whether the estimate reflects a sustained productivity effect.

The evaluation also offers operational lessons. COVID-related delays, the withdrawal from Region 9, changes in geographic coverage, and the abandonment of the planned randomized rollout affected both program implementation and the original evaluation design. These experiences underscore the importance of incorporating flexibility into implementation arrangements while maintaining clear mechanisms for documenting program exposure, beneficiary selection, and

delivery intensity. They also illustrate the value of developing contingency identification strategies when prospective evaluation designs depend on implementation protocols that may change.

The findings should be interpreted in light of the study's identification constraints. The availability of only one pre-intervention observation prevents a direct assessment of the parallel-trends assumption underlying the DiD design. The IPW procedure substantially improves comparability between treated and control households on observed baseline characteristics, while the DiD framework accounts for time-invariant unobserved differences; however, the possibility of differential unobserved trends cannot be fully ruled out. This limitation calls for appropriate caution but does not negate the contribution of the study as the most rigorous evaluation design feasible under the program's operational conditions.

For a potential second phase of the SADP, these findings suggest prioritizing the continuity and effective delivery of extension services, strengthening complementary access to inputs, credits, and markets, and improving the monitoring of beneficiary exposure and practice adoption. Future evaluations would benefit from multiple pre- and post-intervention observations, more precise crop-specific productivity measures, and sufficient follow-up time to assess whether changes in knowledge and practices translate into sustained productivity, economic, and environmental outcomes. Greater attention to gender-differentiated access to extension services would further enhance the equity impact of future investments.

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9. Appendix

9.1. Attrition test

This analysis focuses on farmers who participated in both rounds of the survey, compared to those who were surveyed in the baseline but not in the follow-up (attritors). A total of 40 farmers declined to be surveyed at baseline and 14 at follow-up. The resulting attrition rates are 29.5% for the treated group and 38.7% for the control group. As an attrition check, Table A1 compares baseline characteristics between attritors and non-attritors. Attritors differ on some sociodemographic and dwelling characteristics. However, since attrition is balanced across treatment arms, we do not expect it to substantially bias the estimated program effects, though it may limit their generalizability.

Table A1: Balance Test: Attritors vs Non-attritors (Baseline)

	Attritors	Non Attritors	Difference	
Treated	0.52	0.52	0.01	
Panel A – Sociodemographic:				
HH head (female = 1)	0.16	0.21	**-0.05**	**
HH head age	50.62	51.84	-1.21	
HH Secondary school completed	0.27	0.26	0.01	
HH head married	0.57	0.63	**-0.07**	**
N. HH members	2.86	3.33	**-0.47**	***
N. HH female members	1.37	1.62	**-0.25**	***
% HH female members	0.45	0.47	-0.02	
Dependency ratio (<18, >65)	0.24	0.27	-0.03	
Ethnicity: East Indian	0.56	0.65	-0.09	***
Ethnicity: African	0.16	0.15	0.01	
Ethnicity: Other	0.28	0.20	**0.08**	***
Region 2	0.27	0.36	**-0.09**	***
Region 3	0.37	0.32	0.04	
Region 5	0.36	0.32	0.04	
Panel B – Dwelling characteristics:				
Agricultural assets index	2.91	2.88	0.03	
Nonagricultural assets index	2.92	2.88	0.05	
Wall: Wood & concrete	0.28	0.35	**-0.07**	**
Water: Public - piped into dwelling	0.39	0.46	**-0.07**	**
Electricity: Public network	0.78	0.85	**-0.07**	***
Cooking energy: Gas	0.78	0.87	**-0.10**	***
Has telephone	0.26	0.21	**0.04**	*
Owns dwelling	0.72	0.86	**-0.13**	***
Panel C – Parcel characteristics:				
N. parcels	1.21	1.31	-0.09	
Farm size (Ha)	3.49	2.85	**0.64**	**
% parcels with title	0.41	0.44	-0.03	
Parcel cultivated last year (Ha)	0.75	0.89	**-0.14**	**
Parcel rented (Ha)	21.90	23.01	-1.11	

Table A1 (*continued*): Balance Test: Attritors vs Non-attritors (Baseline)

	Attritors	Non Attritors	Difference	
Panel D – Main agricultural activity:	0.52	0.59	**-0.07**	**
Crop farming	0.39	0.41	-0.03	
Livestock	0.61	0.64	-0.04	
Cash crops	0.28	0.27	0.02	
Cattle	0.36	0.37	-0.01	
Small ruminants	1.21	1.31	-0.09	
Panel E – Production loss by primary cause:				
Drought	0.06	0.05	0.01	
Pest	0.03	0.04	-0.01	
Livestock disease	0.32	0.35	-0.03	
Flooding	0.17	0.19	-0.03	
Theft	0.73	0.84	**-0.11**	***
Any farm conflicts	0.09	0.10	-0.02	
One member of HH received a loan	0.10	0.10	0.00	
Observations	**418**	**802**		

9.2. Structure of the SADP Survey Instrument

Table A2: Modules in the SADP Questionnaire

- Section 0: Metadata and Background
- Section 1: Household Members
- Section 2: Agricultural Plots
- Section 3: Assets
- Section 4: Livestock
- Section 5: Agricultural Production
  - Temporary Crops
  - Permanent Crops
- Section 6: Agricultural Production Assistance
- Section 7: Economic Activities of Household Members

9.3. Construction of Outcome Indicators

Table A3: Construction of indicators

Indicator	Definition	Explanation
Agricultural income (crops)	Gross value of crop production (USD per farm)	Average annual value of bean/bora and cassava production per household/farm, prior to deductions due to post-harvest loss, household consumption, or processing.
Agricultural income (livestock)	Gross value of livestock production (USD per farm)	Value of cattle production per household/farm, based on reported sales and valuation of livestock inventory prior to losses or household consumption.
Crop productivity	Yield (kg/ha) = total crop production ÷ cultivated land area	Farm-level productivity for bean/bora and cassava. Production is measured prior to losses, consumption, or processing, and divided by cultivated area.
Ecosystem pressure (livestock land use)	Hectares of land allocated to livestock production	Total land area (hectares) used for livestock activities, used as a proxy for pressure on fragile ecosystems.
Adoption of sustainable crop practices	Count of practices adopted (0–25)	Number of sustainable crop practices adopted from a predefined list of 25 practices (e.g., intercropping, composting, mulching, soil conservation, water harvesting, pest management, post-harvest handling, climate-smart practices, record keeping).
Adoption of sustainable livestock practices	Count of practices adopted (0–16)	Number of sustainable livestock practices adopted from a predefined list (e.g., artificial insemination, deworming, vaccination, feeding practices, disease control, biosecurity, branding, farm management practices).
Ecosystem-friendly practices index	Count of practices adopted (0–7)	Number of practices aimed at reducing ecosystem pressure, including intercropping, composting, mulching, soil conservation, water harvesting, climate-smart techniques, and cover crops.

Table A4: Detailed List of Crop, Livestock, and Ecosystem-Related Agricultural Practices

1. Sustainable crop practices (25 practices)

- Intercropping techniques
- Composting
- Vermicompost production
- Mulching
- Cover crops
- Vegetative propagation techniques
- Soil conservation measures
- Water harvesting systems
- Climate-smart agricultural practices
- Protective agricultural techniques
- Soil sampling and testing
- Post-harvest management practices
- Post-harvest pest and disease control
- Integrated pest management (crop level)
- Integrated disease management (crop level)
- Use of improved seed varieties
- Crop rotation practices
- Agroforestry practices
- Basic agronomic calibration techniques
- Farm record keeping
- Farm sanitation practices
- Planting protective vegetation (barriers/hedgerows)
- Planting forage or cover vegetation
- Improved fertilization practices
- Fallow management with controlled grazing avoidance

2. Sustainable livestock practices (16 practices)

- Artificial insemination
- Deworming
- Vaccination
- Controlled breeding and reproduction management
- Supplemental feeding practices
- Disease prevention and control practices
- Pest control (livestock-related)
- Vampire bat control and management
- Animal identification and branding
- Biosecurity measures at farm level
- Farm sanitation practices
- Basic feed ration formulation / calibration
- Improved grazing management practices
- Improved housing and shelter conditions
- Agro-processing of livestock products
- Record keeping for livestock management

3. Ecosystem pressure–reducing practices (7 practices)

- Intercropping techniques
- Composting and vermicompost
- Mulching
- Soil conservation works (terracing, contouring, etc.)
- Water harvesting systems
- Climate-smart agricultural practices
- Cover crops

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