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Impact evaluation of an agricultural input subsidy to mitigate COVID-19 effects on small holder farmers: A case of Uganda

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The outbreak of the COVID-19 pandemic shocked most economic activities, including agriculture and food production, with limited access to key inputs such as labor, seeds, fertilizer, and other agrochemicals. Food marketing and trade were equally disrupted as cash flows, liquidity, and credit access were constrained. Different countries, organizations, and households improvised various strategies and measures to mitigate the shocks in the food value chain that would have had far-reaching implications. In Uganda, one international organization, the Agricultural Business Initiative (aBi), supported a project titled "*Building the Resilience of Smallholder Farmers through Increasing Access to Agro-Inputs*" to safeguard the production, trade, and processing of key food staples. This paper assesses the contribution of such emergency projects and draws lessons for similar future interventions. Cross-sectional data collected was used from project beneficiaries and non-beneficiaries as a control group and employ propensity score matching techniques to measure the project's impact. Results show a significant positive impact of the project intervention on crop yields and household crop income. The study recommends partnerships with local government extension workers for promoting sustainability and scaling out. Future similar projects could target to support farmers based on individual capacity in terms of resources, especially land, instead of providing uniform support which may exclude some farmers.

Key words: Agro-inputs subsidy, COVID-19, evaluation, propensity score matching.

INTRODUCTION

The novel coronavirus (COVID-19) pandemic, which originated in China in 2019 and subsequently spread worldwide, reached Uganda in March 2020. Similar to other countries, Uganda implemented a lockdown to restrict movements and interpersonal contacts as a measure to mitigate the spread of the pandemic. This had a profound impact on various economic sectors, including agriculture and food production. While farming

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activities were not directly restricted, access to essential inputs such as labor, seeds, fertilizer, and agrochemicals was severely affected due to the disruption of public transport, closure of businesses, and shifts in business operations. Furthermore, food marketing and trade were significantly disrupted as cash flows, liquidity, and credit access were constrained. Many of the traders and businesses that farmers rely on for transactions were at risk of collapse or, at the very least, experienced a considerable reduction in their operational capacity. According to the FAO (2020), the shocks caused by COVID-19 were projected to lead to a significant reduction in land productivity. One short-term approach to enhancing the resilience of agro-based industries was through the increased utilization of improved seeds and fertilizers by farmers (Magar, 2021). Limited access to these improved inputs has historically been a significant constraint to smallholder farmer productivity.

The situation was further exacerbated by the COVID-19 pandemic, which hindered farmers' ability to access improved inputs. Given that many farmers depend largely on their farms for income, reduced productivity would inevitably translate to decreased farmer income. To effectively manage shocks in food production, support food and nutrition security, and sustain at least survival-levels of trade along key food value chains, it was imperative to bolster farm production and productivity, as well as support food-industry activities.

This paper presents an impact evaluation of a project intervention titled "*Building the Resilience of Smallholder Farmers through Increasing Access to Agro-Inputs*," supported by the Agricultural Business Initiative (aBi), an international organization comprising two companies: aBi Development Limited and aBi Finance Limited. aBi Development Limited offers development finance in the form of matching grants and Business Development Services (BDS) to agricultural producers and agribusinesses, focusing on seven value chains, including pulses and cereals. The primary objective of the project was to safeguard the production, trade, and processing of key food staples by facilitating off-take partners in providing seeds and fertilizers to smallholder farmers cultivating maize, sorghum, beans, sunflower, and soybean.The project's theory of change (aBi, 2020) posited that providing farmers with agro-inputs (seed and fertilizer), advisory services, and information would lead to increased adoption and utilization of agro-inputs in agricultural production (Hemming et al., 2018). This, in turn, was expected to enhance crop yields and consequently increase income (Danso-Abbeam et al., 2018) for beneficiary farmers and small and medium enterprises (SMEs), thereby enhancing their resilience and mitigating the effects of COVID-19. Ultimately, the project aimed to improve food and nutrition security within the communities. However, it's acknowledged that the relationship between agricultural inputs received and crop yield may not always be linear, as found by Mkhonto and Musundire (2019) in their study conducted in Mopani District, South Africa.

Nevertheless, aBi's initiative to support farmers by providing improved seeds for key food crops and fertilizers was deemed highly appropriate to address not only the needs of farmers but also the food requirements of society. Over 50% of the farmers surveyed rely on beans as their primary source of income, with approximately 36% depending on maize. Given Uganda's role as a food source, particularly for neighboring countries in terms of crops like maize and beans, this project was timely.

One of the implementation methodologies employed was a matching grant for beneficiary farmers, requiring them to contribute 20 and 40% of the cost of seed and fertilizer, respectively. A matching grant, as defined by IFAD (2012), is a one-off, non-reimbursable transfer to project beneficiaries for a specific purpose, with the condition that the recipient makes a contribution, either in cash or in kind or both, for the same purpose. It is hypothesized that well-designed matching grants can help address specific barriers faced by farmers, such as limited access to improved production technologies and limited financial capacity to purchase the required inputs. Matching grants can, therefore, alleviate farmers' credit and risk constraints, thereby boosting their economic activities in the short term.

In Rwanda, Hossain et al. (2022) observed that matching grant interventions can have long-term positive impacts on the livelihoods of small-scale producers. McKenzie et al. (2016) reported that matching grants led to more product innovation in the first year, with firms marketing more and making more capital investments in Yemen. In their analysis of lessons learned from World Bank Projects using matching grants, Varangis et al. (2017) found that projects for agriculture generally received higher ratings (73% rated "satisfactory") than non-agriculture projects (47%). However, matching grants may not always be the most cost-effective tool to help farmers if rural markets are limited or if the grant is not properly designed. For example, input subsidy programs scaled up in Sub-Saharan Africa after 2005 partially achieved the intended impact as they suffered from severe design and implementation failures, such as failure to adhere to market-smart principles and neglect of a clear exit strategy (Holden, 2019).Furthermore, the project employed the Lead Farmer model/approach, which has proven to yield positive results. Lead Farmers or Local Market Facilitators, as referred to by some project implementing partners; facilitate farmer mobilization, training, especially on demonstration gardens, input distribution, monitoring fellow farmers, and produce bulking. In other contexts, such as Malawi (Ragasa, 2020), Nigeria (Oyelami et al., 2018), and India (Meena et al., 2020), the Lead Farmer extension approach has been effective in complementing the efforts of extension workers.

A similar intervention, the "Kilimo Plus" initiative, was implemented in Kenya in 2007/2008 as a targeted input for inorganic fertilizer and improved seed. The program provided 50 kg each of basal and top-dressing fertilizer, and 10 kg of improved maize seed to resource-poor smallholder farmers with the goals of increasing access to inputs, raising yields and incomes, improving food security, and reducing poverty. Mason et al. (2017) report that the initiative substantially increased maize production and reduced poverty among recipient households. Significant positive effects have also been reported in other countries, such as Malawi, where the farm input subsidy program increased adoption and use of inorganic fertilizer and improved maize seeds (Koppmair et al., 2017). Recipients of input subsidies commonly used natural resource management technologies compared to non-recipients. However, farmers consider modern inputs and natural resource management practices as complements, not substitutes, to traditional technologies.

In Ghana, Agyemang et al. (2022) report that agricultural productivity increases as farmers' level of agricultural input subsidy increases. They find a higher positive effect on productivity for small-scale farmers than large-scale farmers. Moreover, higher productivity growth can be achieved if the subsidy is targeted and disbursed based on farm size rather than one rate for all, as was used in this specific project. Providing input subsidy to a specific target group of poor smallholder farmers can be more efficient and cost-effective (Houssoun et al., 2019). Farmers' participation in supported projects has been reported to increase technical efficiency resulting from improved access to productive inputs and other support services such as training, information, and extension on input application (Iddrisu et al., 2018; Martey et al., 2015; Sikwela and Mushunje, 2013).

The aim of this paper is to assess the contribution of such emergency projects and provide recommendations/ strategies to improve similar future interventions. Insights from this evaluation are important for designing effective agricultural subsidy interventions for improving productivity and household income for smallholder farmers. The paper contributes to the evidence base to support policies to increase crop productivity and household income by underlining the importance of promoting improved technologies, farmer access to inputs, and produce markets. The paper consists of five sections. After this introduction, part 2 of the study provides an overview of the project—how it was implemented and the intended objectives and outcomes. Part 3 presents the methodology, providing a description of the approaches used in the evaluation. Part 4 provides the findings, and section 5 presents the conclusion and recommendations for improving future similar projects.

Description of the project

The primary purpose of the project was to build resilience among smallholder farmers by increasing their access to agro-inputs using a declining subsidy model. The project aimed to support 37,217 farmers as direct beneficiaries, cultivating at least 37,217 acres to enhance both food and cash crop production. aBi supported the project through its network of agribusiness firms, referred to as Implementing Partners (IPs), located in various regions (Figure 1), including AgroWays Uganda Ltd in Ibanda and Mbarara districts, MMACKS Investments Ltd in Kyegegwa and Kyenjonjo, Arise and Shine Maize Millers Ltd in Kiryandongo and Masindi, Grow More Seeds and Chemicals Ltd in Bulambuli, Manafwa, and Sironko, Acila Enterprises Ltd in Soroti, and Aponye Uganda Ltd in Mubende and Kakumiro districts. Additionally, Ngetta Tropical Holdings Ltd in Lira was contracted later in the second half of 2021 under a performance-based contract. The selection of these IPs was based on their past experience, as they had previously implemented successful projects by providing fertilizer and maize seed to over 191,347 farmers who cultivated more than 295,067 acres of crops (aBi Annual Report, 2019). Implementing the project through IPs aimed to safeguard the relationships among value-chain actors and mitigate disruptions in the supply chain caused by the pandemic.

One of the implementation methodologies was a matching grant for the beneficiary farmers, requiring them to contribute 20 and 40% of the cost of seed and fertilizer, respectively. The implementing partner (IP) was responsible for collecting and remitting the farmers' contributions to aBi promptly to facilitate the procurement and distribution of inputs for the upcoming season. Financial strength and creditworthiness were essential requirements for IPs to participate in the project. The project directly subsidized the procurement and delivery of seed and fertilizers to farmers cultivating food crops (maize, sorghum, beans, sunflower, and soybean) for key aBi strategic agribusiness partners. These subsidies were provided for three crop seasons (2020B, 2021A, and 2021B)[1,] at progressively declining rates of subsidy, reviewable according to response and progress in economic recovery. In the initial season, farmer beneficiaries received complimentary seed and fertilizer for one acre; in the subsequent season, they were required to contribute 20% of the total cost of seed and fertilizer for one acre, and in the final season, their contribution increased to 40% (Table 1). Once the inputs were delivered to the implementing partner (IP), they were disseminated to the farmers through their respective farmer groups and networks. Throughout the three seasons, the project distributed 509 MT of maize seed, 535 MT of bean seed, and 3,157 MT of mineral fertilizer to the five sampled IPs, benefiting approximately 23,326 farmers engaged in maize (14,551) and bean (8,775) cultivation. By the end of the third season, it was

[1] There are two rainy seasons in a year in most regions of Uganda, season A refers to the fist rainy season in a year usually starting around March and season B refers to the second rainy season usually starting around August.

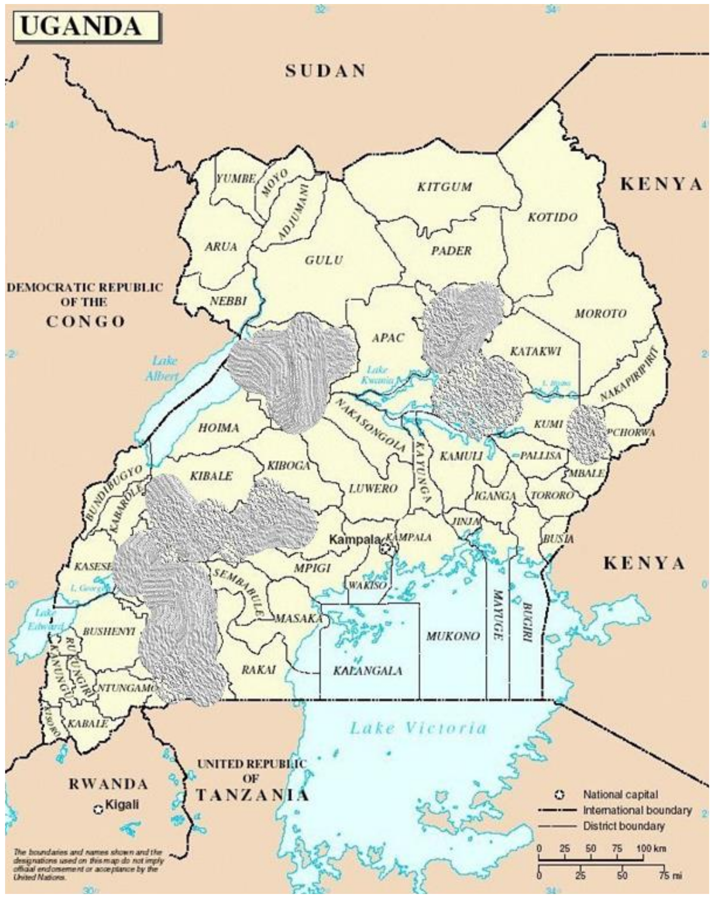

Figure 1. Map of Uganda showing project area (grey shades).

Table 1. Input subsidy distribution to beneficiary farmers.

Season	aBi contribution %	Farmer contribution
2020B	100	Farmer gets free inputs based on his acreage or historical sales through IP
2021A	80	Farmer contributes 20% while aBi reduces contribution to 80%
2021B	60	Farmer contributes 40% and aBi further reduces contribution to 60%
2022A	0	Farmer fully pays for the inputs needed

anticipated that farmers would recognize the advantages of utilizing the inputs and would have developed the capacity to adopt this practice.

Moreover, the project established farmer demonstration gardens to train farmers in good agronomic practices (GAP) and other aspects of postharvest handling practices and marketing, as well as financial literacy. Farmers were also connected to input dealers for collective procurement of inputs. Additionally, the Implementing Partners (IPs) trained local market facilitators to serve as market agents. The IP's extension/field staff supported farmers with demonstrations and technical advice to ensure the proper and safe use of the inputs they received. Given the challenges of social distancing, in addition to demonstrations, extension staff utilized other means such as leaflets, posters, and radio talk shows on local FM radio stations to deliver agronomy, pest and disease management, and market messages to the communities.

The IPs, mainly agribusiness firms, was expected to establish a buy-back arrangement wherein the produce from the farmers would be purchased by the IPs at market price.

This buy-back arrangement served as a means of ensuring a market for the farmers, thereby incentivizing them to demand more inputs and produce more. Additionally, it acted as a mechanism to enhance the efficiency of the matching grant.

METHODOLOGY

Estimation strategy for project impact

The use of inputs such as fertilizer and improved seed is anticipated to boost crop yield and overall output. This increase in production should subsequently lead to higher household income, as farmers have surplus produce to sell beyond meeting their own consumption needs. However, the key question lies in understanding the extent to which the project intervention influenced changes in these variables. Assessing the effectiveness of the project presents challenges, as obtaining data from the same farmers without project support is not feasible, resulting in what is termed as "missing data" (Blundell and Costa, 2000).

To mitigate this issue, a quasi-experimental approach was employed, incorporating a control group as a counterfactual. However, farmers were granted the choice to participate in the project based on their expectations, objectives, and observable and unobservable characteristics. This presents a challenge of self-selection bias, as the project was not randomly assigned directly to the beneficiaries but rather through specific IPs. Consequently, the farmers who received inputs may have inherently higher yields and income than those who did not receive the inputs, irrespective of the project intervention. This discrepancy could stem from various factors; for instance, participating farmers may have previously received training through farmer groups or possess entrepreneurial skills that prompt a swift response to development initiatives.

To mitigate these challenges, various methods have been employed. These include Heckman two-step estimation (Heckman et al., 1997), instrumental variables (Lunduka et al., 2013) difference-in-differences (Karan, 2017), and propensity score matching (Aweke et al., 2021). Given the available data (a one-time cross-sectional dataset), the propensity score matching technique emerges as the most suitable method for this study. The propensity score represents the conditional probability of a farmer participating in the project, considering the observed socioeconomic and demographic characteristics. This conditional probability is estimated using a logistic regression model that incorporates observable characteristics.

$$\Pr(T_i = 1) = \Pr(T_i^* > 0) = 1 - F(-\beta Z_i) T_i^* = \beta Z_i + e_i$$

Where T_i is a binary indicator variable that takes a value of 1 if the farmer participated in the project and 0 if otherwise? F is the cumulative distribution function for the error term which is assumed to have a logistic distribution for the logit model. β is a vector of parameters to be estimated, z is a vector of explanatory variables, e is the error term.

In order to evaluate a causal effect, we need the conditional independent assumption, which states that project participation is random and uncorrelated with income and yield. Once we control for observable characteristics, we can write the project effect as;

$$x(X) = E(Y^1 - Y^0|X) = E(Y^1|T = 1, X) - E((Y^0|T = 0, X)$$

Where the average project effect is

$$x = E\{x(X)\}$$

Y^1 and Y^0 denote income or yield for household i in case it participates in the project or does not participate respectively.

In a counterfactual framework the interest is the average treatment effect (ATT) on the beneficiaries expressed as;

$$ATT = E(Y_i^1 - Y_i^0)$$

In this study, the propensity score matching (PSM) results were subjected to various covariate balancing tests (Rosenbaum and Rubin, 1985; Leuven and Sianesi, 2018). These tests aimed to ensure the equality of means of observed characteristics between the treatment and control groups after matching, thereby verifying that there were no significant differences. Additionally, a propensity score graph was utilized to visually assess if the common support condition was satisfied, ensuring sufficient overlap between the treatment and control groups.

However, it's acknowledged that PSM estimation may not be robust in the presence of hidden bias or selection on unobservables. To address this concern, the sensitivity of the estimated average project effects to hidden bias (unobserved selection) was evaluated using the Rosenbaum (2002) bounds test.

To estimate the impact of the intervention on smallholder households, two main indicators were considered: crop income and productivity (yield) of the supported crops. A comparison of outcome variables (incomes and yield) was conducted between the project participants/beneficiaries and the non-beneficiaries (control group) for the project period. The hypothesis posited that increased access to inputs (improved seed and fertilizer) coupled with training in good agronomic practices would lead to an increase in the yield of the supported crops and income, as a result of increased sales volumes.

Selection of study area

The evaluation study was conducted in selected districts where the project implementing partners were operating. Five agribusiness firms (AgroWays Uganda Ltd, MMACKS Investments Ltd, Arise and Shine Maize Millers Ltd, Grow More Seeds and Chemicals Ltd, and Aponye Uganda Ltd) were chosen to represent the seven aBi partners involved in the project. For each partner, one district was selected (Table 2). Within each district, one sub-county was randomly selected from the list of sub-counties where the project was implemented.

Selection of respondents and sample size

For each project partner, a sample size that allowed meaningful statistical analysis with >90% confidence level, <10% margin of error, 50% population distribution, and design effect and non-response allowance, was selected. A sampling formula (Charan and Biswas, 2013) was used to estimate the sample size including both the beneficiary farmers and the control group as follows:

$$n = \frac{X^2 NP(1 - P)}{d^2(N - 1) + X^2 P(1 - P)}$$

Where n is the minimum size of the sample, N is the given population size, P stands for population proportion assumed to be 50%, d is the degree of accuracy (0.05) as reflected by the amount of error that can be tolerated in the fluctuation of a sample proportion p about the population proportion, and X^2 is the table value of Chi-square for one degree of freedom relative to the desired level of confidence. Using the above formula, a sample size of at least 385 people would be necessary. For propensity score matching, the number of the control group was made higher than the beneficiaries.

The population size (list of farmers who participated in the project) was obtained from the respective project partners categorised by sub-counties of the selected district. From the list of the selected sub-county, 46 farmers were randomly selected. In the neighbourhood of each selected sub-county farmers of matching gender and value chain activity but did not benefit from the project were selected as the control group, targeting 50 non-beneficiary farmers per project partner.

This made a total sample of 480 farmers (Table 2). It was noted

Table 2. Distribution of farmer respondents by implementing partner and project sites.

Project partner	Region	Selected district	Number of beneficiary farmers	Number of control	Total number of farmer respondents
AgroWays	South-western	Mbarara	46	50	96
MMACKS	Western	Kyenjonjo	46	50	96
Arise and Shine	Western	Masindi	46	50	96
Grow More Seeds	Eastern	Bulambuli	46	50	96
Aponye	Western	Mubende	46	50	96
Total	3	5	230	250	480

that the number for the control group should have been higher; however, the study was constrained by limited resources.

Data collection and type of data

The study encompassed a review of relevant literature alongside the collection of both secondary and primary data from beneficiaries, non-beneficiaries, and key informants. Mixed approaches were utilized at various levels and among different respondents. Primary data were gathered through surveys employing questionnaires for individual farmers and the project partners, as well as key informant interviews using interview guides/checklists. Key informants primarily comprised staff of implementing partners, District Agricultural Officers in project areas, and other personnel from institutions and individual businesses collaborating with or having linkages to the Implementing Partners (IPs) Secondary data utilized in the study were sourced from project reports, field data records, monitoring and evaluation reports, among others. These data mainly encompassed variables related to key performance indicators of the project.

The types of data collected from project beneficiary farmers and the control group included demographics, socio-economic and household characteristics, previous and current household income status, level of market participation, profits, sales, acreage, production, and productivity, quality of products, gender relations and responsibilities, as well as specific variables pertinent to the results chain and theory of change. Additional data gathered from project partners pertained to input distribution, farmer training and extension services, and produce marketing.

RESULTS AND DISCUSSION

Previous studies such as Manda et al. (2016) have shown that adoption decisions are driven by household characteristics. Before presenting and discussing results on the impact of the intervention, it is worthwhile to understand the social economic characteristics of the households involved in the study and the changes that may be associated with the project intervention.

Households' socio-economic and demographic characteristics

The key socio-economic characteristics of the smallholder farmers who participated in the project and the selected control group are summarized in Table 3. On average, the farmers were middle-aged, with an average age of 43 years.

The majority were males, which is commonly expected in interventions requiring financial contributions, as rural women may face greater challenges in affording such contributions. Their average years of schooling were 7.2 years, indicating at least a primary school education level, which is considered adequate to influence the adoption of technologies (Singh, 2000).

The farmers were predominantly smallholders, with an average landholding of 3.3 acres. Beneficiaries had slightly larger land holdings compared to the control group, with an average difference of 1.0 acre, and this increased by 19.3% from 3.1 to 3.7 acres after the intervention. Some key informants corroborated this information by stating that some farmers purchased land using proceeds from their produce.

Moreover, the findings indicate that the annual household income for beneficiaries was higher than that for the control group. While the income for beneficiaries increased by 7.8% from UGX 2.92 million to UGX 3.15 million, the income for the control group decreased by 4.1%. This income primarily stemmed from produce and was a result of the intervention, as on-farm enterprises constituted the major income source. The decline in income for the control group could be attributed to reduced yields and lower maize volumes resulting from the use of poor-quality seeds and lack of fertilizer application, exacerbated by drought conditions in most areas.

Furthermore, the majority of farmers marketed their produce individually, with only 31.4% engaging in collective marketing. The proportion of beneficiaries who bulked for collective marketing was slightly higher (46.6%) compared to the control group (4%). As a result of the intervention, some farmers adopted the use of improved seeds, with 70.5% of beneficiaries compared to only 10.9% among the control group. Similarly, the

Table 3. Socio-economic and demographic characteristics of sampled farmers before and after project intervention.

Characteristic	Pooled sample (n = 505)		Project beneficiaries (n = 246)		Control group (n = 259)		t- test
	Before project (2019)	After project (2021/22)	Before project (2019)	After project (2021/22)	Before project (2019)	After project (2021/22)	
Average age of farmer (years)	-	43.0 (13.5)		44.3 (13.0)		41.7 (13.9)	2.15**
Farmer's gender:							
Male		63.3		64.2		62.5	
Female		36.4		35.3		37.4	-
Level of education of farmer (years of schooling)		7.2 (3.5)		7.6 (3.5)		6.8 (3.5)	2.52***
Land size owned (acres)	3.0 (2.7)	3.3 (3.2)	3.1 (2.8)	3.7 (3.4)	2.8 (2.5)	2.7 (2.7)	3.34***
Annual household income (million UGX)	2.68	2.73	2.92	3.15	2.42	2.32	3.24***
Experience growing the crop (years)		11.9 (12.1)		11.0 (11.3)		13.0 (12.9)	0.08
Source of income: on-farm=1; 0 = otherwise	81.8	92.4	83.5	80.1	93.4	91.3	-
Collective marketing and bulking: yes =1; 0=otherwise		31.4		46.6		4.0	8.11***
Currently using improved seed Yes =1; otherwise =0		55.0		70.5		10.9	10.96***
Proportion using fertilizer (maize)	18.5	36.6	25.8	50.6	11.5	3.0	5.29***
Proportion using fertilizer (beans)	25.8	47.9	36.8	61.6	15.6	12.7	6.29***

Standard deviation in parenthesis.

percentage of farmers using fertilizer increased across both groups, with a higher percentage among beneficiaries. The adoption of fertilizer use was more prevalent in beans (47.1%) compared to maize (36.6%) production. Additionally, comparing before and after the intervention, the proportion of beneficiaries who adopted fertilizer use increased by 24.8%. The t-test revealed a significant difference between beneficiaries and the control group after the project, suggesting a substantial impact of the intervention. The study aims to estimate the contribution of the project using propensity score matching (PSM).

Impact attributable to the project interventions

Propensity score matching

Initially, the logit model was estimated to analyze the factors influencing participation in the project and to compute the propensity scores used for matching. The logistic regression results, as shown in Table 4, indicate that older farmers with relatively higher levels of education were more likely to participate in the project. Additionally, the land size owned by the household positively influenced project participation. Balancing tests indicate that before matching, there are differences between the beneficiaries and the control group in the means of covariates. However, after matching, these differences become insignificant, and all covariates are balanced (Table 5). The joint significant effect of the covariates is rejected after matching across all methods. Assessment of the distribution of the propensity scores demonstrates substantial overlap, as depicted in Figure 2. The figure illustrates project beneficiaries with appropriate matches among the control group, indicating support on the treated.

Impact of project intervention

To assess the impact of the intervention, we estimated the average treatment effect on the treated (ATT) after matching. Various matching methods, including nearest neighbor, radius caliper, and kernel matching, were employed for comparison.

The results (Table 6) indicate that farmers who benefited from the project significantly increased their crop yield and income from crops. These findings are consistent across all matching estimators. The average increase in yield attributed to the project intervention ranges from 391 to 401 kg/acre/year, depending on the

Table 4. Logistic regression estimates.

Project participation	coefficient	Std Err	Z
Age of the farmer	0.0111**	0.0057	1.94
Education of the farmer	0.0526**	0.0215	2.45
Farmer's gender	0.0367	0.1339	0.27
Farming experience	-0.0082	0.0067	-1.22
Size of land owned (Acres)	0.0872***	0.0270	3.22
Main source of income: On-farm=1; otherwise =0	-0.0024	0.3004	-0.01
Constant	-0.8620**	0.4251	-2.03
Number of observations	346		
Prob > ch2	0.0002		
Pseudo R^2	0.055		

Table 5. Test for selection bias after matching.

Variable	Matched sample		Bias		t-test
	Treated	Control	% Bias	% Bias reduction	t-values
Age of the farmer	41.78	41.70	-05.5	97.9	0.03
Education of the farmer	7.5	7.4	3.6	93.7	0.19
Farmer's gender	0.65	0.66	-0.7	96.3	-0.03
Farming experience	9.09	8.79	2.8	80.6	0.13
Size of Land owned (Acres)	3.67	3.52	3.5	92.2	0.24
Main source of income: On-farm=1; otherwise =0	0.92	0.90	6.1	82.8	0.29

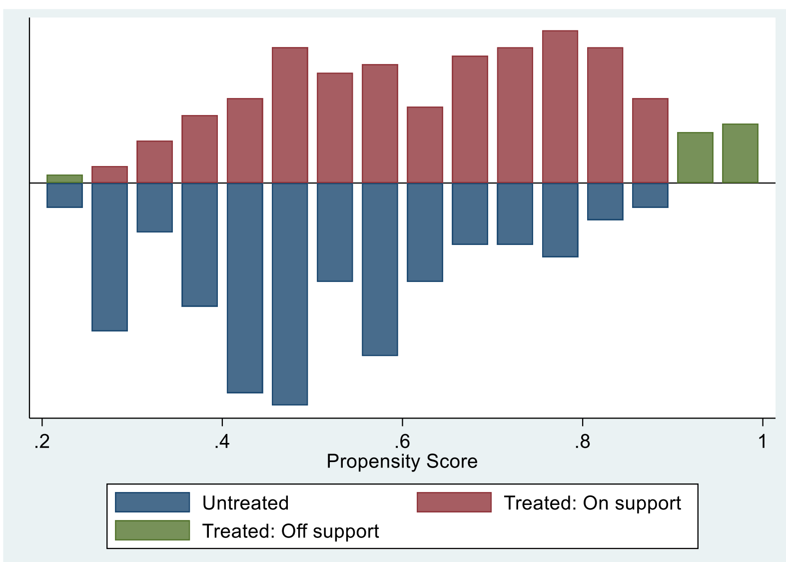

Figure 2. Distribution of the propensity scores and common support for propensity score estimation of beneficiaries and control group.

Testing for hidden bias with sensitivity analysis

Given the positive estimated treatment effects, we tested for hidden bias under the assumption that the treatment effects might have been overestimated. The results reveal that at relatively small critical levels of hidden bias,

Table 6. Propensity score matching results.

Outcome variable	Matching algorithm	Mean outcome treated	Mean outcome control	ATT (SE)	t-stat	Matched observations		
						Number of treated	Number of control	Total
Crop income	Kernel matching	2981570	1930976	1.050.595 ** (528.546)	1.99	48	47	95
	Nearest neighbour	3087945	1880902	1.207.044 * (671.674)	1.80	48	47	95
	Radius	2981570	2008817	972.753 ** (463.315)	2.10	48	47	95
Crop yield	Kernel matching	1127	727	399.6**(204.3)	1.96	152	114	266
	Radius	1127	726	401.0***(150.1)	2.67	152	114	266
	Nearest neighbour	1127	736	391.0**(175.5)	2.23	152	114	266

Standard error in parenthesis.

the results are not significant. However, this does not imply that there is no effect of the intervention on income and yield. Rather, it suggests that the results are sensitive to potential deviations from the unconfoundedness assumption, and thus, caution is advised when interpreting the results. The impact of the project intervention can be attributed to various factors, including training in good agronomic practices, increased use of fertilizer and improved seed, and acreage expansion.

Farmers who received training in good agronomic practices and had access to inputs achieved higher yields and, consequently, increased income from crops due to having more to sell. However, yields could have been better if not for challenges such as drought in some areas, late planting, inadequate seed for beans, and inappropriate fertilizer application by some farmers due to limited knowledge. These findings align well with previous studies, such as Manda et al. (2016) in Zambia, who found that a combination of agricultural practices, including improved crop varieties and the complementary use of organic fertilizers, increased maize yield and income for smallholder households. Similarly, in Tanzania, Arslan et al. (2017) found strong complementarities between the adoption of agronomic practices (use of organic and inorganic fertilizers and high-yielding maize varieties) and a positive impact on yield. Interactions with farmers revealed that the intervention raised awareness to the extent that farmers now appreciate and understand the benefits of using fertilizer and improved seed. This is evidenced by the increased demand for fertilizer reported by some IP staff and other key informants. Additionally, there is growing demand for quality declared seed (QDS). For example, one farmer group, Rwibaale Farmers Marketing Cooperative, a group that was supported by MMACKS and Okeba in Kyenjojo district has expanded its production of QDS. The chairperson reported that all their members currently plant improved seed. Narrating her own experience, she said, "*I planted one acre with 30 kg of improved beans and I harvested 800 kg. Before the project we could plant our local varieties and get only 4 basins (68 kg) an acre*". More farmers are currently ordering for improved seed and fertilizers after realizing the benefits of using them. Other agro input dealers have consequently established outlets in areas they were not before. For example, Grain Pulse has established an outlet in Kamwenge to increase farmers' access to agricultural inputs. These results can be attributed to increased access to information and extension which increase the incentives to adopt modern inputs as well as recommended agronomic practices (Arslan et al., 2017).

Change in acreage for the supported crops

An assessment of the change in acreage under the supported crop reveals an increase after the project. Although the project initially targeted one acre for each beneficiary, on average, farmers allocated more than one acre to the supported crops. Figure 3 illustrates the changes in acreage over the project period. Overall, project beneficiaries allocated more land to maize and beans compared to the control group. While there is a steady increase in land allocated to the crop by the beneficiaries, a slight decline is observed for the control group in 2021.

Farmers appear to allocate larger acreage to maize compared to beans. Maize for beneficiaries

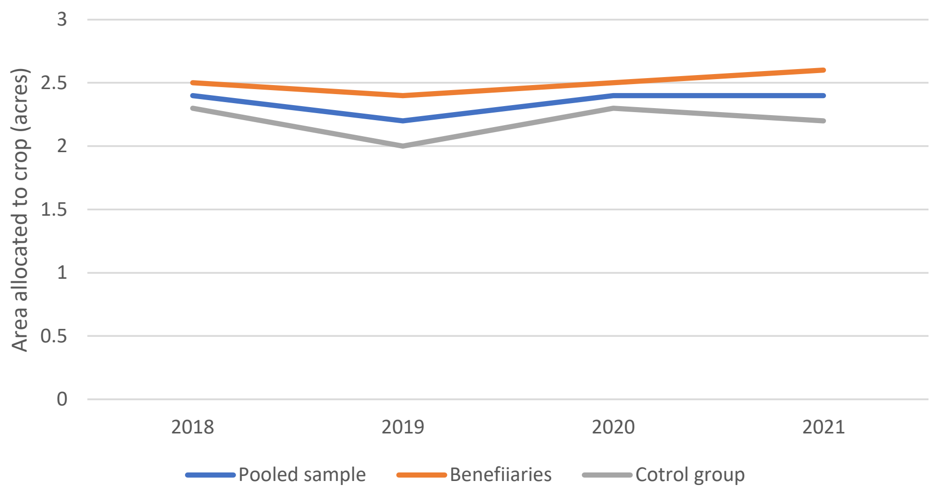

Figure 3. Land allocated to the supported crop over the project period.

Table 7. Change in acreage under the supported crop.

Crop acreage	Pooled sample		Beneficiaries		Control group		t – test
	Maize	Beans	Maize	Beans	Maize	Beans	Maize (bean)
Before project (acres per farmer)	2.2	1.3	2.5	1.2	1.9	1.3	
After project (acres per farmer)	2.9	1.3	3.4	1.4	2.5	1.2	2.63*** (1.35*)
Percentage change	31	0	36.0	16.6	31.5	-7.6	

had the largest acreage, increasing from 2.5 acres before the project to 3.4 acres after the intervention, equivalent to a 36% increase (Table 7).

For the control group, the acreage increased by 31.5% from 1.9 acres before the project to 2.5 acres after the project. The acreage under beans for beneficiaries increased by 16.6%, while that for the control group reduced by 7.6%. Farmers were motivated to increase acreage by the increased yields experienced in the first season. Moreover, the input support and the trainings provided explain the increase in acreages. Similar results have been reported by Fan et al. (2023), who found that new agricultural support and production subsidies, in the form of direct grain subsidy, quality seed subsidy, and input subsidy, increased grain crop acreage in China. Smallholder farmers registered a more positive impact than large farms.

At the farm level, evaluation findings indicate that the volumes of supported crops (beans and maize) increased among both beneficiary and non-beneficiary farmers, except for maize in the latter group (Figure 4). The trend shows an increase in volumes produced from 2019 to 2020, followed by a slight decline in 2021. There was a significant difference in maize volumes produced by the beneficiaries and the control group (Table 8). Maize volumes for the beneficiaries increased by 19.2% annually, from 2.1MT before the project to 2.5MT after the project, while they decreased for the control group by 15%, from 2.4MT to

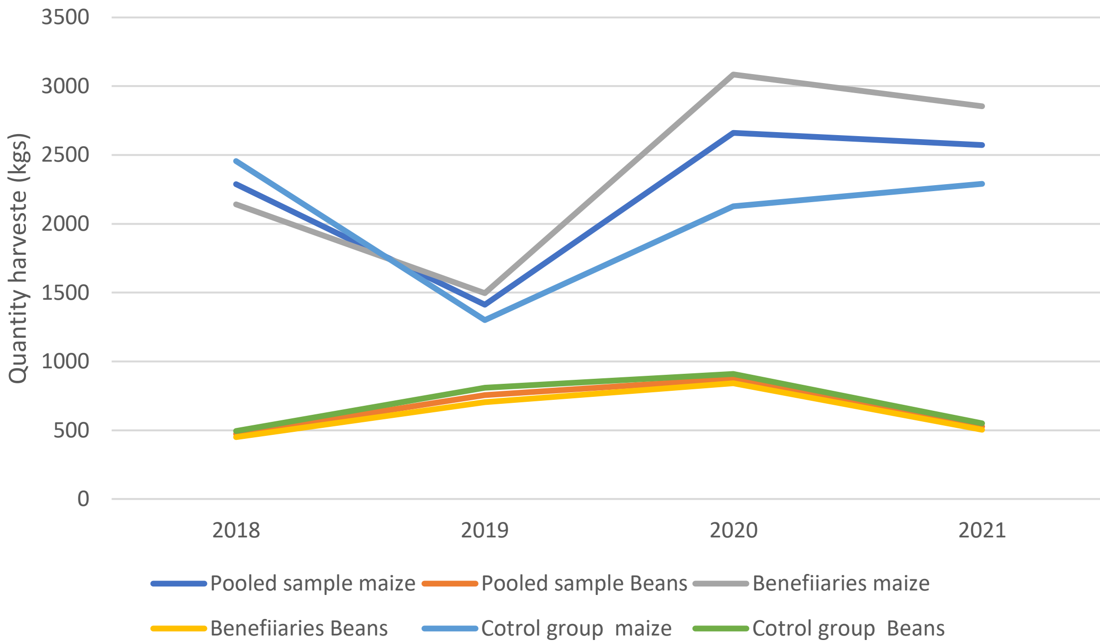

Figure 4. Changes in production volumes over the project period.

Table 8. Change in production volumes by the beneficiary and non-beneficiary farmers.

Crop volumes	Pooled sample		Beneficiaries		Control group		t- test
	Maize	Beans	Maize	Beans	Maize	Beans	Maize (beans)
Before project (kg/farmer)	2,288.7	473.4	2,141.5	450.9	2,455.9	494.5	
After project (kg/farmer)	2,571	528.5	2,855	503.1	2,290	551.5	1.70** (-0.852)
Percentage change	1.2	11.6	19.2	11.5	-15.1	11.5	

2.0MT. The reduction is attributed to prolonged drought, which affected yields. However, the beneficiaries were not as affected because they applied fertilizers and planted early maturing varieties.

The volume of beans increased by 11.5% for both beneficiaries and the control group. The increase in volumes is explained by increased acreage and the use of improved seed. For beans, some farmers in the control group received seed from the beneficiaries after the first harvest. Seeds for improved bean varieties can be recycled for a few years without degeneration.

Increased income can be attributed to several factors, including higher yields and grain volumes resulting from the adoption of improved varieties introduced by the project and the production of high-quality grain facilitated by the training farmers received in postharvest handling. For instance, prior to the project, many farmers cultivated local bean varieties; however, post-project implementation, they transitioned to improved varieties such as NARO Bean 1 and 2 and NABE 14, known for their high yields and ability to fetch higher prices compared to local varieties. Additionally, the quality of maize has improved, with many farmers now utilizing tarpaulins instead of drying maize on bare ground. These findings align with previous studies, such as Khatri-Chhetri et al. (2016), which highlight the positive impact of climate-smart agricultural practices, including the adoption of improved seed, on smallholder farmers' productivity and income. Furthermore, farmers received better prices for their produce due to increased demand for beans and maize, which constituted a significant portion of relief food supplies provided by government and other agencies during the COVID-19 pandemic. Moreover, heightened demand led to increased competition among IPs, other companies, and middlemen involved in the grain business, driving prices higher.

Limitations to the project

The evaluation identified several limitations that impacted project outcomes. Firstly, frequent and prolonged drought significantly contributed to low maize grain yields, particularly affecting the first season, where farmers experienced a yield loss of approximately 200 kg/acre. Additionally, there were delays in the delivery of fertilizer and seed in certain areas during the first season, which hampered the distribution of maize seed and subsequently led to reduced yields due to late planting.

Moreover, COVID-19 restrictions posed challenges by limiting staff movements required for training and monitoring farmers under bean production. These restrictions also increased the operational costs of the project, particularly in terms of transportation for delivering seed and purchasing beans from farmers. Furthermore, some farmers initially exhibited reluctance to accept inputs for the first season. However, their interest increased in subsequent seasons after witnessing the improved performance of their fellow farmers' maize fields. Despite this, some farmers were unwilling to pay or contribute for the inputs, as they had received them for free in the first season. Additionally, financial constraints led some farmers to drop out of the program.

Furthermore, the presence of bad roads exacerbated the situation, with some roads becoming impassable during the rainy season. This made it challenging to reach farmers for extension services and to collect grain, further hindering project implementation.

Conclusions

This study evaluates the impact of a project aimed to enhance the resilience of smallholder farmers against the COVID-19 pandemic by increasing access to agro-inputs through a declining subsidy model. Implemented by various agribusiness entities in collaboration with aBi, the project, although short-term, yielded positive outcomes including increased adoption of improved seed and fertilizers, enhanced crop productivity, and augmented incomes for smallholder farmers. Propensity Score Matching (PSM) results reveal that participating farmers achieved higher yields and income for key crops, such as maize and beans, compared to non-participants. These findings underscore the significant impact of training farmers and enhancing their access to inputs through subsidies on crop productivity.

Moreover, they emphasize the importance of ensuring a ready market for produce to boost crop income for smallholders.

RECOMMENDATIONS

The study recommends enhancing project sustainability and broadening beneficiary reach by fostering collaboration between agribusiness partners and local stakeholders, such as government extension workers. Additionally, it suggests that future similar projects consider supporting farmers based on individual capacity, particularly in terms of resources like land, rather than offering uniform support that may exclude certain farmers. Such an approach could enhance the effectiveness of the declining subsidy model. Further research is warranted to investigate whether project beneficiaries have continued to utilize inputs without subsidies and to explore potential spillover effects in project areas post-project implementation.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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