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Impact Assessment of the development program 2SCALE on Smallholder Farmers in Kenya

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Abstract

Poverty and food security remain pressing challenges in rural Kenya, where smallholder farmers are highly vulnerable to economic and environmental shocks. This study evaluates the impact of the 2SCALE program, a development initiative aimed at improving the livelihoods of smallholder sorghum farmers, using rigorous survey data collected in 2015 and 2017. Employing a Two-Stage Least Squares (2SLS) regression and a difference-in-differences (DiD) framework, the analysis addresses endogeneity and assesses the program's effects on production and income.

The findings reveal that the 2SCALE intervention significantly increased sorghum production, with cultivated area, treatment, and target area identified as key drivers. However, the program's impact on income was statistically insignificant in the short term. Factors such as cultivated area, access to credit, education, and gender significantly influenced income, while intercropping and average price negatively affected production. These results highlight the complexity of smallholder decision-making, with income gains potentially requiring sustained support and complementary interventions to fully materialize.

The study underscores the importance of well-designed development programs and robust impact assessments in addressing rural poverty and food insecurity. By identifying key determinants of productivity and income, this research offers actionable insights for enhancing agricultural resilience and improving the livelihoods of smallholder farmers. These findings contribute to the broader discourse on rural development, emphasizing the need for policies that balance immediate production gains with long-term sustainability and inclusive growth.

Keywords: Impact Assessment, Smallholder farmers, Difference in Difference, Income, Productivity, Development Policies, Kenya, Poverty reduction, 2SLS

Table of contents

Table of figures

Table of tables

List of acronyms

2SCALE – Toward Sustainable Clusters in Agribusiness through Learning in Entrepreneurship

2SLS - Two-Stage Least Squares

Agri-PPPs – Agricultural Public-Private Partnerships

BoP – Base of the Pyramid

DiD – Difference in Difference

FAO – Food and Agriculture Organization of the United Nations

GDP – Gross Domestic Product

Ha - Hectare

IV – Instrumental Variable

KES - Kenyan shillings

Kg – Kilogram

OECD – The Organization for Economic Cooperation and Development

OLS – Ordinary Least Square

PPP – Public-Private Partnerships

RCT - Randomized Controlled Trial

SD – Standard Deviation

1. Introduction

Poverty and food security have been persistent issues for decades, particularly in rural areas where smallholder farmers are most affected. Development economics has long studied these challenges and explored potential solutions. This study conducts an impact assessment of the 2SCALE program (Toward Sustainable Clusters in Agribusiness through Learning in Entrepreneurship), a development initiative targeting rural areas in several African countries.

The impact assessment focuses on smallholder farmers producing sorghum in Kenya, through a two-stage least squares (2SLS) approach. The data used for this study were rigorously collected through a state-of-the-art survey methodology. The survey team, along with enumerators, conducted in-person interviews with the farmers in Kenya, ensuring high-quality, accurate data collection. The project methodology is robust and well-designed, reflecting careful attention to detail in its execution, which strengthens the reliability and validity of the findings.

In Kenya, rural areas face significant development challenges, with widespread poverty and food insecurity. Programs like 2SCALE can help address these issues by supporting smallholder farmers. However, to maximize their effectiveness, reliable impact assessments are crucial. These assessments ensure the true effects of interventions are understood, resources are used efficiently, and the results are trustworthy. Rigorous and transparent evaluations are essential for improving the success of development programs.

The majority of the world's extreme poor live in rural areas, where they are highly vulnerable to food price fluctuations and depend heavily on agriculture, natural resources, and biodiversity for food security and livelihoods (FAO, 2019). In Kenya, rural areas face significant development challenges, and improving agricultural productivity is key to addressing these issues. Studies show that sustained economic growth, especially in agriculture, has been a major driver of poverty reduction, directly improving employment and labor income for the rural poor (Inchauste et al., 2014). However, boosting agricultural productivity alone is not enough, well-designed policies are needed to support these efforts (Abro et al., 2014).

Smallholder farmers are at the centre of efforts to enhance agricultural performance and promote rural development. Targeting this group through policies that improve services and integrate them into value chains can help increase productivity and income (Chamberlin et al., 2007). Agri-Private Public Partnerships (Agri-PPPs) are also seen as key to modernizing the sector, driving inclusive growth, and ensuring smallholders are included in value chains (WEF & McKinsey and Company, 2013; WEF & McKinsey and Company, 2011). Agriculture plays a critical role in Kenya's economy, contributing over a third of the GDP (USAID, 2023), and programs like 2SCALE offer substantial potential for poverty alleviation and food security. However, for these programs to succeed, robust impact assessments are essential to ensure their effectiveness and guide improvements.

The study utilizes pooled cross-sectional data from 2015 and 2017. To assess the program's impact, a difference-in-differences (DiD) approach is employed, comparing changes in income and production before and after the treatment while controlling for external factors. For the income equation, a 2SLS regression is used to address endogeneity, as participation in the program is randomized, making the treatment endogenous. Additionally, the production variable in the income equation is treated as endogenous and is addressed using instrumental variables (IV). Outliers in the dataset are identified using the production equation, applying the three-standard-deviation rule.
This study is organized into seven sections. The first section provides the Introduction, followed by the Research Questions and Objectives in section two. Section three presents the Literature Review, while section four outlines the Methodology. The Data used in the study is discussed in section five. Section six focuses on the Results and Discussion, and section seven concludes with the Conclusion.

2. Research questions and objectives

The *objective* of this research is to evaluate the impact of a development program on smallholder farmers in Kenya, particularly in terms of their income and production. The study compares the household's situation before and after the program intervention (2015 and 2017), using baseline and endline data.

The *research questions* of this study are the following ones:

- Did 2SCALE increased smallholder famer's income in Kenya in 2016?
- Did 2SCALE increase smallholder famer's productivity in Kenya in 2016?

This research is guided by the following *hypotheses*:

- The intervention of the development program 2SCALE in 2016 significantly increased the income of smallholder farmers that participated in the program with respect the ones that did not participate.
- The intervention of the development program 2SCALE in 2016 significantly increased the production of smallholder farmers that participated in the program with respect the ones that did not participate.

3. Literature review

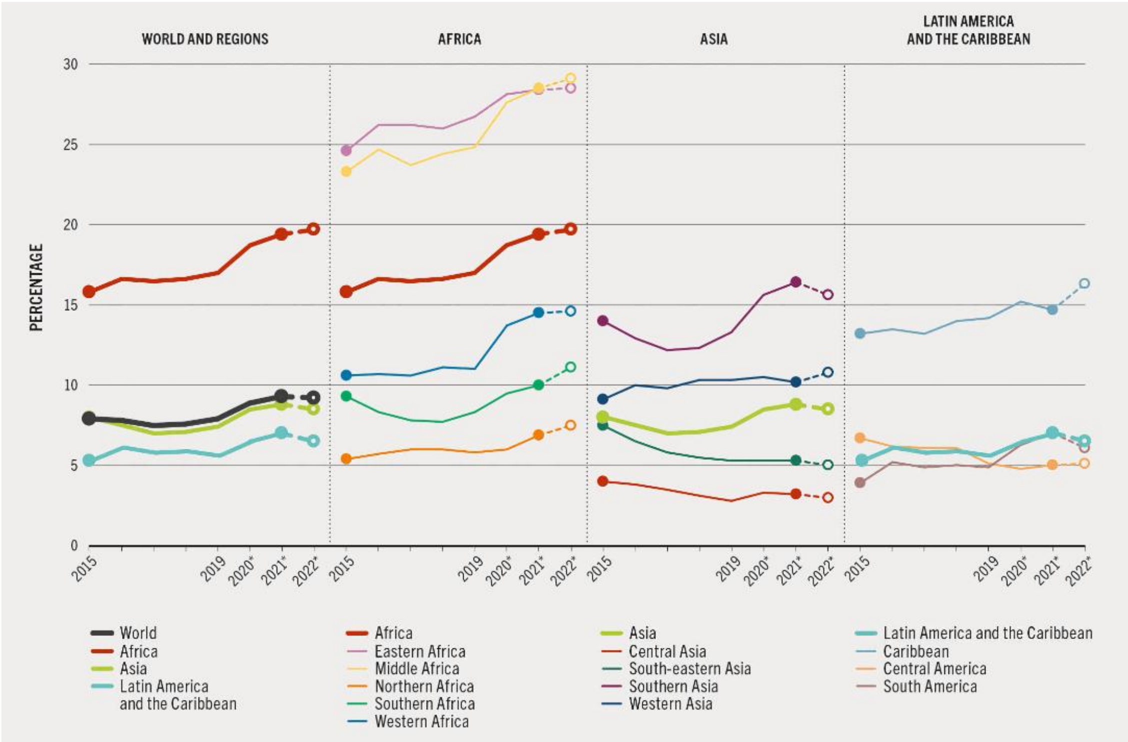
3.1. Context

In the past few decades, global progress on poverty reduction had been unprecedented, benefitting all, including extreme poor[1]. Over the last 35 years, the standard of living of most of the population in the developing world has improved alongside high levels of economic growth and the improved wealth of nations (FAO, 2019).

Even though, today, nearly 700 million people still reside in conditions of extreme poverty, primarily in conflict-affected countries and rural regions. Without intervention, the climate crisis could potentially push 135 million individuals into poverty by the year 2030 (United Nations, 2023). Africa is the region with the highest percentage of people facing hunger - 20 percent, compared with the 8.5 percent in Asia, 6.5 percent in Latin America and the Caribbean, and 7.0 percent in Oceania (FAO et al., 2023). Figure 1 shows that from 2015 to 2022, progress was made towards reducing hunger in most subregions in Asia and in Latin America, but hunger is still on the rise in Western Asia, the Caribbean and all subregions of Africa.

[1] According to the World Bank, USD 2.15 a day is the extreme poverty line and represents the poverty line typical of the world's poorest countries.

Figure 1. Evolution of the reduction of hunger in Africa, Asia, Latin America and the Caribbean



*Notes: Eastern Asia is not shown because the prevalence of undernourishment has been consistency below 2.5 percent since 2010. * Values are based on the projected midranges. The full ranges of the 2020, 2021 and 2022 values can be found in the Annex 2 of The State of Food Security and Nutrition in the World 2023. Source: FAO. 2023. FAOSTAT: Suite of Food Security Indicators. In: FAO. [Cited 12 July 2023].*

Currently, most the world's extreme poor reside in rural areas, being particularly vulnerable to food price volatility and heavily relying on agricultural activities, access to natural resources and biodiversity for their food security and their livelihoods (FAO, 2019). Castañeda et al., 2018 found that globally, the extreme poor have larger families with a greater number of children, low educational attainment and work in agriculture. Robles Aguilar & Sumner, 2020, found similar results, with the extreme poor living in rural areas experiencing more overlapping deprivations in education and in access to basic infrastructure (water, sanitation, electricity, and housing) than their urban counterparts, facing also lower access to health care and economic opportunities.

There is no fast track to eradicating rural extreme poverty, but it demands a deep comprehension of extreme poverty and how it relates to other challenges, together with dedicated and integrated actions, involving participatory processes with stakeholders, building long-term and more sustainable partnerships and trust; and ensuring lasting and coordinated actions across sectors (FAO, 2019).

Historically, poverty tended to decrease as structural transformation happened in a country. Low-income countries, the ones with higher poverty rates, are usually at the early stages of structural transformation: their economies remain mostly agricultural with low levels of productivity, which hampers the development of other sectors. Although structural transformation can accelerate poverty reduction, its progress is not immediate. The political economy, encompassing factors such as monetary and trade policies, determines investment and growth patterns across sectors and regions, which in turn affect employment generation in rural areas, the quality of jobs, and the level of inclusiveness of the growth process (FAO, 2019).

Mellor (2017) and FAO (2017) decompose a structural transformation process into a decline in the share of agriculture in GDP and overall employment, the development of modern industrial and service sectors, and a demographic transformation from high to low birth, death rates a shift from primarily subsistence farming to market-oriented and diversified production systems, and the emergence of rural non-farm sector. Inchauste et al., 2014 found that over the last few decades, the most prominent driver of extreme poverty reduction has been the stimulation of sustained and inclusive economic growth, starting in agriculture, with direct effects on employment and labour income for the rural extreme poor.

A minimum set of investments (basic services, infrastructure, health and education) and policies (land reform and social protection) are required for economic growth, together with the implementation of integrated and dedicated interventions that target explicitly the extreme poor, providing support to increase their participation in society and their potential for benefiting from overall economic growth is required to eradicate extreme poverty (Sen, 2014). Even though growth in agriculture has a greater impact on poverty reduction than in other sectors, the magnitude depends on the structure of the county's economy and institutional arrangements (Christiaensen et al., 2011).

Evidence from Abro et al., 2014 found that improvements in agricultural productivity can have substantial impacts on poverty reduction, but a combined effort to design policy interventions is needed. Fabrizio Quinonez, 2023 found evidence in Paraguay that policies focused on increasing the number of individuals involved in agriculture, rather than just raising farmers' income, could significantly decrease poverty.

In the first Regional outlook of OECD, Resilient & For (2011), it is highlighted the importance of combining policies across different sectors to ensure inclusive and sustainable growth. It is also stressed the importance of the local context to ensure the expected impact in the targeted region. Chamberlin et al., 2007 discloses the importance of targeting small farmers to increase agricultural performance trough policies that aim to the improvement of the services to smallholders and develop more efficient ways to include smallholders in value chains.

One of the 20 pillars of OECD to effectively implement rural policies is to foster monitoring, independent evaluation and accountability of policy outcomes in rural areas in order to ensure that rural policies are having their intended effect. To do so, it is necessary to evaluate rural policy initiatives and outcomes and communicating progress in meeting them in an ongoing manner and implementation. The development of outcomes indictors to assess and benchmark rural well-being trough economic, social, and environmental and other performance indicators is key. Likewise, the provision of accessible data that is easy-to use to help rural communities and stakeholders identify priorities and monitor progress is key. Explore innovative methods of data-collection that address the challenges of confidentiality that are part of small-area analysis and asses the process and outcomes of different steps of public engagement to learn, adjust and improve accordingly is also important for the correct monitoring and evaluation of rural policies (OECD, 2019).

3.2. Public-Private Partnerships in Agriculture

Rankin et al., 2016 defines Agri-PPP or a PPP (Public-Private Partnerships) for agribusiness development as a formalized partnerships between public institutions and private entities aimed at address sustainable agricultural development objectives. These partnerships entail clearly defined public benefits, shared investment responsibilities and risks, and active participation from all partners across different stages of the PPP project lifecycle.

Innovative partnerships that bring together actors from business, government and civil society had been increasingly promoted as a mechanism for improving productivity and driving growth in the agriculture and food sector around the world. A lot of initiatives had been usual in sectors such as infrastructure, health and education, but their application in the agriculture sector is relatively new.

Agri-PPPs had been widely advocated for their potential to help modernize the agricultural sector and generate multiple benefits that can contribute the drive for sustainable agricultural development, ensuring the inclusion of smallholder farmers (WEF & McKinsey and Company, 2011; 2013), However, the rationale behind this approach and the vague definition of the concept raise numerous unanswered questions regarding the types of projects that might be appropriately governed by this mechanism. Additionally, questions persist about the mechanism's efficacy in achieving sustainable and inclusive agricultural development objectives (Horton et al., 2009).

There is no overarching theory that universally explains the success or failure of PPPs, as these outcomes are heavily influenced by the specific contexts in which they occur. Consequently, it is essential to thoroughly examine and detail the unique context surrounding the 2SCALE PPP to gain a comprehensive understanding of its dynamics and potential impact.

3.3. General context in Kenya

With a gross domestic product (GDP) exceeding $100 billion, Kenya has recently achieved lower-middle-income status, showcasing a diverse and dynamic economy. As the gateway to the East African market, which comprises 300 million people, Kenya plays a pivotal role in the region. However, this economic growth has not been inclusive, leaving many Kenyans in poverty. The situation has been further aggravated by the COVID-19 pandemic and enduring challenges such as corruption, inefficient and inequitable systems, exclusion of youth and women, lack of reliable electricity and sanitation, and increasing crises like droughts (USAID, 2023).

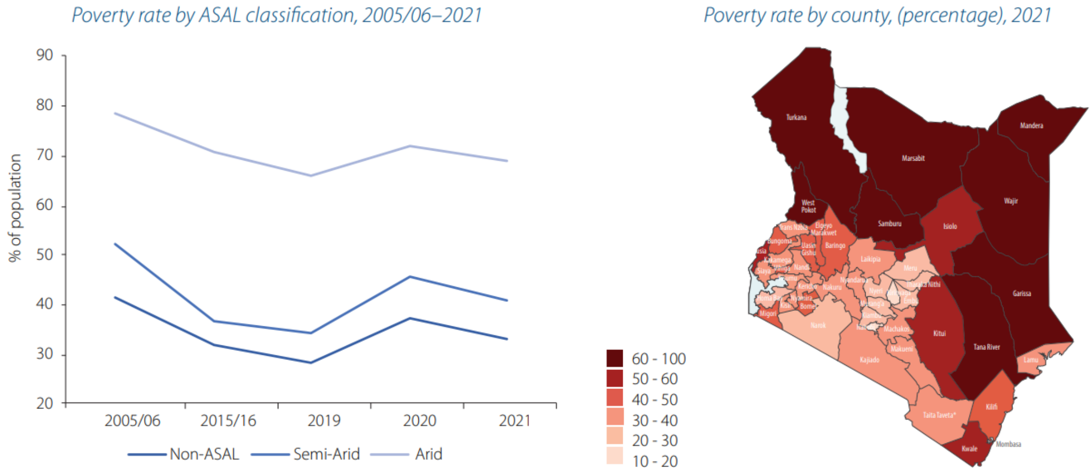
The economy of the country grew by 5.2% in 2023, up from 4.8% in 2022, driven by a rebound in agriculture and moderate growth in the services sector. In 2024, it grew by 5.0% supported by a growth in Agriculture, Forestry and Fishing activities (6.1%), Real Estate (6.6%), Financial and Insurance (7.0%), Information and Communication (7.8%) and Accommodation and Food Services (28.0%) ((Kenya National Bureau of Statistics, 2024). Inflation slightly increased to 7.7% in 2023 from 7.6% in 2022, influenced by core inflation (32% of the increase), fuel inflation (26%), and a 9% year-on-year rise in the producer price index, indicating cost-push inflation (African Development Bank Group, 2024).

Growth has been non-inclusive due to the minimal contribution of structural transformation. This has led to limited poverty reduction and employment creation. On average, structural transformation contributed only 28% to labour productivity growth from 2007 to 2022. Additionally, a quarter of GDP growth came from sectors resilient to shocks. To absorb the 680,000 individuals entering the labour market annually, an output growth rate of 5.8% per year is necessary. With accelerated structural transformation, a GDP growth rate of 7.3% could generate 1.36 million new jobs and reduce unemployment to 7%. Achieving this requires improvements in governance, infrastructure, human capital development, access to finance, and macroeconomic stability (African Development Bank Group, 2024).

The proportion of the population living below the national poverty line decreased from 46.8% in 2005/06 to 36.1% in 2015/16. This decline was largely driven by improvements in rural areas, where poverty fell from approximately 50% in 2005/06 to 38.8% a decade later. In contrast to the declining poverty rates in rural areas, poverty incidence in urban areas, especially outside Nairobi, has remained stagnant. Particularly concerning is the significant lag in wellbeing observed in the north and northeast regions of the country. These areas experienced minimal progress between 2005/06 and 2015/16, continue to face food insecurity, and exhibit low levels of educational attainment, limited access to improved sanitation, and, to a lesser extent, access to improved water sources (World Bank, 2023).

The north and northeast regions of the country, where arid areas are concentrated, are characterized by poverty rates that are persistently higher than the rest of the country (Figure 2) (The World Bank Group, 2023).

Figure 2. Spatial disparities in monetary poverty persist



Note: ASAL refers to Arid and Semi-Arid areas combined.

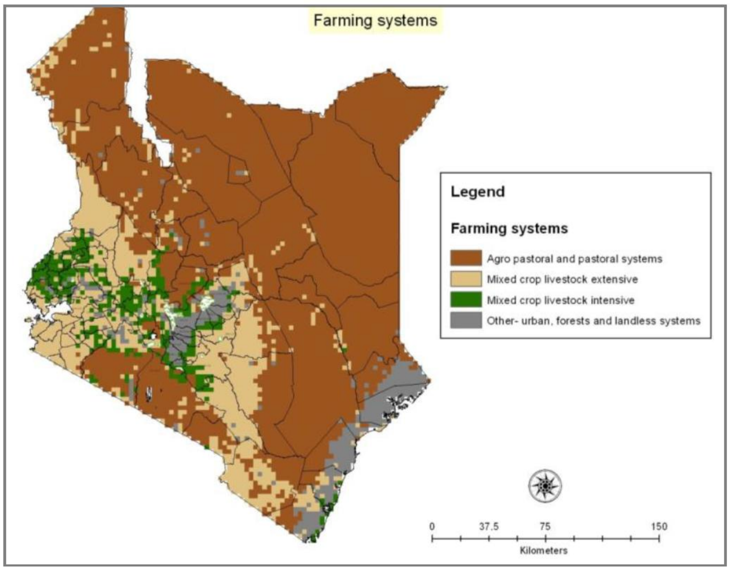
Source: Based on KIHBS and KCHS surveys and KNBS Poverty Report.

The agricultural sector is central to Kenya's economy, contributing more than a third of the GDP (USAID, 2023). It employs approximately 56% of the labour force, accounts for 65% of the country's goods exports, and contributes 26% to the GDP. Predominantly rainfed, only 2% of agricultural land is irrigated, leading to considerable annual fluctuations in production. Maize and beans dominate the agricultural system, covering 85% of cultivated land (Bhunu et al., 2019).

There are about 4.5 million smallholder farmers, with 3.5 million engaged in crop cultivation, 600,000 practicing pastoralism, and 130,000 involved in fishing. Most smallholders practice mixed farming, and currently, 67% of these farmers operate on less than one hectare (Ha) of land (Bhunu et al., 2019).

Kenya's economy heavily relies on its natural resources and climate-sensitive sectors such as agriculture, water, fisheries, forestry, and energy. The agricultural sector, particularly in the arid and semi-arid lands, is most affected by climate change. Addressing these challenges and enhancing farmers' resilience will require innovative approaches. Limited access to credit prevents smallholder farmers from fully utilizing hybrid maize, which 80% of producers plant. Less than 10% of farmers use improved bean varieties due to limited supply. Agricultural mechanization is also lacking, with 50% of farmers relying solely on hand tools. Agricultural extension services are understaffed (Bhunu et al., 2019).

Figure 3. Map showing farming systems in Kenya



Source: Robinson, Timothy P.Thornton, Philip K.Francesconi, Gian N.Kruska, Russell L.Chiozza, F.Notenbaert, An Maria OmerCecchi, G.Herrero, MarioEpprecht, M.Fritz, SteffenYou, LiangzhiConchedda, GiuliaSee, 2005

3.4. 2SCALE program

The 2SCALE programme, is an agribusiness project in Africa that specifically targets smallholder farms and aims to improve the livelihoods, incomes, and food security of farm households. The objective is pursued improving technology, organisational capacity, market access, credit and extension advice connecting farmers, buyers and intermediaries (Bonilla & Rai, 2018).

The program had been divided into two phases, being the first one Toward Sustainable Clusters in Agribusiness through Learning in Entrepreneurship (2012 – 2016), and the second one Incubating and accelerating inclusive agribusiness in Africa (2019 – 2023). The program boosts PPPs between the so-called Business Champions, either African Small and Medium-sized Enterprise or Dutch/international companies, and smallholder farmers and/or serving local and regional Base-of-the-Pyramid[2] (BoP) markets. The companies are drivers of inclusive business. The program operated in a total of 13

[2] Base of the Pyramid: term used to describe the largest but poorest socio-economic group in the world, whic typically live on less than $2.50 a day, according to the World Bank.

countries[3] during the two phases and covers different ranges of commodities including staple food, fresh production, oilseeds and diary and animal protein (2SCALE, 2022).

Than main goals for phase 1 were, (1) Facilitate localized networks that empower farmers to autonomously access good-quality agro-inputs; access relevant services; solve (new) problems (i.e. to innovate); and bargain with services providers and buyers (e.g. by having access to information on alternative supplier and marketing channels), (2) Facilitate innovative inclusive value chain relations and (3) Support enabling environments, in particular access to finance and information (Abalo Adodo et al., 2019).

The main goals of phase 2 include (1) Promote competitiveness of the agricultural and food sector in Africa trough inclusive and sustainable growth, (2) Reduce existing hunger and malnutrition and improve access to nutritious food for BoP consumers, (3) Empower young entrepreneurs and business women in private sector development, local and regional sourcing, processing, marketing and trade, and in creating jobs and (4) Create productive and sustainable food systems by strengthening smallholder farmers' capacity in eco-efficient production (Figure 4).

Figure 4. Kenyan farmers during the intervention of 2SCALE

Source: 2SCALE website

[3] Phase 1: Benin, Ghana, Mali, Nigeria, Kenya, Ethiopia, Mozambique, South Sudan, Uganda and Ivory Coast. Phase 2: Ghana, Mali, Nigeria, Niger, Burkina Faso, Ivory Coast, Kenya, Ethiopia, South Sudan, Egypt.

4. Methodology

4.1. Impact evaluation

Development programs and policies are typically designed to change outcomes such as raising incomes, improving learning, or reducing illness. Most of the times, instead of examining the achievement of changes and intended goals of improving outcomes, the focus is on measuring and reporting the inputs and immediate outputs of program—how much money is spent, how many textbooks are distributed, how many people participate in an employment program—, and the achievement of the expected changes remains a crucial policy question. Impact evaluations are part of a broader agenda of evidence-based policy making, a global trend that reshapes public policy shifting the focus from inputs to outcomes and results that are used both to track national and international targets, and by program managers to enhance accountability, guide program design and policy decisions and determine budget allocations (Gertler et al., 2016).

4.1.1. Impact evaluation in agriculture

The evaluation of agricultural projects needs to consider specific issues that the method does not contemplate in other sectors as the social one. First, agricultural projects are generally designed to enhance production or returns to agriculture, and therefore, impact evaluation of agricultural projects have a focus on production-based indicators like gross margins, crop prices, yields, productivity, agricultural investment, expenditure on agricultural inputs, technology adoption, alteration in land use patterns, crop and varietal diversification and food and home production. The data collection can be challenging, starting with the sample unit. Production is often linked to multiple plots and crops, while the decision-making process is carried out at household level. Yet more challenging is the attempt to evaluate the impact of a project on different types of households, such as smallholders and large holders due to huge differences in production systems (Paul Winters & Lina Salazar & Alessandro Maffioli, 2010).

Second, impact evaluations examine series of indicators to obtain an overall picture of the average effect of the intervention and the mechanism by which the effects are obtained. In agricultural production, profit or production functions are used to examine the relationship between inputs and outputs or profitability. In agricultural projects, there is not only an impact on production inputs and outputs, but also on the combined use of both.

Third, it is important to consider indirect or "spillover" effects that complicate agricultural evaluation due to the transfer of knowledge, new technologies and management practices from project participants to non-participants. In fact, agricultural interventions, especially technology adoption ones, frequently have an explicit aim to facilitate the occurrence of spillover effects. All these factors increase the impact of the operations, but also complicate the evaluation design due to the difficulty to find an "uncontaminated" counterfactual. Therefore, for a correct assessment of the project, it is required to consider how to identify the spillover effect when they exist and to ensure a reasonable, uncontaminated counterfactual since much of the influence of the project may be trough these spillover effect (Angelucci & De Giorgi, 2009, Angelucci & Di Maro, 2016).

4.1.2. Causal Inference and Counterfactuals

Many policy questions involve cause-and-effect relationships and impact evaluations seek to answer such questions precisely assessing the impact of a program on a set of outcomes, being equivalent of assessing the causal effect of the program on those outcomes (Gertler et al., 2016). The following basic impact evaluation formula is used:

$$\Delta = (Y|P = 1) - (Y|P = 0)$$

This formula states that the causal impact (Δ) of a program (P) on an outcome (Y) is the difference between the outcome (Y) with the program − when P=1 − and the same outcome (Y) without program − P=0 −. Once we measure the two key components of this formula, we can answer any question about the program's impact. We can understand an impact (Δ) as the difference in outcomes (Y) for the same unit with and without participation in a program. An issue arises due to measuring the same unit in two different states at the same time is impossible. At any given moment in time, a unit either participated in the program or did not. The unit cannot be observed simultaneously in two different states. This issue is called the counterfactual problem. In the basic impact evaluation formula, the counterfactual is represented with the term $(Y|P = 0)$, that is the outcome that would have been in the absence of the program, for which there is no data. The previous term represents what would have happened to the outcome if a person had not participated in the program (Gertler et al., 2016).

4.1.3. Randomized Control Trials

White et al., 2014 describes Randomized Controlled Trial (RCT) as a method used for impact evaluation, where the population receiving a program or policy intervention is randomly selected from the eligible population, and a control group is also randomly chosen from the same eligible population. RCT needs to be planned from the beginning of programme implementation, and participation in the programme needs to be carefully controlled with the experiment in mind. RCTs cannot be undertaken retrospectively.

The author also explains that RCTs are best used for programmes that seek to achieve clear, measurable impacts attributable to specific interventions and conducive to causal pathway analysis. They are less suitable for emergent programs or those targeting results that are difficult to measure. Four conditions under which random assignment is undesirable or unfeasible have been identified: (i) when quick answers are needed, (ii) when the need for precision is low and the causal question is not the most important goal (iii) in conditions where it is impossible to manipulate assignment such as when the causal question that needs to be answered involves exposure to an undesirable condition, and (iv) when sufficient preliminary and empirical work has not been done and the intervention or programme is at a premature stage.

4.1.4. Difference-in-Difference method (DiD)

The difference-in-differences (DiD) method compares the changes in outcomes over time between a population that is enrolled in a program (the treatment group) and a population that is not (the comparison group) (Gertler et al., 2016). It compares the trends in the control group from before and after the project versus the trends in the treatment group. The double difference then refers to the difference over time (the first difference) and difference between the control and treatment (the second difference). If the trends are statistically grater for the treatment group, it suggests that the project had an impact. The DiD estimator combines cross-sectional and over-time variation to correct for differences between groups when treated and controls start from different levels (Paul Winters & Lina Salazar & Alessandro Maffioli, 2010).

The DiD approach can also be estimated using a regression model in when there is available baseline and post-treatment data for treatment and control groups. If there is, the following regression can be estimated:

$$Y_i = \beta_0 + \beta_1 * P_1 + \beta_2 * T + \beta_3 * P_1 * T + \varepsilon_i$$

Where:

- Y_i is the impact indicator of interest for farmer $i = 1 \ldots N$,
- P_i is equal to one if the farmer is in the treatment group and zero if the farmer is in the control group,
- T is equal to zero if at baseline and one after treatment,
- ε_i is the error term.

With this estimation, the coefficient β_1 controls for initial differences between control and treatment, β_2 controls for general trends over time, and β_3 provides the estimate of impact or the average treatment effect. One advantage of this second specification is that it can be easily extended to the case with several groups and several time periods by adding group and time period dummy variables. The second advantage is that the conceptual framework remains consistent regardless of whether the treatment T is endogenous, as it is not possible to determine its endogeneity in advance.

The main assumption of the DiD estimator is that the control-group trend is identical to the trend that the treated group would have had in the absence of treatment. Note that this assumption is not testable and therefore its validity should always be carefully discussed to ensure that the DiD properly estimates the impact of the program. In case of data availability of several pre-treatment years, a straightforward way to assess the validity of the assumption is to analyse weather there is equality of pre-treatment trends between groups. The equality of pre-treatment trends suggests that the treated and control groups are indeed comparable and reinforces the credibility of the estimations, even though does not formally prove the assumption.

While this does not formally prove the identification assumption (which, as mentioned, is not testable), the equality of pre-treatment trends suggests that the treated and control groups are, indeed, comparable and thus reinforces the credibility of the estimations (Paul Winters & Lina Salazar & Alessandro Maffioli, 2010).

4.2. Instrumental variables (IV)

Instrumental Variables (IV) is a method used to address endogeneity issues in econometric models. Endogeneity occurs when an explanatory variable is correlated with the error term in a regression, leading to biased and inconsistent estimates. This often arises due to reverse causality, omitted variable bias, or measurement error. IV techniques offer a solution by introducing an instrument, a variable that is correlated with the endogenous regressor but uncorrelated with the error term, thus allowing for consistent estimation of causal effects (Wooldridge, 2002, Angrist & Pischke, 2008).

In this approach, the instrument must satisfy two key conditions:

- *Relevance*: The instrument must be strongly correlated with the endogenous variable, ensuring it is a valid predictor of that variable.
- *Exogeneity*: The instrument must be uncorrelated with the error term in the equation, ensuring that it only influences the dependent variable through its effect on the endogenous regressor.

The IV method generally involves two stages (Further explained in 4.2.1Two-stage least squares (2SLS):

- *First Stage*: The endogenous regressor is regressed on the instrument(s), producing a predicted value that is free from the bias of endogeneity.

- *Second Stage*: The dependent variable is regressed on the predicted value from the first stage, effectively removing the bias caused by the endogenous regressor.

For example, in development economics, IVs are often used to address issues of endogeneity when estimating the impact of interventions (e.g., a development program) on outcomes like income, production, or consumption. For instance, if a study seeks to measure the impact of a development program on household income, it may be difficult to isolate the true effect of the program because households with higher income might be more likely to participate in the program (reverse causality). An instrument in this case could be a variable like *distance to the nearest program center*, which influences the likelihood of program participation but is not directly related to household income. Here, the instrument is relevant (it affects program participation) and exogenous (it does not directly affect income, except through the program participation channel) (Barrett, 2008).

The use of IV is particularly valuable in situations where randomization or controlled experiments are not possible, such as in studies of agricultural production or development interventions (Heckman & Robb, 1985). However, the success of IV estimation depends on the validity of the instrument. If the instrument is weakly correlated with the endogenous regressor or correlated with the error term, the IV estimates may still be biased. Therefore, it is important to test the strength and validity of the instrument, using tools such as the F-statistic from the first stage regression, or tests like the Sargan or Hansen J tests for over-identification in cases with multiple instruments (Hansen, 1982, Sargan, 1958).

4.2.1. Two-stage least squares (2SLS)

Stage 1: Instrumental Variable (IV) Estimation for Endogenous Regressors

In the first stage, we regress the endogenous variable(s) (let's call it X) on the instrument(s) (let's call them Z) and any exogenous variables W. The idea is to isolate the part of the endogenous variable X that is uncorrelated with the error term ϵ, which comes from the instruments Z.

The first-stage regression equation is:

$$X = \pi_0 + \pi_1 Z + \pi_2 W + u$$

Where:

- X is the endogenous regressor (the variable you are trying to instrument),
- Z is the instrument (or instruments) used to replace X,
- W represents other exogenous variables that may be included in the model,
- u is the error term from the first-stage regression

The fitted values from this regression ($\hat{X}$) are the predicted values of X, based on the instruments Z.

Stage 2: Final Regression of the Dependent Variable on the Predicted Values from Stage 1

In the second stage, we use the fitted values $\hat{X}$ from the first stage in the main equation to estimate the effect of the endogenous variable on the dependent variable Y, correcting for endogeneity.

The second-stage regression equation is:

$$Y = \beta_0 + \beta_1 \hat{X} + \beta_2 W + \varepsilon$$

Where:

- Y is the dependent variable (the outcome you are estimating),
- $\hat{X}$ is the predicted value of X from the first-stage regression (the part of X that is uncorrelated with the error term),
- W represents any other exogenous variables,
- ε is the error term in the second stage regression.

4.3. Pooled cross-sectional data

Pooled cross-sectional data is a robust methodological approach that combines observations from multiple cross-sectional datasets collected at different time periods (Wooldridge, 2002). This technique enhances the sample size and allows for a richer analysis of variations across different entities while accounting for temporal changes. By integrating data from diverse years, researchers can examine trends and relationships among variables, providing insights into how factors such as income, education, and production evolve over time. The use of pooled cross-sectional data facilitates the application of various econometric techniques, such as Ordinary Least Squares (OLS) regression, enabling a comprehensive exploration of dynamic relationships. However, it is crucial to consider the assumption of independence among observations and the potential challenges in establishing causality, as the pooled nature of the data may obscure individual-level dynamics. In section *6. Results and Discussion*, an econometric regression model is estimated using OLS on pooled cross-sectional data to analyse the production and income of smallholder farmers in Kenya.

4.4. Study area selection

In Kenya, the partnership with the business champion, named Shalem, focused on enhancing the efficiency of the sorghum value chain. Key activities included farmer training through a field school, developing tailored financial packages, and introducing disease-resistant sorghum varieties. The program is assessed trough analysing the impact of the training, crop diversity; access to credit, likely shaped by the financial package; food security outcomes; the commercialization of products within client-relationship of the activities included under the control variable, that can have an impact on income and production.

The selected project it is considered a success by 2SCALE since smallholder farmers still grow sorghum, and still follow the same operating model selling directly to the business champions. For the analysis, the focus area are the partnerships established with the aggregator in Shalem, which bought sorghum to increase efficiency of the sorghum value chain and promoted a training innovation in which a group of farmers uses best practices to jointly cultivate a sample plot. The data used for the analysis is from two areas with similar characteristics in which one area represents the treatment group and the other one the control group (Figure 5).

Figure 5. Geographic area of interest in Kenya including business champions, capital, control and treatment areas

Source: (1) Author, (2) Bonilla & Rai, 2018

5. Data

This study uses data from an impact evaluation conducted through baseline and endline surveys by Dalberg Global Development Advisors, under the supervision of the American Institutes for Research. Household surveys were administered to 800 and 750 smallholder farmers in Kenya in 2015 and 2017, respectively, resulting in a pooled cross-sectional database with data points from two distinct years. The survey targeted households engaged in farming activities on owned or rented land, growing sorghum on at least 0.25 acres (0.10 Ha). The respondent was the individual in the household responsible for farming activities. The survey covered the most recent harvest prior to August for both 2015 and 2017.

5.1. Description of the variables used

The dependent variables are household total income and production. Total income is calculated from the survey data by summing income from various farming activities (sorghum, millet, local maize, soybeans, cassava, etc.), other economic activities such as running shops, selling prepared food, providing transport services, carpentry, and other income sources like remittances and is expressed in the local currency, Kenyan shillings (KES). Production data focuses exclusively on the target crop involved in the program intervention, which in this case is sorghum, and is expressed in Kilograms (Kg).

The explanatory variables are categorized into four groups: (1) Farm Household Characteristics, (2) Farming Practices and Inputs, (3) Production and Economic Metrics, and (4) Resource Management and Support.

5.1.1. Farm household characteristics

The analysis incorporates various household characteristics, including household ID, year, gender, age, education, treatment status (whether the household is involved in program activities or not), household size, total area cultivated and the area cultivated with the target crop that is Sorghum (Table 1). These variables are essential for capturing the demographic profile of the farmers and their households.

Table 1. Farm household variables

Variable	Variable name	Type	Categories	
Household ID	id	numerical		
Year	year	dummy	1	2017
			0	2015
Gender	gender	dummy	1	Male
			0	Female
Age	age	categorical	1	Younger than 25
			2	Between 25 And 35 Years Old
			3	Between 36 And 45 Years Old
			4	Between 46 And 55 Years Old
			5	Between 56 And 65 Years Old
			6	Between 66 And 75 Years Old
			7	Between 76 And 85 Years Old
Education	education	categorical	1	No education
			2	Secondary education*
Treatment status	treatment	dummy	1	Treatment
			0	Control
Household size	hh_size	numerical		
Total area cultivated	cultivated_area	numerical		
Area cultivated with sorghum	target_area	numerical		

Source: Author

**being secondary education the highest level of education found on the survey*

5.1.2. Farming Practices and Inputs

Include household farming experience, dimension of the cultivated area being the units of expression acres, number of cultivated crops, and agricultural practices such us intercropping, removing of residues after harvesting, check of pests, use of organic and inorganic fertilizer and use of pesticides, which are expressed as dummies (Table 2).

Table 2. Farming practices and inputs variables

Variable	Variable name	Type	Categories
Dimension of the cultivated area	cultivated_area	numerical	
Number of cultivated crops	n_crops	numerical	
Intercropping	intercrops	dummy	1 Yes 0 No
Removing of residues after harvesting	removes_residue	dummy	1 Yes 0 No
Check of pests	checs_pests	dummy	1 Yes 2 No
Use of organic fertilizer	uses_fertilizer_organic	dummy	1 Yes 0 No
Use of inorganic fertilizer	uses_fertilizer_inorganic	dummy	1 Yes 0 No
Use of pesticides	uses_pesticides	dummy	1 Yes 0 No

Source: Author

5.1.3. Production and Economic Metrics

The variables included are as follows: the production obtained from sorghum (production), the area cultivated with sorghum (target_area), the yield from sorghum (yield), the average price paid for sorghum (avg_price), which is calculated as the average between the two main buyers to whom the farmers sell, the income derived from the sale of sorghum (income_target_crop), the profit obtained from sorghum (profit_target_crop), and the total income (total_income_calc), as explained previously. These variables are numerical and allow us to evaluate production outcomes and the economic viability of the crops.

5.1.4. Resource Management and Support

The variables included are land quality, whether the farmer is currently part of a cooperative, and whether the farmer received a loan. The first variable is categorical, with levels ranging from 1 to 6, where 1 represents lower land quality and 6 represents higher land quality (Table 3). Membership in a cooperative and receiving a loan are represented by dummy variables. Regarding the loan variable, we did not include it as a numerical variable because the majority of farmers did not receive a loan, resulting in many missing values (NA). These variables allow us to examine the resources available to the farmers and their access to cooperative support and financial assistance.

Table 3. Resource Management and Support variables

Variable	Variable name	Type	Categories	
Quality of the land	land_quality	categorical	1	White
			2	Grey
			3	Yellow
			4	Red
			5	Other (specify)
			6	Black/Dark
Being part of a farmer's cooperative	coop_now	dummy	1	Yes
			0	No
Received a loan	loan	dummy	1	Yes
			0	No

Source: Author

5.2. Data Processing, Variable Transformation and Validity Checks

For the analysis, the original sample size was of 1,536 observations across 26 variables, with 804 observations from 2015 and 759 from 2017. To process the data, all negative values for variables such as production, price, target area, income, and profit were replaced by NA, as negative values for these variables are unreasonable. After this change, the sample size was reduced to 928 observations, of which 598 were from 2015 and 330 from 2017.

The next step was to create dummy and categorical variables for those mentioned in section *5.1. Description of the variables used*. Additionally, transformations such as logarithmic scaling were applied to certain variables to improve the distribution and better fit the data for analysis.

Different models were developed to explain the production and income of smallholder farmers. For model validation, visual inspections of the residuals versus fitted values were performed, along with Q-Q plots and Scale-Location plots. In addition, several statistical tests were conducted: the Durbin-Watson Test for autocorrelation (Durbin & Watson, 1950), the Breusch-Pagan Test for heteroscedasticity (Breusch & Pagan, 1979), the Shapiro-Wilk Test for normality of residuals (Shapiro & Wilk, 1965), and the Variance Inflation Factor for multicollinearity.

Considering our sample size, the assumptions of consistency and asymptotic normality are satisfied for our OLS regression. We can consider our estimator consistent since, as the sample size increases, it converges to the true value of the parameter being estimated. Moreover, under the large-sample approach, with a sufficiently large sample size, the distribution of the estimator can be approximated by a normal distribution. The Central Limit Theorem states that, regardless of the original distribution of the data, the distribution of the sample mean approaches a normal distribution as the sample size grows large. This justifies our use of OLS regression in this context.

The Breusch-Pagan test indicated the presence of heteroskedasticity in our model. To address this issue, Robust Standard Errors were computed using the Heteroskedasticity-Consistent Standard Error Estimator proposed by White, 1980. This robust method for estimating standard errors is designed to provide valid standard errors even when the error terms exhibit non-constant variance, allowing for more reliable hypothesis testing and confidence intervals in the presence of heteroskedasticity. To carry out the 2SLS analysis, the *iv_model* function of R-studio was used.

Outlier removal in this analysis is guided by the understanding that, in a large sample, not all observations may be directly comparable or belong to the same estimated relationship. Although efforts were made to select observations a priori during the sampling process and based on theoretical considerations, it is inevitable that some observations remain that do not align well with others. Consequently, these outliers are removed *ex post*, as this approach, while not ideal, is preferable to forcing the estimator to incorporate observations that may distort comparisons within the analysis.

To ensure that these extreme values did not skew the results, we applied an outlier removal method based on the 3-standard deviation (SD) rule. This approach is widely accepted for its effectiveness in identifying and excluding values that deviate significantly from the mean. Specifically, under the assumption of a roughly normal distribution, approximately 99.7% of values are expected to fall within 3 SDs of the mean. By removing observations for which the residuals of the production regression exceeded this threshold, we retained the integrity of the data while minimizing the influence of atypical values. This method is supported by statistical literature as a standard approach for identifying outliers (Pincus, 1995; Crosby et al., 1994; Hair et al., 2010) and has been shown to mitigate the effects of extreme values in both univariate and multivariate contexts (Hampel, 1974; Wilcox, 2010). Consequently, this technique allowed for a robust analysis by reducing the impact of outliers without compromising the dataset's overall representativeness.

Outliers are identified based on production data rather than income, as production is typically more observable and tends to have higher data quality. This choice is made to enhance the accuracy of the outlier removal process, given that production data generally provide a more reliable basis for identifying extreme values. After removing the outliers, the sample size of our data resulted in 923 observations, from which 593 are from 2015 and 330 are from 2017.

Various reasons were considered to explain the presence of outliers, such as (1) variation in farm size, (2) variation in farming experience, (3) variation in land quality, and (4) data reporting errors.

Since only five observations were removed as outliers, the analysis focused on these specific households, comparing the data with the one of the remaining sample. The removed observations were all from the 2015 data. The production values for these outliers were 20 Kg (for three households, representing three of the five removed observations), 36 Kg, and 100 Kg —substantially lower than the mean production value of 1046 Kg for 2015. Consequently, the yields of these households were also much lower than the average (see Summary statistics below).

Other variables for these outliers appeared similar to the mean values from the summary statistics, and no clear pattern emerged to explain their presence. Possible explanations for these outliers include data collection errors or the occurrence of unusually poor production years for these farms.

5.3. Summary statistics

Summary statistics of the variables used for the analysis for both 2015 and 2017 are given in Table 4. Having the summary statistics for the two years it allows for a detailed comparison of trends and changes over time within the same groups and better understand how each group's characteristics evolved before and after the intervention. This separation helps identify whether any observed differences between the groups in 2017 can be attributed to the treatment, as opposed to pre-existing trends or external factors that may have affected the groups differently in each year. It also enhances our ability to check the parallel trends assumption, which is fundamental to the validity of the DiD approach. Ultimately, having year-specific summary statistics strengthens the analysis by providing a clearer context for understanding the impact of the intervention and ensuring the reliability of the conclusions drawn from the data.

Table 4. Summary statistics, imputed data at baseline (2015) and endline (2017)

	Mean	**Std. Dev.**	**Min**	**Max**
2015 (n=593)				
total_income	93,530	131,033.8	0	1,736,600
production	1,046	1245.215	20	9000
farming_experience	20.44	12.54356	0	60
targat_area	1.661	1.165793	0.10	10
avg_price	30.65	83.42368	1.00	2000.00
income_target_crop	33,750	42281.2	270	500,000
cultivated_area	3.804	2.174251	0.50	12
2017 (n=330)				
total_income	448,119	4,413,978	0	80,104,600
production	2,169.3	2406.134	25	18,900
farming_experience	24.26	12.2384	0	64
targat_area	2.339	1.473594	0.25	10.00
avg_price	33.58	13.43384	10.80	197.53
income_target_crop	69,910	86,403.79	900	800,000
cultivated_area	4.443	3.185861	0.50	37.75

Source: Own elaboration using RStudio 4.4.1

In 2015, household income and production metrics demonstrated substantial variability. The average total income was 93,530 KES, with a large SD of 131,033, highlighting significant income disparities among households. Production levels averaged 1,046 Kg, with a SD of 1,245, reflecting considerable differences across households, ranging from 20 to 9,000 Kg. Farming experience averaged 20.44 years, but ranged widely from 0 to 60 years, showcasing a diverse level of expertise among households. The average target area and cultivated area were 1.66 and 3.8 Ha, respectively, indicating variability in land use, with some households cultivating very small plots while others managed larger areas. Price per Kg averaged 30.65 KES but varied greatly, with a SD of 83.42 and a maximum of 2,000, pointing to substantial market fluctuations. Income from target crops averaged 33,750 KES, though this figure also varied significantly, underscoring the variability in crop profitability.

By 2017, some metrics had shifted markedly. Average household income rose sharply to 448,119 KES, though income disparity widened dramatically, as indicated by a SD of 4,413,978 and an extreme range extending up to 80,104,600. Production more than doubled, with an average of 2,169 Kg and a SD of 2,406, ranging from 25 to 18,900 Kg. Farming experience increased to 24.26 years on average, with an upper limit of 64 years. The target area and cultivated area also expanded to averages of 2.34 and 4.44 Ha, respectively, suggesting some households increased their land use. Average price per Kg saw a modest increase to 33.58 KES, with reduced variability as reflected by a SD of 13.43. Income from target crops surged to an average of 69,910 KES, though the wide SD of 86,403 highlighted diverse profitability outcomes among households.

Comparing 2015 and 2017, we see marked changes, particularly in income and production levels, as well as in the disparity across observations. The increase in target and cultivated areas over time, along with rising yields, suggests shifts toward more intensive or profitable agricultural practices. However, the high variability in both years underscores uneven access to these benefits among households, highlighting persistent disparities in income and production outcomes.

6. Results and Discussion

This section shows the results of the panel data analysis for the production and income estimation.

6.1. Production Regression Estimation

Table 5, Table 6 and Table 7 show the Descriptive Statistics of the regression Residuals, the Regression Model Performance Metrics and the T-test of coefficients of the *production* regression (Equation 1) respectively, and Figure 6 shows a visual representation of the residuals.

Equation 1. Estimated regression for production

$$\log_{production} = treatment + year + did + log_{target\ area} + log_{avg\ price} + log_{cultivated\ area} + gender + education + farming\ experience + intercrops + coop_{now} + loan + \varepsilon_i$$

Table 5. Residuals Distribution Summary of production regression

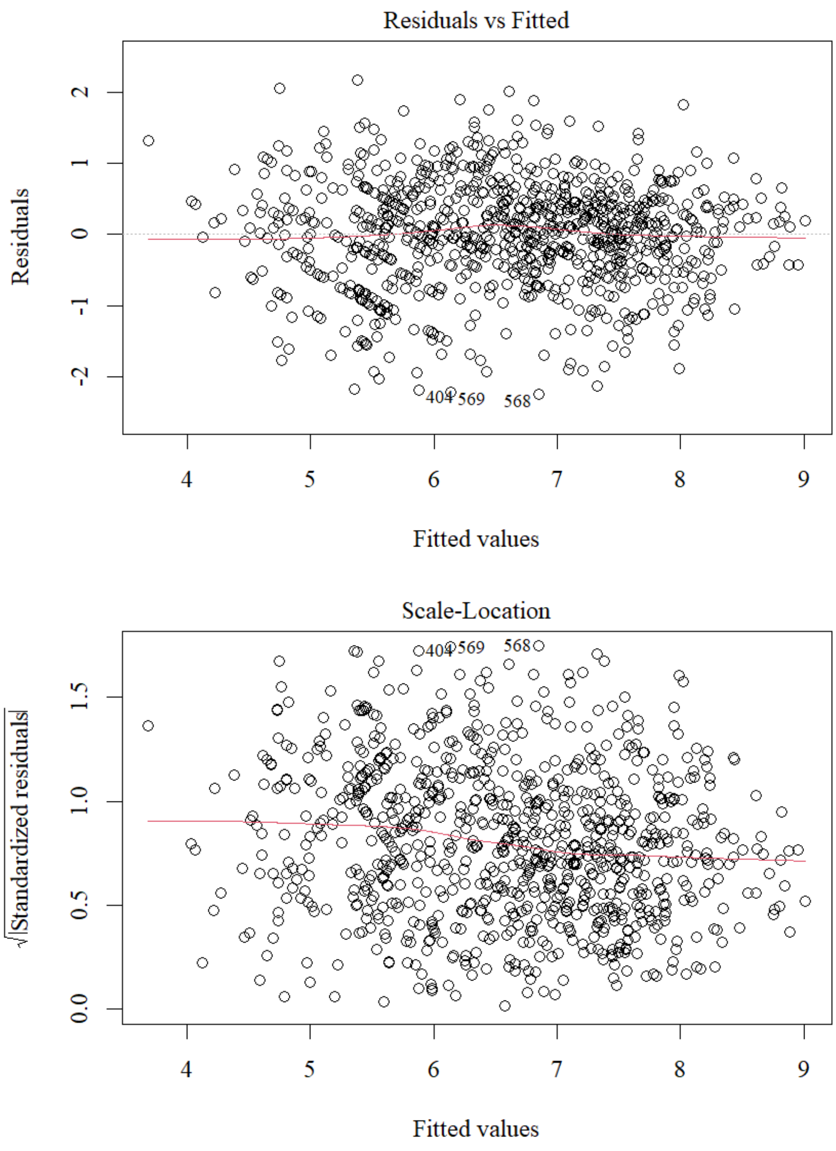
Residuals				
Min	*1Q*	*Median*	*3Q*	*Max*
-2.24581	-0.43312	0.05354	0.46275	2.16696

Source: Own elaboration using RStudio 4.4.1

The residual summary on Table 5 offers insight into the model's predictive accuracy for production. The residuals, centred around zero, reflect a balanced spread but also reveal variability across observations. A minimum residual of -2.24581 suggests that, for certain cases, the model underestimates production considerably, indicating higher-than-expected production levels in those observations. The first quartile residual of -0.43312 shows that 25% of the residuals fall below this value, suggesting a slight tendency toward underestimation for a subset of the data.

The maximum residual of 2.16696 similarly shows the extreme overestimation of production in certain observations. Notably, the first and third quartile residuals (-0.43312 and 0.46275, respectively) are approximately equal in magnitude, but opposite in direction, reflecting a balanced proportion of under- and over-estimation, which points to a robust model. The median residual, close to zero at 0.05354, indicates that, overall, the model does not exhibit a strong bias toward over- or underestimation and lies at an intermediate point, further confirming the model’s balanced predictive performance. This range of residuals highlights that while the model generally performs reasonably well, there are cases with some prediction errors.

Figure 6. Residuals vs Fitted plot (1) and Scale-Location plot (2) of production regression



Source: Own elaboration using RStudio 4.4.1

The diagnostic plots provide further insights into the model fit and the assumptions underlying the regression. The *Residuals vs. Fitted plot* shows that the residuals are randomly scattered around the horizontal line at zero, suggesting that a linear model is suitable for capturing the relationship between predictors and production (Figure 6 (1). The absence of noticeable patterns or clusters supports the assumption of linearity.

The *Scale-Location plot* supports these findings, indicating a relatively constant variance of residuals across fitted values, or homoscedasticity (Figure 6 (2)). The red line representing the trend in residual spread appears mostly flat, with only minor deviations. This consistency suggests that residual variance does not systematically increase or decrease with fitted values, thereby supporting the homoscedasticity assumption.

Overall, the diagnostic analysis suggests that the model meets the assumptions of linearity and homoscedasticity, lending confidence to the validity of the model's estimates. Although there is slight skew in the residuals indicating occasional overestimation, the balance near zero is a positive indication of the model's general performance.

Table 6. Model Fit and Summary Statistics of production regression

Residual standard error	0.7384 on 909 degrees of freedom
Multiple R-squared	0.6589
Adjusted R-squared	0.654
F-statistic	135 on 13 and 909 DF
p-value	< 2.2e-16

Source: Own elaboration using RStudio 4.4.1

The regression output provides several key indicators of the model's fit and overall performance (Table 6). The residual standard error is 0.7384, measured over 909 degrees of freedom, indicating the average deviation of the observed values from the predicted values in terms of log production. This relatively low residual error suggests that, on average, predictions are close to observed values, though some variability remains unexplained.

The Multiple R-squared value of 0.6589 implies that approximately 65.89% of the variation in production is explained by the model, which is a moderate-to-strong fit. The Adjusted R-squared is slightly lower at 0.654, accounting for the number of predictors included and indicating that the model's explanatory power is relatively robust even when adjusted for complexity. An R-squared of this magnitude suggests a correlation of roughly 80% between observed and predicted values, reinforcing that the model's fit is strong. This high degree of correlation shows that the model's predictions closely align with actual values, highlighting the effectiveness of the included variables in capturing the primary drivers of log production.

The F-statistic of 135, with 13 and 909 degrees of freedom, is highly significant, as indicated by the p-value of less than 2.2e-16. This very low p-value shows that the model provides a statistically significant improvement over a model without predictors.

Table 7. T test of coefficients of production regression

	Estimate	Std. Error	T value	P-value
intercept	5.7679981	0.4600895	12.5367	< 2.2e-16 ***
treatment	1.0499681	0.0850374	12.3471	< 2.2e-16 ***
year	-0.1337700	0.1099265	-1.2169	0.2239565
did	0.4590424	0.1180259	3.8893	0.0001078 ***
log_target_area	0.8074124	0.0475638	16.9753	< 2.2e-16 ***
log_avg_price	-0.2461075	0.1092815	-2.2521	0.0245570 *
log_cultivated_area	0.2869204	0.0483116	5.9390	4.08e-09 ***
gender	-0.0989573	0.0561544	-1.7622	0.0783654 .
education	0.2942083	0.1488946	1.9759	0.0783654 .
farming_experience	-0.0060156	0.0020871	-2.8822	0.0040416 **
intercrops	-0.1320202	0.0506840	-2.6048	0.0093437 **
coop_now	0.1177300	0.0647700	1.8177	0.0694448 .
loan	0.1589396	0.0712244	2.2315	0.0258889 *
land_quality	-0.0157658	0.0297119	-0.5306	0.5958108

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Source: Own elaboration using RStudio 4.4.1

The output shown at Table 7 are robust standard errors using the Huber-White or Sandwich Estimator to address for possible heteroskedasticity.

The model results reveal several significant predictors of the outcome, highlighting both economic and social influences. The *intercept*, being highly significant, represents the baseline level of production when all other variables are zero, which is 5.76 Kg. The *treatment* variable has a significant positive effect, meaning that receiving treatment leads to a direct increase in production, indicating a clear benefit from the treatment itself.

The *DiD* term is also positive and significant. This suggests that, after controlling for time-variant factors that could affect production and isolating the effect of the 2SCALE intervention, the additional change in production for treated farmers—beyond what would be expected from general trends over time—reflects a meaningful impact of the intervention on production for smallholder farmers who received the treatment.

Additionally, increases in *target area* and *cultivated area* are both positively associated with production, meaning that larger areas for cultivation directly lead to higher production, as expected. A 1% increase in target area, is associated with a 0.81% increase in production, and a1% increase in cultivated area, is associated with a 0.29% increase in production.

This positive relationship could be primarily because increasing the area under cultivation directly allows for more land to be planted with crops, resulting in a higher total volume of production, assuming yields per Ha remain constant. Larger cultivated areas can enable farmers to benefit from economies of scale, where the per-unit costs of inputs, such as seeds and fertilizers, decrease as output increases (Xiao et al., 2015; Aragón et al., 2022).

This expanded land area also provides opportunities for improved agricultural practices, such as crop rotation and intercropping, which can enhance overall yields. Furthermore, a larger cultivated area allows for greater crop diversification, reducing the risk of total crop failure and optimizing productivity across various crops. Farmers who cultivate more land may also gain better access to resources, including agricultural extension services and credit, which can further bolster production capacity. Additionally, cultivating larger areas can enhance market opportunities, enabling farmers to meet market demand more effectively.

On the other hand, *average price* shows a significant negative relationship with production, meaning that higher prices are associated with lower levels of production, specifically, a 1% increase in price is associated with a 0.25 % decrease in production. This inverse relationship could be driven by several market dynamics.

In typical firm supply theory, an increase in price is expected to lead to an increase in production, as producers respond to higher prices with higher output. However, in the context of smallholder agriculture in Kenya, this relationship may differ due to the non-separability of household and farm decisions. In non-separable agricultural households, the roles of producer and consumer are interconnected, unlike a traditional firms where supply and demand decisions are separate (Errington, 1995; Evenson, 1988).

If markets were complete, it would be possible to separate household decisions into consumption (demand) and production (supply). However, in these agricultural households, which often lack access to complete markets, production decisions are influenced by both consumption needs and income effects. When the price of sorghum rises, it may have both a substitution effect and an income effect on the household's production decisions (Barrett, 2008).

The *substitution effect* occurs when a change in the price of a good leads households to substitute it with other goods that have become relatively cheaper or more expensive. For example, if the price of sorghum rises, households may *shift resources* (such as labour or land) to sorghum production, as it becomes more profitable compared to other crops. On the *consumer side*, when the price of sorghum increases, it becomes relatively more expensive compared to other goods, leading households to reduce consumption and seek alternatives. On the *producer side*, a price increase for sorghum might lead households to allocate more resources to sorghum production due to the higher returns it offers compared to other activities.

The *income effect*, on the other hand, reflects how a price change impacts a household's real income or purchasing power, influencing both consumption and production decisions. When the price of sorghum increases, households that sell sorghum experience a rise in income, which may lead to higher consumption or even a reduction in production as the household becomes financially secure. However, households that consume a large portion of their own sorghum may respond by increasing production to offset the higher cost of consuming sorghum themselves (Hal R. Varian, 1967).

In traditional settings with complete markets, consumption and production decisions can be easily separated. However, in non-separable agricultural households with incomplete markets, these effects are interconnected, meaning that production decisions are influenced by both consumption needs and changes in income. This creates a complex decision-making environment, where both the income and substitution effects play a role in shaping household behaviour. Thus, an increase in the price of sorghum can lead to a decrease in production in these households, as the substitution and income effects balance out in ways that differ from the behaviour observed in traditional firms.

Intercropping, likewise, has a negative effect, indicating that this farming practice is associated with a reduction in production levels. This cultivation method, although associated with negative effects on production in the short run, can be viewed as a strategic investment whose full benefits are realized over time. In the short run, farmers may reduce their overall production to improve soil fertility, enhance pest control, or optimize resource use for future productivity. The practice of planting multiple crops in the same field may not show immediate positive outcomes because the benefits, such as increased resilience, better pest management, or improved soil health, take time to materialize. Thus, in the context of this study, where we are still in the short run, the potential long-term benefits of intercropping have not yet been fully realized, which could explain the observed negative relationship with production levels in the present.

This short-term reduction in production can be explained by the competition between crops. The presence of multiple crops in the same field often leads to competition for essential resources such as light, water, and nutrients, which can reduce the overall productivity of each crop. This effect may be intensified by the complexity of managing diverse crops with different growth cycles and nutrient requirements, leading to inefficiencies in resource use. Furthermore, although intercropping is sometimes thought to offer pest control benefits, it can also introduce challenges in pest management, as the presence of multiple species might attract different pests or complicate pest control strategies (Mir et al., 2022; Huss et al., 2022).

Social factors such as *gender* and *education* are also significant. *Gender* shows a negative association, indicating potential disparities based on gender, as the model uses a dummy variable where 1 represents male and 0 represents female. This implies that being female is positively related to production outcomes. One possible explanation for this relationship is that women may adopt more sustainable farming practices due to their heightened risk aversion. As risk-averse individuals, female farmers might prioritize stable, long-term investments in their crops, which can lead to more consistent production levels (FAO, 2023).

Meanwhile, *education* is positively associated with production, suggesting that higher education levels contribute positively to outcomes. This positive relationship may be due to the ways in which education equips farmers with knowledge about improved farming practices, effective resource management, and an understanding of market trends. Educated farmers are more likely to access and apply information on agricultural advancements, make informed decisions, and have better access to support programs and credit facilities, all of which can enhance their productivity and increase overall production.

Additionally, education can provide farmers with better access to incentives such as government programs, subsidies, and market opportunities, which can further stimulate their motivation and capacity to increase production. As a result, education not only contributes to improving technical skills but also opens doors to better economic opportunities, which can significantly boost agricultural outcomes (African Development Bank, 2022).

Farming experience, however, has a negative effect on production, with more years of experience slightly reducing output. This might suggest diminishing returns to experience, where the benefits of increased knowledge and skills level off over time. While experience is often associated with a deeper understanding of farming practices and better resource management, it also comes with a reduced level of risk aversion. In the early stages of farming, less experienced farmers may be more cautious and, therefore, tend to overproduce as a way to mitigate perceived risks to their harvest (Feder et al., 1985, Bird & Fafchamps, 2004).

However, as farmers gain experience, they become more aware that the risks they face are often external—such as unpredictable weather, market fluctuations, or pests—that they cannot control through increased production alone. As a result, experienced farmers are likely to adopt a more balanced approach to production, factoring in the diminishing returns of overproduction. The net effect of farming experience, therefore, is a combination of increased knowledge and reduced risk aversion, leading to more cautious production decisions that can, at times, result in lower output (Guiso & Paiella, 2008).

Cooperative membership is positively associated with production, suggesting that being part of a cooperative leads to a direct increase in production, likely due to better access to resources, markets, and shared knowledge. Cooperatives enhance access to agricultural inputs such as seeds, fertilizers, and tools, often at lower costs due to bulk purchasing. They also provide access to financial resources like credit, which may be otherwise unavailable to individual farmers. Additionally, cooperatives improve farmers' market access, enabling them to sell at better prices or secure more stable contracts, while also reducing transaction costs (Ahmed & Mesfin, 2017).

Moreover, cooperatives facilitate the exchange of knowledge and best practices among members, helping farmers adopt improved farming techniques, pest control methods, and market strategies. By connecting farmers to these critical resources, markets, and knowledge networks, cooperatives play a key role in boosting productivity and increasing overall production (Fuyane & Mushunje, 2016).

Finally, access to *loans* is also positively correlated with production. It can boost agricultural production by providing funds for critical inputs like seeds, fertilizers, and machinery, leading to higher yields. Credit also enables hiring labour during peak seasons, enhancing productivity.

Empirical research supports this, showing that access to credit in Nigeria and India significantly raised farm output by enabling modern technology adoption and better practices. Access to institutional credit also reduces reliance on high-interest informal loans, helping farmers make sustainable investments (Ameh & Lee, 2022).

6.2. Income Regression Estimation

In estimating the income equation, production is an endogenous variable that may introduce endogeneity into the model. This endogeneity arises because production is likely correlated with the error term in the income equation. The potential sources of endogeneity include simultaneity, where higher income can lead to increased production and vice versa, omitted variable bias, where unobserved factors (e.g., access to credit or land quality) affect both production and income, and reverse causality, where higher income leads to increased investments in production. Additionally, measurement errors or sample selection bias could further contribute to this endogeneity.

To address these issues, IVs are used to isolate the exogenous variation in production and obtain fitted values for production in the second stage. These IVs must be correlated with production but uncorrelated with the error term in the income equation, allowing for consistent estimation of the causal relationship between production and income.

In the current analysis, the first stage of the 2SLS process has already been completed in the previous section, where the regression for production was estimated (6.1. Production Regression Estimation). In that stage, IVs were used to account for the endogeneity of production, ensuring that the variation in production explained by the instruments is exogenous and not correlated with the error term in the income equation (Equation 2).

The estimated coefficients from that regression provide the fitted values of production, which capture the part of production that is influenced by the exogenous instruments. These fitted values are now ready to be used in the second stage, where they will replace the endogenous production variable in the income equation to obtain consistent estimates of the causal effect of production on income.

Equation 2. IV Estimation for Endogenous Regressors of Production

$$\log_{production} = treatment + year + did + log_{target\ area} + log_{avg\ price} + log_{cultivated\ area} + gender + education + farming\ experience + intercrops + coop_{now} + loan + u$$

In the previous equation, production is treated as the endogenous regressor for income. The variables *treatment*, *year*, *DiD*, *average price*, *cultivated area*, *gender*, *education*, and *loan* are used as instruments. Among these, *farming experience*, *target area*, *intercrops*, and *cooperative membership* are excluded instruments.

The variable *intercrops* is considered endogenous because, although it is a choice made by the farmer, the decision commits them to a period of 5 to 10 years. Given that this study compares data from 2015 to 2017, there is insufficient time for farmers to alter this choice. Similarly, the same reasoning applies to *cooperative membership* and *loan* decisions, as these typically involve long-term commitments rather than short-term microcredits.

Equation 3. Final Regression of Income on the Predicted Values from Production

$$log_{income} = log_{production} + treatment + year + did + gender + education + log_{avg\ price} + log_{income\_target\_crop} + \log_{cultivated\_area} + loan + \varepsilon$$

In Equation 3, income is the dependent variable, and production is the predicted value of production from the first-stage regression (Equation 2). The rest of the variables represents exogenous variables for income.

Table 8, Table 9 and Table 10 show the Descriptive Statistics of the regression Residuals, the Regression Model Performance Metrics and the T-test of coefficients of the *income* regression (Equation 3) respectively.

Table 8. Residuals Distribution Summary of income regression

Residuals				
Min	*1Q*	*Median*	*3Q*	*Max*
-6.55386	-0.46613	0.02684	0.55627	4.91494

Source: Own elaboration using RStudio 4.4.1

The residual summary in Table 8 provides insights into the distribution of the differences between observed and predicted values in the model. The minimum residual is -6.5539, while the maximum is 4.9149, indicating that the largest underprediction is approximately 6.55 units, and the largest overprediction is about 4.91 units. The first quartile (1Q) and third quartile (3Q) residuals are -0.4661 and 0.5563, respectively, showing that 50% of the residuals lie within this range. The median residual, at 0.0268, is close to zero, suggesting that the model does not systematically over- or underpredict the dependent variable.

Table 9. Model Fit and Summary Statistics of income regression

Residual standard error	0.9522 on 855 degrees of freedom
Multiple R-squared	0.4045
Adjusted R-squared	0.3976
Wald test	50.14 on 10 and 855 DF
p-value	< 2.2e-16

Source: Own elaboration using RStudio 4.4.1

The regression results shown on Table 10 indicate that the model explains approximately 40.45% of the variation in the dependent variable, as reflected by the Multiple R-squared value. While this suggests a moderate fit, it is reasonable given the complexity of socio-economic factors influencing the outcome. The Adjusted R-squared, at 39.76%, accounts for the number of predictors, indicating that not all variables contribute substantially to explaining the dependent variable.

The Residual Standard Error of 0.9522 shows that, on average, the model's predictions deviate from the observed values by less than one unit, suggesting an acceptable level of precision. Additionally, the Wald test statistic (50.14) and its highly significant p-value (< 2.2e-16) demonstrate that the predictors, taken together, have a statistically significant impact on the dependent variable. These results highlight the relevance of the model while leaving room for further refinement and exploration of additional factors to improve explanatory power.

Table 10. T tests of coefficients of income regression

	Estimate	Std. Error	T value	P-value
intercept	6.157068	0.789890	7.7948	1.871e-14 ***
log_production	0.137827	1.913107	0.0720	0.9425843
treatment	0.244101	0.179539	1.3596	0.1743167
year	0.161272	0.103972	1.5511	0.1212461
did	0.096626	0.149372	0.6469	0.5178831
gender	0.232727	0.091166	2.5528	0.0108597 *
education	0.464464	0.238013	1.9514	0.0513327 .
log_avg_price	0.363194	1.776520	0.2044	0.8380575
log_income_target_crop	0.088896	1.888346	0.0471	0.9624636
log_cultivated_area	0.572373	0.077871	7.3503	4.624e-13 ***
loan	0.372815	0.105731	3.5261	0.0004442 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Source: Own elaboration using RStudio 4.4.1

The regression results (Table 10) suggest that income is primarily driven by *cultivated area* and *access to loans*, with *education* and *gender* emerging as additional determinants. The explanation of the positive relationship between cultivated area and education follows the same reasoning than in the previous section (6.1. Production Regression Estimation).

Notably, the D*iD* term for the project does not have a statistically significant impact on income, but it also does not negatively affect it—a common risk in development interventions. The lack of significance for *production* may be attributed to the two-stage modelling approach, though cultivated area's significance underscores the importance of agricultural activities as a primary source of income.

Additionally, *average price* and *income from the target crop* are not statistically significant, which could be due to short-term price variability or farmers' limited ability to optimize production and income from these crops within the study's time frame. This suggests that while these factors may contribute to income under different circumstances, their effects may require longer periods or complementary interventions, such as improved market access or price stabilization mechanisms, to become significant.

Interestingly, while the project shows a positive impact on production, its effect on income appears to be delayed. This suggests that the project's benefits on income might only materialize in the long term, as farmers adapt their practices and fully leverage increased production. Such a dynamic underscores the importance of patience and long-term support in development projects, as farmers need time to "appropriate" the benefits and translate them into sustained income growth. These results are scientifically significant and encourage further investment in initiatives like this one to ensure long-term success for smallholder farmers.

As a final step to confirm that the DiD term has no significant effect on income, a reduced-form regression was conducted. This approach involved removing production from the income equation and including the excluded instruments as predictors. This reduced-form estimation allowed for the decomposition of the DiD coefficient into its direct effect on income and its indirect effect through production (which was excluded in this model). In principle, this setup should still yield a zero coefficient for DiD if the program truly has no effect on income. The results of this reduced-form analysis confirmed that the DiD coefficient remained statistically insignificant, corroborating the findings from the structural form regression presented in this thesis. While the reduced-form regression table is not shown, this additional analysis strengthens the conclusion that the program had no measurable short-term impact on income during the study period.

7. Conclusion

The study's findings reveal that while the 2SCALE intervention significantly increased sorghum production, its impact on income remains statistically insignificant in the short term. Key predictors of production include treatment, cultivated area, and target area, with intercropping and average price showing negative effects. Cultivated area and access to loans emerge as primary drivers of income, while education and gender also play significant roles. The results suggest that income gains may require more time to materialize, underscoring the need for sustained support and complementary interventions to help smallholder farmers fully leverage production increases for long-term income growth.

The conclusion aligns with existing literature on smallholder agriculture, emphasizing the complexity of household decision-making and the interplay of socio-economic factors. Barrett, 2008 highlights how interconnected consumption and production decisions shape responses to price changes. The findings on intercropping echo Mir et al., (2022) and Huss et al., (2022), who emphasize its long-term soil health benefits despite initial productivity trade-offs. The role of cooperatives, as noted by Fuyane & Mushunje (2016), underscores their value in improving resource access and market opportunities. Consistent with Ahmed & Mesfin, 2017, cultivated area and credit access emerge as key drivers of productivity and income. These insights stress the need for development interventions that balance immediate production goals with long-term sustainability.

The findings of this study contribute to addressing the persistent challenges of poverty and food insecurity in rural Kenya by providing evidence-based insights into the effectiveness of development initiatives like 2SCALE. By identifying key factors driving sorghum production and farmer income, such as cultivated area, credit access, and cooperative involvement, this research offers actionable recommendations for enhancing agricultural productivity and resilience. The use of robust methodologies ensures the results can inform targeted policies and interventions, enabling more efficient allocation of resources to support smallholder farmers, reduce vulnerability, and improve livelihoods in rural areas.

8. Bibliographical references

2SCALE. (2022). *HIGHLIGHTS REPORT 2022*.

Abalo Adodo, Mathias Ahounou, Geneviève Audet-Bélanger, Tekalegn Ayano, Judith Chabari, Assefa Degefu, François Dossouhoui, Peter Gildemacher, Olugbenga Stephen Idowu, Alhassan Issahaku, Peter Kirimi, E. L., Arnoldus Maatman, Janet Macharia, Douglas Magaja, Jacqueline Ndambuki, David Njenga, Irene Njogu, Francis Nthuku, Thompson Ogunsanmi, … Allan Wayira and Bertus Wennink. (2019). *Insights from the 2SCALE project*.

Abro, Z. A., Alemu, B. A., & Hanjra, M. A. (2014). Policies for agricultural productivity growth and poverty reduction in rural Ethiopia. *World Development*, *59*. https://doi.org/10.1016/j.worlddev.2014.01.033

African Development Bank Group. (2024). *AFRICAN ECONOMIC OUTLOOK 2024 Driving Africa's Transformation The Reform of the Global Financial Architecture*.

Ahmed, M. H., & Mesfin, H. M. (2017). The impact of agricultural cooperatives membership on the wellbeing of smallholder farmers: empirical evidence from eastern Ethiopia. *Agricultural and Food Economics*, *5*(1). https://doi.org/10.1186/s40100-017-0075-z

Ameh, M., & Lee, S. H. (2022). Determinants of Loan Acquisition and Utilization among Smallholder Rice Producers in Lagos State, Nigeria. In *Sustainability (Switzerland)* (Vol. 14, Issue 7). https://doi.org/10.3390/su14073900

Angelucci, M., & De Giorgi, G. (2009). Indirect effects of an aid program: How do cash transfers affect ineligibles' consumption? *American Economic Review*, *99*(1). https://doi.org/10.1257/aer.99.1.486

Angelucci, M., & Di Maro, V. (2016). Programme evaluation and spillover effects. *Journal of Development Effectiveness*, *8*(1). https://doi.org/10.1080/19439342.2015.1033441

Angrist, J. D., & Pischke, J. S. (2008). Mostly harmless econometrics: An empiricist's companion. In *Mostly Harmless Econometrics: An Empiricist's Companion*. https://doi.org/10.1111/j.1475-4932.2011.00742.x

Barrett, C. B. (2008). Smallholder market participation: Concepts and evidence from eastern and southern Africa. In *Food Policy* (Vol. 33, Issue 4). https://doi.org/10.1016/j.foodpol.2007.10.005

Bhunu, S. M., Grenra, D. M., & Kasalu-Coffin, E. (2019). *Note to Executive Board Representatives Focal Points: Executive Board-128 th Session E Agenda: 7(c)(ii)(a) Republic of Kenya Country Strategic Opportunities Programme*.

Bird, D., & Fafchamps, M. (2004). Market Institutions in Sub-Saharan Africa: Theory and Evidence. *The International Journal of African Historical Studies*, *37*(2). https://doi.org/10.2307/4129030

Bonilla, J., & Rai, N. (2018). *Impact Evaluation of 2SCALE: Endline Report APRIL 2018*. www.air.org

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, *47*(5). https://doi.org/10.2307/1911963

Castañeda, A., Doan, D., Newhouse, D., Nguyen, M. C., Uematsu, H., & Azevedo, J. P. (2018). A New Profile of the Global Poor. *World Development*, *101*. https://doi.org/10.1016/j.worlddev.2017.08.002

Chamberlin, J., Diao, X., Kolavalli, S., & Breisinger, C. (2007). *Smallholder Agriculture in Ghana*. www.ifpri.org

Christiaensen, L., Demery, L., & Kuhl, J. (2011). The (evolving) role of agriculture in poverty reduction-An empirical perspective. *Journal of Development Economics*, *96*(2). https://doi.org/10.1016/j.jdeveco.2010.10.006

Crosby, T., Iglewicz, B., & Hoaglin, D. C. (1994). How to Detect and Handle Outliers. *Technometrics*, *36*(3). https://doi.org/10.2307/1269377

Durbin, J., & Watson, G. S. (1950). Testing for Serial Correlation in Least Squares Regression: I. *Biometrika*, *37*(3/4). https://doi.org/10.2307/2332391

Errington, A. (1995). Peasant Economics: Farm Households and Agrarian Development (Second Edition). By Frank Ellis. Cambridge: Cambridge University Press (1993), pp. 309, £15.95, US$32.95. ISBN 0-521-45711-4. *Experimental Agriculture*, *31*(3). https://doi.org/10.1017/s0014479700025552

Evenson, R. E. (1988). Agricultural household models: Extension, application and policy. *Journal of Development Economics*, *28*(1). https://doi.org/10.1016/0304-3878(88)90028-4

Fabrizio Quinonez. (2023). *Exploring Poverty Dynamics in Paraguay*.

FAO. (2017). The state of agriculture and food 2017. Leveraging Food Systems for inclusive rural transformation. In *The State of the World*.

FAO. (2019). *FAO FRAMEWORK ON RURAL EXTREME POVERTY Towards reaching Target 1.1 of the Sustainable Development Goals*.

FAO. (2023). The status of women in agrifood systems. In *The status of women in agrifood systems*. https://doi.org/10.4060/cc5343en

FAO, IFAD, UNICEF, WFP, & WHO. (2023). The State of Food Security and Nutrition in the World 2023. In *The State of Food Security and Nutrition in the World 2023*. https://doi.org/10.4060/cc3017en

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: a survey. *Economic Development & Cultural Change*, *33*(2). https://doi.org/10.1086/451461

Fuyane, M. M., & Mushunje, N. (2016). The role of cooperatives in empowering smallholder farmers to access markets: A case study of Eastern Cape and KwaZulu Natal cooperatives in South Africa. *International Journal of Development and Sustainability*, *5*(11).

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. J. (2016). Impact Evaluation in Practice, Second Edition. In *Impact Evaluation in Practice, Second Edition*. https://doi.org/10.1596/978-1-4648-0779-4

Guiso, L., & Paiella, M. (2008). Risk aversion, wealth, and background risk. *Journal of the European Economic Association*, *6*(6). https://doi.org/10.1162/JEEA.2008.6.6.1109

Hair, J., Anderson, R., Babin, B., & Black, W. (2010). *Multivariate Data Analysis (7th ed). Pearson.*

Hal R. Varian. (1967). Intermediate Microeconomics A Modern Approach(9th). In *Angewandte Chemie International Edition, 6(11), 951–952.*

Hampel, F. R. (1974). The Influence Curve and Its Role in Robust Estimation. *Journal of the American Statistical Association*, *69*(346). https://doi.org/10.2307/2285666

Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, *50*(4). https://doi.org/10.2307/1912775

Heckman, J. J., & Robb, R. (1985). Alternative methods for evaluating the impact of interventions. An overview. *Journal of Econometrics*, *30*(1–2). https://doi.org/10.1016/0304-4076(85)90139-3

Horton, D., Prain, G., & Thiele, G. (2009). Perspectives on Partnership: A literature review. *International Potato Centre Working Paper*.

Huss, C. P., Holmes, K. D., & Blubaugh, C. K. (2022). Benefits and Risks of Intercropping for Crop Resilience and Pest Management. In *Journal of Economic Entomology* (Vol. 115, Issue 5). https://doi.org/10.1093/jee/toac045

Inchauste, G., Azevedo, J. P., Essama-Nssah, B., Olivieri, S., Nguyen, T. Van, Saavedra-Chanduvi, J., & Winkler, H. (2014). Understanding Changes in Poverty. In *Understanding Changes in Poverty*. https://doi.org/10.1596/978-1-4648-0299-7

Kenya National Bureau of Statistics. (2024). *Statistical Release Quarterly Gross Domestic Product Report First Quarter, 2024 Kenya National Bureau of Statistics*.

Mellor, J. W. (2017). Agricultural Development and Economic Transformation. In *Agricultural Development and Economic Transformation*. https://doi.org/10.1007/978-3-319-65259-7

Mir, M. S., Saxena, A., Kanth, R. H., Raja, W., Dar, K. A., Mahdi, S. S., Bhat, T. A., Naikoo, N. B., Nazir, A., Amin, Z., Mansoor, T., Myint, M. Z., Khan, M. R., Mohammad, I., & Mir, S. A. (2022). Role of Intercropping in Sustainable Insect-Pest Management: A Review. *International Journal of Environment and Climate Change*. https://doi.org/10.9734/ijecc/2022/v12i111390

OECD. (2019). OECD Principles on Rural Policy. In *OECD iLibrary*.

Paul Winters & Lina Salazar & Alessandro Maffioli. (2010). Designing Impact Evaluations for Agricultural Projects. *Inter-American Development Bank*.

Pincus, R. (1995). Barnett, V., and Lewis T.: Outliers in Statistical Data. 3rd edition. J. Wiley & Sons 1994, XVII. 582 pp., £49.95. *Biometrical Journal*, *37*(2). https://doi.org/10.1002/bimj.4710370219

Rankin, M., Nogales, E. G., Santacoloma, P., Mhlanga, N., & Rizzo, C. (2016). Public–Private Partnerships for Agribusiness Development: A review of international experiences. In *FAO Bulletin*.

Resilient, B., & For, R. (2011). OECD Regional Outlook. In *Building*. https://doi.org/10.1787/9789264260245-en

Robinson, Timothy P.Thornton, Philip K.Francesconi, Gian N.Kruska, Russell L.Chiozza, F.Notenbaert, An Maria OmerCecchi, G.Herrero, MarioEpprecht, M.Fritz, SteffenYou, LiangzhiConchedda, GiuliaSee, L. (2005). Global livestock production systems. In *Poultry Science* (Vol. 84, Issue 11).

Robles Aguilar, G., & Sumner, A. (2020). Who are the world’s poor? A new profile of global multidimensional poverty. *World Development*, *126*. https://doi.org/10.1016/j.worlddev.2019.104716

Sargan, J. D. (1958). The Estimation of Economic Relationships using Instrumental Variables. *Econometrica*, *26*(3). https://doi.org/10.2307/1907619

Sen, K. (2014). Inclusive growth: When may we expect it? when may we not? *Asian Development Review*, *31*(1). https://doi.org/10.1162/ADEV_a_00022

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis of Variance Test for Normality (Complete Samples). *Biometrika*, *52*(3/4). https://doi.org/10.2307/2333709

The World Bank Group. (2023). *KenyaPoverty and Equity Assessment 2023. From Poverty to Prosperity: Making Growth More Inclusive*.

United Nations. (2023). *UNITED NATIONS DEVELOPMENT PROGRAMME 2 Foreword 4 Our Offer 6 Global Ambition: Poverty and Inequality 8 Global Ambition: Climate, Nature and Energy 12 Global Ambition: Accountable and Inclusive Governance 16 Global Ambition: Development Financing 20*.

USAID. (2023). *INCLUSIVE ECONOMIC GROWTH*.

WEF & McKinsey and Company. (2011). Realizing a New Vision for Agriculture: A roadmap for stakeholders. *Geneva, World Economic Forum (WEF)*.

WEF & McKinsey and Company. (2013). Achieving the New Vision for Agriculture: New Models for Action. *World Economic Forum (WEF)*.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, *48*(4). https://doi.org/10.2307/1912934

White, H., Sabarwal, S., & De Hoop, T. (2014). *Randomized Controlled Trials (RCTs)*. www.unicef-irc.org

Wilcox, R. R. (2010). Fundamentals of modern statistical methods: Substantially improving power and accuracy. In *Fundamentals of Modern Statistical Methods: Substantially Improving Power and Accuracy*. https://doi.org/10.1007/978-1-4419-5525-8

Wooldridge, J. M. (2002). Econometric Analysis of Cross Section and Panel Data. *Booksgooglecom*, *58*(2). https://doi.org/10.1515/humr.2003.021

World Bank. (2023). *KEY INDICATORS International Poverty Line(%)*. www.worldbank.org/poverty

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