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Agricultural Transformation in Senegal: Impacts of an integrated program

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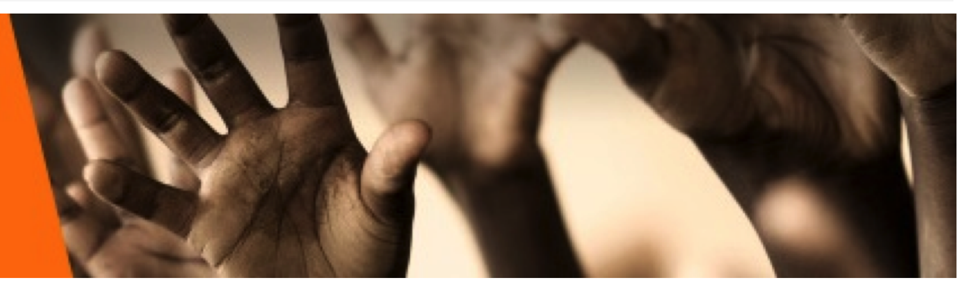

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Agricultural Transformation in Senegal:
Impacts of an integrated program

Abstract

This paper evaluates the impact of an agriculture transformation program on poverty, migration, food security and agricultural revenue. We used Inverse Propensity Score Matching (IPSM) techniques, to correct the selection bias arising from the non-randomness of the allocation of farmers to the treatment. The results find that ANIDA farms are better equipped with irrigation technologies, and so, appear more resilient to climatic events such as droughts. They spent $2,905 USD per hectare on inputs and produced 10,526 kg per worker more than traditional farmers. The intention to migrate, the depth and severity of poverty are significantly below those of beneficiaries' households. The ANIDA program is a model that should be promoted in all municipalities of the country, in order to modernize the agricultural sector. The analysis is limited by the fact that the non-compliance rate of the program is high and needs more investigation to better understand the underlying factors.

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List of abbreviations

ANIDA	National Agency for insertion and agriculture development
ATE	Average treatment effect
ATT	Average treatment effect on the treated element
ATU	Average treatment effect on the untreated
IPSM	Inverse Propensity Score Matching
IV	Instrumental variable
LATE	Local Average Treatment Effect
MDGs	Millennium Development Goals
RCT	Random control treatment
SDGs	Stainable Development Goals
GIEs	Economic interest Groups
FGT	Foster-Greer-Thorbecke

Executive summary

This paper evaluates the impact of an agricultural transformation program on poverty, migration, food security and agricultural revenue. It also participates in the literature on the spillover effects of agricultural technologies diffusion in an African environment, by using data on a unique experience of an integrated farm program of National agency of integration and agriculture development (ANIDA).

We used Inverse Propensity Score Matching (IPSM) techniques, which allowed us to correct the selection bias arising from the non-randomness of the allocation of farmers to the treatment and comparison groups, in order to estimate ATE, ATT and ATU estimators. We divided the population into four groups defined by the potential treatment indicators $T_1$and T_0 . The main reason for this strategy is that only a mean treatment effect for the subpopulation of compliers can be given a causal interpretation, and this population parameter is called the Local Average Treatment Effect (LATE). We assume that being assigned to the program has no impact on farmer's outcomes and that in actual fact, these outcomes are only affected when the farmers enter the ANIDA farm. So, we applied the generalized estimator WALD to the beneficiary sub-population (LATE).

The results indicate that ANIDA farms are not only better equipped with irrigation technologies, but they also have better infrastructure and more agricultural assets compared to conventional farms. Given their water storage facilities and irrigation technologies, ANIDA farms appear more resilient to climatic events such as droughts. If we consider the average treatment effect (ATE) ANIDA farmers spent on inputs (seeds, fertilizers and pesticides), it was $3,486.4 USD per hectare more than conventional farms during the three seasons considered. ANIDA farms produced 10, 526 kg per worker more than traditional farms. With the per hectare production outcome, 7,902 kg more was produced by ANIDA farms in comparison with traditional farms. The ANIDA Program has significantly increased the production per full-time worker and the yield per hectare of the population (ATE), by respectively, 10,526 kg, and 7,902 kg per hectare. Using ATE, the program employs on average 25 equivalent full-time farmers per GIE, which is more than a non-ANIDA farm. The effect on the sample population (ATE) is the same while it decreases slightly to 21 for non-beneficiary farms. These outcomes are not adjusted for the non-compliance problem.

With regard to LATE, results were statistically significant for underemployment and expenses on inputs. The program has significantly increased the production of farmers working full time and the mean yield per hectare. Results are positive for production per hectare and full time worker, but statistically significant. The ATE on per capita income is estimated at $109 USD, showing that the program has a significant impact on per capita income within the population. Indeed, the ATE on per capita consumption is estimated at $172 USD and the ATET at $197 USD. The effects seem higher on the sub-population of compliers (LATE), as ANIDA reduced the depth and severity of poverty by 20% and 34%, respectively.

This study also participates in the literature on the spillover effects of agricultural technologies diffusion in an African environment. Two types of spillover effects are detected. First, in ANIDA farms, non-beneficiary producers can observe the crop grown, the agricultural practices, the seeds used, the presence in the village of traders that buy ANIDA farm production, and they can use this information in their farms, or to sell their produce. Second, spillover effects occur when beneficiaries of the program use acquired knowledge in their non-ANIDA farms. The results show that these channels are poorly used by non-beneficiary farmers. Indeed, there are only 8 among 332 non-beneficiary producers who take advice from members of an ANIDA farm; 10 out of 332 apply learned farming practices through an ANIDA farm. The results fail to establish a positive impact of the program on beneficiaries through their own plot. Despite a higher average cost per hectare, ANIDA farms are more profitable than traditional farms. Their net return per hectare reached 20%, while that of non-beneficiaries was only 5%. In addition to their positive impact on the beneficiaries' living conditions, ANIDA farms have greater economic externalities in terms of increased demand for intermediate goods, capital goods and job creation.

Beneficiaries' households are also better off in terms of income and per capita consumption. The incidence of poverty on the beneficiaries is lower than on non-beneficiaries. The depth and severity of poverty are significantly below those of beneficiaries' households. Moreover, the intention to migrate and the search for a new job are less present in the group of beneficiaries.

These results are encouraging for the Senegalese Government that is considering the experience of ANIDA as the model that should be promoted in all rural municipalities of the country, in order to modernize the agricultural sector.

Our analysis has some limitations. They include the fact that the non-compliance rate of the program is high and needs more investigation to better understand the underlying factors. The cost-benefit analysis does not take into account the cost of ANIDA administration. To generalize this program is important to investigate the cost-benefit analysis further.

I. Introduction

1.1 Context of the study

The UN-initiated Millennium Development Goals (MDGs) and the Stainable Development Goals (SDGs) have brought agricultural growth at the forefront of government and donor agendas in developing countries, particularly in Sub-Saharan Africa. Against the backdrop of rapid population growth, boosting small farmers' production is crucial for increasing their revenue, reducing their food insecurity, and leading them out of poverty. Extensive agriculture no longer offers strong growth potential for African agriculture. A sustained growth in agricultural productivity is essential to reaching these objectives, among other important achievements. However, fundamental constraints need to be addressed to rescue smallholder agriculture from the low-productivity trap. Major identified obstacles in Sub-Saharan Africa include low water control by irrigation, low adoption of more productive technologies, lack of access to knowledge, input and output markets, credit constraints, insurance, and coordination defaults. Generally, these constraints interact in a complementary manner (Pan, Smith & Sulaiman, 2015; Anderson & Feder, 2007). The distribution of fertilizers, or improved seed varieties does not necessarily increase crop yields for small producers if they remain under heavy rainfall variations, or if they are not taught the agricultural practices allowing for the optimal use of these inputs. Even if production actually increases, insufficient demand pushes producer prices down, and lowers the income of small farmers. A holistic approach is required to intervene simultaneously on several constraints to increase yields in a sustainable way.

1.2 Research questions and objectives

This paper contributes to the literature on agricultural technologies adoption by examining the impact on detailed measures on poverty, migration, food security and agricultural revenue.

Important aspects of subjective poverty and monetary poverty are covered. Food security is tackled in many dimensions: quantitative availability, qualitative aspects relating to the types and diversity of food, and social consumption patterns, such as meal frequency. Internal and external migration is analyzed. This study also participates in the literature on the spillover effects of agricultural technologies diffusion in an African environment, by using data on a unique experience of integrated farm program. Two types of spillover effects are detected. First, in ANIDA farms, non-beneficiary producers can observe the crop grown, the agricultural practices, the seeds used, the presence in the village of traders that buy ANIDA farm production, and they use this information in their farms, or to sell their produce. Second, spillover effects occur when beneficiaries of the program use acquired knowledge in their non-ANIDA farms. The effects of these two mechanisms of technology diffusion are evaluated.

II. Literature review

However, many interventions for rural poverty alleviation reported in the literature put emphasis on one constraint, rather than recognizing how these constraints are interdependently linked, which slows increases in productivity. One area of differentiation of the impact assessment of studies is the nature of the intervention. It can be made available to farmers, improve seed varieties that enhance crop adaptation to climate change, reinforce crop resistance to insect pests, or increase yields (Ali & Abdulai, 2010; Asfaw, Kassie, Simtowe, & Lipper, 2012; Becerril & Abdulai, 2010; Kassie, Shiferaw & Muricho, 2011; Khonje, Manda, Alene & Kassie, 2015; Awowide, 2016; Mendola, 2007). The intervention may also include participation in the food supermarket chain by small producers of vegetables (Raoantal, 2012), or access to irrigated agriculture by smallholder farmers (Del carpio, Loayza & Datar, 2011; Hussain, Wijerathna, Arif, Murtiningrum, Mawarni, & Suparmi, 2006; Khan & Shah, 2012; Solomon & Ketema, 2015; Salomon & Ketema, 2015), or to mineral fertilizers (Lambrecht, Vanlauwe, Merckx & Maertens, 2014).

Despite its importance, empirical evidence on the impacts of integrated programs is very sparse. A notable exception is Abro and Ali. (2014), who analyzed the effects of a public investment in the rural area of Ethiopia between 1994 and 2009 for the development of irrigated production systems, access and improvement of the quality of the land, and the development of the processing of agricultural products. However, before designing new programs to achieve the Sustainable Development Goal on hunger and nutrition, it would be essential to document whether combined interventions on various development barriers are effective in increasing agricultural productivity. More precisely, how effective are the integrated programs in actually achieving a durable use of new technologies? Can they improve productivity and introduce effective production diversification? Can they significantly improve the living conditions of farmers in terms of increasing revenue and reducing poverty through better nutrition? Can they be designed to be more effective in putting emphasis on the role of rural women, who have limited access to land and agricultural inputs, and are more exposed to extreme poverty? We propose to address these issues by studying the program of the ANIDA, an agricultural development program that promotes the use of drip irrigation systems and a complementary package of improved inputs, intensive extension, and marketing services through farms implemented in many provinces. We take advantage of this opportunity since the program applied the stratified randomization method to select the farm members, and we address the need to control and balance the influence of covariates, such as gender and age. By applying experimental methods, we evaluate the program's impact on productivity, migration, underemployment and several dimensions of smallholder well-being. While ANIDA officials stated that all the beneficiaries were randomly selected from the candidates meeting criteria of eligibility, we cannot be sure that the exercise was perfectly conducted. If the implementation of the randomized control trial (RCT) is not perfect, the average effect of the contribution of the ANIDA Program to the outcomes is not consistently estimated by the difference between the beneficiary (treated) and non-beneficiary (control) groups. Due to problems of sampling, non-randomness and partial compliance, inverse propensity score techniques and instrumental variable methods are applied to obtain consistent estimators of the program effects (Imbens & Wooldridge, 2009; Diagne & Demont, 2007; Imbens, 2004).

There are, however, a few published studies which examine integrated projects that were recently implemented in Sub-Saharan Africa, and that the ANIDA program can be compared to. Two such works were conducted in Mozambique and East and Central African. Cunguara and Darnhofer (2011) used data of the national agricultural survey of 6149 rural households conducted in 2005 to estimate the impact of the adoption of a program of improved agricultural technologies on farmers' incomes. They found that only the use of the tractor increased the farm household income by 5%, but this impact was not significant. Furthermore, the results suggest that the share of non-farm income and the size of the cultivated area have a significant impact on income for households adopting any of the four technologies. Nkonya, Kato, Oduol and Pali (2013) used the double difference method and pooled data to analyze the impacts on household welfare of a new research approach – integrated agricultural research for development (IAR4D) that was being experimented with in SSA. They showed a non-significant difference in the two approaches, while a significant and positive effect was detected when whole country data were pooled.

III. Methodology and data

3.1 ANIDA Program: selection of beneficiaries and the theory of change

The National Agency for the Integration and Agricultural Development (ANIDA) Program, which was proposed a few days after 99 young Senegalese men (and women) were repatriated from the Canary Islands, Spain, was established by law in 2006 with a mission to fight illegal emigration to Europe, and to stabilize the population via agriculture. The program, which became fully operational in February 2008, is being implemented through the creation of agricultural cluster projects in ten districts of the country. As part of the site selection, a Committee to select settlement sites for farms has been set up. Before any development, preliminary studies on agronomy, topography, hydrology, hydrogeology, soil sociology, among others, are carried out on the potential project sites. The results of these studies are used to establish management plans and set the mode of development of farms. As part of the selection of farmers, prospective farmers are asked to apply for farms in the cluster project of their choice. A candidate should meet certain criteria to be eligible. One criterion is that the candidate lives in a village located less than three kilometers away from the ANIDA farm, have a valid national ID card and be aged between 18 and 50. Beneficiaries are randomly selected from the eligible candidates.

Our paper analyzes the causal effect of the implementation of a modern farm combining improved inputs, modern agricultural practices and modern management in an experimental evaluation framework. ANIDA is part of a strategy aimed at transforming Senegalese agriculture away from the traditional rain-fed system into a modern and mechanized system. The pathway for achieving this goal includes the following elements: i) revitalizing old state farms, bringing additional farmlands under cultivation, and providing access to land for those interested in agriculture, ii) providing support and finance for farmers to acquire seeds and other production inputs, iii) providing extension services and maintaining adequate infrastructure in the farm clusters, including roads linking farms to markets, and iv) providing market insurance for production. All these factors are combined to achieve higher productivity and yields compared to farmers in traditional agriculture. These advantages are expected to be translated into greater yields, more food security, less poverty and less migration. Another potential impact worthy of attention is the diversification of ANIDA farms in terms of production. While the first farms were exclusively specialized in horticulture, other ANIDA farms now combine fish farming and horticulture. We can expect that this diversification will increase the working time for farmers, reducing their rate of underemployment and increasing their income. Fish farming and animal husbandry are practiced year round, while horticulture is performed between November and February (first season) and between March and June (second season). While conducting these activities during the horticultural periods and the hot season (from July to October), farmers can engage in livestock and fish farming. Reports indicate that farm productivity and revenue have risen dramatically in ANIDA cluster projects compared to farmers in the traditional agricultural system, and the effects are felt on poverty status, emigration and employment.

3.2 Evaluation design

The Rubin Causal Model (RCM) developed by Roy-Rubin Model (Roy, 1951; Rubin, 1974) has been adopted in this paper to evaluate the impact of the ANIDA Program, building on the literature on the impact assessment of farming technologies (Awotide, Karimov, Diagne & Nakelse, 2013; Kassie, Shiferaw & Muricho, 2011; Abebaw & Haile, 2013). The main components of this model are the farmers, the treatment and the results (income, poverty, consumption, etc.).

The treatment is a binary variable Ti that is set to 1 if the farmer has benefited from the ANIDA program and 0 otherwise. The farmer has two hypothetical potential outcomes, Yi(0) and Yi(1) representing its potential outcome with and without treatment, respectively. Roy-Rubin's model defines three parameters, which help estimate the effect of the treatment (Imbens & Wooldridge, 1992). The first parameter is the average treatment effect (ATE) on the population, which is defined as ATE = E(Y_i(1)) - E(Y_i (0)). The second is the average treatment effect on the treated element (ATT), which is estimated as ATT= E(Y_i(1)|T=1) - E(Y_i (0) |T=1). ATT measures the effect of the treatment on the sub-population of the beneficiaries, while the third parameter, the average treatment effect on the untreated (ATU), provides an estimate of the impact of the treatment on the sub-population of non-beneficiaries. ATU is defined as ATU= E(Y_i(1)|T=0) - E(Y_i (0) |T=0).

The fundamental problem in the estimation of these parameters is to find an appropriate comparison group that is free of selection bias. Usually, two approaches are adopted in the literature to deal with the selection bias. The majority of studies use quasi-experimental methods, including Propensity Score Matching (PSM), which consists of constructing a counterfactual comparison group based on observable characteristics (Mendola, 2007; Beceril, 2010; Wu, 2010; Kassie, 2011; Abebaw, 2013; Ali, 2010, 2015; Solomon, 2015). Although PSM allows for the control of selection bias on observable characteristics, it cannot eliminate the selection on unobservable characteristics (Rosenbaum, 2002). This has led some authors to adopt treatment effect models (Kabunga, 2014), also known as endogenous regime change models (Asfaw, 2012), which have the advantage of controlling the selection bias on observable and on unobservable characteristics. Another approach is the experimental one, which involves constructing both treated and control groups at random. This approach is used when the program adopts a randomized control trial (RCT) method to select the beneficiaries (Awotide, Awoyemi, Diagne & Ojehomon, 2011; Awotide, 2013).

The experimental approach seems to be more appropriate for our study, given that the ANIDA Program had randomly chosen the farmers from the pool of applicants to the program (B=0 and B=1). In the case of a perfectly implemented RCT, the impact of the ANIDA Program is assessed by simply examining the differences in mean outcomes of the treated (B=1) and control (B=0) farmers (Schultz, 2004; Scriven, 2008; Duflo, Glennerster & Kremer, 2008). However, the RCT is unlikely to be perfect in the ANIDA Program. Indeed, it was observed that some selected farmers did not participate in the program and reassigned themselves into the control group. Some of these cases had been replaced by new members who should have been on a waiting list drawn up at the time of selection of beneficiaries. It is not certain whether the waiting lists were used systematically, even many years after, to replace those leaving the ANIDA program. As a result, all these changes are likely to challenge the RCT, and thus, may introduce a problem of non-compliance, or endogeneity into the analysis, which Imbens and Angrist (1994) consider to be one of the problems associated with randomization. Statistic and econometric literature offers a number of methods to correct this sample selection bias.

Based on the impact assessment literature (Imbens & Wooldridge, 2009), the Inverse Propensity Score Matching (IPSM) techniques, which allow the correction of selection bias arising from the non-randomness of the allocation of farmers to the treatment and comparison group, are mobilized to provide a consistent estimator of ATE, ATT and ATU (Lee, 2005; Diagne & Demont, 2007; Awotide, 2013):

$$ATE = \frac{1}{n}\sum_{i=1}^{n}\frac{(T_i - p(X_i))Y_i}{p(X_i)(1-p(X_i))} \quad (1)$$

$$ATT = \frac{1}{n_1}\sum_{i=1}^{n}\frac{(T_i - p(X_i))Y_i}{(1-p(X_i))} \quad (2)$$

$$ATU = \frac{1}{1-n_1}\sum_{i=1}^{n}\frac{(T_i - p(X_i))Y_i}{(1-p(X_i))} \quad (3)$$

Where n is the sample size, $n_1$is the number of treated, $Y_i$is the outcome of individual *i*, X_i and $p(.)$ is the propensity score andX_i represents the pretreatment characteristics obtained prior to the intervention. Also, they are not expected to change over time (Beceril, 2010; Wu, 2010; Kassie, 2011; Abebaw, 2013). These characteristics include age, gender, and educational background, which gives an idea about the wealth of each household and the farmer's main activity. The selection criteria for the program, such as the distance from the village to the farm, and the possession of a valid identity card at the time of the starting of the farm, are also considered in view of the control for the bias induced by the program. The propensity score is calculated based on a logit regression on these pretreatment characteristics. However, the estimates of ATE, ATT and ATU cannot be interpreted as causal effects due to the problem of non-compliance that IPSM cannot fix (Awotide & al., 2011; Awotide & al., 2013). This problem is related to the farmer's decision to effectively participate in the ANIDA Program based on some unobservable, such as anticipated benefits. Hence, we apply instrumental variable (IV) techniques to correct the possible influence of observable or unobservable variables.

Typically, we follow Imbens and Angrist (1994) who have solved the problem of non-compliance in the population, which is a variant of IV. In this framework, the treatment status indicator variable can then be expressed as$T = zT_1 + (1 - z)T_0$, whereT_1 represents the potential treatment status given z=1 and T_0 means potential treatment status given z=0. Following the terminology of Angrist and al. (1996), the population is divided into four groups defined by the potential treatment indicators $T_1$and T_0. We distinguish the compliers as those who adhere to their assigned treatment (individuals who have T_1>T_0 $or T_1$=1 and T_0=0), the always takers represent those who manage to always take the treatment regardless of their assignment (individuals who have T_1=T_0=1), the never takers who are those who never take the treatment regardless of their assignment (individuals who have T_1 =T_0=0), and finally the defiers; that is, those who do the opposite of what their assignment asked them to do (individuals who have T_1<T_0 or T_1=0 and T_0=1). The main point for this strategy is that only the mean treatment effect for the subpopulation of compliers can be given a causal interpretation, and this population parameter is called Local Average Treatment Effect (LATE). LATE is estimated as follows:

$$LATE = \frac{E(Y|z = 1)-E(Y|z = 0)}{E(T|z = 1)-E(T|z = 0)} \quad (4)$$

Where z is an instrument, which is a variable highly correlated with actual participation in the ANIDA Program, but is not correlated with unobservable characteristics affecting outcomes (Khandker, Shahidur R.; Koolwal, Gayatri B.; Samad & Hussain, 2010). In this study, the instrument z is a dummy, which indicates the program assignment of farmers by ANIDA. We assume that being assigned to the program has no impact on farmer's outcomes, and that these outcomes are only affected when the farmers enter the ANIDA farm. LATE can be estimated by Wald estimator as:

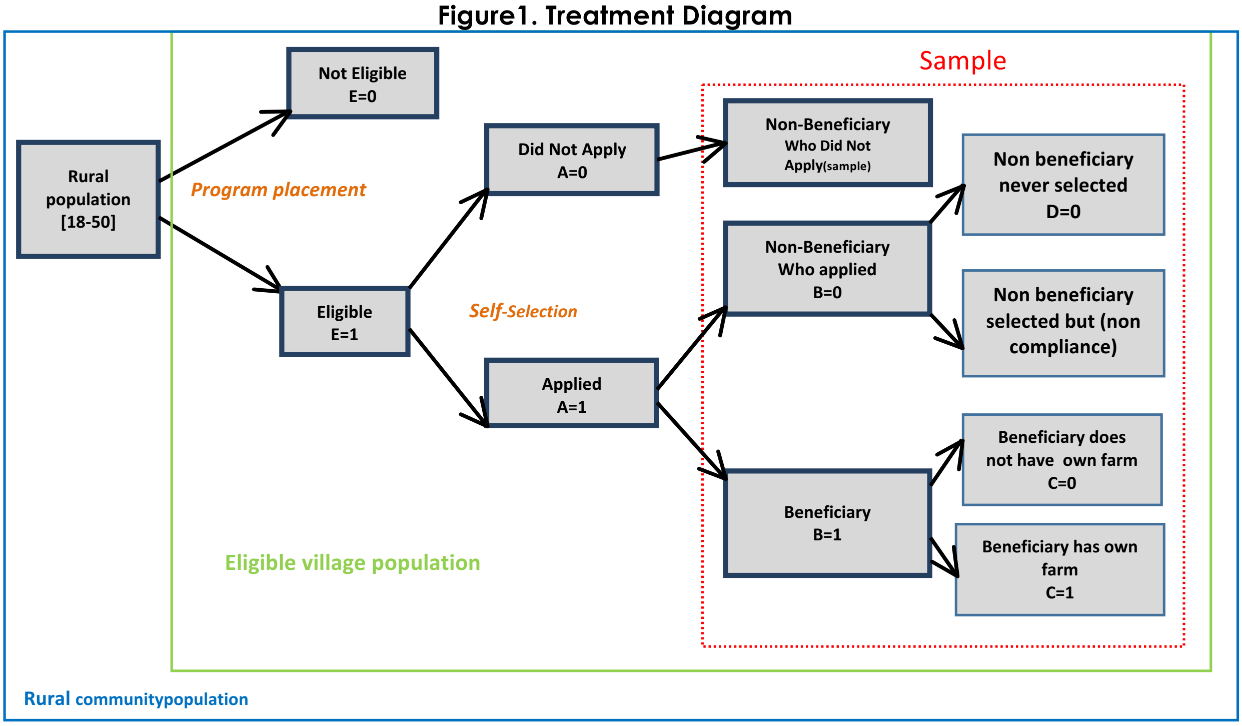
$$LATE_{Wald} = \left(\frac{\sum_{i=}^{n} Y_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=}^{n} Y_i(1-z_i)}{\sum_{i=1}^{n}(1-z_i)}\right) \times \left(\frac{\sum_{i=}^{n} T_i z_i}{\sum_{i=1}^{n} z_i} - \frac{\sum_{i=}^{n} T_i(1-z_i)}{\sum_{i=1}^{n}(1-z_i)}\right)^{-1} \quad (5)$$

3.3. Sampling and data

3.3.1. Sampling strategy

The evaluation of the impact of ANIDA farms relied first on secondary data collected by the program on eligible candidates before the selection of process started. However, existing data was insufficient, since it did not provide information on current outcomes and observable characteristics of both beneficiaries and non-beneficiaries. Primary data were collected both on beneficiaries and not beneficiaries. In combining the rules of village eligibility and the selection of beneficiaries, seven types of farmers were potentially identifiable in the ANIDA Program for primary data collection. Different stages leading to effective treatment were considered in order to identify the likely biases and make sure the data base would allow for the construction of a credible control group (see Figure 1). The first stage is program placement. Given survey data on the various groups, the impact of ANIDA farms was analyzed using different control groups (see Figure 1).

Figure1. Treatment Diagram



The first type (E=0) is the farmer who was neither qualified for an ANIDA farm, nor applied for one. Typically, he lives in the rural commune where the ANIDA farm was being implemented, but in a village located at more than 3 km from the farm. The second type (A=0) includes farmers who were qualified for the ANIDA Program, but did not apply. The eligibility criteria are as follows: being aged between 18 and 50, holding a national ID card, and residing within a 3-km distance from the program farm. The third type of farmer (B=0) was qualified, he applied, but was not selected for an ANIDA farm. An appointed committee draws beneficiaries from the applicants' pool. The draw is random, but stratified so that the final pool of beneficiaries is composed of 40% women and 70% of individuals aged between 18 and 35. The fourth type of farmer (B=1) was one who was qualified and selected for ANIDA. The fifth type of farmer (C=0) was the one who was qualified, selected and only worked in an ANIDA farm. In the terminology of Angrist and Imbens (1996), they are compliers (beneficiaries who adhere to their assigned treatment). The sixth type of farmer (C=1) worked simultaneously in an ANIDA farm and a traditional farm. The seventh type of farmer (D=1) was one who was qualified, was selected, but did not integrate into the ANIDA farm, or left it after less than one month (the never takers). Data were collected on all these groups of farms except for those living in non-eligible villages (E=0).

Given the survey data on the various groups, the impact of ANIDA farms was analyzed using different control groups and different levels of analysis (household, individual, and land). The first comparison was between the groups of beneficiaries (B=1) and non-beneficiaries (D=1) from the pool of applicants in the treatment villages. Differences in the performance of these two categories of farmers reflect the marginal effect of irrigation and other support for ANIDA farms. Both these types of farmers satisfied the observable qualifying conditions (such as age, location or gender) and both applied for the program (unobserved characteristics that may determine the likelihood of applying were common to both farmers). After correcting the selection bias and non-compliance, differences in performances can be explained by the effect of irrigation and other services made available to the farm cluster, and they exclude any effects of qualifying condition(s) or unobserved characteristics.

Another interesting aspect of the impact evaluation of ANIDA farms was to measure the spillover effects of the program on farming techniques and land productivity. Indeed, some ANIDA beneficiaries tended land outside of program farms (C=1). Comparing the productivity of their land to that of corresponding non-beneficiaries (D=1) should provide an estimate of spillover effects.

3.3.2. Data

A sample of 13 was selected from the 54 farms of ANIDA. For each farm, eligible villages were listed and around three of them were randomly selected to have the eligible villages (E=1). For each village, a census was conducted to construct survey frame for non-beneficiaries farmers' households. In each household, parcel workers aged 18 to 50 years were identified. In addition to the head of household, one household member was randomly selected and interviewed. A census of beneficiaries was conducted in each farm. Some information, such as the phone number, age, sex, the ANIDA status of the interviewee was gathered. Consequently, we were able to identify farmers who were qualified, selected, and were still working on the farm (B=1). The census also allowed us to form the group of beneficiaries who only worked in an ANIDA farm (C=0), and the group of beneficiaries who worked in an ANIDA farm and a traditional farm simultaneously (C=1). A survey was conducted for the group of farmers who were qualified, were selected, but did not integrate into the ANIDA farm, or left it after less than one month.

The number of small farmers in the sample totaled 835 (Table 1). Of these, 373 were beneficiaries. This group was divided into two sub-groups: 239 only worked on an ANIDA farm, and 134 tended both an ANIDA farm and a non-ANIDA farm. For non-beneficiaries, 90 were selected to participate in the program, but did not integrate into the ANIDA farm, 82 had applied for the program but were not selected, and 290 were eligible but did not apply to join an ANIDA farm.

Table 1: Distribution of the survey sample

Region	Name of the farm	**Total number of beneficiaries (B=1)**	Beneficiary with a non-ANIDA farm (C=1)	Beneficiaries without a non- ANIDA farm (C=0)	Non-beneficiaries who were selected but did not integrate into an ANIDA farm (D=1)	Non-beneficiaries who applied but were not selected to join the ANIDA Program (D=0)	Non-beneficiaries not having applied for any ANIDA Program (A'=0)	**Total number of non-beneficiaries (A=0+D=0+D=1)**
Dakar	TivaouanePeulh	**30**	5	25	12	8	25	**45**
Thies	DarouNdoye	**20**	3	17	3	16	15	**34**
	Djilakh	**73**	44	29	11	12	49	**72**
	Ndieguene	**16**	4	12	0	1	22	**23**
	Ngomène	**82**	21	61	0	22	16	**38**
	Keur Gallo (Niakhene)	**14**	14	0	8	10	7	**25**
	Aga Babou	**14**	0	14	3	3	12	**18**
Louga	KeurMomar Sarr (NDIBA)	**16**	4	12	24	0	4	**28**
Ziguinchor	Kafesse	**65**	25	40	9	6	36	**51**
Kaolack	Gapakh	**9**	8	1	4	3	42	**49**
	TaibaNiassene	**11**	0	11	9	0	5	**14**
Fatick	Diossong	**12**	2	10	7	0	20	**27**
	MbinYad	**11**	4	7	0	1	37	**38**
Total		**373**	**134**	**239**	**90**	**82**	**290**	**462**

IV. Application and results

4.1 Descriptive analysis

Table 1 shows the profiles of the treatment group (B = 1) and the control group. On the one hand, this consists of producers who had applied but were not selected by ANIDA (B = 0), and on the other, of those who were selected, but had never worked on an ANIDA farm (D = 1). Recipients were different from non-beneficiaries in relation to the observable characteristics corresponding to the program's selection criteria. From a gender perspective, women should represent at least 40% of the beneficiaries. In the sample, their weight was 49% in this group, whereas it was only 20% among non-beneficiaries. The information campaign conducted by the program before the selection of beneficiaries probably encouraged women to be candidates and discouraged many men who thought the project focused on women.

Another criterion that a producer had to meet to be eligible for the program was the possession of a valid identity card. The proportion of producers who met this condition was less than 4% of beneficiaries, compared to non-beneficiaries. This result is surprising because we expected a possession rate of 100% in the treatment group. Therefore, it is highly likely that this criterion was not applied rigorously enough during the selection process. However, the two groups were similar with regards to other eligibility criteria. The producers of both groups had the same average age (42 years). Beneficiaries and non-beneficiaries lived within a 2 km radius of the ANIDA farm and were thus in the enrolment area defined by the program (within 3 km). For characteristics other than those used in the selection process, other trends appear. The level of education was generally lower among members of the ANIDA Program. The literacy rate was 54%, but it was estimated at 77% among non-beneficiary producers. Most of the beneficiaries were farmers (99.7%) while in the group of non-beneficiaries, only 54% practiced agriculture as their main activity. However, households in both groups were about the same size (11 members) and the area of cultivated land in the household was not significantly different in average.

Table 2: Descriptive statistics by treatment status and test of mean differences (continued)

		Control group			Treatment group	Difference between treated and control groups	Significance of the difference (T-test)
Variables	Non-beneficiaries not having applied for any ANIDA Program	Farmers who applied but were not selected)	Farmers who were selected but did not integrate into ANIDA farms	All control groups	Beneficiary farmers		
Demographic characteristics of the farmers		Average	Average	Average	Average		
Age	46,61 14,36	45,13 -12,82	38,31 -10,57	41,49 -12,13	42,78 -10,92	1,29	1,2
Woman(dummy)	0,49 0,50	0,26 -0,44	0,16 0,36	0,2 0,4	0,49 0,5	0,28	6,50***
Distance from the village to the farm	3,03 4,37	1,87 1,29	2,88 1,75	2,39 1,63	1,99 3,4	-0,41	-1,48
Possession of a valid ID card at the time of implantation of the farm (dummy)	0,96 0,20	0,96 0,19	0,93 0,25	0,95 0,22	0,91 0,29	-0,04	-1,66*
Education level							
Agriculture as the main activity	0,86 0,35	0,78 0,42	0,32 0,47	0,54 0,5	0,997 0,05	0,46	17,46***
Literacy (dummy)	0,64 0,48	0,73 0,45	0,81 0,39	0,77 0,42	0,54 0,5	-0,23	-5,31***
None (dummy)	0,58	0,61	0,5	0,55	0,63	0,08	1,67*
Observations	289	82	90	462	373		
Sub sample used	A'=0	D=0	D=1	D=1+D=0+A'=0	B=1		

Table 2: Descriptive statistics by treatment status and test of mean differences (continued)

		Control group			Treatment group	Difference between treated and control groups	Significance of the difference (T-test)
Variables	**Non-beneficiaries not having applied for any ANIDA Program**	**Farmers who applied but were not selected**	**Farmers who were selected but did not integrate into ANIDA farms**	**All control groups)**	**Beneficiary farmers**		
		Average	Average	Average	Average		
Primary (dummy)	0,49 0,31 0,46	0,49 0,33 0,47	0,5 0,28 0,45	0,5 0,31 0,46	0,48 0,27 0,44	-0,04	-0,91
Secondary or over (dummy)	0,06	0,05	0,14	0,09	0,1	0	0,11
Size of household	0,24 10,17 5,78	0,22 12,05 8,14	0,35 11,36 5,83	0,29 11,69 7,02	0,3 11,45 6,17	-0,24	-0,39
Observations	289	82	90	462	373		
Sub sample used	A'=0	D=0	D=1	D=1+D=0+A '=0	B=1		

Standard-deviations in parentheses; *p< 0.05, **p< 0.01, ***p< 0.001
Source: Field Survey, 2016.

4.1.1 Characteristics of the farms

We evaluated the production of three crop seasons between November 2014 and October 2015. The productions and the acreages of the two vegetable seasons were aggregated to calculate horticultural yields. Returns were calculated for each of the main crops: horticulture, cereals, crops, millet, sorghum and maize for grain crops. Table 3 gives the yields by ANIDA farms and non-ANIDA farms. Agriculture was the main activity of individuals in our sample as described above. Given the distribution of activities in both types of operations (Table 3), market gardening and cereals were the main crops grown in both ANIDA farms and non-ANIDA farms. In the first, market gardening was practiced by nearly 90 of the Economic interest group (GIEs). The activities of cereal crops and gardening were also very common with 38% of ANIDA farms growing cereals and 41% practicing arboriculture. With regards to non-ANIDA farms, 32% cultivated horticultural crops, and 43.35% grew grain. This difference in the composition of production has an impact on revenue; income from a ton of garden products is higher than income from a ton of grain.

Table 3: Main activities practiced during the November-February, 2015 and March-June 2015 crop seasons

Activity	ANIDA farm			Non-ANIDA farm		
	Yes	**No**	**Total (B=1)**	**Yes**	**No**	**Total (B=0+A'=0)**
Horticulture	334 89,54%	39 10,46%	373 100,00%	149 32,25%	313 67,75%	462 100,00%
Cereals	141 37,80%	232 62,20%	373 100,00%	269 58,23%	193 41,77%	462 100,00%
Arboriculture	154 41,29%	219 58,71%	373 100,00%	8 1,73%	454 98,27%	462 100,00%
Fish farming	0 0,00%	373 100,00%	373 100,00%	11 2,38%	451 97,62%	462 100,00%
Other activities (cattle breeding, etc.)	180 48,26%	193 51,74%	373 100,00%	99 21,43%	363 78,57%	462 100,00%

Source: Field Survey, 2016.

ANIDA farms are also better equipped with irrigation technologies, but also in terms of infrastructure and agricultural assets, they have more, compared to conventional farms. Given their water storage facilities and irrigation technologies, ANIDA farms appear more resilient to climatic events such as droughts.

Different types of outcomes were examined: incomes from various sources, subjective poverty, food security, and intention to migrate. The definitions of poverty, food security, and migration variables are presented in Table 4. Both indicators of monetary poverty and subjective poverty were utilized. The official rural poverty line was used to calculate the Foster-Greer-Thorbecke (FGT) (1984) indicators.

Table 4: Poverty, Food Insecurity and Migration Result - Definition

Results	Definition
Income poverty	FGT indexes are applied using the official rural poverty line (598 CFA per day)
Food insecurity	Dummy = 1 if the household has struggled to meet its food needs over the last 12 months.
Intention to migrate internally	Dummy = 1 if the individual declares he is willing to migrate within the country or abroad
Under-employment	Dummy = 1 if the individual seeks to increase his revenues
Does your income allow you to live well?	Dummy = 1 if the individual feels his income allows him to live well

Statistic results also show the impact of the ANIDA Program on labor and land productivity, the per hectare expenditures on inputs, the annual household income, the per capita consumption expenditures, food security, migration and under-employment. If the RCT were perfect, the full compliance hypothesis would be verified and the difference in the mean outcomes of the beneficiaries and non-beneficiaries would give the overall impacts of the program. In addition to the differences related to socio-demographic characteristics, ANIDA farms seem to be more productive than non-ANIDA farms. The land productivity of ANIDA farms was 6,059 kg/ha higher than that of non-beneficiaries' farms. Regarding labor productivity, production per full-time worker was estimated at 14,627 kg per full-time worker for the treated group, compared to 5,927 kg per full-time worker for the control group. On average, ANIDA farms spent more on inputs than traditional farms.

Compared to non-ANIDA farms, the crop revenue per hectare for vegetable crops of ANIDA farmers was greater with a gap that reached $1,367.80 USD per hectare. However, crop revenue per hectare for cereal crops of non-ANIDA famers was higher than that of beneficiaries of ANIDA, but the difference was not significantly different to zero. Cereals were not the main crops for ANIDA farms. Finally the crop revenue per hectare for crop portfolio of ANIDA farmers was greater than that of non-ANIDA farmers. This higher productivity translates into an improvement of welfare in the beneficiaries' household. Indeed, the households of producers working in ANIDA farms had a higher income than non-beneficiaries. The total annual income of these beneficiaries was estimated at $1,601.60 USD while it was estimated at 1,088 million FCFA for those involved in an ANIDA farm, an average income gap of $574 USD. The main source of households' income for a beneficiary was earnings from an ANIDA farm (70%). Regarding non-beneficiaries' households, their income mainly came from agricultural activities (62%). Moreover, the average consumption was higher in beneficiaries' households ($4,310 USD) compared to those of producers in the control group ($2,920 USD). Household consumption included food items (cereals, vegetables, fish, meat, etc.), school and health expenses, and exceptional expenses on goods and services (naming ceremonies, weddings, birthdays, funerals, etc.) The consumption of own production was valued at market prices and added to food consumption. The expenses were estimated for the month that preceded the field interview.

Beneficiaries' households were also better off in terms of income and per capita consumption. There was no difference in terms of incidence of poverty on the beneficiaries between the two groups. The poverty rate was evaluated at 85% for both beneficiaries and non-beneficiaries. However, the depth and severity of poverty were significantly below those in beneficiaries' households by 12% and 21%, respectively. Besides, in the group of beneficiaries there was less intention to migrate in order to search for a new job. Indeed, the proportion of individuals willing to migrate was estimated at 5% in the group of beneficiaries, compared to 9% in the control group. Regarding individuals looking for employment, their share was 35% among farmers working in ANIDA farms, against 49% among non-beneficiary producers.

The statistics above suggest that the beneficiaries of the ANIDA Program had a higher standard of living than non-beneficiaries. This was reflected not only on the poverty status of their households, but also in the intention to migrate and underemployment. However, these differences between the two groups cannot be directly attributed to the ANIDA Program, since they differ in certain characteristics (such as gender, education level) that need to be controlled. Thus, the full compliance hypothesis was not verified.

4.2 Econometric analysis

4.2.1 Quality of the randomness selection

Considering age criterion, 70% should have been between 18 and 35 years of age. Indeed, two out of three beneficiaries were not in this interval (Table 5). The high level of this ratio is certainly due to errors in the declarations of age that are common among rural populations. Around three beneficiaries had no identity card at the time of selection, while nine lived more than three kilometers from an ANIDA farm.

Table 5: Proportion of ineligible beneficiaries according to the programme criteria

Beneficiary	Number	%
Does not meet any criteria	0	0,00
Has no identification card	3	0,80
Is not in the age group 18-35 years	233	62,47
Lives less than 3 km from an ANIDA farm	9	2,41
Meets all criteria	128	34,32
Total Beneficiaries	373	100
Sub sample used	**B=1**	

Controlling for gender and being aged between 18 and 35 years, we checked more formally if other characteristics, as education and characteristics of the household, may predict selection into the program. We regressed both the intent to treat and the treated variables on selection criteria and some individual characteristics of farmers (results not produced). As expected, the selection criteria were statistically significant. However, other covariates, such as education or having migrated to the country's interior, turned out to be significant. We concluded that random assignment was not perfectly implemented.

Table 6 shows the results of the logit regression to calculate the propensity score. The sample includes all the candidates whose files were retained. It appears that the program's selection criteria acted significantly on the probability of being a beneficiary of the project. Indeed, women have a higher probability of being beneficiaries than men. In addition, young people were more likely to be selected by the program.

Table 6: Estimation of the probability of being a beneficiary of the ANIDA program (logit regression)

	Coefficient	Standard-errors
Age	-0,03**	0,01
Producer sex (Ref = Male)		
Wife.		
	1,38***	0,35
Producer of educational attainment Producer educational attainment (Ref=No educated)		
Primary	-0,10	0,32
Secondary ortertiary	0,75	0,63
Possession of a valid identity card (Ref=Has not a valid identity card)		
Yes	0,91	1,52
Transfer of migrants received(logarithm)	0,12***	0,04
Area of planted cropland (ha) per household	0,00	0,01
Constant	0,81	1,63
Observations	835	
AIC	298.8	
BIC	328.2	
area under ROC curve	0.7371	
Sensitivity	98.65%	
Specificity	10%	
Sub sample used	B=1+B=0+A'=0	

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.2.2 Inverse propensity score matching and instrumental variable

Table 7 presents the results of the effect of the ANIDA Program on several indicators (labor and land productivity, use of inputs, number of full-time workers, per capita income, poverty, and underemployment) by the Inverse Propensity Score Matching (IPSM) and instrumental variable methods. The first method estimates the average effect of the ANIDA Program on the population (ATE), the beneficiaries (ATET) and non-beneficiaries (ATU).

We first examine the outcomes obtained through estimates, using the IPSM techniques. The outcomes in Table 7 cover the period between November 2014 and February 2016. If we consider the average treatment effect (ATE), ANIDA farmers spend $US3486.4 on inputs (seeds, fertilizers and pesticides) per hectare more than conventional farms during the three seasons considered. This outcome was significant at 10% and had a direct impact on agricultural productivity. By using more inputs, ANIDA farms were expected to have higher production. They produced 10,526 kg per worker more than traditional farms. With the per hectare production outcome, the difference was 7,902 kg also in favor of ANIDA farms. The ANIDA Program significantly increased the production per full-time worker, and the yield per hectare of the population (ATE) by 10,526 kg and 7,902 kg per hectare, respectively. The effect on the sub-population of beneficiaries (ATET) was even more important (10,678 kg and 8,396 kg per ha, respectively). Using ATE, the program employed on average 25 equivalent full-time farmers per GIE, more than a non-ANIDA farm. The effect on the sample population (ATE) was the same, while it decreased slightly to 21 for non-beneficiary farms. These outcomes were not adjusted for the non-compliance problem. To deal with the latter, we applied WALD, the generalized estimator, to the beneficiary sub-population (LATE). With regards to LATE, results were statistically significant for underemployment and expenses on inputs. The program significantly increased the production by farmers working full time and the mean yield per hectare. Results were positive for production per hectare and full time workers, but not statistically significant.

Table 7: Effect of the ANIDA program on the productivity of the farm, the per hectare expenditure on inputs and the number of full-time worker equivalent

Standard-deviations in parentheses

	Production per full time worker (kg)	Production par hectare (kg/ha)	Expenses on inputs ($US/ha)(a)	Number of full time worker equivalents
Inverse Propensity Score Matching				
ATE	10 526***	7 902***	3486.442***	24,98***
	3 715	1 399	209.586	1,26
ATET	10 678**	8 396***	3472.48***	25,75***
	4 423	1 979	415.076	2,13
ATU	9 541	6 334	3514.568***	21,99***
	25 627	5 807	867.848	6,89
Locale Average Treatment effect				
LATE by WALD	35 119	4 994	3165.226***	31,16***
	15 831	3 362	458.586	4,89
LATE generalized	28 007	3 159	3592.694***	33,53***
	14 612	2 987	314.086	3,11
Observations	835	835	835	835
Sub sample used	B=1+B=0+A'=0	B=1+B=0+A'=0	B=1+B=0+A'=0	B=1+B=0+A'=0

*p< 0.05, **p< 0.01, ***p< 0.001

The ATE on per capita income was estimated at US$109, showing that the program had a significant impact on per capita income within the population. Considering the subset of beneficiaries, the effect of the program (ATET) was higher and was estimated at US$111. This increase in per capita income led to a rise in consumption, not only in the general population but also in the group of beneficiaries. Indeed, the ATE on per capita consumption was estimated at $ 172, and the ATET at US$197. The program affected non-beneficiaries in the same way, but the effect was lower and insignificant. For instance, the average effect on the per capita income on untreated farms (ATU) was estimated at US$102 while the effect on per capita consumption was evaluated at US$ 86. The program reduced the incidence of food insecurity by 3%, and 4% of farmers felt that their income allowed them to live well in the population although this result was not significant. The revenue generated in ANIDA farms did not significantly affect the prevalence of poverty, but did significantly reduce the depth and severity of poverty in the entire population (ATE) by 12% and 18%, respectively. The effects seemed to be higher on the sub-population of compliers (LATE), as ANIDA reduced the depth and severity of poverty by 20% and 34%, respectively. These results suggest that even though the program did not have a significant impact on poverty in general, it further affected extreme poverty, bringing the poorest closer to exiting poverty. The IPSM techniques can only control the observable characteristics. To check the robustness of the results provided by the IPSM, an instrumental variable method was used. This helps control the bias related to unobservable characteristics, in addition to those associated with observable traits, and provides a causal effect on compliers called LATE. The results obtained with this method were consistent with those of the IPSM techniques (Table 8). The estimation by IV, using the WALD estimator increased the average program effect on per capita income by US$84 of the beneficiaries (LATE Wald). However, the WALD estimator assumes that the selection program is perfectly random. Where randomization is not verified, the generalized Wald formula proposed by Abadie (2003) is more suitable. The implementation of that estimator provided a medium effect of US$204.6. In addition, the IV showed that the program also increased households' per capita consumption, reduced poverty incidence, food insecurity depth, and severity of poverty and plans to migrate. However, with regards to underemployment, the results seem mixed. The IV provided a positive and significant effect of the program on under-employment, unlike the IPSM method.

Table 8: Impact of ANIDA program on production per hectare, per capita income, per capita consumption, poverty rate, depth of poverty, severity of poverty, food insecurity, intention to migrate and underemployment

	Per capita income ($US)	Per capita consumption ($US)(a)	Poverty prevalence	Depth of poverty	Severity of poverty	Does your income allow you to live well?	Food insecurity	Intention to migrate	Underemployment
Inverse Propensity Score Matching)									
ATE	109,182***	171,624***	0,01	-0,12**	-0,18***	0,04	-0,03	0,02	0,02
	30	60	0,08	0,06	0,05	0,04	0,06	0,02	0,06
ATET	111,544***	197,156**	0,02	-0,11	-0,17**	0,05	-0,02	0,02	0,05
.	41	89	0,11	0,08	0,08	0	0,09	0,03	0,08
ATU	102	87	0	-0,14	-0,21	-0,04	-0,03	0,03	-0,08
	142	178	0,23	0,22	0,24	-0,01	0,22	0,12	0,25
Local Average Treatment Effect									
LATE by WALD	83,828*	79	0,02	-0,20**	-0,34***	-0,04	0	-0,01	0,05
	47	150	0,06	0,07	0,1	-0,01	0,07	0,04	0,08
LATE generalized	204,392***	415,356***	-0,14	-0,42***	-0,56***	-0,01	-0,15	0,05	0,37***
	70	148	0,1	0,1	0,13	0,11	0,1	0,06	0,13
Observations	835								
Sub sample used	B=1+B=0+A'=0								

Robust Standard-errors in parentheses
*p< 0.05, **p< 0.01, ***p< 0.001

These results add to the very scarce empirical literature on the diffusion of agricultural technologies in an African environment. They consolidate those of Cunguara et al. (2011) and Nkonya, et al. (2013), which shows that tractor adoption increases household income by 5% (Cunguara et al.,2011) and the training and access of producers to credit and other services improve their income (Nkonya et al., 2013). These results conclude that the transformation of sub-Saharan African agriculture is possible if the authorities organize the producers, offer them training adapted to their needs, support the acquisition of agricultural equipment and access to credit.

4.2.3 Spillover effects

Table 9 shows various channels through which ANIDA farms can have effects on traditional farms. The results reveal that these channels were poorly used by non-profit farmers who made little use of information generated by ANIDA farms. Indeed, there were only 8 among 332 non-beneficiary producers who took advice from members of an ANIDA farm; 10 out of 332 applied learned farming practices through an ANIDA farm. Furthermore, the influence of ANIDA farms in choosing to grow garden crops seemed low given that only 2% of producers admit to being influenced in their choice by an ANIDA farm. However, a significant proportion (10%) sold their crops to traders they became acquainted with through an ANIDA farm.

Table 9: ANIDA influence on traditional farms

Channel	Yes	No	Total
Take agricultural advice from a member of the ANIDA farm	11 2,41%	451 97,59%	462 100%
Cultural practices applied in traditional farms and learned from ANIDA farms	14 3,01%	448 96,99%	462 100%
If you do currently market gardening, did ANIDA influence you in your choice?	10 2,11%	452 97,89%	462 100%
If you were already involved in gardening before the implantation of ANIDA farms, does it make you focus more on market gardening than on rain-fed crops?	15 3,31%	447 96,69%	462 100%
Are there any cultures that you practice in your farm because you have seen that ANIDA farm also practices these cultures?	17 3,61%	445 96,39%	462 100%
Do you sell your production to merchants that you got to know because they just buy crops from the ANIDA farm?	45 9,64%	417 90,36%	462 100%
Observations			462
Sub sample used			B=0+A'=0

Source: Field Survey, 2016.

Another channel by which the ANIDA program can have a demonstrable effect is through its farmers who may have changed agricultural practices on their own plots. To verify this potential influence, we compared productivity in beneficiary plots with that of non-beneficiary plots, controlling for some observables. Table 10 shows the estimates of the average treatment effect (ATE), the average treatment on the treated (ATET), and on non-treated (ATENT) using the IPSM techniques. Results fail to establish a positive impact of the program on non-beneficiaries through their own plots. **Error! Reference source not found.** shows that the production value per hectare was more important in the ANIDA program plots than in non-beneficiary plots. However, this result was not statistically significant.

Table 10: Demonstration effect of ANIDA program through the own plots of its beneficiaries

	Production value per capita (FCFA)	Volume production per head (kg)	Production valueper Ha (FCFA)	Volume production per Ha (kg)
ATE	62811.2 (0.67)	25.88 (0.08)	15961.3 (0.08)	-496.7 (-0.70)
ATET	59178.7 (0.16)	17.47 (0.01)	-6197.1 (-0.01)	-523.2 (-0.19)
ATENT	64764.0 (0.50)	30.41 (0.07)	27099.7 (0.10)	-483.4 (-0.46)
Observations	596	596	596	596
N1 (C=1)	134	134	134	134
N0(B=0+A'=0)	462	462	462	462

The impact assessment of ANIDA farms shows their positive and significant impact on beneficiaries' income and consumption; however, this does not mean they are profitable. They could be if it were determined that the farm's gross revenue covers the cost of agricultural inputs, covers capital depreciation, guarantees a remuneration of labor at market price, and obtains a significant net return. We verified whether ANIDA farms would satisfy this condition by conducting a cost-benefit analysis. A representative farm was defined for the ANIDA program. A representative farm was also constructed for the non-beneficiary farms located in the same area as an ANIDA farm. Thus, the ANIDA program can be compared to traditional farms. We estimated the gross income by subtracting the cost of non-labor variable inputs (seeds, fertilizers, pesticides, etc.) from the value of the production. The cost of labor and the value of the depreciation of capital were deducted from the gross income to obtain net earnings, and all variables were estimated by hectare. The calculations cover three crop seasons, respectively for the periods: November 2014 to February 2015, March 2015 to June 2015, and July 2015 to October 2015.

4.2.4 Cost-benefit analysis

Despite a higher average cost per hectare, we found ANIDA farms to be more profitable than traditional farms. Their net return per hectare reached 20% while that of non-beneficiaries was only 5%. This performance was due to ANIDA farms' larger per hectare yield than conventional farms. Better quality vegetable products allowed ANIDA farms to charge higher prices when exporting part of their production. In addition, the economic activity of an ANIDA farm was higher than that of traditional farms. For the representative ANIDA farm, values per hectare of intermediate consumption, working time, and the stock of capital were much larger than those used a traditional farm. In addition to their positive impact on the beneficiaries' living conditions, ANIDA farms had greater economic externalities in terms of increased demand for intermediate goods, capital goods and job creation.

Table11. Profitability of ANIDA program and traditional farms, November 2014-October 2015 (FCFA)

Item	ANIDA Farm	Traditional farm (non-ANIDA)
Inputs		
Seeds	948 272	75 647
Fertilizers	656 496	78 832
Pesticides	499155,6	59 889
Urea	-	63 473
Total costs of inputs	2 103 924	277 841
Total area of farms (hectare)	7,3	1,7
Inputs Costs per hectare	**288 209**	**163 436**
Labor cost		
Number of working days in the farm	1 720	262
Labor expenditures	2 580 000	393 000
Labor cost per hectare	**353 425**	**231 176**
Capital depreciation	**502 311**	**127 799**
Expenditures per hectare		
Total cost per hectare	**1 143 944**	**522 411**
Farm Production value	10 054 427	931 840
Production value per hectare	**1 377 319**	**548 141**
Net return per hectare	233 374	25 730
Ratio Net return /Total cost (percent)	**20,4%**	**4,9%**

Source CRES, 2016.

V. Conclusions and policy implications

Transforming traditional peasant agriculture into modern and high-yielding agriculture is a major goal of the current agricultural policy in sub-Saharan Africa. Through the ANIDA Program, the government of Senegal is testing a model that provides an integrated package of agricultural technologies, including irrigation, marketing support and access to credit. This research paper examines to what extent this program has allowed a significant improvement in the welfare of beneficiary producers, compared to those who remain in traditional agriculture. Using an experimental framework, the impact of the ANIDA Program on revenue, consumption and migration was estimated. The descriptive statistics show that the selection criteria were not rigorously applied, women were well targeted, the literacy rate was higher among the beneficiaries, and the average age of the beneficiaries was comparable to that of the recipients. Econometric estimations by IPSM and IV techniques revealed positive impacts of the ANIDA Program. Beneficiaries' households were also better off in terms of income and per capita consumption. Therefore, they seemed to be less affected by poverty than non-beneficiaries. The incidence of poverty on beneficiaries was lower than on non-beneficiaries. The depth and severity of poverty were significantly below those of beneficiaries' households. Moreover, the intention to migrate and searching for a new job were less present in the group of beneficiaries. Indeed, the proportion of individuals who intended to migrate was significantly lower than that of the control group. Regarding individuals who sought new employment, once again, in the group of beneficiaries, this number was significantly lower than in the group of non-beneficiaries. These results are encouraging for the Senegalese Government that is considering the experience of ANIDA as the model that should be promoted in all municipalities of the country, in order to modernize the agricultural sector. However, the non-compliance rate of the program is high and needs further investigation to better understand the underlying factors.

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