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Impact of the adoption of new rice technologies: a solution for food security in Senegal

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Abstract

In Senegal, rice is the most widely consumed cereal. It has a consumption rate of about 78.1kg/head/year. This high rate of consumption gives rice a prominent place in the country's culinary habits. To meet the high demand for rice, it is more than important to bring reforms in Senegalese agriculture, which is strongly dominated by a family form, to an intensive one with the adoption of new rice technologies. The objective of this article is to assess the impact of the adoption of new rice technologies on food security in Senegal. To achieve this objective, data from the Agricultural Policy Support Project (PAPA) for irrigated rice and the Directorate of Agricultural Analysis, Forecasting and Statistics (DAPSA) for mountain rice in 2017 are used. The adoption of rice technologies is broken down into three levels of treatments, namely T1 (fertilizer), T2 (fertilizers and improved seeds), and T3 (fertilizers, improved seeds, and motorized equipment). Using the localized mean response (LARF) function of the instrumental variable (access), the results show that the adoption of T2 treatment has a positive and significant impact of 2.363 kg on the monthly rice consumption of farm households. However, T1 and T3 treatments have a negative impact on household rice consumption of 17.528 kg and 16.74 kg respectively.

Keywords

Agriculture, Regression Analysis, Probit, New rice technologies, Food security, Intervention Analysis, Senegal.

1. Introduction

Agriculture is essential to Africa's future as it provides abundant and continuous food availability to people (Gaymard, 2009). While increasing its productivity is a way to solve the problem of food production (Bakehe, 2018), food supply and food prices are still determined in the long run by agricultural productivity (Ambagna and Niee Foning, 2014). Among these products, rice is a fundamental part of the household diet (Krupnik et al., 2012).

In Senegal, agriculture is characterized by a dominant family form, mainly rain-fed, and is the pivotal sector of the economy. It is practiced in a semi-arid area that is largely subject to the risks of drought, land degradation and the effects of climate change. In 2012, less than 4% of harvested areas were irrigated, despite a high potential for surface water and runoff (Higgins et al., 2014). The agricultural sector accounted for 12.9% of GDP in 2011 (FAO, 2014) and nearly 70% of the population worked in agriculture (Faostat, 2013). It has great potential to improve food and nutrition security and significantly reduce poverty, especially in rural and peri-urban areas.

In the country, cereals are the basis of the diet. The latter is predominated by rice with a consumption rate of about 78.1 kg/head/year for rice, 30.2 kg/head/year for millet, 9.2 kg/head/year for maize and 0.7 kg/head/year for sorghum (Niang et al., 2017). In order to meet this strong demand, particularly for rice, the use of imports makes it possible to meet the needs of households. Rice imports during the decade 2002-2011 averaged 845,000 tons, compared to an average national production (in paddy) of about 320,000 tons (Manzelli, 2015).

Vall et al. (2017) argue that household vulnerability to food insecurity in Senegal is closely related to rice availability and access. The local supply of rice, estimated at 1,011,269 tons (Dapsa, 2019), does not cover consumption needs, which are between 1,700,000 and 1,800,000 tons (Mendez Del Villar and Dia, 2019). Indeed, 18.8% of households are food insecure (Ensan, 2013). Thus, improving the performance of the agricultural sector is becoming one of the main levers in the face of food insecurity (Saliga and Alinsato, 2021). As a result, the increase in productivity is strongly influenced by the adoption of high-yield technologies (Diagne, 2006) or by improved varieties (Sarr et al. 2018). Mendola (2007) and Diagne et al. (2012) argue that the adoption of improved rice technologies contributes to poverty reduction and improved food security.

The objective of this article is to assess the impact of the adoption of new rice technologies on food security in Senegal using the Localized Average Response Function (LARF). The data used come from the 2017 PAPA survey for irrigated rice and the DASPA survey for upland rice. The sample is composed of 1200 households, of which 526 opt for irrigated rice cultivation and 674 for rainfed rice.

The interest of this article is an extension of the work of Mendola (2007) and Diagne et al. (2012), although they differ from them on several levels. Mendola (2007) specifically analyzes improved varieties of Aman rice using the propensity score to assess the impact of technology adoption on poverty, while Diagne et al. (2012) examine the impact of Nerica adoption on rice yield and total household consumption expenditure using the Marginal Treatment Effect (MTE) and the Local Average Treatment Effect (LATE) approach. In this paper, we combine three different levels of processing (fertilizers, improved rice varieties, and motorized equipment) to assess the impact of these technologies on food security. Taking into account the instrumental variable makes it possible to control the effect of observable and unobservable variables to limit selection biases.

The article is organized as follows. First, we present the theoretical framework for the adoption of new technologies. Second, we detail the research methodology. Finally, the results and discussions are presented.

2. Conceptual framework for the adoption of new technologies and productivity

2.1. Improving productivity from inputs

The literature shows that the adoption of new agricultural technologies is an alternative way out of poverty and food insecurity for many developing countries (Bandiera and Rasul, 2006). Research in the field of agriculture and food production technologies, with an emphasis on improved varieties, has undoubtedly been successful in ensuring food security in developed regions. In addition, the systematic use of improved seeds and production equipment has led to improved productivity, such as rice varieties in the Office du Niger region of Mali, improved maize seeds in Ghana and cuttings of improved cassava varieties in Nigeria (FAO, 2001).

According to Conley and Udry (2010), technological transformations play a key role in the development process. Several studies confirm the importance of new technologies in the development process and in increasing agricultural production. Hailu et al. (2014) show that the use of chemical fertilizers and high-yielding seed varieties has a positive impact on farmers' incomes in northern Ethiopia. Alene and Manyong (2006) argue that the transfer of a set of technologies to producers can significantly increase cowpea yields by about 2,149 kg per hectare in northern Nigeria. Duflo et al. (2011) show that fertilizer use has a positive impact on production in western Kenya.

However, Omilola (2009) demonstrates that new agricultural technologies do not necessarily lead to poverty reduction through increased production in developing countries. Indeed, barriers to technology adoption, initial asset endowments, and market access constraints can hinder the ability of smallholders to reap the full benefits of agricultural productivity growth (Schneuder and Gugerty, 2011). In addition, Suri (2011) shows that the adoption of new technologies generally generates additional costs so that low-yield farmers do not adopt these technologies.

2.2. Improving food security through inputs

The Green Revolution is concrete evidence of the impact of the adoption of new agricultural technologies on increasing global food production. This is how agronomic research has made it possible to create new early, productive varieties that are resistant to drought and pests. These new varieties are used in rural areas where production is carried out by managers who have benefited from training and the support of specialized advisors (Issoufou et al., 2017). In many African countries, researchers and policymakers see seeds of improved varieties as an indispensable factor in increasing productivity, reducing poverty and achieving food security (FAO, 2016).

Amare et al. (2012) measured the impact of the adoption of Pigeonpea's improved technologies on consumer spending and poverty in four rural districts of Tanzania. They show that the use of agricultural technologies can reduce poverty and significantly increase consumer spending. In a similar vein, Mulugeta and Hundie (2012) assessed the potential impact of agricultural technology adoption on household consumption in southeastern Ethiopia. They find that the adoption of improved wheat-based technologies has a positive and significant effect on the food consumption of these farming households per adult equivalent per day.

In addition, Adékambi et al. (2009) show that the adoption of Nerica varies significantly increases household spending in Benin. Dontsop Nguezet et al., (2011) also measured the impact of the adoption of Nerica rice varieties on income and poverty among Nigerian rice farming households. Using the LATE on cross-sectional data from 481 farmers, the results revealed a positive and significant impact on the incomes and well-being of farm households. Therefore, the adoption of Nerica increased spending by 49.1% and household income per capita by 46.0% on average.

3. Research materials and methods

3.1 Sampling and Data Collection

In Senegal, the number of households engaged in agriculture is estimated at 648,052 households at the national level. The proportion of agricultural households practising rainfed farming is 29% at the urban level and 85.9% at the rural level and 67.4% at the national level. The proportion of agricultural households practising irrigated farming is estimated at 5.2% at the urban level, 7.9% at the rural level and 7% at the national level (ANSD, RGPH-5, 2023). The crops grown are mainly food crops (91%) and mainly include millet (38%), cowpea (24%), maize (20%), rice (9%) and sorghum (8%). The rice-growing population can therefore be estimated at 5184 households at the national level. This population is mainly located in Casamance (which is a region with a very old rice-growing tradition) and the Senegal River valley (where rice cultivation is practiced intensively).

The data used come from the survey on agricultural policy support projects (PAPA) for irrigated rice and the Directorate of Analysis, Forecasting and Statistics Agricultural (DAPSA) for 2017 upland rice. The sample is composed of 1200 households, of which 526 choose irrigated rice and 674 mountain rice.

To assess the impact of new rice technologies on food security, the Potential Results Framework will be used. We assume that there are three binary variables that represent the status of rice farmers at three levels. For the first level of treatment, $T = 1$ for rice farmers use only fertilizers (npk and urea) and $T = 0$ otherwise. The second level of treatment corresponds to $T = 1$ for those who combined the improved seed and fertilizer and $T = 0$ otherwise. Finally, the third level of treatment, $T = 1$ for those who combined improved seeds, fertilizers and motorized equipment. Thus, Y_{i1} and Y_{i1} are two random variables that represent the level of the outcome indicator (monthly rice consumption) for household i, regardless of whether or not it has adopted the different levels of treatment, respectively. The impact of adoption according to the different levels of treatment is then the difference in household consumption between adopters and non-adopters $\beta = Y_{i1} - Y_{i0}$.

However, the fundamental problem with any impact evaluation is that an individual cannot be both a beneficiary or a non-beneficiary of the same programme (Diagne and Demont, 2007). It is therefore impossible to observe Y_{i1} and Y_{i0} simultaneously for the same focus, this is Rubin's (1974) counterfactual.

$$Y_i = T_i Y_{i1} + (1 - T_i) Y_{i0} = Y_{i0} + T_i (Y_{i1} - Y_{i0}) = Y_{i0} + \alpha T_i \quad (1)$$

Based on the work of Rosenbaum and Rubin (1983), the causal effect can be determined for all producers in our sample. However, the T_i, Y_{i0} and Y_{i1} parameters must be independent of the socio-economic and demographic characteristics of rice farmers (Arouna and Diagne, 2013). Therefore, it is necessary to distinguish between the monthly rice consumption of the household that adopts new rice technologies and that of non-adopters.

3.2. Estimation of ATE

The mean treatment effect (ATE) is then obtained as follows:

$$ATE = E(\alpha) = E(Y_1 - Y_0) = E(Y_1) - E(Y_0) \quad (2)$$

When the non-beneficiary population is well defined, then this impact[1] is not biased. That is, the two groups must be identical, and their only difference is whether or not new rice technologies are adopted.

We can also identify the mean causal effect for the treated group, denoted ATE

$$ATE = E(Y_1 - Y_0 | \mathrm{T} = 1) \quad (3)$$

It represents the average effect of treatment on the treated population, which chose one of three levels of treatment. It is different from the ATE parameter except in the case where the effect of the treatment is constant.

Since the problem of adoption is related to self-selection, the adoption of these technologies can therefore be motivated by the observable and unobservable characteristics of individuals, hence the choice of the instrumental variable to make our estimates.

The use of this instrumental variable approach assumes the existence of at least one Z instrument that explains the state of the treatment, but which is redundant in explaining the results of Y_0 and Y_1 after controlling for the effects of the explanatory variables. The role of the instrumental variable is to introduce an exogenous variation in the treatment variable to allow a causal interpretation (Heckman and Vytlacil, 2005; Abadie, 2001). The instrumental variable is used to estimate the Local Average Treatment Effect ($LATE$), which is the average impact for subpopulations that have adopted one of the three levels of treatment.

The instrument can be distributed randomly or non-randomly. Thus, the non-random nature of our instrument (access to T_1 , T_2 and T_3 technology), allows us to use the $LARF$ (Localized Mean Response Function) estimator of Abadie (2001) to evaluate the impact of new technologies on food security. Our instrumental variable (access) corresponds to the access of

[1] This estimate is naïve because it compares the average level of monthly household consumption between adopters and non-adopters (Wooldrige, 2002).

new technologies. Thus, depending on the level of access to T_1 , T_2 and T_3 technologies, the value of the access variable takes the value 1 ($Z_1 = 1$). This estimator allows you to run five models. The first concerns the observed pattern. The second is the probit model of determinants of the instrument. The third is a compliers population share estimation model and the last is an impact model (LATE parametric estimation of population parameters).

However, the actual intake of a T treatment is independent from one individual to another or from one group of individuals to another. In a study population, the following can be distinguished: the "Always-takers" who are the individuals who will "always" participate whether they are assigned to the treatment or the control group, the "Never-takers" who are individuals who are likely not to take the treatment even if they are assigned to the treatment group, the "Compliers are subjects dealt with if they are assigned to the treaty group and not dealt with if they are in the control group and finally the "Dechallenges" who do the opposite of the "Compliers". The existence of these different groups in a study can lead, in the context of an impact assessment, to a problem of "non-compliance" and make it difficult to estimate the average effect of the treatment in the population. This is because the number of rice farmers randomly assigned to the treatment may be different from the number of rice farmers who actually received the treatment. Thus, the method to determine the impact of treatment would be to estimate the average intention-to-treat effect, etc. to ignore the non-compliance and to compare the results of the number of individuals assigned to treatment and control. This method does not allow us to have a real measure of the effect of the treatment. Untreated rice farmers could also be compared to those who were actually treated, but the results of the estimates may be biased because individuals that do not conform to their allocation and are likely to be a non-random subset of those that have been assigned to treatment.

To neutralize this bias, the second estimator set up by Abadie (2003) is a generalization of the first. This estimator is equal to the average treatment effect in the local subpopulation ($LATE$) for "compliers". In this case, the instrument is not totally independent of the potential outcomes Y_0 and Y_1 but becomes so under the condition that the independent variables x determining the result Y. The latter estimator is most consistent with our work and will be adopted.

The rice farmer uses a given technology and cannot do so without first adopting it (Diagne and Demont, 2007), $Y_0 = 0$ for any rice farmer and the variable of adoption status can be written as a sequence: $\mathrm{T} = \mathrm{Z}T_i$. The subpopulation of potential adopters of technologies by treatment level (T_1= fertilizer adoption (npk and urea)), T_2= adoption of improved seed and fertilizer combination, and T_3= adoption of improved seed, fertilizer and power equipment combination) (compliers) is defined by condition $T_1 = 1$ and effective adopters $T = 1$. We assume that Z is independent of the potential variables Y_1, Y_0 and T_1 conditioned by the explanatory variables x, for any function $g\ (Y, T; x)$. The estimator of the average impact on the subpopulation of adopters of potential new rice technologies ($LATE$) is then described in the following equation (Abadie, 2003). The $LARF$ function is used for the estimation of the $LATE$ because in this work, the instrument is not random. Thus, to evaluate the $LATE$, it is necessary to identify the " compliant2 " or obedient. To do this, we will use Abadie's (2003) weighted approach to

[2] "Compliant" or obedient defined as those who respect their missions, i.e., in our case, those who are treated if they have access to a given level of treatment and untreated, otherwise ($T_1 > T_0$, i.e. $T_0 = 0$ and $T_1 = 1$).

identify the representativeness and characteristics of these conform with a weight k defined as follows:

$$\mathrm{E}(\mathrm{g}(\mathrm{Y},\mathrm{T},\mathrm{x})|T_1 = 1) = \frac{1}{P(T_1=1)} E(k.g(Y,T,x)) \quad (4)$$

$$\text{Where } k = 1 + \frac{z}{P(Z = 1|\mathrm{x})}(1 - T) \quad (5)$$

It represents the weight that takes the value of 1 for the adopters of potential new rice technologies depending on the level of treatment and negative values if not. The conditional probability $P(Z) = 1|\mathrm{x}$ is found in the formula of the weight k will be estimated using the Probit model (Arouna and Diagne, 2013).

Where $E(k.g(Y,T,x))$ is the mean of $g(Y,T,x)$ for the population and $P(T_1 > T_0)$ is the proportion of compliant in the total population?

The function k is a weighting that identifies "conforming" or obedient, but does not produce appropriate weights when the treatment differs from $Z(k < 0\ if\ T \neq$ Z. Thus, the equation can be specified as follows:

$$E(Y_1 - Y_0|X, T_1 > T_0) = E(Y|X, T_1 > T_0 = \alpha_0 + \alpha_1 T + \beta X + \Upsilon TX \quad (6)$$

With $T = 1$ if the producer adopts agricultural technologies that are divided into three levels of processing. T_1 for those who adopted fertilizer only and T_0 otherwise, T_2 for those who simultaneously adopted fertilizers and improved rice varieties or T_0 otherwise, or T_3 for those who adopted fertilizers, improved rice varieties, and motorized equipment at the same time and $T = 0$ otherwise. α_0, α_1, β and Υ parameters to be estimated and $LATE = \alpha_1 + \Upsilon X$.

4. Results and discussions

The non-random nature of our instrument (access) allows us to use the LARF estimator to assess the impact of new technologies on food security. This estimator allows you to run five models: the observed model, the instrument probit model, the parametric model (LARF regression of the result), the population share estimation model, and the impact model (LATE parametric estimation of population parameters).

4.1. Estimation of instrument determinants

In this model, the total number of parameters is equal to the number of independent variables and the constant. It is used to predict the probability of adoption and also to estimate the population of "compliers".

Table 1: Device Determinants

Variables	Number of obs = 755 Prob>chi2=0.000 User ID R2=0.2502	Number of obs = 754 Prob>chi2=0.000 User ID R2=0.1897	Number of obs = 511 Prob>chi2=0.000 User ID R2=0.3738
	Acces_engrais	Accès_sem&fertilizer	Accès_engrais_sem_amél_équip_moto

Contract	0,848 *	0,548	-0,832
Credit	1,503 ***	-0,068	-0,232
No. of Parcel	-0,167 ***	0,017	0,031
M_OP	1,321 ***	1,338 ***	0,687
Insurance	1,462 ***	-0,200	1,694 ***
Cons	-0,269 ***	0,123	-2,886 ***

Note: significance level 1%; 5% and 10% respectively for ***; **and*.

Table 13 presents the results of the device determinants by the three levels of treatment. We note that the number of observations is respectively 755; 754 and 511 for T1 salary levels; T2 and T3. These three models are globally significant at the 1% threshold with Pseudo R2s of 0.250 2; 0.189 7 and 0.373 8 respectively for T1; T2 and T3.

The analysis of the estimate of the adoption of T1 treatment shows that the variables contract, credit, nbre_parcelle, m_OP, insurance are the main determinants of access to T1 treatment (access to NPK and urea fertilizers). The adoption of the T2 treatment shows that variable m_OP is the only determinant of fertilizer access and improved seeds (instrument of the second estimate). The third estimate shows that there is only one determinant of access to fertilizers, improved seeds and motorized equipment (instrument of the third estimate), which is the insurance variable. We note that the fact that a rice farmer has an agricultural contract facilitates his access to fertilizers. This variable explains the instrument at the 10% threshold. This result means that rice farmers who have agricultural contracts have more access to fertilizers.

The role of the agricultural contract is to allow farmers to have advantages, either by facilitating access to credit, new technologies and markets. Thus, this result can be explained by the facilities that the contract offers rice farmers in access to fertilizers. The credit variable also has a positive and significant effect on access to NPK and urea fertilizers at the 1% threshold. This result means that when Senegalese rice farmers are beneficiaries of agricultural credit, it facilitates their access to fertilizers. Indeed, holding cash allows farmers to access input markets.

In Kenya, Duflo et al,. (2011) argue that farmers often postpone the decision to purchase fertilizers to the future, which may reduce their decision to adopt fertilizers under liquidity constraints. In this case, the farmer faces the problem of financial access. Our results are consistent with those of Alene and Manyong (2006) who show that farmers' access to credit increases the use of certain inputs. Variable Nbre_parcelle has a significant negative effect on fertilizer access at the 1% threshold. We find that when the more plots a rice farmer owns, the more difficult it is for him to access fertilizers. This result can be explained by the fact that the more different plots the rice farmer has to farm, the more expenses he faces. These high charges can be a problem of financial access to fertilizers.

Variable M_OP has a positive and significant impact on access to fertilizers (instrument of the first estimate) at the 1% threshold and on access to fertilizers and improved seeds (instrument of the second estimate) also at the 1% threshold. This result implies that rice farmers who are members of a farmers' organization have easier access to fertilizers than non-members of farmers' organizations. Similarly, when a rice farmer is a member of a PO, it facilitates simultaneous access to fertilizers and improved seeds. Farmers' organizations are groups that advocate the interests of producers, they participate in social dynamics. Indeed, the state's disengagement from the agricultural sector means that farmers' groups have developed their own initiatives aimed at facilitating access to and use of agricultural technologies (Basse, 2015). The insurance variable explains in a positive and significant way the access to fertilizers at the 1% threshold and the simultaneous access to fertilizer and improved seeds at the 1% threshold. Analysis of this variable shows that when rice farmers are beneficiaries of agricultural insurance, this increases their likelihood of accessing fertilizers and fertilizers and improved seeds simultaneously. Since the purpose of insurance is to cover the risks incurred by the farmer, he can afford to make investments.

4.2. Impact of the adoption of new technologies on food security

Table 2 presents the results of estimating the impact of the adoption of T1 (access to fertilizers), T2 (access to fertilizers and improved seeds), and T3 (access to fertilizers, improved seeds, and motorized equipment) treatments on the total rice consumption for one month in farm households. Analysis of the table shows that out of 747 observations, 348 belong to the conventional group, of which 194 belong to the T1 treatment.

Table 2: Impact of the adoption of new technologies on household rice consumption

Consumption Total Rice in the Household	Fertilizer	sem_amél Fertilizer	Engrais_sem_amél &équip_moto
	N = 747 N1=348 Nz1=194	N = 754 N1= 356 Nz1=119	N = 511 N1 = 112 Nz1 = 8
LARF			
LATE	-17,528 ***	2,363 ***	-16,74 ***
Observed			
Diffmo	-6,268 ***	-2,354	7,84 *
Mo_N1	62,237 ***	65,961 ***	76,54
Mo_N0	68,505 ***	68,315 ***	68,69

Note : significance level 1%; 5% and 10% respectively for ***; ** and *.

The LARF estimator shows that the adoption of T1 treatment has a significant negative impact on household rice consumption of 17.528 kg. This result is contrary to that found by Gine et al., (2015). They found that fertilizer subsidies have a positive but not significant impact on household dietary diversity in Tansania. Indeed, the use of fertilizer has a significant impact on rice production. It can lead to increased returns but also increased risks if not managed properly. Proper fertilization can strengthen the resistance of rice plants to diseases and environmental stresses. Nevertheless, excessive use of nitrogen fertilizers can lead to "lodging", i.e. rice stalks grow too high and fall off, thus reducing yield. In addition, excessive fertilizer can contaminate soil and water with nitrates and other chemical compounds, which is harmful to the environment. This excessive use of nitrogen and phosphorus fertilizers can, in the long term, lead to deficiencies of sulphur or other microelements in the soil, which is detrimental to plant health. Thus, the negative impact of the T1 treatment on monthly household consumption can be justified by a misuse of fertilizer leading to negative results.

The second estimate shows that out of 754 observations, 356 fall under the treaty group, including 119 from the T2 treatment. The results show that the adoption of T2 treatment has a positive and significant impact on food safety of 2.363 kg per month at the 1% threshold. These findings support work that argues that the adoption of seeds from improved varieties of rice, wheat, and cowpea can contribute to increased production (Awotide et al., 2012; Arouna and Diagne, 2013; Tesfaye et al., 2016). Indeed, the use of fertilizers and improved seeds contributes to an overall increase in the productivity of more sustainable rice farming, by reducing the need for pesticides and optimizing the use of natural resources. However, in Senegal, a household consumes an average of 57.7kg of rice per month. Thus, the increase in fertilizer use and improved seeds, which is 2,363kgs, remains low. Hence the importance of stepping up efforts to train rice farmers in the use of new technologies for better productivity while improving household consumption of rice.

The third estimate shows that out of 511 observations, 112 are treated, including 8 T3 treatments. The results show that the adoption of the T3 treatment has a negative impact of 16.74 kg on the monthly rice consumption in farming households. Indeed, barriers to technology adoption, asset endowments, and market access constraints can hinder the ability of poorer farmers to share in the gains of agricultural productivity growth (Schneider and Gugerty, 2011). This result can also be explained by the fact that the rice farmers who use this third level of treatment (T3) are in agribusiness. Their production is not intended for self-consumption but for marketing. These rice farmers are located mainly in the Senegal River Valley and in the Anambé Basin. However, it would be more than important to better develop large areas to allow Senegalese rice cultivation to be more productive in order to meet the country's demand for rice.

5. Conclusion

The 2008 food crisis has shown that there is a greater need than ever to find solutions to increase the productivity of cereals, especially rice. Thus, improving production systems through the adoption of high-efficiency technologies can be an adequate solution to the problems of food insecurity. There is ample evidence that the adoption of improved technologies can increase agricultural productivity, overcome poverty and improve food security.

Using data from the 2017 AHS and DASPA surveys, the instrumental variables method was used to assess the impact of the adoption of new technologies on food security. Using the LARF estimator, the results show that the adoption of T1 (fertilizer) and T3 (fertilizer, improved seeds, and motorized equipment) treatments decreases the monthly consumption of farm households by 17.528 kg and 16.74 kg, respectively. On the other hand, the adoption of the T2 treatment (fertilizers and improved seeds) has a positive and significant impact of 2.363 kg on the monthly rice consumption of farming households in Senegal.

In terms of policy implications, our work has shown how important it is to invest in new agricultural technologies to improve food security. Therefore, the establishment of effective distribution channels for these rice technologies is essential to ensure food security, especially in rural areas. Our results reveal that the adoption of fertilizers and improved seeds is the only option that has a positive and significant impact on food security. Therefore, effective awareness mechanisms will encourage rice farmers to adopt optimal technologies.

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