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Table of Contents

List of Tables

List of Figures

List of abbreviations and acronyms

AEZ: Agroecological Zones

AIC: Akaike Information criterion

ATE: Average Treatment Effect

ATT: Average Treatment Effect on the Treated

ATU: Average Treatment Effect on the Untreated

BIC: Bayesian Information Criterion

BVP: Bivariate Probit Model

BVP-E: Extended Bivariate Probit Model

CFA: Communauté Financière Africaine

FAO: The Food and Agriculture Organization (FAO) is a specialized agency of the United Nations

FIML: Full Information Maximum Likelihood

FOC: First Order Conditions

GDP: Gross Domestic Product

GLS: Generalized Least Squared

GPS: Global Positioning System

IFPRI: International Food Policy Research Institute

IPAR: Initiative Prospective Agricole et Rurale

ISRA: Institut Sénégalais de Recherches Agricoles

MTE : Meta Technical Efficiency

OLS: Ordinary Least Squares

PAPA : Project d'Appui aux Politiques Agricoles

PNAR : Programme National d'Autosuffisance en Riz

PSM : Propensity Score Matching

RGPHAE : Recensement General de la Population et de l'Habitat, de l'Agriculture et de l'Elevage

SFA: Stochastic Frontier Analysis

TE : Technical Efficiency

TGR: Technological Gap Ratio

TH: Transitional Heterogeneity effect

USAID: Unites States Agency for International Development.

Chapter 1

1. Introduction

1.1. Introduction

The adoption of new and profitable technologies (certified seed, inorganic fertilizer, irrigation, mechanization, etc.) is crucial to increase agricultural productivity, generate more incomes, and reduce poverty. However, the level of adoption of agricultural technologies is still low in African countries. For example, the average fertilizer used per hectare stood at 9 kg over 2002-2003 in the Sub-Saharan Africa region compared to 100 kg in South Asia, 135 kg in Southeast Asia and 73 kg in Latin America (Crawford, Jayne, & Kelly, 2006). According to Gebeyehu (2016) who cited Dethier & Effenberger (2011), the fertilizer use intensity in 2012 was 23.7 kg per hectare in Ethiopia, 44.3 kg/ha in Kenya, 39.9 in Malawi, 181.7 in Brazil, and 163.67 in India.

As a critical consequence of this low adoption in Sub-Saharan African countries, agricultural productivity is very low. For example, cereals yield in Africa was on average 1.45 tons/ha over the period 2000-2017, while during the same period it was 3.61 tons/ha for Asian countries and 6.05 tons/ha for Northern American countries (FAOSTAT, 2019). Regarding rice which is one of the imported and consumed commodities in Africa, the corresponding land productivity is also very low compared to other regions of the world. In fact, the average rice yield was estimated at 2.37 tons/ha for African countries compared to 4.36 tons/ha among Asian countries and 7.87 tons/ha among Northern American countries over 2000-2017. Among West African countries, the average rice yield over 2000-2017 stood at 1.51 tons/ha in Guinea, 1.68 tons/ha in Nigeria, 2.17 tons/ha in Cote d’Ivoire, 2.92 tons/ha in Benin and 3.24 tons/ha in Senegal. Therefore, there is a real need to assess the agricultural sector in African countries in order to identify context-specific reasons for the underuse of improved inputs.

In the technology adoption literature, several studies list factors that influence the adoption of new or advanced technologies. Feder, Just, & Zilberman (1985) identified several factors such as farm size, land tenure, labor availability, risks and uncertainty, credit constraints, and household characteristics. Sunding & Zilberman (2001) also modeled technology adoption as dependent on farmer’s characteristics such as education, age, or risk preferences. Other factors identified in the literature include market intervention, social network, specialization, farmer organization, extension services, transaction costs (Batz, Peters, & Janssen, 1999; El-Osta & Morehart, 2000; Garforth, Angell, Archer, & Green, 2003; Millar, 2011; Miller & Tolley, 1989). A recent review of the literature on agricultural technology adoption was done by Ugochukwu & Phillips (2018).

The importance of assessing the determinants of technology adoption resides in the identification of agricultural policy options to reverse the current trend of low technology adoption. Evidence that investment in agricultural inputs is profitable, even in the presence of production risks, could finally trigger the Green Revolution in Africa. However, to produce high quality and relevant policy recommendations, two central inputs are required. The first ingredient is the data used for the research. As usually said ‘garbage in, garbage out’. Without good data quality, any nice or sophisticated research methodology would result in bad or at least misleading findings and policy recommendations. This work took advantage of a huge project of data collection conducted in Senegal between 2017 and 2018. This data collection process received technical support from the International Food Policy Research Institute and Michigan State University. This project aimed to provide key information on local agriculture. To the best of our knowledge, we are the first to use this rich dataset to analyze technology adoption in Senegal.

The second major input to inform policymaking, in addition to good data, is the identification of the right methodology to apply for generating relevant policy recommendations. A good methodology is as important as a good dataset. In methodological terms, we have decided to apply methods that are at the frontier of applied economic research to address each of our research problems. The most relevant microeconometrics approaches have been selected and applied in this research work.

The entry point of this dissertation is the exploration of the decision to adopt improved technologies such as certified seed and chemical fertilizers in crop production. When a farmer makes an adoption choice in the presence of two or more agricultural technologies, should the econometrician analyze these choices separately or together? If these technologies are complements or substitutes, the choice of one technology is not independent of the others. Thus, the modeler would benefit from considering a simultaneous analysis of the different choices. Although many studies have focused on the analysis of the determinants of the adoption of agricultural technologies, very few have taken into account the issue of dependency between technologies available on the market. However, since Feder (1982) and Feder et al. (1985), it is obvious that agricultural technology choices analysis should be carried out in a multidimensional context. Thus, the chapter 2 of this dissertation, following some recent studies (Abay et al., 2018; Ogada, Mwabu, & Muchai, 2014; Teklewold, Kassie, & Shiferaw, 2013), considers a joint adoption of certified seeds and inorganic fertilizers in Senegal. A bivariate probit model is adopted to analyze the joint adoption of certified seeds and inorganic fertilizers. The standard assumption in this model is that the joint distribution is a bivariate normal distribution with a constant correlation. In this chapter, we challenge this assumption of constant correlation parameter. To the best of our knowledge, no study before this one went in that direction in the literature of agricultural technology adoption. However, in the statistics literature, it is well known that the conditional correlation between two random variables given a set of covariates is not constant but depends on the covariates (Filippou, Marra, & Radice, 2017; Marra & Radice, 2011, 2013; Vatter, 2016). Therefore, this chapter contributes to the literature by first testing the presence of a heterogeneous correlation between the two decisions under consideration, and second, when a heterogeneous correlation is confirmed to the identification of the drivers of that heterogeneous correlation. The main advantage of this flexible bivariate probit model lies in the fact that it allows better targeting of the policy implications of joint modeling.

As a consequence of the arguments developed in chapter 2, we consider in chapter 3 the impact of joint technology adoptions on rice farmers' technical efficiency and production per hectare. Recent studies (Kassie, Teklewold, Marenya, Jaleta, & Erenstein, 2015; Manda, Alene, Gardebroek, Kassie, & Tembo, 2016) went in that direction by assessing the impact of multiple technology adoptions on various outcomes. Using similar logic, chapter 3 uses a two-step approach to estimate the level of productivity and technical efficiency of rice for each technology adoption group, and then to identify the treatment effects of technology choices on the technical efficiency and rice productivity measured as the potential production per hectare. Three technology choices were considered: irrigation, rice certified seeds, and inorganic fertilizers. These technologies are critical for rice production in Senegal dominated by the irrigated system. Since the choice of improved inputs influences the mix of production factors, farmers in the various groups may operate under different production frontiers. Under these conditions, estimating a common production function will bias the estimated productivity levels. Hence the adoption here of the stochastic meta frontier approach (Battese, Rao, & O'donnell, 2004; Huang, Huang, & Liu, 2014; O'Donnell et al., 2008). A stochastic meta frontier framework is an extension of the standard stochastic frontier analysis to the case of heterogeneous frontiers of production in a selected industry. This framework has the advantage to disentangle the overall (meta) technical efficiency into group-specific technical efficiency (managerial efficiency) and the technology gap ratio which measures the gap between group-specific frontiers and the metafrontier. Even though the metafrontier approach takes into account the heterogeneity of the frontiers, it does not account for selection bias in the choice of technologies. This chapter combines the metafrontier framework with an impact assessment approach appropriate in the context of a multinomial treatment variable. We specifically use the multinomial treatment effects model proposed by Deb & Trivedi (2006a, b) that accounts for selection bias due to both observed and unobserved.

The remaining chapters complement the first two in the sense that they focus on the motives of market participation, especially the drivers of the decisions to buy inputs or sell part of produced outputs. In chapter 4, we investigate the decision of farm households to invest in agricultural inputs, especially on those we named ‘risky inputs’ that include seeds and inorganic fertilizers. We qualified these inputs as risky because farmers need to make these decisions before the realization of rainfall, while the return of such investment is highly correlated with rainfall volume and distribution over the rainy season. Following the theoretical model by Karlan, Osei, Osei-Akoto, & Udry (2014) extended by Magruder (2018), this chapter develops a model of investment in risky inputs. The model mainly focuses on credit constraints, production risks, and imperfect information. In the empirical estimation, a Heckman model is used to identify the main drivers of the investment decision and the level of investment. The main advantage of the Heckman model is that the investment decision as well as the level of investment are simultaneously analyzed. Moreover, in order to test the return on investment in risky inputs, an endogenous switching regression model is used to identify the causal effect of this investment decision on agricultural profit and household food security. This framework accounts for selection bias and allows one to estimate the common treatment effects statistics (average treatment effects, average treatment effect on the Treated, etc.), but also the heterogeneity effect which is the difference of performances between the two groups under each level of treatment. The outcome variables considered are per hectare profit and the food availability per capita.

In chapter 5, the analysis in chapter 4 is extended to analyze the joint input-output market participation in Senegal. From the production theory, firms produce to sell and maximize their profit. To accomplish that, they make input choices. Therefore, the decision to adopt technologies or invest in inputs are directly linked to productivity, and thus correlated with the decision to market produce. Hence, the joint modeling of these decisions should be a standard choice in empirical works. From the farm household perspective, these decisions may have a big impact on their likelihood. For example, a staple producer can buy improved inputs to produce enough for his consumption. When the production is large enough, this farmer may decide to sell the surplus. Thus, in a context where improved inputs are profitable, farmers should purchase inputs to maximize production in order to satisfy self-consumption and generate income for the purchase of other goods and services. In the literature, only Teklewold (2016) had simultaneously analyzed the decisions to adopt technologies and to sell output in a multivariate probit framework. Our framework goes beyond that adopted by these authors at least for two reasons. First, all the market participation regimes are considered and analyzed in a multinomial framework. Second, the impact of market participation regimes on the agricultural gross income per hectare is analyzed. Thus, in this chapter, we develop a theoretical farm household model of input-output market participation. Empirically, we use a multinomial endogenous treatment effects model, which accounts for the selection bias on observed and unobserved factors, to assess the welfare impact of market participation regimes.

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Chapter 2

2. Modeling Interrelated Inputs Adoption in Rainfed Agriculture in Senegal

Authors

Anatole Goundan, Moussa Sall, Christian Henning

2.1. Introduction

Adoption of new and profitable technologies is crucial for smallholder farmers to increase their productivity (yield), and then their production, which in turn will allow them to move from subsistence farming towards market-oriented production. However, the level of adoption of agricultural technologies is still low in African countries. For example, the average amount of fertilizer used per hectare stood at 9 kg over 2002-2003 in Sub-Saharan Africa compared to 100 kg in South Asia, 135 kg in Southeast Asia and 73 kg in Latin America (Crawford, Jayne, & Kelly, 2006). According to Dethier & Effenberger (2011) (cited in Gebeyehu, 2016), the fertilizer use intensity in 2012 was 23.7 kg per hectare (kg/ha) in Ethiopia, 44.3 kg/ha in Kenya, 39.9 kg/ha in Malawi, 181.7 kg/ha in Brazil, and 163.67 kg/ha in India. The low adoption rate in Sub-Saharan Africa may be explained by apparent financial constraints. As a response, policy reforms have been launched by almost all African countries to disseminate new agricultural technologies and make them accessible to farmers. In Senegal, fertilizer subsidies mainly focus on fertilizer price paid by farmers, still set at levels well below international prices. Over 2006-2010, according to the agricultural ministry, the Senegalese government spent more than $20 million on fertilizer subsidies per year. The Senegalese government also provides certified seeds to farmers at subsidized prices, but the seed value chain is not totally controlled by parastatal institutions as is the case for chemical fertilizer.

At farm household level, various technology options are available (certified seeds, inorganic fertilizers, agricultural mechanization, etc.). These different agricultural technologies can act as complements or substitutes. For example, various studies have shown that the production per unit of land area increases significantly if farmers adopt both certified seeds and chemical fertilizers (Abay et al., 2018; Ogada, Mwabu, & Muchai, 2014; Teklewold, Kassie, & Shiferaw, 2013). Therefore, for agronomic or economic reasons, technology choices by farmers may be interrelated and the choice of multiple technologies will be more relevant to maximize production or revenue. Consequently, agricultural technology adoption usually takes place in a multivariate choice setting. In addition, various surveys conducted in different contexts have shown that farmers do not usually adopt a single technology. Studies that consider the adoption of only one technology (i.e. fertilizer use or adoption of improved seeds) may be biased since they do not consider the potential dependency between the decisions to use different elements of a technology package (Dorfman, 1996; Feder, 1982; Feder, Just, & Zilberman, 1985). Abay et al. (2018) argue that studies based on univariate technology adoption models show a partial view of technology adoption status at hand and are subject to endogeneity and simultaneity problems.

In Senegal, the literature on agricultural technology adoption, especially agricultural inputs, remains very limited. Regarding the adoption of seeds or fertilizers, only two papers are found, namely Thuo et al. (2011, 2014). Both studies use data collected between 1998-2006 in the peanut basin of Senegal. In the first one, Thuo et al. (2011) analyzed the adoption of chemical fertilizer among groundnut and millet farmers. They found that education, larger family size and farm size encourage the use of chemical fertilizers. Their study also revealed a decrease in fertilizer application intensity over the period under consideration. On the other hand, Thuo et al. (2014) were interested in the joint adoption of a groundnut variety (La Fleur 11) and chemical fertilizer. They found that the two decisions were independent. Groundnut variety adoption was positively associated with ownership of draft power but negatively related to farmers' level of experience. Conversely, greater farm size and number of plots increased the probability of fertilizer use, while this probability was negatively affected by access to off-farm income and ownership of draft power.

This paper contributes to the literature on agricultural technology adoption in several ways. First, our analysis focuses on two common technologies (certified seeds and inorganic fertilizers) in the context of rainfed agriculture in Senegal. Studies on agricultural technology adoption in Senegal is very limited in scope and coverage (Thuo et al., 2011; 2014). Second, we consider a flexible framework that simultaneously models the decision to adopt improved seeds and fertilizers. The dependence between the two decisions (correlation) is modeled as a function of different covariates. For example, from one agroecological area to another, farmers may have different motives to make joint adoption decisions or not. Knowledge of input complementarity may influence the set of technologies to adopt. Risks related to crop production or climate change affect both individual technology adoption and joint adoption. Third, to the best of our knowledge, this is the first time that a country representative agricultural survey is used to analyze agricultural technology adoption in Senegal.

The rest of the paper is organized as follows: Section 2 presents background information on agricultural input policies in Senegal. The theoretical framework and the empirical model are discussed in sections 3 and 4. Section 5 presents the study area, the data used for analysis, and a short description of selected variables. Section 6 displays and discusses the results. Section 7 provides concluding remarks and policy implications.

2.2. Input subsidies in Senegal

Input subsidy policies pursued by most governments in developing countries are generally aimed at improving productivity in the agricultural sector through easier access to and better use of improved seeds and fertilizers by producers. Overall, the agricultural sector in Senegal has always been supported by the different governments since independence through input subsidies, especially for fertilizers and seeds. Among the various public policies in favor of agriculture, Senegal has recently chosen to focus on subsidies (Seck, 2017). Fertilizer is the main target of subsidy programs. Fertilizer subsidies represent 30% of total agricultural subsidies and aim to improve the availability and use of fertilizer through a reduced purchase price (Seck, 2017). The government plays a key role in the access and distribution of fertilizers. It sets the minimum levels of manufacturing and imports of fertilizers as well as their market prices.

Fertilizer subsidy usually focuses on the producer price which is set below the price on the international fertilizer market. Thus, the government plays a role in regulating the domestic market of supply and demand through legislation, taxation, credit system, and establishment of basic infrastructure (port infrastructure, roads, and rural tracks, etc.). The level of subsidy remains relatively high since the country aims to increase the uptake of improved inputs in order to improve its productivity. However, the process of distribution of inputs established is far from being efficient due to several unclear procedures to select private operators (IPAR, 2015). In addition, significant delays in reimbursement to private businesses by the government can affect the efficiency of subsidies.

On the other hand, the level of private investment in this area remains very low due to an inadequate institutional environment that often results in opacity surrounding the allocation of quotas between suppliers, as well as the absence of reliable control over the actual quality and quantity of fertilizer sold to farmers (Seck, 2017). Indeed, the current architecture for input subsidies in Senegal suffers from multiple failures that would limit their effects on productivity. In addition, the lack of relevant information and data makes it almost impossible to assess the effectiveness of fertilizer subsidies, which would legitimize the continuation of such policy or suggest changes. It is therefore of interest to conduct a study on the input sector to provide new guidance for a better operationalization of the subsidies which remain a necessity for the agricultural development of Senegal.

2.3. Conceptual framework

In this paper, we model the farm household's choice of improved inputs (certified seed and fertilizer) in the risky environment following a framework similar to that by Koundouri, Nauges, & Tzouvelekas (2006). This framework assumes that technology choice by farmers is influenced by the distribution of risky agricultural output. The output distribution in this model is represented by its first and higher-order central moments (Antle, 1983, 1987; Antle & Goodger, 1984). The approach adopted could be seen as an extension of that by Koundouri et al. (2006) in various aspects. First, we consider a multi-output framework, while these authors modeled the production risk for a single output. Our setting is preferred since farm households in developing countries are generally involved in several crop farming. Therefore, we assume that farmers decide to adopt technologies to maximize their overall farming returns. In addition, crop diversification is a risk management strategy for farmers (Di Falco & Chavas, 2009). Moreover, Antle (1987) and Kim & Chavas (2003) argue that strong assumptions are required to estimate any behavioral equation-based single farming activity. Second, we extended the single technology adoption to multiple technology adoption (two in this case). A similar approach was also adopted by Ogada et al. (2014) who studied the adoption of maize improved variety and inorganic fertilizer in Kenya. Third, we follow the risk-value model that is more general than the prospect theory or expected utility-based models. The latter are special cases of the risk-value model (Antle, 2010). This model assumes that the behavior of decision-makers is not the same in presence of negative or positive outcomes.

Let consider a farm household that chooses variable inputs to produce n crops in a risky environment (weather shocks, pests, price uncertainty, etc.). The stochastic output is defined as

$$q = f(x, z, e) \qquad (2.1)$$

where q is output per unit of land, x represents variable inputs, z is a vector of farm or household-specific variables such as agroecological zones, access to extension services, e is weather variables (rainfall and temperature), and $f(.)$ is well-behaved (i.e., continuous and twice differentiable) production function. For simplicity purposes, we consider x, z, and e as scalars. We assume that q follows a distribution $\phi(q|x, z, e)$.

The gross income from all farming activities when w is the unit cost of variable inputs is defined as

$$\pi = q - wx \qquad (2.2)$$

Let define the expected net returns as $\mu_1 - wx > 0$, where $\mu_1$is the first moment of q.

The objective function in the risk-value model depends on the expected outcome, and on negative and positive deviations from this expected outcome.

$$\max_x V[\mu_1(x), \eta_2(x), \varphi_2(x), \eta_3(x), \varphi_3(x)] \qquad (2.3)$$

Where $\eta_j(x)$ are the *j*th central moments for negative deviations, $\varphi_j(x)$ is the *j*th central moments for positive deviations, and $j \geq 2$.

The first-order condition of equation (2.3) in the elasticity form is as follow

$$\mu_1^* - \frac{wx}{\mu_1} = s_2\left(V_{2\eta}\eta_2^* - V_{2\varphi}\varphi_2^*\right) + s_3\left(V_{3\eta}\eta_3^* - V_{3\varphi}\varphi_3^*\right) \qquad (2.4)$$

where $s_j = \mu_j/(\mu_1(\mu_1 - wx)^{j-1})$, $\eta_j^* = \partial \ln \eta_j / \partial \ln x$, $\varphi_j^* = \partial \ln \varphi_j / \partial \ln x$, $\mu_1^* = \frac{\partial \ln \mu_1}{\partial \ln x}$, $V_{j\eta} = -(\mu_1 - wx)V_{\eta_j}/V_{\mu_1}$, and $V_{j\varphi} = -(\mu_1 - wx)V_{\varphi_j}/V_{\mu_1}$. In the model (4), $V_{j\eta}$ and $V_{j\varphi}$ represent the risk attitude to negative and positive deviations from the expectation and are interpreted as disappointment and elation in the risk value model. Input will have a symmetrical impact of the *j*th central moment of the outcome if $\eta_j^* = \varphi_j^*$. In the empirical investigation, we compared results using partial moments (η_j , φ_j) with that from the full moments (μ_j).

From equation (2.4), input use is a function of its cost (w), expected profit (μ_1), partial moments of profit (η_j and φ_j), and farm and household characteristics. Therefore, the adoption of productivity-enhancing technology such as inorganic fertilizers or improved seeds will depend on expected technology returns, *risk premium* (R), and any information-related costs required to efficiently use the technology (Koundouri et al., 2006).

For a selected crop *k*, a farm household will adopt a technology *t* (*t=1* for adoption and *t=0* for non-adoption) if and only if the gap between expected utility associated to certainty equivalent of the use of technology and the non-adoption is greater than any additional premium related to the technology (*VI*).

$$E[U(\mu_1 - wx - R)]_{k,t=1} - E[U(\mu_1 - wx - R)]_{k,t=0} > VI_{t=1} \qquad (2.5)$$

2.4. Empirical model

From equation (2.5), the adoption of an improved input for a selected crop depends on the expected total gross income per unit of land, its higher-order partial moments, farm and household characteristics, and any sources of information that are useful about technologies. Following Koundouri et al. (2006), we estimate the first three moments of the total gross income from crop production. As stated by Antle (1983, 1987, 2010), the specification of the mean gross income distribution is critical in this framework. Therefore, following Antle (1987) and Ogada et al. (2014), we adopt a quadratic functional form for the first moment of the gross income. The variables considered in this quadratic function are farm size in hectares, fertilizer use in kilograms, total rainfall, and average temperature over the rainy season. These weather-related variables are obtained using farm household coordinates and the dataset from the Climate Hazards Center of the University of California, Santa Barbara (https://www.chc.ucsb.edu/data). We include also three agroecological zones in the model (Senegal River Valley, Groundnut Basin, and Casamance), a soil quality index, and three dummies for household level overall technology choice: (i) adoption of certified seeds for at least one crop, but with no use of fertilizer, (ii) adoption of fertilizer only for at least one crop, (ii) adoption of certified seeds and fertilizers.

$$\pi_i = g(x_i) + \mathbf{z}_i{}'\gamma + u_i \qquad (2.6)$$

where π_i is the gross income per hectare for ith farm household from all crops produced, $g(x_i)$ denotes the quadratic specification in inputs $\boldsymbol{x}$, $\mathbf{z}$ are additional variables included in the moments (dummy for technology adoption and agroecological zones). As suggested in the literature, a Feasible Generalized Least Squared (FGLS) was used to estimate equation (6). The empirical variance is estimated as follow

$$\log\left[(\pi_i - \widehat{u_i})^2\right] = g'(x_i) + \mathbf{z}_i{}'\gamma + u'_i \qquad (2.6')$$

where $\widehat{u_i}$ are the residuals from an OLS estimation of equation (2.6), $g'(x_i)$ is a linear function of inputs. The log transformation is preferred to ensure the positivity of the predicted variance. The predicted variance is used as a weight in the GLS estimation to consistently estimate the mean gross income per hectare (μ_1) and the residuals (u_i^{GLS}) useful for higher-order moments. The higher-order moments are estimated following

$$\mu_i^j = g'(x_i) + \mathbf{z}_i{}'\gamma_j + u_i^j \qquad (2.7)$$

$$\eta_i^j = g'(x_i) + \mathbf{z}_i{}'\gamma_{j,n} + u_{i,n}^j \quad \text{if } u_i^{GLS} < 0 \qquad (2.8)$$

$$\varphi_i^j = g'(x_i) + \mathbf{z}_i'\gamma_{j,p} + u_{i,p}^j \qquad \text{if } u_i^{GLS} > 0 \qquad (9)$$

Equation (2.7) represents the full higher-order moments' specification, equations (2.8) and (2.9) are for partial moments. Equation (2.8) and (2.9) are combined in a kind of threshold regression for their joint estimation. The dependent variable in equation (2.7) is the residuals u_i^{GLS} raised to the power *j* (2, 3), while the dependent variables in (2.8) and (2.9) are the absolute residuals u_i^{GLS} raised to the power j. For the variance specification (2nd moment) of (2.7) and for all partial moments, a log transformation is preferred to preserve the positivity of predicted moments. Equations (2.7) to (2.9) were estimated using OLS corrected for heteroscedasticity following MacKinnon & White (1985). The predicted mean and higher-order partial (full) moments are used in the adoption model as explanatory variables.

From equation (5), the adoption of an improved input can be modeled using a probit model. Since certified seeds and fertilizers are generally proposed to farmers as complementary technologies, their adoption may not be independent. In addition, the return to certified seeds will be higher if farmers use inorganic fertilizers as a complementary technology. Therefore, simultaneous modeling is more appropriate (Abay et al., 2018; Feder et al., 1985; Ogada et al., 2014; Teklewold et al., 2013; Yu et al., 2012). Hence, the two technology decisions may be modeled in a bivariate probit setting. Following Greene (2012), the model can be written as:

$$y_1^* = \mathbf{x}_1'\beta_1 + \varepsilon_1, \quad CS = 1 \; if \; y_1^* > 0 \text{ and 0 otherwise;}$$

$$y_2^* = \mathbf{x}_2'\beta_2 + \varepsilon_2, \quad CF = 1 \; if \; y_2^* > 0 \text{ and 0 otherwise.}$$

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} | \, \mathrm{x}_1, \mathrm{x}_2 \Big) \sim N \left[\begin{matrix} 0 \\ 0' \end{matrix} \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right] \qquad (2.10)$$

where y_k^* is the latent variable associated with the adoption of technology k (1,2), *CS* and *CF* are the binary choice variables for certified seeds (CS) and chemical fertilizers (CF), $\mathbf{x}_1$ et $\mathbf{x}_2$ are the explanatory variables associated with the two decisions, and ρ is the correlation (dependence) between the two decisions.

The model (10) is the standard bivariate probit model. This model assumes a constant correlation between the two decisions. The assumption is quite strong, as the correlation between the two decisions may be heterogeneous across farmers. From a statistical point of view, the correlation between the two dependent distributions should not be constant. As stated by Vatter (2016), the conditional correlation between two random variables Y1 and Y2 given X is not constant, but depends on the "value of the conditioning variable explicitly". See Vatter

(2016) for short proof. Therefore, there is a need to account for variable or heterogeneous correlation while modeling joint adoption. To the best of our knowledge, this is the first-time heterogeneous correlation is accounted for in the technology adoption literature. For simplicity, we assume that the correlation is a linear function of factors such as access to extension services, farmer organization membership, access to credit, agroecological zones, production risk, and other information-related factors.

$$\rho = \frac{\exp(\mathbf{x'}_3\beta_3) - 1}{\exp(\mathbf{x'}_3\beta_3) + 1} \qquad (2.11)$$

where β_3 are the parameters of interest. A positive and significant β_3 means the selected covariate increases the dependency between the two inputs under consideration, while a negative sign can be interpreted as decreasing the likelihood of adopting the two inputs. Readers interested in non/semi-parametrical specification of the correlation equation (2.11) are referred to Ieva, Marra, Paganoni, & Radice (2014); Marra & Radice (2017); Giampiero Marra & Radice (2011, 2013); McGovern, Bärnighausen, Marra, & Radice (2015).

We argue here that information and production risk are critical in technology adoption, especially for the correlation between interrelated technologies. For a two-dimensional technology adoption model, a standard maximum likelihood can be used. For higher-dimensional model, advanced methods are required (Filippou, Marra, & Radice, 2017; Vatter, 2016; Vatter & Nagler, 2018).

2.5. Data

Data used in this study were collected under the PAPA[1] project, which is an initiative of the Government of Senegal funded by USAID-Senegal as part of the "Feed The Future" initiative implemented for a 3-year period (2015 - 2018) by the Ministry of Agriculture and Rural Facilities with a technical support provided by the International Food Policy Research Institute (IFPRI).

A two-stage sampling method was used with the primary units being the census districts (CDs) as defined by the 2013 General Census of Population, Housing, Agriculture and Livestock (RGPHAE[2]) and the secondary units being agricultural households. In order to have a better

[1] The 'Project d'Appui aux Politiques Agricoles' (PAPA) is an ambitious country-wide project. The website of the project is http://www.papa.gouv.sn/, where more information about the project are available.

[2] Recensement Général de la Population, de l'Habitat, de l'Agriculture et de l'Élevage

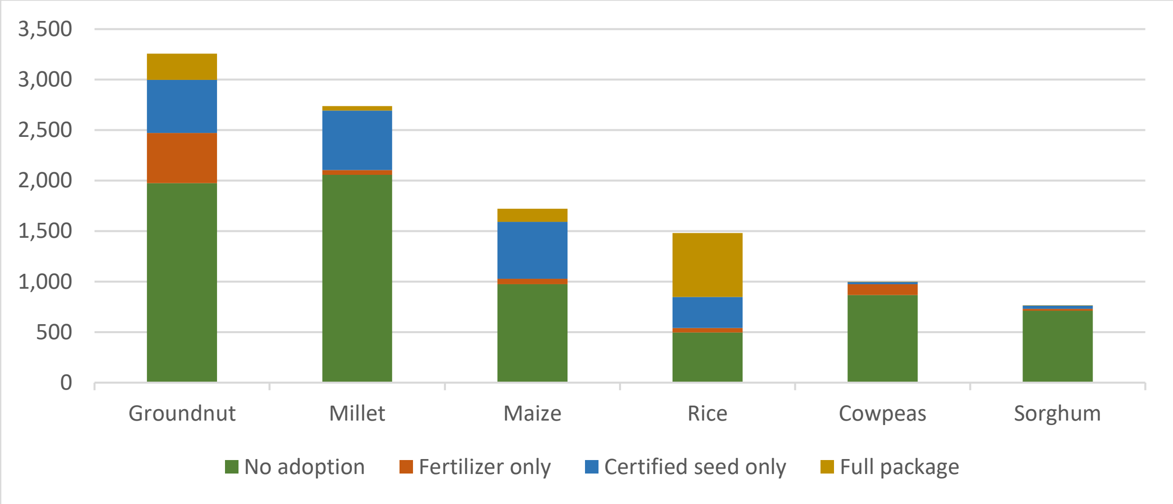
picture of rice production in the country, we combine the rain-fed led agriculture survey (4,533 farm households) and the irrigated rice oriented survey (730 farm households) distributed across all the 42 agricultural departments of the country (except the urban departments of Dakar, Pikine, and Guediawaye). Data collection took place between April and May 2017. After data cleaning, the final sample size for this analysis is 5207 farm households. We remove all households that have a very small land size (less than 0.1 hectares, a total of 33 households).

2.5.1. Certified seeds and fertilizer adoption in Senegal

This section discusses the joint adoption of certified seeds and chemical fertilizers at crop level. Figure 2- 1 shows the number of households involved in the production of each crop and the associated technology adoption pattern. Among farming activities, the top 5 crops include groundnut (63% of households), millet (53%), maize (33%), rice (28%), and cowpeas (19%).

In terms of the use of certified seeds or inorganic fertilizer, Figure 2- 1 shows that except for rice production, most households do not use any of the two selected inputs to produce crops. For rice production, only 33 percent of farmers do not use any improved inputs compared to 93 percent in sorghum production, 86 percent for cowpeas, 75 percent for millet and 61 percent for groundnut. It is obvious that technology adoption pattern is specific to cropping systems. For millet and maize, technology adopters put priorities on the adoption of certified seeds, while for rice production a simultaneous adoption of certified seeds and inorganic fertilizers is the most common choice. For the groundnut system, the major cash crop in Senegal, the technology choice is more heterogeneous; respectively 41 percent, 39 percent, and 20 percent of adopters have used chemical fertilizers, certified seeds, and the two technologies, respectively. For all farm households in the sample, about 33 percent had adopted certified seeds for at least one crop, while 45 percent of them had used inorganic fertilizers.

Figure 2- 1 Multiple technology adoption across crops in Senegal



Source: PAPA data (2017).

One key statistic of technology adoption is the intensity of chemical fertilizer use. Table 2- 1 displays for each crop the mean fertilizer uses per hectare along with the three quartiles and the standard deviation. Results reveal that rice producers have the highest rate of fertilizer application in the sample (192 kg/ha) followed by maize producers (63 kg/ha), and 20 kg/ha for groundnut and millet producers. At household level, the average fertilizer intensity is estimated at 69 kg/ha[3]. This high level of fertilizer use intensity is mainly driven by fertilizer use in the irrigated rice system which is clearly oversampled. When only rainfed agriculture is considered, the fertilizer application rate is much lower. In fact, the average inorganic fertilizer used per hectare is around 27.8 kg in the rainfed system compared to 271.3 kg in the irrigated system.

Table 2- 1 Distribution of fertilizer use per crop

	Observation	Quartile 1	Mean	Median	Quartile 3	Standard deviation
Groundnut	3258	0	20.02	0	0	49.72
Millet	2739	0	20.06	0	0	55.28
Maize	1721	0	62.62	0	100	111.56
Rice	1482	0	191.66	131.05	366.67	198.42
Cowpeas	1001	0	2.48	0	0	22.90
Sorghum	764	0	4.19	0	0	27.35
Total	**5207**	**0**	**69.04**	**0**	**64.52**	**134.23**

Source: PAPA data (2017).

[3] This result is based on the sample of households in the survey. With the sampling weight, the estimated country's fertilizer use intensity is about 62 kg/ha.

From Figure 2- 1, we know that not all technologies are of equal importance across crops. Table 2- 2 displays the distribution of crop production per hectare across technology adoption groups. For millet, the two common technology choices are "no technology adoption" (75%) and "only fertilizer use" (21.4%). In terms of millet yield, the mean millet output per hectare is greater when fertilizer is adopted (530 kg/ha) compared to the situation where no improved inputs are used (424 kg/ha). For sorghum, almost all producers do not use any technologies (93%). For maize production, the most productive technology in the sample is fertilizer. In the rice system, the most productive technology is the joint use of certified seeds and inorganic fertilizers. As with maize, fertilizer adoption seems to be the best choice for groundnut farmers.

Table 2- 2 Crop yield across technology adoption groups in Senegal

	No technology adoption	Only CS adoption	Only CF adoption	Both technology adoption	Full sample
Millet	423.58 (393.19)	312.27 (301.22)	529.99 (406.05)	489.48 (422.27)	445.46 (397.65)
Sorghum	522.93 (576.08)	464.27 (458.1)	499.78 (323.59)	1777.22 (1191.35)	525.41 (572.74)
Maize	559.84 (718.48)	458.16 (497.91)	788.04 (826.18)	771.65 (692.63)	647.57 (756.57)
Rice	1152.94 (1647.23)	595.42 (508.79)	2010.28 (2105.68)	3347.88 (2463.43)	2254.31 (2332.57)
Cowpeas	212.05 (305.26)	260.83 (307.33)	316.38 (600.43)	128.7 (19.71)	219.57 (315.42)
Groundnut	583.85 (753.37)	570.56 (835.19)	728.2 (663.5)	586.84 (545.55)	605.33 (739.97)

Source: PAPA data (2017).

2.5.2. Variables used in the adoption model

For the empirical part of this paper, we applied the theoretical model to study the joint technology adoption for groundnut production (the main cash crop in Senegal) and rice production (the main staple in the country). The adoption models include several explanatory variables based on economic theory and empirical literature on technology adoption. The most common factors used in the literature of technology adoption include farm and households' characteristics, and risk-related or transaction costs factors (Abay et al., 2018; D'souza, Cyphers, & Phipps, 1993; Feder et al., 1985; Gebremedhin & Swinton, 2003; Isham, 2002; Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Kassie, Shiferaw, & Muricho, 2011; Lee, 2005; Marenya & Barrett, 2007; Neill & Lee, 2001; Teklewold et al., 2013). For the estimation of the farm household-specific production risk parameters, we also include variables such as rainfall, temperature, and soil quality index. The description and summary statistics (mean and standard deviation) of the variables used in the econometric models are given in **Table 2- 3.**

Table 2- 3: Definitions and summary statistics of variables used in the analysis

			Rice producers		Groundnut producers	
	Variable	Description	***Mean***	***Std dev.***	***Mean***	***Std dev.***
Technology adoption	tech_none	No technology	0.33	0.47	0.61	0.49
	tech_CS	Certified seed only	0.03	0.17	0.15	0.36
	tech_CF	Fertilizer only	0.20	0.40	0.16	0.37
	tech_both	CS and CF adoption	0.44	0.50	0.08	0.27
Outcome	profit_ha	Total gross crop income (1000 FCFA/ha)	216.71	265.12	108.65	148.95
Production inputs	x1_land	Land use (ha)	2.68	5.65	5.52	4.77
	x2_fert	Fertilizer use (ha)	436.79	1944.65	179.91	482.66
	x3_rainfall	Total rainfall (mm)	781.63	407.03	652.70	245.15
	x4_temp	Temperature (degree C)	35.47	2.26	35.19	1.07
	SQI	Soil quality index	0.25	0.06	0.28	0.06
	profit_dum	Share of negative profit	0.07	0.26	0.05	0.21
Household variables	Gender	Gender (1=Female)	0.10	0.30	0.05	0.23
	Age	Age (years)	52.75	12.42	53.15	13.49
	education	Education (1=Yes)	0.45	0.50	0.38	0.48
	Hhsize	Household size	9.46	5.08	10.58	5.63
	wealth_index	Wealth index	3.10	1.74	3.06	1.77
	livestock_act	Livestock income dummy	0.31	0.46	0.34	0.48
	non_farm_act	Off-farm income dummy	0.34	0.47	0.26	0.44
	farmsize	Land holding (ha)	3.45	6.87	6.92	8.99
	organization	Farmer organization	0.27	0.44	0.10	0.29
	extension	Extension services	0.30	0.46	0.09	0.29
	extension_need	Extension services (need)	0.86	0.35	0.75	0.44
	insurance_need	Agricultural insurance (need)	0.45	0.50	0.40	0.49
	credit_received	Credit access	0.09	0.28	0.04	0.19
Infrastructures and locations	distance2market	Distance to market (km)	15.05	12.27	12.31	10.29
	distance2road	Distance to road (km)	16.19	16.85	8.27	9.49
	zone_vfs	Distance to the regional city	68.11	48.54	45.28	31.09
	zone_vfs	AEZ: Basin	0.26	0.44	0.02	0.14
	zone_bassin	AEZ: Casamance	0.01	0.12	0.58	0.49
Sample size			1462	1462	3257	3257

Source: PAPA, 2017.

It shows that 33 percent of rice producers do not use any fertilizers or improved seeds, whereas for groundnut production, only 39 percent of producers use at least one of these inputs. Rice households manage lower total land area (2.7 ha) on average compared to groundnut households (5.5 ha). Table 2- 3 also shows that on average, a household's head in the sample is about 53 years old and is generally a man. At least 27 percent of rice households have a member that belongs to a farmer organization, while only 10 percent of groundnut households have a member in a farmer organization. In terms of access to extension services and credit, results also show a greater proportion among rice producers than groundnut producers. In general, rice producers have a better access to services than groundnut producers. Regarding the overall household wealth indicator[4], households in the two samples have very close scores (on average 3 over 6). Concerning access to infrastructures, groundnut households seem to be closer than rice households, on average.

2.6. Results and discussion

This section presents results based on our econometric specification. As presented in section 2.4, the study proceeds in two steps. The first step estimates the moments of crop profit (gross crop income) per hectare that are used to characterize production risk. That production risk is an input for the second step which focuses on the drivers of bivariate technology adoption in Senegal. This second step is the main interest of this study. Therefore, we directly present the results for that step. The results of the first step are displayed as supplementary materials at the end of the chapter (see Table A2- 1 and Table A2- 2). However, it is worth noting that results from the first step show that the hypothesis of symmetric input effects of profit distribution is strongly rejected among rice producers and groundnut producers in Senegal. Moreover, positive deviations from the profit mean are weakly related to inputs use. For partial moments, results also reveal a strong correlation between the 2nd and 3rd partial moments. A simple regression between these two variables displays an adjusted R-squared of 0.82 for the groundnut sample and 0.93 for the rice sample. To avoid multicollinearity, we do not include the third partial moment in the adoption equations. Multicollinearity between variance and skewness was also found in a similar context by Ogada et al. (2014).

Before the estimation of the bivariate probit model, it is critical to address the potential endogeneity of three variables included in the model: farmer organization, extension services, and off-farm income. We follow the control function approach explained in Wooldridge (2015). The first step consists of a probit model to compute the generalized residuals. This residual is used as an additional covariate in the bivariate probit. As instruments, we use distance to road, distance to the regional city, and the household's need for extension services

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[4] The wealth index is computed as a count of a selected dummy variables related to household's assets. The formula used is: $WI = \sum_{i=1}^{6} D_i$, where D is a dummy variable, i stands for various dimensions considered. The dimensions included are : use of running water for cooking and drinking, access to electricity or solar power for light, quality of the roof (1 if the material used for the roof is either cement, tile, slate or metal sheet, 0 otherwise), quality of the wall (1 if the wall is made of cement, 0 otherwise), quality of the floor (1 if the floor is tiled, cement, or carpet, 0 else) and number of rooms available for household's members (1 if the ratio of household size to the number of rooms is less than or equal to 2, zero otherwise).

and for agricultural insurance. Results from these probit models are presented in the appendix (Table A2- 3).

Two model specifications are considered and compared: (i) Standard Bivariate Probit (BVP), (ii) Extended Bivariate Probit (BVP-E) which identify predictors for the correlation parameters. These models are estimated using the package GJRM by Marra & Radice (2017) under the free statistical software *R* (Team & others, 2013).

2.6.1. Joint adoption of rice certified seeds and chemical fertilizers

Table 2- 4 presents the results of the two models in the competition (BVP and BVP-E) for rice technology adoption. Estimated coefficients for the two models are very similar. The main difference is about the impact of expected profit on the probability of adopting fertilizer which is only significant in the second model. The fact that estimates are similar across model specifications show that the choice of a BVP or a BVP-E has little impact on the direct effect of a covariate. However, since in a bivariate probit model the impact of a covariate depends on the direct effect and the indirect effect, which is a function of the correlation between the two marginal distributions (Greene, 2012). Therefore, if the hypothesis of heterogeneous correlation across households is accepted, the BVP-E model may generate more reliable marginal effects. Discussion of the marginal effects will reveal whether if it is worth investing on more complex model such as BVP-E in our context. When a flexible BVP model is considered, results show that the main drivers of heterogeneous correlation between the decision to adopt rice certified seeds and that to adopt chemical fertilizers for rice are education, farm size, and profit variance. The first two covariates have a negative coefficient, which reveals that households whose heads were educated display lower dependency between the two decisions. Similar results for households with larger farm size. On the other hand, the expected profit variance has a positive impact on the dependence between the two decisions. This reveals certified seeds and chemical fertilizers are more interrelated in the presence of production risk. Regarding the standard BVP model, one important aspect is whether the correlation parameter is significant. Results show that the correlation between the two technology adoption decisions for rice is positive, quite high (0.63), and statistically significant. This means that the two decisions are not independent if BVP is the correct specification. The complementarity between certified seed and chemical fertilizer is not uncommon in the literature (Abay et al., 2018; Kassie et al., 2013; McGuirk & Mundlak, 1991; Ogada et al., 2014; Singh & Kohli, 2005; Teklewold et al., 2013). For the heterogeneous dependency specification, the predicted average

correlation is about 0.73 and highly significant. Therefore, the average correlation from the heterogeneous correlation's model is higher than when the standard model is used.

Table 2- 4 Bivariate probit estimates for rice technology adoption

	Standard BVP		Extended BVP		
	Certified seed	Fertilizer	Certified seed	Fertilizer	Correlation
Head gender (1=Female)	0.44 (0.365)	0.564** (0.237)	0.395 (0.35)	0.61*** (0.235)	
Head's age (years)	-0.008** (0.003)	-0.001 (0.005)	-0.007** (0.003)	-0.002 (0.004)	
Education	0.601** (0.241)	0.694*** (0.207)	0.579** (0.228)	0.716*** (0.197)	-0.353** (0.172)
Household size	0.057*** (0.018)	0.06*** (0.02)	0.052*** (0.017)	0.066*** (0.02)	
Wealth index (0/6)	-0.157** (0.068)	-0.101 (0.062)	-0.148** (0.064)	-0.092 (0.061)	
Livestock income dummy	1.049*** (0.25)	1.251*** (0.248)	1.024*** (0.232)	1.298*** (0.241)	
Off-farm income dummy	-0.163 (0.104)	-0.274** (0.116)	-0.144 (0.1)	-0.306*** (0.107)	
Land holding (ha)	0.001 (0.011)	-0.01 (0.01)	-0.003 (0.011)	-0.004 (0.013)	-0.099*** (0.027)
Organization membership	0.537*** (0.123)	0.518*** (0.142)	0.536*** (0.123)	0.557*** (0.132)	0.367 (0.342)
Extension services	0.476*** (0.146)	0.38* (0.215)	0.46*** (0.14)	0.439** (0.196)	
Access to credit	1.013*** (0.339)	0.565* (0.316)	0.958*** (0.33)	0.605* (0.317)	
distance to market, KM	0.007 (0.009)	0.022** (0.009)	0.008 (0.009)	0.021*** (0.008)	
AEZ: VFS	-0.532 (0.387)	0.224 (0.459)	-0.534 (0.377)	0.176 (0.453)	
Profit mean	0.014* (0.007)	0.014 (0.009)	0.012* (0.007)	0.017** (0.008)	
Profit Variance (Lower)					0.015*** (0.005)
Profit variance (Upper)					0.033*** (0.009)
Organization membership (res)	0.968* (0.586)	0.574 (0.579)	0.956* (0.539)	0.667 (0.575)	
Extension services (res)	-0.464** (0.225)	-0.448* (0.25)	-0.469** (0.217)	-0.454** (0.23)	
Off-farm income dummy (res)	2.71*** (0.813)	4.02*** (0.74)	2.609*** (0.77)	4.106*** (0.709)	
Constant	-4.745*** (1.507)	-5.626*** (1.277)	-4.513*** (1.399)	-5.935*** (1.25)	0.741*** (0.24)
Correlation	0.632		0.726		
Correlation (Lower)	0.49		0.55		
Correlation (Upper)	0.732		0.846		
Log-Likelihood	-1177.981		-1147.594		
Degree of freedom	37		42		
Akaike criteria	2429.962		2379.189		
Schwartz criteria	2625.601		2601.266		
Sample size	1462		1462		

Notes: This table presents the estimates of the two bivariate probit models using the sample of rice producers. Robust standard errors clustered at the Communes level (116 communes are present in total in the sample) in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

To select the best model specification, we used AIC and BIC. The results show that the extended BVP has the lowest values of AIC and BIC. This suggests that the model BVP-E fits better the data at hand than the BVP. Concerning endogeneity of farmer organization, extension services, and off-farm income, results show that for the adoption of certified seeds, all these factors are endogenous. For the decision to use inorganic fertilizers, farmer organization seems to be exogeneous. Since estimates from a bivariate model could not be interpreted directly, Table 2- 5 reports the marginal effects of covariates on marginal technology adoptions and joint technology adoption.

Table 2- 5 shows that there is a very small difference between marginal effects from the two model specifications. Therefore, from an empirical point of view, there is no new insight from the more complicated model specification (BVP-E compared BVP) for rice technology adoption. In other words, there is not much information provided to policymakers by adopting the most general bivariate probit instead of the standard model. However, opposite results may be found in other contexts. Consequently, one has to check that before using the standard bivariate probit.

Regarding marginal effects, results reveal that several factors has a significant effect on technology adoption among rice-producing households. Expected higher agricultural profit enhance the probability of adoption of rice certified, inorganic fertilizer and joint adoption of inorganic fertilizer and improved maize variety. Similarly, increased access to livestock income of 1 percent results in an increase in the probability of certified seed adoption by 0.27 percent, inorganic fertilizer adoption by 0.29 percent, and joint adoption of 0.26 percent.

Increased access to agricultural extension services is critical in promoting the adoption of certified seeds, the adoption of inorganic fertilizer, and their joint adoption. Our results show that a 1 percent increase in farmers' access to extension services strongly increases the probability of CS adoption by 0.1 percent, CF adoption by 0.12 percent, and their joint adoption by 0.11 percent. This is consistent with the findings of Feder et al. (1985), Olwande, Sikei, & Mathenge (2009), and Kassie et al. (2013).

Another policy instrument is a farmer organization, which is found here to positively affect rice technology adoption in Senegal. Indeed, a 1 percent increase in farmers' participation in an organization strongly increases the probability of CS adoption by 0.13 percent, CF adoption by 0.14 percent, and the joint adoption of the two technologies by 0.13 percent. Similar results are found in the literature (Abay et al., 2018; Kassie et al., 2013; Kassie, Zikhali, Manjur, & Edwards, 2008; Teklewold et al., 2013; Wollni, Lee, & Thies, 2010).

Access to credit is also revealed to have a strong relationship with rice technology adoption. Improvement of credit access index by one percent improves significantly the three probabilities under consideration, especially the probability of joint adoption of CS and CF. The marginal effects of the different levels of education variables are very high, positive and significant. These results suggest that households whose heads were educated, either formal education or education in local languages, have a higher likelihood to adopt technologies for rice production. These results corroborate those of Gerhart (1975), Ogada et al. (2014), and Thuo et al. (2011).

Table 2- 5 Marginal effects of covariates on the probability of technology adoption for rice

	Standard BVP			Extended BVP		
	Certified seed	Fertilizer	Joint adoption	Certified seed	Fertilizer	Joint adoption
Head gender (1=Female)	0.116***	0.126***	0.116***	0.116***	0.124***	0.105***
	(0.023)	(0.042)	(0.035)	(0.024)	(0.043)	(0.037)
Head's age (years)	-0.001**	-0.001	-0.002**	-0.001**	-0.001	-0.002**
	(0)	(0.001)	(0.001)	(0)	(0.001)	(0.001)
Education	0.15***	0.164***	0.154***	0.15***	0.165***	0.148***
	(0.017)	(0.031)	(0.025)	(0.017)	(0.031)	(0.028)
Household size	0.014***	0.015***	0.014***	0.014***	0.015***	0.013***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Wealth index (0/6)	-0.03***	-0.034***	-0.037***	-0.028***	-0.033***	-0.035***
	(0.005)	(0.009)	(0.008)	(0.005)	(0.009)	(0.008)
Livestock income dummy	0.266***	0.29***	0.271***	0.269***	0.294***	0.262***
	(0.021)	(0.038)	(0.031)	(0.021)	(0.038)	(0.037)
Off-farm income dummy	-0.05***	-0.053**	-0.046**	-0.052***	-0.054**	-0.041**
	(0.013)	(0.023)	(0.02)	(0.013)	(0.022)	(0.021)
Land holding (ha)	-0.001	-0.001	0	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Organization membership	0.122***	0.136***	0.133***	0.127***	0.142***	0.133***
	(0.015)	(0.027)	(0.022)	(0.015)	(0.027)	(0.023)
Extension services	0.099***	0.112***	0.115***	0.104***	0.118***	0.113***
	(0.015)	(0.028)	(0.022)	(0.015)	(0.028)	(0.023)
Access to credit	0.184***	0.214***	0.233***	0.181***	0.216***	0.226***
	(0.029)	(0.054)	(0.043)	(0.031)	(0.055)	(0.043)
distance to market, KM	0.003***	0.003***	0.003***	0.003***	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
AEZ: VFS	-0.037	-0.059	-0.099**	-0.042	-0.07	-0.109**
	(0.031)	(0.064)	(0.043)	(0.034)	(0.064)	(0.046)
Profit mean	0.003***	0.004***	0.003***	0.003***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Notes: This table presents the estimates of the two bivariate probit models using the sample of rice producers. Robust standard errors clustered at the Communes level (116 communes are present in total in the sample) in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Conversely, a negative marginal effect was associated with off-farm income. On average, farmers who generated an off-farm income had a 0.05 percent lower probability of using CS and CF, and 0.04 percent lower probability to adopt the two technologies. Similar results were found by Thuo et al. (2014) for groundnut production in Senegal and by Rahim, Ruben, & van Ierland (2005) in the Sahel context. Therefore, in Senegal, off-farm activities and rice production activity are not complementary (Thuo et al., 2014).

The household wealth index is found to decrease the probability of adopting rice technologies. This result suggests that wealthier households do not seem to use their endowments to buy improved technologies. On the other hand, the age of the heads of households has a negative effect on the adoption of certified rice seeds and on the joint adoption. In other words, households whose heads are old are less likely to adopt certified seed and to jointly adopt certified seed and chemical fertilizer.

2.6.2. Joint adoption of groundnut certified seeds and chemical fertilizers

Table 2- 6 presents the results of standard and extended bivariate probit of technology adoption for groundnut production in Senegal. Unlike results for rice technology adoptions, the correlation parameter is quite low (0.18), but significant. On the other hand, when the more flexible specification of the dependence between the two technologies is used (BVP-E), results reveal farmer organization, agroecological zone, and variance of the total household profit per hectare as main drivers of decisions dependence among groundnut producers. All these factors have a positive impact on the joint distribution of certified seeds and inorganic fertilizer adoptions. In other words, households that are members of farmer organizations and those who are in the Groundnut Basin are more likely to jointly use the two technologies than others. Similarly, households that expect negative or positive deviations from the profit mean tend to adopt both technologies with a higher correlation. As for the rice study case, production risk is a key determinant of the dependence between technology choices.

In terms of the best model to use, AIC favors the flexible model specification, while the smallest BIC is found for the most restrictive model. For a parsimonious reason, the restricted BVP model is preferred. Considering this model (BVP), the correlation is positive and significant, therefore, one could not reject the hypothesis of dependency between the two decisions to adopt improved inputs for groundnut production. In order to get an economically meaningful interpretation of findings, Table 2- 7 reports the marginal effects of covariates on technology adoption decisions.

Expected higher agricultural profit enhanced the probability of adoption of groundnut certified, inorganic fertilizer and joint adoption of inorganic fertilizer and improved maize variety. More variable agricultural profit per hectare seems also to have a positive impact on technology adoption. This means that households that expect more volatile returns are more likely to adopt technologies in order to increase the expected return.

Table 2- 6 Bivariate probit estimates for groundnut technology adoption

	Standard BVP		Extended BVP		
	Certified seed	Fertilizer	Certified seed	Fertilizer	Correlation
Head gender (1=Female)	-0.097 (0.2)	-0.896*** (0.214)	-0.059 (0.195)	-0.951*** (0.215)	
Head's age (years)	0.001 (0.011)	0.045*** (0.011)	0 (0.011)	0.048*** (0.011)	
Education	-0.035 (0.344)	-1.231*** (0.299)	0.007 (0.334)	-1.33*** (0.302)	
Household size	0.011 (0.03)	-0.105*** (0.028)	0.015 (0.029)	-0.114*** (0.028)	
Wealth index (0/6)	-0.09*** (0.029)	0.026 (0.029)	-0.078*** (0.028)	0.02 (0.029)	
Livestock income dummy	-0.127 (0.417)	-1.453*** (0.39)	-0.023 (0.404)	-1.61*** (0.393)	
Off-farm income dummy	0.043 (0.077)	-0.049 (0.078)	0.049 (0.076)	-0.051 (0.079)	
Land holding (ha)	0.024 (0.021)	0.096*** (0.02)	0.019 (0.02)	0.105*** (0.02)	
Organization membership	0.156 (0.117)	0.093 (0.118)	0.155 (0.111)	0.102 (0.116)	0.224* (0.131)
Extension services	0.081 (0.106)	0.366** (0.144)	0.059 (0.101)	0.36** (0.141)	
Access to credit	0.363 (0.572)	-2.067*** (0.555)	0.42 (0.558)	-2.242*** (0.564)	
distance to market, KM	-0.023*** (0.007)	0.031*** (0.008)	-0.022*** (0.007)	0.033*** (0.008)	
AEZ: Basin	0.665 (0.896)	4.311*** (0.836)	0.492 (0.864)	4.633*** (0.842)	0.484*** (0.126)
Profit mean	0.045*** (0.013)	0.093*** (0.016)	0.041*** (0.012)	0.083*** (0.015)	
Profit variance (Lower)	0.033*** (0.006)	0 (0.004)	0.032*** (0.005)	0.007 (0.005)	0.019*** (0.005)
Profit variance (Upper)	0.012*** (0.004)	0.003 (0.002)	0.011*** (0.003)	0.009*** (0.003)	0.013*** (0.003)
Constant	-1.713 (1.885)	4.238** (1.754)	-1.969 (1.843)	4.796*** (1.771)	-0.512*** (0.154)
Correlation	0.177		0.061		
Correlation (Lower)	0.085		-0.105		
Correlation (Upper)	0.266		0.239		
Log-Likelihood	-3161.892		-3149.331		
Degree of freedom	41		45		
Akaike criteria	6405.784		6388.661		
Schwartz criteria	6655.415		6662.646		
Sample size	3257		3257		

Notes: This table presents the estimates of the two bivariate probit models using the sample of groundnut producers. Robust standard errors clustered at the Communes level (288 communes are present in total in the sample) in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

As for rice technology adoptions, increased access to agricultural extension services is critical in promoting the adoption of CS and/or CF. Our results show that a 1 percent increase in farmers' access to extension services strongly increases the probability of CS adoption by 0.03 percent, CF adoption by 0.08 percent, and their joint adoption by 0.03 percent. Therefore, the impact of extension workers is more critical for fertilizer adoption.

Regarding farmer organization, which is a central institution in a rural area, results showed a positive effect on groundnut technology adoption in Senegal. Similar results are found for households' heads age and farm size. As for extension services, larger farm size has a higher marginal effect on fertilizer adoption (0.023) compared to certified seeds (0.01) or joint adoption (0.008).

Table 2- 7 Marginal effects of covariates on the probability of technology adoption for groundnut

	Standard BVP			Extended BVP		
	Certified seed	Fertilizer	Joint adoption	Certified seed	Fertilizer	Joint adoption
Head gender (1=Female)	-0.069** (0.033)	-0.204*** (0.035)	-0.073*** (0.017)	-0.069** (0.032)	-0.204*** (0.034)	-0.065*** (0.015)
Head’s age (years)	0.003** (0.001)	0.01*** (0.001)	0.003*** (0.001)	0.003** (0.001)	0.01*** (0.001)	0.003*** (0.001)
Education	-0.073** (0.044)	-0.274*** (0.044)	-0.092*** (0.022)	-0.078** (0.043)	-0.28*** (0.043)	-0.085*** (0.02)
Household size	-0.003 (0.004)	-0.023*** (0.004)	-0.007*** (0.002)	-0.004 (0.004)	-0.023*** (0.004)	-0.006*** (0.002)
Wealth index (0/6)	-0.018*** (0.005)	0.001 (0.005)	-0.005** (0.002)	-0.015*** (0.005)	-0.001 (0.005)	-0.004** (0.002)
Livestock income dummy	-0.105** (0.055)	-0.328*** (0.055)	-0.116*** (0.027)	-0.101** (0.053)	-0.341*** (0.053)	-0.105*** (0.024)
Off-farm income dummy	0.007 (0.014)	-0.009 (0.014)	0 (0.007)	0.007 (0.013)	-0.008 (0.014)	0 (0.006)
Land holding (ha)	0.01*** (0.003)	0.023*** (0.003)	0.009*** (0.001)	0.01*** (0.003)	0.023*** (0.003)	0.008*** (0.001)
Organization membership	0.039** (0.02)	0.029 (0.021)	0.019** (0.01)	0.039** (0.02)	0.032 (0.02)	0.017** (0.009)
Extension services	0.037** (0.02)	0.086*** (0.02)	0.033*** (0.01)	0.034** (0.02)	0.08*** (0.019)	0.027*** (0.009)
Access to credit	-0.031 (0.078)	-0.437*** (0.079)	-0.123*** (0.039)	-0.046 (0.076)	-0.446*** (0.076)	-0.117*** (0.035)
distance to market, KM	-0.003*** (0.001)	0.006*** (0.001)	0.001 (0)	-0.003** (0.001)	0.005*** (0.001)	0.001 (0)
AEZ: Basin	0.376*** (0.116)	0.991*** (0.116)	0.365*** (0.059)	0.381*** (0.112)	1.01*** (0.112)	0.33*** (0.053)
Profit mean	0.015*** (0.002)	0.023*** (0.002)	0.01*** (0.001)	0.014*** (0.002)	0.02*** (0.002)	0.008*** (0.001)
Profit variance (Lower)	0.007*** (0.001)	0.002*** (0.001)	0.002*** (0)	0.007*** (0.001)	0.004*** (0.001)	0.003*** (0)
Profit variance (Upper)	0.003*** (0)	0.001*** (0)	0.001*** (0)	0.003*** (0)	0.003*** (0)	0.001*** (0)

Notes: This table presents the estimates of the two bivariate probit models using the sample of groundnut producers. Robust standard errors clustered at the Communes level (288 communes are present in total in the sample) in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Access to credit, surprisingly, is revealed to have a negative and significant relationship with groundnut technology adoption. Farm households that have access to credit seem to invest less on technology adoption and on fertilizer. In the same direction, the marginal effects of education are very high, negative, and significant. The highest effect (0.28) is found for fertilizer adoption. These results suggest that households whose heads are educated, either formal education or education in local languages, are less likely to buy fertilizers for groundnut. This result may be related to the fact that farmers could get appropriate yield for this commodity without fertilizer. Therefore, there is little incentive to adopt fertilizer. On the other hand, most farmers prefer to use their past production as seeds for the next season. Descriptive statistics do not reveal any big yield gap between the use of self-produced seeds and certified seeds. Consequently, more educated households would prefer to produce groundnut without the use of improved inputs. Therefore, there is a need for policymakers to investigate the value-added of improved inputs for groundnut proposed to farmers.

Results also show that gender, household size, household wealth, and livestock income are also revealed to negatively and significantly affect groundnut technology adoption. Unlike results found for the rice model, women-headed households have lower probability to adopt groundnut technologies than male-headed households. Likewise, larger households used to adopt technologies less than smaller ones. Contrary to the result for rice, being involved in livestock activities tend not to be complementary to groundnut production, at least in terms of adoption technology. Conversely, participating in off-farm activities does not have any significant impact on groundnut related technology adoptions as far as certified seeds and chemical fertilizers are concerned.

2.7. Conclusion

In this paper, we describe agricultural technology adoption patterns in Senegal and identify their determinants using a flexible bivariate probit. The most recent farm survey data collected in 2017 in Senegal is used for this purpose. The descriptive statistics reveal that the adoption rate depends on technologies and crops under consideration. Only 7 percent of sorghum producers have used improved inputs (certified seeds and/or chemical fertilizers) compared to 14 percent for cowpeas producers, 25 percent for millet, 39 percent for groundnut, and 67 percent for rice producers. For millet and maize, the most popular technology is certified seeds, while for the rice production, the joint adoption of certified seeds and chemical fertilizers is the most common choice. In the groundnut system, the major cash crop in Senegal, improved inputs choice is more heterogeneous; respectively 41 percent, 39 percent, and 20 percent of adopters have used chemical fertilizers, certified seeds, and the two technologies respectively. In terms of quantity of chemical fertilizers used per hectare, results reveal that rice producers have the highest rate of fertilizer application in the sample (192 kg/ha) followed by maize producers (63 kg/ha), and 20 kg/ha for groundnut and millet producers. For cowpeas and sorghum, the intensity of fertilizers is very low and is less than 5 kg per hectare.

Our econometric results show that the decision to adopt certified seeds and that to adopt chemical fertilizers are not independent in the context of Senegal, but the two technologies are complementary. Therefore, our choice to use a multivariate model is appropriate. On the other hand, the use of a more flexible bivariate probit fits better the data, especially for rice samples. Consequently, the hypothesis of a constant correlation between two decisions (probability distributions) needs to be tested. As drivers of the dependence between the decisions to adopt certified seeds and chemical fertilizers for rice production are education, farm size, and production risk. Regarding the drivers of technology adoption for rice and groundnut, the key factors identified include extension services, farmer organization membership, credit access, education level of the household head, size of the farm operated by the household, livestock activity, off-farm activity, household size, age of household head, production risks, and agroecological zones.

These findings have some direct policy implications for Senegal. Firstly, it is important to promote complementary technologies, especially chemical fertilizer and certified seeds, as a package to facilitate their adoption. Especially for rice production, descriptive statistics show that farmers that adopted the two technologies were three times more productive than those who did not adopt any of these technologies. Due to households' limited financial capital, policymakers should ensure that the technologies are available and affordable to farm households.

Furthermore, results show that farmer organization membership is central for agricultural technology adoption. In addition, extension services also encourage farmers to adopt advanced technologies. It would be interesting to directly associate research with extension in the same structure to increase efficiency by pooling resources and to better facilitate the scaling up of technologies. In the presence of market failure or absence of markets, these instruments (organization membership, extension services) facilitate the exchange of key information, influencing farmers' behavior. There is a need for policymakers to promote and help rural farmers´ associations, as well as support extension services that disseminate information on agricultural technologies and best practices.

Additionally, access to credit has a positive effect on the adoption of certified seeds and fertilizers. Removing credit constraints and easing access to inputs in the production areas are essential to increase the adoption of capital-intensive technologies. The heterogeneity of technology adoption across regions and agroecological zones calls for location-specific technology promotion policies.

Production risks are found to influence both marginal technology adoption distribution and the joint distribution of technology adoption, policymakers need to design policies that account for uncertainty associated with agricultural activities. Solutions like agricultural insurance would be a good option to increase technology adoption in Senegal.

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Supplementary materials

Table A2- 1 Estimates of Full- and Partial-Moment Function of Senegalese Rice Production

	μ_1	μ_2	μ_3	η_2	φ_2	η_3	φ_3
(Intercept)	-1886.553*** (588.735)	12.485*** (1.914)	-67.012 (417.809)	10.428*** (1.787)	6.662 (4.838)	15.641*** (2.681)	9.993 (7.257)
x1_land	-27.775*** (9.642)	-0.273*** (0.041)	0.801 (7.075)	-0.263*** (0.036)	0.021 (0.066)	-0.395*** (0.055)	0.031 (0.1)
x2_fert	0.07** (0.04)	0*** (0)	-0.012 (0.023)	0.001*** (0)	0 (0)	0.001*** (0)	0 (0)
x3_rainfall	0.389*** (0.142)	-0.003*** (0)	-0.022 (0.067)	-0.003*** (0)	-0.001 (0.001)	-0.004*** (0)	-0.001 (0.001)
x4_temp	104.97*** (30.765)	-0.177*** (0.049)	5.08 (12.193)	-0.123*** (0.046)	-0.175 (0.123)	-0.185*** (0.068)	-0.263 (0.185)
x11	0.065** (0.039)						
x12	0 (0)						
x13	0.004*** (0.001)						
x14	0.664** (0.262)						
x22	0 (0)						
x23	0*** (0)						
x24	-0.002 (0.001)						
x33	0** (0)						
x34	-0.026*** (0.007)						
x44	-2.828*** (0.805)						
tech_CS	0.762 (1.648)	-0.012 (0.336)	-33.33** (16.854)	-0.074 (0.348)	0.048 (0.78)	-0.111 (0.522)	0.072 (1.17)
tech_CF	1.56 (1.077)	-0.114 (0.19)	-48.031** (25.058)	-0.181 (0.194)	0.091 (0.437)	-0.272 (0.291)	0.136 (0.656)
tech_both	1.701 (1.238)	-0.062 (0.212)	-11.949 (17.989)	-0.066 (0.195)	-0.072 (0.484)	-0.099 (0.292)	-0.108 (0.726)
SQI	21.228*** (8.097)	2.743*** (0.971)	-181.292 (259.997)	2.499** (1.063)	0.598 (2.16)	3.749** (1.595)	0.897 (3.239)
profit_dum	-19.486*** (1.385)	-1.335*** (0.274)	-54.566 (33.399)	-1.017*** (0.334)	-0.941 (0.606)	-1.525*** (0.501)	-1.411 (0.91)
zone_vfs	-0.671 (2.916)	-0.395** (0.207)	44.195 (65.61)	-0.398** (0.213)	0.032 (0.45)	-0.598** (0.319)	0.047 (0.675)
R-Sq adjusted	0.414	0.243	-0.001	0.244	0.244	0.244	0.244
Fisher Statistics	52.688	47.789	0.826	23.431	23.431	23.431	23.431
Sample size	1462	1462	1462	890	572	890	572

Table A2- 2 Estimates of Full- and Partial-Moment Function of Senegalese Groundnut Production

	μ_1	μ_2	μ_3	η_2	φ_2	η_3	φ_3
(Intercept)	66.897 (168.743)	11.135*** (1.821)	280.848 (406.34)	12.733*** (1.723)	-4.651 (4.899)	19.099*** (2.585)	-6.977 (7.349)
x1_land	-4.605*** (1.317)	-0.078*** (0.011)	-5.18*** (1.941)	-0.065*** (0.012)	-0.032 (0.026)	-0.098*** (0.018)	-0.049 (0.04)
x2_fert	-0.008 (0.034)	0*** (0)	0.019 (0.013)	0** (0)	0 (0)	0** (0)	0 (0)
x3_rainfall	0.18*** (0.048)	-0.001*** (0)	-0.213*** (0.08)	-0.001*** (0)	0 (0.001)	-0.002*** (0)	0 (0.001)
x4_temp	-4.802 (9.341)	-0.206*** (0.046)	-0.774 (12.362)	-0.25*** (0.043)	0.124 (0.127)	-0.375*** (0.065)	0.186 (0.19)
x11	0.032*** (0.004)						
x12	0*** (0)						
x13	0.001*** (0)						
x14	0.094*** (0.036)						
x22	0 (0)						
x23	0*** (0)						
x24	0.001 (0.001)						
x33	0 (0)						
x34	-0.011*** (0.003)						
x44	0.196 (0.259)						
tech_CS	0.909 (0.571)	0.406*** (0.129)	51.375 (34.495)	0.345** (0.139)	0.218 (0.314)	0.518** (0.208)	0.327 (0.471)
tech_CF	0.572 (0.552)	0.091 (0.116)	10.539** (5.566)	-0.082 (0.137)	0.438** (0.249)	-0.123 (0.205)	0.658** (0.374)
tech_both	2.596*** (0.731)	0.808*** (0.126)	59.715** (24.326)	0.729*** (0.136)	0.187 (0.3)	1.094*** (0.204)	0.28 (0.45)
SQI	-1.321 (3.607)	1.387** (0.799)	-207.678 (137.338)	0.53 (0.841)	2.824 (1.917)	0.794 (1.262)	4.236 (2.875)
profit_dum	-10.08*** (0.522)	-2.142*** (0.186)	-48.277** (22.536)	-1.893*** (0.226)	-0.57 (0.422)	-2.839*** (0.339)	-0.856 (0.633)
zone_bassin	-2.313*** (0.656)	-0.999*** (0.117)	-49.196** (24.084)	-0.909*** (0.123)	-0.179 (0.293)	-1.364*** (0.184)	-0.268 (0.44)
R-Sq adjusted	0.188	0.084	0.013	0.089	0.089	0.089	0.089
Fisher Statistics	38.765	30.993	5.255	16.143	16.143	16.143	16.143
Sample size	3257	3257	3257	2109	1148	2109	1148

Table A2- 3 First stage estimates for addressing potential endogeneity (probit model).

	Rice sample			Groundnut sample		
	Farmer organization (0,1)	Extension services (0,1)	Off-farm activity (0,1)	Farmer organization (0,1)	Extension services (0,1)	Off-farm activity (0,1)
Head gender (1=Female)	0.053 (0.127)	-0.091 (0.134)	0.338*** (0.121)	0.089 (0.155)	0.133 (0.14)	0.155 (0.108)
Head's age (years)	-0.003 (0.003)	-0.005 (0.003)	0 (0.003)	-0.006** (0.003)	0.007*** (0.002)	-0.003* (0.002)
Education	0.06 (0.08)	-0.056 (0.084)	0.268*** (0.077)	0.426*** (0.069)	0.247*** (0.067)	0.125** (0.052)
Household size	0.024*** (0.008)	0.013* (0.008)	0.017** (0.007)	0.026*** (0.005)	-0.003 (0.006)	0.008* (0.005)
Wealth index (0/6)	-0.029 (0.023)	0.103*** (0.025)	-0.041* (0.024)	-0.026 (0.02)	0.012 (0.019)	0.039*** (0.015)
Livestock income dummy	0.114 (0.082)	0.224*** (0.086)	0.434*** (0.077)	0 (0.069)	0.089 (0.067)	0.44*** (0.051)
Land holding (ha)	0.006 (0.005)	-0.002 (0.006)	-0.007 (0.006)	0.006* (0.003)	0.008*** (0.003)	-0.018*** (0.005)
Access to credit	0.57*** (0.122)	0.184 (0.131)	-0.085 (0.132)	0.877*** (0.127)	0.038 (0.159)	-0.006 (0.13)
distance to market, KM	-0.012*** (0.003)	-0.012*** (0.003)	0.009*** (0.003)	-0.018*** (0.004)	0.001 (0.004)	0.011*** (0.003)
Distance to road (km)	0.012*** (0.002)			0.007* (0.004)	-0.014*** (0.004)	-0.012*** (0.003)
Distance to the regional city (km)						-0.001 (0.001)
	0.418*** (0.076)			0.266*** (0.068)	0.067 (0.066)	-0.12** (0.052)
	0.203* (0.114)			0.275*** (0.091)	0.802*** (0.11)	0.13** (0.06)
AEZ: VFS	0.521*** (0.103)	1.329*** (0.107)	-0.369*** (0.115)			
AEZ: Basin				-0.73*** (0.077)	-0.261*** (0.075)	-0.498*** (0.06)
Log Likelihood	**-766.049**	**-766.049**	**-766.049**	**-866.109**	**-866.109**	**-866.109**
Sample size	**1462**	**1462**	**1462**	**3257**	**3257**	**3257**

Chapter 3

3. Multiple Technology Adoptions, Technical Efficiency and Yield in Senegalese Rice Sector: A Meta-frontier Framework

Authors

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3.1. Introduction

Improved technology adoption is central to crop production. Appropriate technologies use can help improve farmers' welfare, especially through productivity and efficiency. Many studies have analyzed the relationship between improved inputs use and efficiency (Kalirajan and Shand 2001; Alene and Hassan 2006), productivity (Crost et al. 2007; Abate et al. 2015; Battese et al. 2017) or welfare (Amare et al. 2012; Bezu et al. 2014). Most of these studies considered only one improved input and quantified the impact on yield, income, efficiency, or poverty. However, some agricultural technologies were revealed to be complementary (Ogada et al. 2014; Abay et al. 2018). This is why technologies are generally proposed as a package. Indeed, the introduction of an agricultural innovation without the appropriate agronomic practices will limit its impact. Therefore, when farmers are exposed to such complementary technologies (multiple choices), it would be interesting to compare the impact of the different technology options. Thus, such analysis will offer a larger view for discussing policy options.

This article's objective is to analyze the impact of three technologies that are critical for rice production: irrigation, certified seeds, and chemical fertilizers in the rice. As stated previously, the aim will be to consider the impact of individual technology use as well as the combination of the three technologies on technical efficiency and land productivity in Senegal. These technologies are important for the country since a lot of investments (irrigation equipment, input subsidies, etc.) were made by the Senegalese government to reach self-sufficiency for rice. In fact, the 2014–2017 National Program for Self-Sufficiency in Rice (PNAR) was specifically formulated to achieve this goal. Over recent years (2013–2016), the country's rice production has experienced a 160% increase.

Senegal has dedicated crucial efforts to boosting agricultural production, mainly through area expansion and productivity intensification. These have relied on the assumption that local rice can compete with imports in terms of quality and quantity (Fiamohe et al. 2018). Rice cultivation in Senegal is based on five major rice-producing systems (irrigated, rainfed, mangrove, upland, and lowland). Unlike irrigation, the other rice cropping systems depend on rainfall, are less intensive, and use fewer inputs, inducing lower yields (1–2 t/ha). Rice produced is mainly intended for self-consumption. Irrigated rice cropping is characterized by an intensive system with total water control, mechanization of most production and post-harvest operations, and the systematic use of fertilizers inducing higher yields, between 5 and 6.5 t/ha. As a comparison, the average West African rice yield for the same years is 1.82 tons, but the Senegalese rice system is still characterized by poor value addition, impeding the country from realizing its income and employment generation potential.

The rice system in the Senegal River valley is based on small and medium-sized family farms varying between 0.25 and 1 ha. It is practiced in the Senegal River valley (45,000 ha on an annual average) and the Anambe basin in the south of the country (4,500 ha). Rice production (irrigated) in the Senegal River valley is between 47% and 75% of domestic production, depending on the years. Of this production, 69% is marketed, of which one-third represents in-kind payments for input credits (FNDASP, 2017). This reveals a rise in the flow of rice from the valley to the consumption basins (major cities in the country including Saint Louis, Touba, Thies, and Dakar).

Therefore, it is well known that irrigation is central to the country's self-sufficiency program. In addition, access to inputs, especially inorganic fertilizers, is facilitated for parastatal agencies. Moreover, there is a complementarity among irrigation, certified seeds, and fertilizer use. The combination of these three technologies by a farmer may create some differences in farming; thus, there may exist heterogeneous production behavior across different groups of farmers. Therefore, improved inputs use is expected to shift the production frontier upward for adopters. Consequently, the first objective of this study is to test the existence of heterogeneous rice production frontiers in the sample due to technological choices. The second objective is to analyze technical efficiency across farmers in the presence of potentially heterogeneous production frontiers. The last objective is to assess the impact of technological choices on rice production per hectare.

This article contributes to the literature on the impact of technology adoption on efficiency in several aspects. First, unlike in many studies, three common rice technologies are considered (irrigation, certified seeds, and chemical fertilizer). Second, we assume that the production frontier is different across farmers, based on technology choices. This assumption is tested using the meta-frontier stochastic frontier as proposed by Huang et al. (2014). This framework explicitly separates the overall farm efficiency into managerial efficiency and the technology gap. Managerial efficiency is the farm-specific technical efficiency relative to its group-specific frontier of production. On the other hand, the technology gap measures the distance between the group-specific frontier of production and the best available technology frontier (meta frontier) in the economy under consideration. The third main contribution of this article is the use of an impact evaluation approach that accounts for potential multinomial selection processes where the expected benefits of technology choices induce the adoption decisions. We specifically use a multinomial endogenous treatment effects model proposed by Deb and Trivedi (2006a, b) to account for selection bias due to both observed and unobserved heterogeneity and to assess the differential impacts of the adoption of a single technology as well as a combination of them. Fourth, this article uses a recent survey representative of irrigated and rainfed rice production in Senegal.

The article is organized as follows. The first section describes the methodology of the stochastic meta frontier used, the second presents the data, and the third provides the empirical results. The final section presents the conclusion.

3.2. Conceptual framework

3.2.1. Sample selection and efficiency analysis

The assessment of the adoption of best farming practices or improved inputs on farmers' performances (yield, productivity, efficiency, income, etc.) has been the main target of economists for decades (Birkhaeuser et al. 1991; Adesina and Zinnah 1993; Feder et al. 2003). Regarding the impact on productivity or efficiency, one of the most-used approaches is the stochastic frontier analysis (SFA) (Aigner et al. 1977; Meeusen and van den Broeck 1977). In this framework, the common approach consists of assuming a homogeneous function of production for all farmers to be estimated. Then, efficiency or productivity scores are derived. The last step is to compute certain statistics (mean, median, or other quantiles) to test differences among farmer groups.

However, the issue of selection bias was raised in the SFA literature (Sipilainen and Oude Lansink 2005; Solis et al. 2007; Kumbhakar et al. 2009; Greene 2010) since farmers self-selected into different groups. The decision to belong to a selected group may be affected by observable factors as well as unobservable factors (Villano et al. 2015). Still, one has to decide which aspects of the framework are affected by this type of endogeneity. Three options are available: selection on the production function, selection on the inefficiency term, or selection on the noise term.

The first authors that raised and accounted for sample selection bias in an SFA framework used ad-hoc approaches such as the Heckman model (Bradford et al. 2001; Sipilainen and Oude Lansink 2005; Solis et al. 2007) or propensity scores matching (PSM) (Mayen et al. 2010). In a linear framework, the Heckman model works well, but in a non-linear setting such as the stochastic frontier framework, its application is not straightforward (Greene

2010). As was shown in the meta-frontier framework (Battese et al. 2004; O'Donnell et al. 2008; Huang et al. 2014), one could not directly compare efficiency scores across groups of farmers when they do not operate under the same production frontier. Consequently, the use of the PSM approach is limited in this context. On the other hand, Greene (2010) proposed a theoretically robust approach that assumes that the selection bias affects only the noise term in the SFA model. Similarly, but with different assumptions, Kumbhakar et al. (2009) suggested a theoretical model in which the selection bias affects the level of farm inefficiency. Even though the last two approaches are theoretically well formulated, they have some limitations. According to Mayen et al. (2010), they assume different technologies across groups without a formal test for differences in technology. In addition, they are computationally demanding or may suffer from what Mayen et al. (2010) called a "common vexing occurrence" issue.

Therefore, we follow the simple approach proposed by Rao et al. (2012). The main objectives of this approach are to (i) consistently estimate the production frontier for each group of farmers, (ii) test the differences in technology use, (iii) estimate technical efficiency or productivity scores, and (iv) assess treatment effects of technology choices on outcomes accounting for selection bias. The first three objectives are reached using the meta-frontier framework as extended by Huang et al. (2014). This framework explicitly assumes (and tests) that each group of farmers may have its own production frontier, and if this is the case, there is a meta frontier of production that envelopes all individual frontiers. If the assumption of heterogeneous frontiers is not rejected, three efficiency scores are proposed: technical efficiency (managerial efficiency), technological efficiency, and meta-technical (overall) efficiency. The managerial efficiency is the farm-specific technical efficiency relative to the group-specific frontier of production. This efficiency score is comparable only within groups of farmers. On the other hand, the technological efficiency measures how close individual frontiers are to the meta frontier, which is the best available technology frontier in the economy under consideration. The overall technical efficiency is by construction the product of the first two efficiency scores. For the last target, since our treatment variable is multinomial, we use a multinomial endogenous treatment effects model (Deb and Trivedi 2006b) to account for selection bias due to both observed and unobserved heterogeneity and to assess the differential impacts of the adoption of a single as well as multiple improved technologies. The next sections briefly present the two approaches used for empirical estimations.

3.2.2. Meta Stochastic Production Frontier framework

The objective of this study is to analyze the technical efficiency of rice producers in Senegal in the presence of technology heterogeneity. As explained previously, the meta stochastic frontier approach (MSFA) is adopted.

A two-step approach is used to estimate the meta frontier. The first step estimates the group-specific frontiers and the second step constructs the frontier boundary of all individual frontiers. This methodology has been first proposed by Battese et al. (2004) and O'Donnell et al. (2008). Their approach had been extended recently by Huang et al. (2014).

Let's consider *J* production systems and that each system has N_j farms. Wang (2002) proposed a more general framework of the stochastic frontier that accounts for inefficiency and production risk (variance).

$$\boldsymbol{Y_{ij}} = \boldsymbol{f^j}(\boldsymbol{X_{ji}})\boldsymbol{e^{V_{ji}-U_{ji}}}, i = 1, 2, \dots, N_j;\ \text{j=1, 2, …, J} \qquad \textbf{(3.1)}$$

With $\boldsymbol{V_{ji} \sim N(0, \sigma_v{}^2)}$; $\boldsymbol{U_{ji} \sim N^+(\mu_i, \sigma_u{}^2)}$

Where $\boldsymbol{Y_{ij}}$ and $\boldsymbol{X_{ji}}$, denote respectively the rice output and input vector of the $\boldsymbol{i^{th}}$ production unit in the $\boldsymbol{j^{th}}$ group, and $\boldsymbol{f^j}$ the individual group-specific production technology. Following the standard SFA modeling, the random error terms are represented by $\boldsymbol{V_{ji}}$ (which is assumed to be independent and identically distributed with mean zero and variance $\boldsymbol{\sigma_v{}^2}$), and $\boldsymbol{U_{ji}}$ are non-negative random errors that account for technical inefficiency (which follows a truncated-normal/half-normal distribution). Due to the cross-section data used and for the sake of simplicity, we consider only a half-normal distribution. In this study, after estimating group-specific production frontiers, we test whether the various groups share homogenous technology, using a likelihood ratio test. Therefore, depending on the model specification supported by data, heteroscedastic inefficiency $(\boldsymbol{\sigma_u})$, or production's risk $(\boldsymbol{\sigma_v})$ will be modeled as a function of a set of environmental variables, $\boldsymbol{Z_{ji}}$, specific to each group of farmers.

In the empirical section, we adopted the following Cobb-Douglas stochastic production frontier function:

$$y_i = \alpha + \textstyle\sum_k \beta_k x_i^k + \boldsymbol{v_i} - \boldsymbol{u_i} \qquad \textbf{(3.2)}$$

Where y_{it} is the log of the rice output, x_i^k is the log of the input *k*.

The technical efficiency of each farm within its group is computed as:

$$\boldsymbol{TE_i^j} = \frac{Y_{ji}}{f^j(X_{ji})e^{V_{ji}}} = \boldsymbol{e^{-U_{ji}}} \qquad \textbf{(3.3)}$$

After estimating the group production frontiers, the common meta stochastic frontier, $\boldsymbol{f^M(X_{ji})}$**,** is estimated using the group-specific frontiers, $\boldsymbol{f^j(X_{ji})}$**,** and is expressed as:

$$\boldsymbol{f^j(X_{ji}) = f^M(X_{ji})e^{-U_{ji}}} \qquad (3.\textbf{4)}$$

Where all comments related to (3.1) are applicable to (3.4). Once the meta-frontier is estimated, the inefficiency score $\boldsymbol{U_{ji}}$ will measure the gap between the group-specific technology boundary and the best available technology boundary. This gap is known as the technology gap ratio (TGR) and is defined as:

$$\boldsymbol{TGR_i^j} = \frac{f^j(X_{ji})}{f^M(X_{ji})} = \boldsymbol{e^{-U_{ji}} \leq 1} \qquad \textbf{(3.5)}$$

For any selected farm, its performance can be decomposed into three different statistics: (i) the technology gap ratio ($\boldsymbol{TGR_i^j} = \frac{f^j(X_{ji})}{f^M(X_{ji})}$) which is the distance between the farm-specific frontier and the meta frontier, (ii) the technical efficiency score ($\boldsymbol{TE_i^j} = \frac{f^j(X_{ji})e^{-U_{ji}}}{f^j(X_{ji})} = \boldsymbol{e^{-U_{ji}}}$) which is the farm efficiency score relative to its production frontier, and (iii) the meta technical efficiency ($\boldsymbol{MTE_{ji}} = \frac{Y_{ji}}{f^j(X_{ji})e^{V_{ji}}} = \boldsymbol{TGR_i^j \times TE_i^j}$) of the farm, which is the overall performance with respect to the meta-frontier. Therefore, in the meta-frontier stochastic framework, the overall efficiency of a decision-making unit relative to the best technology available is a product of the technology adoption choice by that unit (TGR) and its ability to better use that technology.

3.2.3. The multinomial endogenous treatment effects model

We model farmers' technology choices (irrigation, certified seed, and fertilizer) and their impact on outcome variables using a multinomial endogenous treatment effect model as proposed by Deb and Trivedi (2006a, b). The main advantage of this approach as an impact evaluation setting is that it accounts for selection bias due to both observed (through the farm or household characteristics) and unobserved heterogeneity (via latent variables). This approach specifies a joint distribution of endogenous multivalued treatment and outcome using observed and unobserved characteristics to link treatment and outcome equations.

The framework proposed by Deb and Trivedi (2006a, b) has two components: treatment equation and outcome equation; these equations are linked by unobserved and observed characteristics. Let d_{it} be binary variables representing the observed market choice (treatment) by farmer *i* and *C* the number of possible choices.

$$d_{it}(T_i) = \begin{cases} 1, \; if\; T_i = t & (\mathrm{t} = 0,1,2, \dots, \mathrm{C}) \\ 0, & otherwise \end{cases} \quad (3.6)$$

The probability of treatment can be represented as:

$$Pr[d_{it}|z_i, l_i] = z'_i\alpha_t + \sum_{k=1}^{T} \delta_{tk} l_{ik} + \varepsilon_{it} \quad (3.7)$$

ε_{it} is the error term, and $Pr[d_{it}|z_i, l_i]$ is supposed to be a multinomial logistic function g, z denotes exogenous covariates with their associated coefficients α_t, l_{ik} which stand for unobserved characteristics (unobserved heterogeneity) common to individual ***i***'s choice and outcome such as motivation or level of information. l_{ik} are assumed to be independent of ε_{it}. We also assume that *t=0* denotes the control group (no technology adoption).

For the model to be identified, a set of restrictions are imposed. First, we impose $\delta_{tk} = 0 \; \forall \; t \neq k$, i.e. each market regime choice is affected by a unique unobserved factor. In addition, we assume that $\delta_{tt} = 1$, which implies that the scale of effects of unobserved factor is normalized and equal to 1 in the treatment equation. See Deb and Trivedi (2006a, b).

The outcome equation is as follows

$$y_i = x'_i\beta + \sum_{t=1}^{T} \theta_t d_{it} + \sum_{t=1}^{T} \pi_t l_{it} + \epsilon_i \quad (3.8)$$

Where ϵ_i is the error term, y_i is supposed to follow a normal density distribution f, x denotes exogenous covariates with associated coefficients β, θ_t are the treatment effects relative to the control. The outcome y_i is affected by unobserved characteristics l_{it} that affect selection into treatment. If π_t is positive (negative), treatment and outcome are positively (negatively) correlated through unobserved characteristics, i.e., there is positive (negative) selection.

In practice, l_{it} are non-observed. Following Deb and Trivedi (2006a, b) we assume that they are *i.i.d* and drawn from a normal distribution and their joint distribution h can be integrated out of the joint density distribution of selection and outcome variables as follows:

$$\boldsymbol{\omega}(y_i, d_{it}|x_i, z_i) = \int \{\boldsymbol{f}(y_i, |x_i, d_{it}, l_{it}) * \boldsymbol{g}(z_i, l_i)\}\, \boldsymbol{h}(l_{it}) dl_{it} \qquad (3.9)$$

For a given specification of *f*, *g* and *h*, the integral (3.9) do not have a closed solution form. Then, the full estimation of equations (3.7) and (3.8) is based on a simulation-based estimation framework. This method finds the values of parameters that maximize the simulated log-likelihood function associated with a joint density distribution of selection and outcome variables (equation 3.9). For a large number of simulations (S), the maximization of the simulated log-likelihood is equivalent to maximizing the log-likelihood (Train 2009). The simulated log-likelihood function of $\boldsymbol{\omega}(y_i, d_{it}|x_i, z_i)$ is:

$$\mathbf{ln}\, \boldsymbol{L}(y_i, d_{it}|x_i, z_i) = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \mathbf{ln}\, \widehat{\boldsymbol{\omega}}(y_i, d_{it}|x_i, z_i) = \sum_{i=1}^{N} \ln\left(\frac{1}{S}\sum_{s=1}^{S}\{\boldsymbol{f}\big(y_i, |x_i, d_{it}, \hat{l}_{its}\big) * \boldsymbol{g}\big(z_i, \hat{l}_{its}\big)\}\right)$$

Where $\hat{l}_{its}$ is the sth draw (from a total S draws) of a pseudo-random number from the density *h*.

Since our outcome variable is continuous, we assume that it follows a normal (Gaussian) distribution function. The resulting model was estimated using a Maximum Simulated Likelihood (MSL) approach using the Stata command ***mtreatreg*** proposed by Deb (2009).

3.3. Data presentation and descriptive results

3.3.1. Data presentation

Data used in this study were collected under the PAPA[5] project, which is an initiative of the Government of Senegal funded by USAID-Senegal as part of the “Feed the Future” initiative. It was implemented over a period of three years (2015–2018) by the Ministry of Agriculture and rural facilities with the International Food Policy Research Institute (IFPRI).

Data from two surveys (rainfed and irrigated crop systems) were used to construct these rice production data. The first survey was representative of the rainfed cropping system in Senegal (42 of 45 departments in the country). A total of 4,533 farm households were interviewed, among them 851 rice farming households.

[5] Official website of the project is http://www.papa.gouv.sn/.

The second survey collected information on irrigated rice in the two agroecological zones where irrigation is mainly practiced (Senegal River valley and Anambe basin). Irrigated rice production accounts for about 70–75% of the country's total rice production. Most farmers surveyed were involved in rice production, for a total of 630 rice producers over the 730 farm households surveyed. The Senegal River valley (SRV) is the largest irrigation zone, with about 75% of irrigated rice production. Therefore, the sampling takes into consideration the differentiation in sampling size from the two targeted zones (75% of the sample size from SRV and 25% from the Anambe basin (AB).

The initial sample size was 1,465 rice-farming households. We removed those households that had cultivated fewer than 0.01 hectares (10 observations) and more than 15 hectares (10 observations), which are almost the first (0.02 ha) and the 99th centiles (12.4 ha) of the cultivated area.

3.3.2. Technology adoption and rice yield

Table 3- 1 presents the sample distribution across technology choices along with the observed land productivity (average, median, and standard deviation). Results show that 33% (467/1,415) of rice producers in the sample did not adopt any of the three technologies under consideration.

Table 3- 1: Technology adoption and rice yield (kg/ha) in Senegal

		Observation	Average yield	Median yield	Standard deviation
Group 0	No technology in rainfed	467	1204	800	1696
Group 1	Fertilizer use in rainfed	158	882	750	683
Group 2	Fertilizer use in irrigated	130	3165	2679	2296
Group 3	Fertilizer and certified seed in rainfed	120	1410	1020	1522
Group 4	Fertilizer and certified seed in irrigated	497	3806	3500	2386
Group 5	Other technology choices	43	815	800	567
All	Total	1415	2268	1233	2303

Source: Authors' calculations based on PAPA data (2017).

On the other hand, 35% of rice farmers practiced irrigation in combination with the other two improved inputs. This suggests that technology adoption is more frequent for irrigated rice than for rainfed rice production. One important observation is that very few rice farmers adopted solely certified seeds. One can conclude that farmers are aware of the complementarity between certified seeds and inorganic fertilizers. They can use fertilizer alone but seldom certified seeds alone. Regarding production per hectare, results show that irrigation-based production is the most productive and that the use of certified and inorganic fertilizers increases land productivity. The average yield of irrigated rice is about three times higher than that of rainfed rice in Senegal.

Table 3- 2: Rice yield (kg/ha) across regions of Senegal

	Observation	Average yield	Median yield	Standard deviation
Ziguinchor	307	1507	930	1960
Saint-Louis	364	4703	4541	2325
Tambacounda	23	1317	933	1458
Kaolack	4	188	200	63
Thies	1	8000	8000	
Fatick	4	875	650	780
Kolda	354	1337	971	1262
Matam	95	3199	2800	1812
Kaffrine	7	720	450	486
Kedougou	63	980	900	665
Sedhiou	193	766	667	517
Total	1415	2267.86	1233	2303

Source: Authors' calculations based on PAPA data (2017).

Across regions (**Table 3- 2**), results show also that irrigation-oriented regions (Saint Louis and Matam) are the most productive.

3.3.3. Definition and summary statistics for variables used

Table 3- 3 describes all variables used in the econometric analysis along with a Kruskal Wallis test that checks whether the distribution of these variables is identical across the treatment groups.

In the sample, the average cultivated area for rice stood at 1.2 ha. Farm households produced about 3.8 tons of rice per year, with an average yield of 2.3 tons/ha. They employed about seven workers and used about 290 kg of chemical fertilizers and 100 kg of seeds. Among rice-producing households, more than 50% produced only rice. Extension workers had visited about 30% of households. In approximately 27% of households in the sample, at least one member belonged to a farmers' organization.

The access to credit is very limited: only 8.7% of households had received credit during the production season. Most household heads were male (90%) and literate (45%), with an average

age of 53 years of age. About two out of five households in the sample own transport means (*charrette*, in French), while about 21% own an agricultural machine.

Table 3- 3: Summary Statistics of most Variables used in the analysis

		Sample description		Kruskal Wallis test over adoption level	
Variable	Description	Mean	SD	Chi-squared	p-value
Sexe	Household head is male	0.900	0.300	3.874	0.423
Hhsize	Household size (persons)	9.371	5.018	23.611	0.000
Age	Household head's age	53.054	12.457	9.884	0.042
HeadLiterate	Household head is literate	0.443	0.497	7.599	0.107
Organization	Farmers organization	0.276	0.447	128.139	0.000
extension_services	Extension services	0.310	0.463	158.459	0.000
Credit	credit access	0.087	0.283	19.950	0.001
Rice_only	Rice specialization	0.536	0.499	213.120	0.000
production_kg	Rice production, tons	2.997	7.745	539.704	0.000
production_kg_ha	Rice yield, kg/ha	2.322	2.321	543.433	0.000
Land	Rice cultivated area, ha	1.248	1.593	161.234	0.000
Labor	labor (number of workers)	6.328	4.036	118.987	0.000
Capital	Agricultural capital (XOF 1000)	135.627	961.665	30.189	0.000
lcap2	Dummy for zero capital value	0.223	0.417	16.660	0.002
qte_fertilizer	Fertilizer use, kg	289.945	628.462	982.299	0.000
lfert2	Dummy for zero fertilizer use	0.339	0.474	914.841	0.000
seed_kg	Seed use, kg	99.980	147.358	151.237	0.000
other_cost	other cost (XOF 1000)	42.857	108.853	519.480	0.000
Machine	Agricultural equipment (1=yes)	0.215	0.411	22.861	0.000
moyen_transport	Transport equipment (1=yes)	0.380	0.486	100.837	0.000
SQI	Soil quality index	0.251	0.060	35.018	0.000
temperature_2016	Tempature for 2016 (mean)	35.495	2.314	900.916	0.000
temperature_deg_sd	Tempature for 2016 (sd)	2.282	0.633	141.677	0.000
rainfall_2016	Rainfall for 2016 (total)	781.970	410.664	889.286	0.000
rainfall_mm_sd	Rainfall for 2016 (sd)	104.749	47.683	899.294	0.000
zone1	AEZ: Senegal River Valley	0.037	0.190	9.585	0.048
zone2	AEZ: Ferlo	0.276	0.447	340.610	0.000
zone3	AEZ: Casamance	0.077	0.267	29.057	0.000
zone4	AEZ: Other	0.609	0.488	481.904	0.000
Sample size		1361	1361		

Source: Authors' calculations based on PAPA data (2017). Notes: The Kruskal Wallis test is conducted for each variable in the Table based on technology adoption groups.

Across technology adoption groups, the Kruskal Wallis H tests showed a statistically significant difference in all factors considered in Table 3- 3 except for gender and literacy rate when considering a 5% level of significance. Therefore, some of these variables may explain their heterogeneous behavior regarding input choices. However, such tests do not account for comparability across groups, nor do they control for the effect of other covariates. Consequently, further analysis is required to establish causality.

3.4. Results and discussion

3.4.1. Rice production function estimates

Results from the stochastic frontier models estimated on the sample of rice farms in Senegal are presented in Table 3- 4. A Cobb-Douglas specification with a half-normal distribution is used in this application. Seven inputs were considered: rice allocated area (ha); labor used for rice production measured as the number of workers; the value of agricultural equipment in the local currency; quantity in kg of chemical fertilizer; certified seeds used; non-certified seeds used; and overhead costs in local currency. Since our dataset shows a lot of zero values for some important inputs such as fertilizer quantity, value of agricultural capital, and other costs, we used the approach proposed by Battese (1997) and adopted by several authors in the literature (Rao et al. 2012; Villano et al. 2015; Abdul-Rahaman and Abdulai 2018). For these variables, the undefined logarithm is replaced by zero and a dummy variable is created to account for these zero values.

Agroecological zone differences are accounted for by including a dummy for the Casamance zone. Using likelihood ratio tests, heteroscedastic specification in both inefficiency and idiosyncratic error are preferred. For the inefficiency variance, we include gender, age dummies (younger and older heads), literacy dummy, access to extension services, farmer organization, and credit. The production variance is explained by the rice cultivated area and the soil quality index.

The log-likelihood of the pooled SFA is found to be less than that obtained by summing the log-likelihood for individual SFA (-1502 vs. -1327). Therefore, the hypothesis of homogeneous technology across farmers is rejected as having a high level of significance for rice production in Senegal, meaning that across groups, farmers operate under different frontiers of production. The meta-frontier approach is therefore appropriate.

Across equations, land use has the highest elasticity. This finding suggests that farmers could be advised to use more land than what they presently use to increase production, especially for farmers who used only fertilizers in the irrigated system. The return to labor was found to be insignificant for all groups of rice farmers. This result may be linked to the abundance of the labor force in developing countries. Similar results have been reported by Abdul-Rahaman and Abdulai (2018) in Ghana.

Table 3- 4: Parameters of group production frontiers, meta-frontier framework

		Pooled	Frontier 1	Frontier 2	Frontier 3	Frontier 4	Frontier 5	Meta-frontier
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Frontier	Lland	0.719***	0.768***	0.503***	0.977***	0.707***	0.899***	0.823***
		(0.034)	(0.062)	(0.088)	(0.121)	(0.111)	(0.033)	(0.011)
	Llabor	-0.059*	-0.002	0.100	0.034	-0.145	0.016	-0.009
		(0.030)	(0.065)	(0.084)	(0.078)	(0.097)	(0.028)	(0.009)
	Lcap	0.070***	0.028	-0.008	0.066*	0.057	0.027*	0.033***
		(0.016)	(0.035)	(0.050)	(0.039)	(0.053)	(0.016)	(0.005)
	lcap2	0.776***	0.205	0.291	1.008**	0.633	0.231	0.310***
		(0.177)	(0.380)	(0.548)	(0.429)	(0.589)	(0.194)	(0.052)
	Lfert	0.279***		0.240***	0.201**	0.376***	0.129***	0.217***
		(0.027)		(0.079)	(0.081)	(0.059)	(0.018)	(0.010)
	lfert2	1.250***						0.412***
		(0.140)						(0.056)
	Lseed	0.025	0.113**	0.008	-0.161***	-0.068	-0.003	0.014***
		(0.018)	(0.051)	(0.054)	(0.055)	(0.051)	(0.010)	(0.005)
	lother_cost	0.073***	0.050	0.090*	0.004	0.087*	-0.022**	-0.006
		(0.018)	(0.045)	(0.049)	(0.051)	(0.046)	(0.009)	(0.005)
	lother_cost2	0.325*	0.190	0.438	-0.530	0.774	-0.444***	-0.375***
		(0.176)	(0.405)	(0.428)	(0.529)	(0.482)	(0.102)	(0.053)
	SQI	0.161	3.833***	0.307	-2.140**	1.474	0.273	1.401***
		(0.347)	(0.771)	(1.043)	(0.936)	(1.580)	(0.448)	(0.109)
	zone4	-0.816***	0.051	-0.290**	-0.455*	-0.185	-0.958***	
		(0.057)	(0.195)	(0.144)	(0.247)	(0.147)	(0.042)	
	Extension services*							0.620***
								(0.111)
	Rice specialization*							0.999***
								(0.072)
	Farm size*							1.577***
								(0.136)
	Constant	5.573***	4.861***	5.315***	7.476***	4.623***	8.222***	4.876***
		(0.295)	(0.605)	(0.738)	(0.955)	(1.022)	(0.224)	(0.138)
Inefficiency variance	extension_services	-0.240*	-31.177	0.741	-0.565	0.363	-0.186	
		(0.128)	(1,792.525)	(0.660)	(0.612)	(0.376)	(0.149)	
	Organization	0.002	0.933*	-0.081	-2.339	-0.108	-0.131	

		(0.122)	(0.560)	(0.564)	(2.107)	(0.367)	(0.143)	
	Credit	-0.605***	0.520	0.672	-25.194	-1.542***	-0.218	
		(0.209)	(1.376)	(0.925)	(1,247.476)	(0.523)	(0.176)	
	HeadLiterate	-0.099	-0.286	-0.072	1.139*	0.154	-0.269*	
		(0.108)	(0.406)	(0.376)	(0.673)	(0.361)	(0.143)	
	Sexe	0.043	-0.298	0.792	3.919	-0.136	-0.245	
		(0.176)	(0.554)	(0.689)	(3.708)	(0.448)	(0.265)	
	age45	-0.141	0.523	-0.251	-0.524	-0.388	-0.158	
		(0.118)	(0.416)	(0.422)	(0.536)	(0.384)	(0.154)	
	age65	-0.433***	-0.115	-0.414	-0.759	-0.710	-0.341*	
		(0.154)	(0.501)	(0.508)	(0.914)	(0.459)	(0.194)	
	Rice_only	-0.385***	0.043	1.207**	1.470	-0.497	-0.073	
		(0.114)	(0.458)	(0.535)	(1.137)	(0.390)	(0.175)	
	Constant	0.202	-1.305**	-1.770	-5.810	0.670	0.746**	-1.446***
		(0.206)	(0.656)	(1.165)	(4.364)	(0.434)	(0.320)	(0.049)
Error variance	Lland	-0.313***	-0.277***	-0.011	-0.200	1.960***	1.410***	
		(0.078)	(0.101)	(0.404)	(0.183)	(0.684)	(0.398)	
	SQI	5.374***	2.000	-5.050	13.803***	-62.042***	-35.486***	
		(1.222)	(1.450)	(4.188)	(2.902)	(24.019)	(8.809)	
	Constant	-2.822***	-1.420***	-0.499	-4.627***	10.673**	3.042*	-5.303***
		(0.345)	(0.386)	(1.066)	(0.807)	(5.175)	(1.553)	(0.200)
Log Likelihood		-1502	-522.3	-138.0	-142.6	-110.1	-414.3	-154.9
Wald Chi2		3197	397.6	185	215.0	4172	4702	37418
Degree of freedom		11	9	10	10	10	10	13
Observations		1,361	462	158	130	114	497	1,361

Notes: ***, ** and *: 1, 5 and 10% levels of significance, respectively. Variable names with * stand for the corresponding region level average. Farm size represents a dummy for small size rice area (less or equal to 1 hectare). Frontier 1: “No technology in rainfed”, Frontier 2: “Fertilizer use in rainfed”, Frontier 3: “Fertilizer use in irrigated”, Frontier 4: “Fertilizer and certified seed in rainfed”, Frontier 5: “Fertilizer and certified seed in irrigated”.

Our results confirmed also that the use of chemical fertilizer has a strong positive effect on the production frontier. Conversely, the elasticity of certified seeds was significantly positive for non-adopters, negative for the irrigated system when only fertilizers were adopted, and non-significant for other groups. Based on our descriptive statistics, farmers preferred to adopt the full package or adopt only inorganic fertilizers. This finding suggests that only using certified seeds does not improve farm productivity. Agroecological dummies in the production frontiers were significant and negative, implying that rice productivity is heterogeneous across agroecological zones in Senegal.

3.4.2. Rice technical efficiency estimates

presents a summary statistic of the group-specific technical efficiency, technology gap ratio, and meta-technical efficiency by technology adoption groups. The group-specific technical efficiency cannot be compared across groups because it is estimated with respect to different frontiers. This indicator reports the relative technical efficiency: the lower the score, the less efficient the farmers using their production technology. The technology gap ratio (TGR) measures how far the group-specific frontier is to the best available rice production frontier. A lower TGR score suggests that farmers operate on a lower frontier of production compared to the meta frontier. This can be compared across groups as the closest or farthest technology relative to the meta frontier. Finally, the meta-technical efficiency is the global efficiency score and is comparable across groups and farmers.

Results show that the average relative technical efficiency is 74% for non-adopters, 64% for the group of fertilizer adopters in the rainfed system, 73% for the group of fertilizer adopters in the irrigated system, and about 50% for full adopters (certified seeds and fertilizers) in rainfed and irrigated systems. This shows that traditional rice farmers have a better command of their technology than do modern rice farmers, especially when farmers had adopted both certified seeds and chemical fertilizer. Since fertilizer adopters seem to be more efficient than farmers that jointly adopted CS and CF, we may infer that the most challenging technology would be certified seeds (CS). These results reveal a significant knowledge gap among farmers. Modern technology adopters may need more information or training on these technologies to increase their efficiency. In terms of ranking technologies (TGR), on average, full adopters in irrigated systems seem to operate under a technology very close to the meta frontier (85%), followed by traditional rice producers (74%) and full adopters in rainfed systems (72%). As expected, improved inputs combined with irrigation for rice allow farmers to operate under the best available production frontier for rice. Nevertheless, these full adopters in irrigation may need to improve their productivity for some production factors in which traditional rice producers seem to perform better.

Regarding the meta (overall) technical efficiency (MTE), results indicate that traditional rice producers in Senegal have the highest score of technical efficiency (55%), followed by full adopters in irrigation systems (44%) and full adopters in rainfed rice production (36%). The MTE score at the sample level stands at 45%, which suggests that rice production in Senegal could double with the same level of inputs if farmers were fully efficient. There is an urgent need to design a good capacity-building program for rice farmers on rice production's best practices. Issues relating to sowing techniques, proper use of plant protection products, the correct dosage of chemical fertilizers, and the correct period of their application should in particular be addressed.

Recently, AfricaRice and the country's agricultural research institute (ISRA) have introduced rice advice technology to improve the combination of input use with the technical itinerary.

Table 3- 5 presents a summary statistic of the group-specific technical efficiency, technology gap ratio, and meta-technical efficiency by technology adoption groups. The group-specific technical efficiency cannot be compared across groups because it is estimated with respect to different frontiers. This indicator reports the relative technical efficiency: the lower the score, the less efficient the farmers using their production technology. The technology gap ratio (TGR) measures how far the group-specific frontier is to the best available rice production frontier. A lower TGR score suggests that farmers operate on a lower frontier of production compared to the meta frontier. This can be compared across groups as the closest or farthest technology relative to the meta frontier. Finally, the meta-technical efficiency is the global efficiency score and is comparable across groups and farmers.

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Recently, AfricaRice[6] and the country's agricultural research institute (ISRA)[7] have introduced rice advice technology to improve the combination of input use with the technical itinerary.

Table 3- 5: Rice production efficiency scores by farmers' groups (mean and standard deviation)

	Sample size	Group specific Technical Efficiency	Technology gap ratio	Meta (overall) Technical Efficiency
No adoption	462	0.742 (0.121)	0.742 (0.117)	0.551 (0.125)
CF adoption in rainfed system	158	0.637 (0.164)	0.489 (0.15)	0.313 (0.129)
CF adoption in irrigated system	130	0.731 (0.215)	0.458 (0.164)	0.333 (0.16)
CF and CS adoption in rainfed system	114	0.521 (0.255)	0.719 (0.152)	0.364 (0.188)
CF and CS adoption in irrigated system	497	0.518 (0.241)	0.848 (0.072)	0.437 (0.204)
Total	**1361**	**0.629 (0.223)**	**0.722 (0.18)**	**0.445 (0.188)**

Notes: Standard deviations are in parenthesis. CF stands for chemical fertilizer, and CS for certified seeds.

The study reveals that efforts to fill the efficiency gap identified for farmers' groups are not identical across groups. For traditional rice producers, there is room to increase the relative

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[6] The Africa Rice Center (AfricaRice), http://www.africarice.org, is a leading pan-African rice research organization committed to improving livelihoods in Africa through strong science and effective partnerships. AfricaRice is a CGIAR Research Center—part of a global research partnership for a food-secure future.

[7] The Senegalese Institute of Agricultural Research (ISRA, in French), https://www.isra.sn, is an applied scientific and technical research institute. A public scientific institution, it was created in 1974 to design, organize, and carry out all research relating to the rural sector in Senegal.

technical efficiency by 25 percentage points and to shift the production frontier by about 25 percentage points. For full adopters of improved inputs, the challenge is more related to their managerial skills. For households that adopted only fertilizers in both systems (rainfed and irrigation), results reveal a huge technology gap to fill. To sum up, policymakers need to adjust interventions for each group of farmers depending on where the highest gap is identified.

3.4.3. Technology choice, factors mix and land productivity

From the meta frontier framework, one could analyze different scenarios of technology choices and its implications on land productivity. For example, we could identify the technology choice that would generate the highest yield for each group of farmers. In our context, five individual rice production frontiers and one reference rice technology (meta frontier) are available. Table 3- 6 gives the number of observations in each group of farmers and the predicted rice production per hectare for various groups of farmers using a selected rice technology. Figures in bold are the predicted yield for each group of farmers (rows) using their observed technology choice. Other figures give the "counterfactual" potential yield had they made another technology choice. For each row (group of farmers), if the number in bold is higher than the other numbers in that row, it is concluded that the farmers in this group made the **best choice of technologies** given their mix of factors of production. Otherwise, another choice of production frontier would have been more optimal based on their factors mix in terms of yields per hectare. This analysis did not consider the potential cost of another input or of switching to another technology (learning curve). Where possible, we will briefly discuss the potential increase or decrease in cost among the different choices and the existence of a significant cost of mastering the destination technology. More detailed analyses could be carried out using our results as a starting point. The last column gives the expected yield if farmers were using the reference technology.

Results show that non-adopters would have gained about 487 kg per hectare if they had applied certified seeds and fertilizers in an irrigated context. However, it should be noted that there are more barriers when switching from a traditional technology to the most advanced technology in another production system (rainfed vs. irrigated). This technology is very expensive, and the learning and transitioning cost remain a huge challenge. On the other hand, the other three technology options (frontiers 2, 3, and 4) generate barely half the yield of their initial choice. Thus, it can be concluded that non-adoption of an improved input is the best feasible choice for these farmers.

For farmers that had initially adopted fertilizer in the rainfed system, they would reach higher rice yield by combining fertilizer with certified seeds or/and irrigation. If the cost is affordable, three better choices are available to them. The potentially simpler choice would be to jointly adopt certified seeds and fertilizer for a yield gain of 433 kg per hectare. However, these farmers would reach 2.5 times their current yield by producing irrigated rice using fertilizer and certified seeds. Despite the huge yield gain for this group in shifting from their current choice to the full package, it should be noted that this group gets only half the yield of current irrigated rice farmers making an identical choice. This shows the importance of the mix of factors of production in the level of yield reachable.

Table 3- 6: Predicted rice yield across technologies and group of farmers

	Sample size	Frontier 1	Frontier 2	Frontier 3	Frontier 4	Frontier 5	Meta frontier
Non-adopters	462	**1147 (383)**	557 (353)	650 (249)	388 (152)	1634 (498)	1539 (419)
Fertilizer adopters (1)	158	1014 (345)	**1287 (701)**	1836 (838)	1721 (771)	3253 (1754)	2707 (1448)
Fertilizer adopter (2)	130	1278 (457)	2968 (1264)	**3927 (1591)**	3549 (1239)	7773 (2063)	9290 (3166)
Certified seeds and fertilizer adopters (1)	114	1188 (309)	1676 (707)	2315 (1064)	**2476 (998)**	3945 (1771)	3462 (1441)
Certified seeds and fertilizer adopters (2)	497	1192 (328)	2706 (1176)	3853 (1408)	3647 (1250)	**7240 (2424)**	8719 (3400)
All rice farmers	1361	1164 (367)	1750 (1334)	2410 (1798)	2210 (1721)	4649 (3160)	5198 (4159)

Note: Standard deviations are in parenthesis. Figures in bold represent the expected yield based on the current choice of technology. (1) stands for rainfed system, and (2) represents irrigation-based system.

For fertilizer adopters in the irrigated production system, results reveal that they could expect higher rice production only by adding certified seeds to their current choice. Importantly, this choice would result in doubling their potential yield from a current 3.9 metric tons per hectare to 7.8 metric tons per hectare. In addition, this potential yield is the highest predicted using this technology. This suggests that this group of farmers has on average a better factors mix to produce rice using this technology. Since the targeted technology is not too different from their current technology, and the additional cost is not critical, it would be good for these farmers to opt for this technology choice.

In the group of farmers that jointly adopted certified seeds and fertilizer, they would get 60% higher yield if they were using the same technology in the irrigated instead of the rainfed system. Even if the expected gain is substantial, the change from rainfed to irrigated production requires huge costs and skills that may outweigh the gain in the short term. However, if the government could facilitate this transition, the expected gain for these farmers is certain.

For irrigated rice producers that had already adopted certified seeds and fertilizer, results show that they could not make a better choice among the five options considered here. It seems to appear that farmers in this group selected a mix of factors of production that better fit the technology they used. This is the only group that could not make a better choice if alternative technologies were costless.

When it comes to the meta frontier (reference technology), as expected, farmers would get higher potential yield compared to their current yield. However, with respect to the five individual production frontiers analyzed earlier, two trends emerge: (i) the groups of farmers that have the highest yield along the reference frontier, and (ii) the groups with the highest rice yield with one of the individual frontiers. Indeed, the meta frontier allows farmers in the irrigated system to reach higher rice production per hectare, while farmers in the rainfed system would reach the maximum rice yield by transitioning to irrigated rice.

3.4.4. The treatment effect of technology adoption on efficiency scores

The previous sections directly compare the overall efficiency (MTE) and predicted yields of rice production across groups of farmers. Even though the meta-frontier framework assumes a different production frontier for each group of farmers, it is difficult to interpret observed differences across groups as caused only by the technology choice. In fact, farmers are not randomly assigned to treatment groups. Some of the factors determining technology adoption may also influence efficiency and productivity. Therefore, as discussed in the *Technology Adoption and Rice Yield* section, we estimate a multinomial endogenous treatment effects model.

Because we are primarily interested in the effects of the use of improved inputs on rice technical efficiency and predicted yields, we do not discuss the determinants of farmers' choices. The estimation results are provided as supplementary materials at the end of the article. It is worth noting that in the selection equation, various factors affecting technology adoption were considered, including gender, family size, transport means, education, access to extension services, access to credit, farm size, soil quality index, farmer organization membership, and access to mechanization. We also controlled for heterogeneity among farmers in the outcome equation by accounting for, among others, gender, education, farmer organization, extension services, credit, average rainy season temperature for 2016, average rainfall during the wet season for 2016, quantity of fertilizer used per hectare, quantity of certified seed used per hectare, value of agricultural equipment per hectare, farm size, soil quality, and agroecological zones fixed effects.

Table 3- 7: Treatment effects of technology choices

	Technical Efficiency	Group specific yield (kg/ha)	Meta yield (kg/ha)
CF adoption in rainfed system	-0.338***(0.006)	-439***(142)	1,000***(80)
CF adoption in irrigated system	-0.163***(0.011)	-1,716***(213)	502***(159)
CF and CS adoption in rainfed system	-0.155***(0.007)	832***(119)	338**(135)
CF and CS adoption in irrigated system	-0.097***(0.011)	2,307***(185)	639***(135)

Notes: The baseline is farm households that did not adopt any improved inputs in the rainfed system. The sample size is 1 361 households and 1 000 simulation draws were used. ***P < 0.01, **P < 0.05, *P < 0.1. Robust standard errors are in parenthesis.

Table 3- 7 presents the estimates of the impact of rice technology choices on technical efficiency, predicted yield from individual frontiers of production, and predicted rice yield using the meta frontier (reference technology).

As already observed in Table 3- 5, results show that farmers that used improved inputs (certified seeds, fertilizer, or irrigation) were less efficient than non-adopters of those inputs. The treatment effects of use of improved inputs are negative on rice production technical efficiency. Even though the efficiency gap decreases from the simple choice of fertilizer to the combined choice of irrigation, fertilizer, and certified seeds, the conclusion is that there is a knowledge gap among rice farmers. Adopting fertilizers is 34 percentage points and 16 percentage points less efficient than no technology adoption strategy respectively in rainfed and irrigated systems. The joint adoption of certified seeds and fertilizer has a negative impact of 16 percentage points in the rainfed system and 10 percentage points in the irrigated system.

Regarding the expected land productivity of rice production from the use of each technology choice, results show that the joint adoption of certified seeds and fertilizer in rainfed or irrigated fields have a higher expected yield than the "no adoption" choice. Results also reveal that an irrigation system is a superior technology. On the other hand, the adoption of fertilizer did not really affect the land productivity when selection bias was controlled for. These results show that in the two rice production systems, it is critical for farmers to adopt the two proposed technologies (certified seeds and chemical fertilizer) to expect higher yield compared to the reference technology (no technology adoption). The expected productivity gain from such adoption is 840 kg/ha in the rainfed system and 2,574 kg/ha for the irrigated system. If the mix of factors of production remains unchanged, farmers that have currently adopted only fertilizer in rainfed or irrigated systems should give up such a choice. *Ceteris paribus*, farmers performed better than farmers in the reference group.

On the other hand, if all farmers were using the reference rice technology, the use of improved inputs would have a positive effect on rice yield. These results clearly reveal the positive impact of improved inputs on rice production per hectare if farmers were using the right technology and the right factors mix. Technology and factors mix are crucial to get the maximum benefits of a production technology. Using the best technology with the wrong factor mix would lead to a lower productivity. Therefore, it is important to identify clearly what is the right factor mix of each technology choice. One interesting pattern of the results is that the best technology choice depends upon the system of production considered. In the rainfed system, the best improved inputs choice is to use only fertilizer. This result certainly means that water control (irrigation) is an important factor in the adoption of certified seeds. As far as irrigated rice production is concerned, the joint adoption of certified seeds and fertilizers is the most interesting choice to be made by the rice growers. This confirms the correlation between water control and the use of certified seeds. Another result of this work is that with the production technology, the use of fertilizers in rice production in Senegal is sufficient to obtain the best possible yield.

3.5. Conclusion

In Senegal, as in many developing countries, rice plays a central role in the diet. In addition, the major share of rice consumption in Senegal is satisfied by imports. Therefore, one of the most important objectives for the country’s successive governments is to implement policies that lead to rice self-sufficiency. Among other policies to pursue are the promotion of irrigated rice access to good quality inputs, especially through subsidies. Thus, this article contributes to the debate on the relationship between farm inputs and farm productivity by using a recent farm household survey to analyze the level of technical efficiency in the rice sector. A special focus was put on the role of the most important technologies used for rice production, especially irrigation, certified seeds, and inorganic fertilizer. On the methodological side, this study applies the most advanced and appropriate techniques to analyze technical efficiency by accounting for heterogeneous rice production frontiers (meta-frontier framework) and selection bias in a multinomial setting (multinomial endogenous treatment effects model). These approaches allowed for the estimation of the unbiased and consistent impact of technology choices on rice yield and technical efficiency.

The estimates revealed both the presence of heterogeneous production frontiers and selection bias. The estimated technical efficiency was very low, suggesting that with the right policies, the country's rice production could double with any additional investment in inputs. Across groups, the traditional rice system is the most efficient. A huge technological gap was also observed, especially for farmers that partially adopt improved inputs (certified seeds and inorganic fertilizer). In terms of impact on yield, results show that the most productive choice for farmers is to adopt certified seeds and fertilizer in the irrigated system. However, if all farmers were using the reference rice technology, it was found that the use of improved inputs would have a positive effect on rice yield. Regarding current input choice by farmers, results reveal that most farmers made a wrong technology choice, except farmers using an irrigated system who had adopted both certified seeds and fertilizers.

A number of policy implications can be drawn from the findings of this study. First, results suggest that public policies aimed at increasing rice production to cover the local rice demand should support innovations that increase farmers' skills in terms of technology management and best practices of rice production based on local experience. The positive impact of irrigation on rice yield is an additional motive for the government to continue implementing irrigation-related policies and to make irrigation more accessible to farmers. On the other hand, as shown in many studies, certified seeds and inorganic fertilizers are complementary inputs, so policymakers should promote them as a package for a maximum impact and facilitate farmers' access through input credits or the promotion of contract farming. Finally, technology choice is a serious challenge for farmers, as most of them did select the wrong improved inputs. Therefore, there is a need to assist them in selecting the right improved inputs based on their other factors mix.

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Supplementary materials

Table A3- 1: Determinants of rice technology choices (multinomial logit model)

	Technology choices			
	Group 1	Group 2	Group 3	Group 4
HeadLiterate	-0.018	-0.641***	-0.361	-0.496***
	(0.199)	(0.236)	(0.235)	(0.186)
Sexe	0.221	0.211	-0.473	0.915***
	(0.357)	(0.349)	(0.354)	(0.313)
hhsize	0.021	-0.075***	0.015	-0.056***
	(0.021)	(0.025)	(0.020)	(0.020)
extension_services	0.284	1.284***	1.269***	1.924***
	(0.307)	(0.264)	(0.282)	(0.215)
organization	0.278	1.419***	0.938***	2.215***
	(0.312)	(0.313)	(0.304)	(0.259)
credit	0.906	2.241***	2.445***	2.977***
	(0.647)	(0.591)	(0.573)	(0.542)
moyen_transport	0.700***	2.026***	0.943***	1.849***
	(0.211)	(0.242)	(0.253)	(0.197)
Rice_only	-0.418*	2.705***	0.494*	2.540***
	(0.249)	(0.318)	(0.300)	(0.222)
machine	-0.157	0.735**	1.131***	0.427
	(0.247)	(0.309)	(0.280)	(0.260)
land	1.045***	0.830***	1.098***	1.166***
	(0.163)	(0.187)	(0.170)	(0.166)
SQI	-3.497**	-3.581*	-1.370	-7.894***
	(1.738)	(1.920)	(1.952)	(1.532)
Constant	-1.702***	-3.343***	-2.995***	-2.609***
	(0.580)	(0.691)	(0.580)	(0.521)
Pseudo R-Squared	0.283	0.283	0.283	0.283
Log-Likelihood	-1382	-1382	-1382	-1382
Wald chi2 (44)	572.8	572.8	572.8	572.8
Observations	1,361	1,361	1,361	1,361

Note: Robust standard errors are in parentheses. Significance : *** p<0.01, ** p<0.05, * p<0.1. Notes: **Group 0**: "No technology in rainfed" (the reference group), **Group 1**: "Fertilizer use in rainfed", **Group 2**: "Fertilizer use in irrigated", **Group 3**: "Fertilizer and certified seed in rainfed", **Group 4**: "Fertilizer and certified seed in irrigated".

Table A3- 2: Determinants of technical efficiency and rice yield (results of outcome equations)

		Technical efficiency	group-specific yield	Meta-frontier specific yield
Treatment level	Fertilizer use in rainfed	-0.350***	-352.930***	-374.900***
		(0.003)	(130.888)	(126.321)
	Fertilizer use in irrigated	-0.233***	-1,223.273***	565.874***
		(0.003)	(204.627)	(190.203)
	Fertilizer and certified seed in rainfed	-0.214***	840.206***	488.732***
		(0.002)	(170.264)	(158.449)
	Fertilizer and certified seed in irrigated	-0.121***	2,573.704***	519.205***
		(0.002)	(177.284)	(159.016)
Exogenous factors	Sexe	-0.007***	207.307***	352.979***
		(0.001)	(72.160)	(127.917)
	HeadLiterate	0.033***	30.210	79.707
		(0.002)	(42.623)	(66.690)
	Organization	-0.021***	-131.031**	-173.610**
		(0.001)	(57.690)	(76.900)
	extension_services	0.068***	48.262	-15.846
		(0.001)	(63.435)	(77.583)
	Credit	0.027***	-273.338***	-490.802***
		(0.002)	(88.369)	(151.511)
	Temperature, std dev		-521.381***	647.623***
			(106.018)	(198.817)
	Temperature, mean		231.843***	55.778
			(38.545)	(60.966)
	Rainfall 2016, total		-1,723.250***	-5,991.150***
			(325.184)	(560.888)
	Rainfall 2016, std dev		644.753*	3,633.476***
			(380.071)	(620.137)
	qte_fertilizer_ha		2.524***	5.048***
			(0.246)	(0.301)
	qte_seed_cert_ha		-1.339**	-0.247
			(0.612)	(0.775)
	capital_ha		0.000**	0.000***
			(0.000)	(0.000)
	Land	-0.003***	-10.152	105.229***
		(0.000)	(19.425)	(21.854)
	SQI		2,742.356***	10,701.581***
			(573.991)	(655.888)
	zone2	-0.077***	512.802***	952.050***

		(0.002)	(115.531)	(135.919)
	zone4	-0.001	-774.030***	-615.309***
		(0.002)	(107.317)	(139.118)
Unobserved factors	Lnsigma	-5.455***	6.416***	5.694***
		(0.144)	(0.079)	(0.988)
	Fertilizer use in rainfed	0.156***	183.997	861.977***
		(0.001)	(154.389)	(99.055)
	Fertilizer use in irrigated	0.047***	-175.503***	70.337
		(0.001)	(54.737)	(142.419)
	Fertilizer and certified seed in rainfed	0.016***	-56.329	-317.121***
		(0.001)	(114.528)	(103.642)
	Fertilizer and certified seed in irrigated	0.023***	-355.514***	-152.701***
		(0.001)	(118.193)	(55.222)
	Constant	0.578***	3,111.978*	19,701.250***
		(0.002)	(1,787.482)	(2,834.558)
Log-Likelihood		-808.8	-12308	-12613
Wald chi2		25265	30460	29625
N simulations		1000	1000	1000
Observations		1,361	1,361	1,361

Note : Robust standard errors are in parentheses. Significance : *** p<0.01, ** p<0.05, * p<0.1.

Chapter 4

4. Investing in Risky Inputs in Senegal: Implications for Farm Profit and Food Production

Authors

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4.1. Introduction

Access to input markets is considered to have positive effects on agricultural productivity and therefore on poverty reduction and food security. However, in Sub-Saharan Africa few farmers invest on inputs even though the returns of such an investment was high (De Groote et al. 2005; Duflo, Kremer and Robinson 2008; Marenya and Barrett 2009; Karlan et al. 2014). This low level of investment is partly related to the random nature of agricultural production. Rainfed agricultural production is a risky endeavor, risks relate to climate, presence of pests (invasions of plant bugs), presence of herds of cattle that can destroy crops, etc. Agricultural production and returns on investments are highly dependent on rainfall occurrence (Karlan et al. 2014; Rosenzweig and Udry 2013) and on the other risks previously mentioned. In Senegal, D'Alessandro et al. (2015) observed that a major limiting factor to the widespread adoption of improved seeds and fertilizer among smallholder farmers is the reluctance to assume risks associated with increased productivity. This is intuitive because agricultural production processes take place over time. Farmers must make some decisions regarding inputs before the beginning of the production season and therefore before the occurrence of the shocks affecting the productivity of these inputs. Furthermore, once a shock has occurred there is no way to retrieve the invested resources. This implies that when a farmer decides to invest in inputs, he/she does so without any certainty about the outcome of such a decision. Therefore, investments in agricultural inputs such as seeds (improved seeds or not) and fertilizers are considered risky investments.

Solutions exist in theory to manage this risk. The literature identifies several strategies for managing production risks. Some of these include diversification (Di Falco, Bezabih and Yesuf 2010; Bezabih and Di Falco 2012; Bezabih and Sarr 2012; Obiri and Driver 2017; Birthal and Hazrana 2019; Ullah and Shivakoti 2014), formal insurance products such as index-based products (Velandia et al. 2009; Enjolras, Capitanio and Adinolfi 2012; D'Alessandro et al. 2015; Obiri and Driver 2017; Wang, Ye and Shi 2016), agronomic practices such as conservation farming practices, mulching, sustainable land management (Liniger et al. 2011; Obiri and Driver 2017; Choudhary et al. 2016) and adoption of risk-reducing inputs or technologies[8] such as improved and high yield seeds, fertilizer, pesticides, and irrigation

[8] It must be worth noting that although these inputs or technologies are expected to have risk reducing effects, they can also potentially increase risk. For example, (Horowitz and Lichtenberg 1993) find that both fertilizer and pesticides may be risk-increasing inputs.

(Barnett, Barrett and Skees 2008; Kahan 2008; Obiri and Driver 2017). Thus, the adoption of such innovations can mitigate the consequences of risks by enabling farmers to optimize their production choices and thus achieve higher profits (Rosenzweig and Udry 2013). In a nutshell, the adoption or use of these risky inputs allows farmers to make riskier but more profitable decisions.

However, not all producers have easy access to these solutions. The literature has shown that investment constraints are due to farmers' inability to use existing theoretical solutions due to incomplete financial and insurance markets resulting in low access to capital, insurance, information, etc. Therefore, farmers who do not have access to a well-functioning insurance market will tend to act conservatively by investing less on their farms and making crop decisions (crop choice, production techniques, etc.) that reduce the volatility of farm profits (Rosenzweig and Udry 2013). Thus, farmers' investments in developing countries are conditioned by their financial environment and incomplete insurance markets that limit risky decisions that can lead to high expected profits. Risk-averse producers will prefer production choices that reduce risk even if it means giving up riskier choices that lead to higher expected profits. Karlan et al. (2014) show that when farmers are insured, they are able to find the funds to facilitate their investments.

To increase participation in input markets, policies in Sub-Saharan Africa have focused on reducing risk (insurance, climate information systems) or increasing access to capital (access to credit). In Senegal, where rural households depend mainly on agriculture, policies and programs have encouraged farmers to invest in risky inputs by subsidizing the purchasing price of inputs (fertilizers and seeds), managing the risk associated with rainfall through the introduction of subsidized insurance products and promoting climatic information systems and improving access to credit or agricultural implements (Sall 2015; CIAT and BFS/USAID 2016; Ribeiro and Koloma 2016).

These efforts show the importance of such investments. However, in Senegal, empirical results on the constraints to private investment in risky inputs is scanty despite the high return on investment demonstrated in other countries in sub-Saharan Africa (Duflo et al. 2008; Karlan et al. 2014; Wiredu, Zeller and Diagne 2015; Manda et al. 2016; Liverpool-Tasie 2017; Mensah and Brummer 2015; Suri 2011). Therefore, there is a real need to produce evidence for the country. To help reduce this gap and better inform these constraints, this study aims to understand the factors that influence the decision to invest in seeds and inorganic fertilizers, the level of investment, and the welfare impacts of such investment.

The rest of the paper is organized as follows. The next section briefly summarizes the literature on risks faced by smallholder farmers. Section 3 discusses the theoretical framework of household decision making under uncertainty and our empirical specifications. In section 4, we present the source of data and briefly describe the sample. Section 5 presents and discusses the results and finally, section 6 concludes the study and highlights some policy recommendations on risky inputs adoption policies.

4.2. Review of the literature

Agricultural commodities production are subjects to many risks that cause distortions in production, incomes and hence farm households' welfare. These risks, which includes climatic risks, biological risks, and market risks are numerous, complex, interconnected, and vary in their levels of frequency and severity. Risk in general play a crucial role in a great variety of economic decisions and is widely acknowledged as one of the factors that shape agricultural behavior such as farmers' technology adoption decisions (Byerlee 1993; Knight, Weir and Woldehanna 2003; Gillespie, Davis and Rahelizatovo 2004; Baerenklau and Knapp 2005). For instance, several studies (Rosenzweig and Udry 2013; Alem et al. 2010; Zerfu and Larson 2010; Gebregziabher and Holden 2011; Berhane et al. 2015; Fufa and Hassan 2006; Cavatassi, Lipper and Narloch 2011; Yu et al. 2011; Dercon and Christiaensen 2011) have observed that in anticipation of covariate shocks, such as droughts, poor farm households are especially prone to selecting less risky technology portfolios so as to evade lasting damage and these often also generate lower returns on average.

The presence of risk, therefore, stifles agricultural investments and imposes ex-ante barriers to the use of technologies, which in a nutshell, affect agricultural productivity and economic growth (Barnett et al. 2008; Di Falco and Chavas 2009; Dercon and Christiaensen 2011; Demeke et al. 2016). At the same time, a substantial strand of the empirical literature suggests that uninsured risk and uncertainty may be the main driver of the low levels of adoption of new and improved technologies. For example, in India, Lamb (2003) shows that in the absence of incomplete insurance, risk avoidance as a strategy employed by farmers may be key in understanding limited fertilizer use. Hence the protection from downside risk has been observed to be a key determinant of technology uptake among subsistence agricultural households (Liu and Huang 2013; Mobarak and Rosenzweig 2012; Elabed and Carter 2014; Karlan et al. 2014; Cai et al. 2015; Farrin and Miranda 2015).

However, limited access to credit or formal insurance markets makes it challenging for farm households to manage the myriad production risks that they face. Therefore, farm households mostly rely on a range of alternative strategies to avoid or minimize losses. Most of these are centered on the adoption of agronomic practices such as conservation farming practices, mulching, sustainable land management (Liniger et al. 2011; Di Falco and Veronesi 2013; Obiri and Driver 2017; Choudhary et al. 2016), and diversification which could be crop or income-based (Mishra and Goodwin 1997; Harwood et al. 1999; Adger et al. 2003; Ullah and Shivakoti 2014; Obiri and Driver 2017; Birthal and Hazrana 2019). Another strand of literature also suggests the adoption of the so-called "risk-reducing inputs or technologies" such as improved and high yield seeds, inorganic fertilizer and pesticides (Holzmann and Jørgensen 2001; World Bank 2005; Barnett et al. 2008; Kahan 2008; Chetaille et al. 2011; Obiri and Driver 2017). However, these "risk-reducing inputs or technologies" have also been observed to be potentially risk increasing (Just and Pope 1979; Horowitz and Lichtenberg 1993; Gardebroek, Chavez and Lansink 2010; Moser and Mußhoff 2017).

In parallel, several other studies have evaluated the impact of these "risk-reducing inputs or technologies". In fact, the general conclusion of these studies is that interventions built on the adoption of productivity-enhancing technologies such as quality fertilizers, better seeds, improved livestock, etc. improve household welfare outcomes. For instance, Graf et al. (2015) show that potential gains from adopting productivity-enhancing technologies increase the incomes of smallholder farmers between 80-140%. In Burkina Faso, Koussoubé and Nauges (2017) find that the profitability of fertilizer use, which they measured through the marginal value cost ratio (MVCR), was 1.4 on plots on which fertilizers were applied. In using the endogenous switching regression approach, Abdoulaye et al. (2018) found that the adoption of improved maize varieties in Nigeria increased maize grain yield by 574 kg/ha and per-capita total expenditure by US$ 77 (US$ 0.21/day). Furthermore, they found that poverty incidence among adopters would have been higher by 6% without adoption. Similarly, by using the endogenous switching regression approach, Asfaw (2010) finds that the adoption of improved varieties of chickpea and pigeonpea in Ethiopia and Tanzania has a significant positive impact on crop income.

Biru et al. (2019) in a panel data analysis via a multinomial endogenous switching regression model found that the adoption of improved technologies significantly increases the consumption expenditure of Ethiopian farm households. Furthermore, they observed that the likelihood of a household remaining poor or vulnerable decreased with the adoption of different complementary technologies. In Ethiopia, Mekonnen (2017) finds a positive and significant effect of improved technology adoption on rural households' crop productivity and welfare. Cunguara and Darnhofer (2011) find that rural Mozambican households using improved maize seeds and tractors have significantly higher incomes.

Kassie et al. (2014) found that on average, the adoption of improved maize varieties in Tanzania reduced the probabilities of chronic and transitory food insecurity from between 0.7 and 1.2 % and between 1.1 and 1.7 %, respectively. Comparably, Zeng et al. (2017) in evaluating the impact of improved maize varieties adoption on child nutrition outcomes using a household survey from rural Ethiopia, found positive and significant impacts of adoption on child height-for-age and weight-for-age. They further observed that such impacts were largest among children with the poorest nutrition outcomes. Kassie et al. (2011) also found that the adoption of improved groundnut varieties significantly increases crop income of Ugandan farm households and reduces poverty. Similarly, Khonje et al. (2015) found that the adoption of improved maize in Zambia had significant poverty-reducing impacts. They find that adoption leads to significant gains in crop incomes, consumption expenditure, and food security. Wopereis-Pura et al. (2002) in evaluating the effect of nitrogen application on rice yield, grain quality, and profitability in the Senegal River valley, finds that the benefit to cost ratios of nitrogen application for farmers ranged from 2.8 in the wet season to 5.4 in the dry season.

4.3.Conceptual framework and estimation strategies

4.3.1. Theoretical framework

In microeconomic theory, uncertainty occurs when the outcome of a decision is not known with certainty. While the decision-maker may know the probabilities of the different possible outcomes, the outcome of the decision is only known when it occurs (Jehle and Reny 2011). This phenomenon is observed in agricultural production where farmers make production decisions before rainfall and other risks are realized. Thus, farmers have no certainty about what their product will be when they decide what crops to produce, what investments to make, etc. Here, our focus is on investment decisions on risky inputs, particularly seeds and fertilizers for cereals production. The risky nature of these expenditures is exacerbated by their high opportunity cost in a context where liquidity constraints are severe.

We model farmers' decision to purchase risky inputs (seed and inorganic fertilizer) in Senegal following the theoretical framework suggested by Karlan et al. (2014) and extended by

Magruder (2018). The model accounts for credit constraints, production risks, and imperfect information. A two-period model is considered where farmers purchase inputs (x) at time 0 before random rainfall risk is realized at period 1. Uncertainty related in period 1 implies the existence of several potential states of the world, s ∈ S. This state of the world occurs with probability π_s and affects the production that a farmer can obtain from any input choice.

Another barrier to technology adoption is related to incomplete information, especially about purchased inputs mainly in developing countries (Bold et al. 2017; Magruder 2018). In addition to rainfall variability faced by farmers, the quality of inputs is crucial for its potential productivity under different various states of the world. For example, a test of fertilizer and seed products in local markets in Uganda by Bold et al. (2017) showed that about 30% of nutrients were missing in fertilizer, and hybrid maize seeds contained less than 50% of authentic seeds. However, various instruments may be used by farmers to reduce this risk. Farmer organization and extension services allow farmers to get more information about inputs and the most reliable input providers. Thus, information emerges in the model as an additional dimension of the state space, t ∈ T. Suppose the farmer's beliefs about the probability of any technological realization t are given by π_t.

A household obtains the utility u_s^0 at period zero and $u_{t,s}^1$ at period 1. Preferences are represented by a Von Neuman and Morgenstern utility function. The household consumes c^0 in the initial period (t=0) and $c_{t,s}^1$ in the second period (t=1) and maximizes its expected utility:

$$u(c^0) + \beta \sum_{t,s \epsilon TxS} \pi_t \pi_s u(c_{t,s}^1) \qquad (4.1)$$

Subject to budget constraints:

$$c^0 = y - x - a \qquad (4.2)$$

$$c_{t,s}^1 = f_{t,s}(x, z) + Ra \qquad (4.3)$$

$$x \geq 0 \qquad (4.4)$$

$$a \geq \bar{a} \qquad (4.5)$$

where y is its wealth at period 0 that the household uses to buy its inputs x and saves a, which is a risk-free asset that has a return R in the next period. β is the discount factor. $f_{s,t}(x)$ is a state-specific production function.

Constraint (4.5) represents a constraint on borrowing. Thus, this model incorporates all three constraints: Credit is constrained by $\bar{a}$, the risk is generated through the realization of s, and incomplete information enters through the realization of t.

In time 1, we assume there are two states of the world that may be good (g) or bad (b) rainfall; thus, the state of nature that is known at period 1 is $s \epsilon S = \{g, b\}$. In the case of complete information, the expected yield is higher when the state of the world is 'good': $f_b(x) < f_g(x)$. Considering the full information context and assuming the Inada conditions on $\mathrm{f_s}$(x), farmers solving this problem realize the following first-order conditions:

$$u'(c^0) = \beta \sum_{s \epsilon S} \pi_s \, f'_s(x) \, u'(c_s^1) \qquad (4.6)$$

and

$$u'(c^0) = \beta R \, E\big(u'(c_s^1)\big) + \lambda_a \qquad (4.7)$$

The derivative of the first-order conditions on x with respect to $\bar{a}$ shows that if credit constraints bind (a = $\bar{a}$), then optimal input use is increasing in the amount of available credit ($\frac{dx*}{d\bar{a}} < 0$). Second, it is straightforward to observe that risk (or imperfect insurance) reduces input use: If there were perfect insurance, then $c_s^1 = c^{1I} \;\; \forall$ s. If we denote $\lambda^I{}_a$, the multiplier associated with full insurance, then the two first-order conditions point out that

$$\beta R + \lambda^I{}_a / \, E\Big(u'(c^{1I})\Big) = \; \beta E(f'_s(x)) \qquad (4.8)$$

In contrast, in the absence of perfect insurance, we know that for some λ_a,

$$\beta R + \frac{\lambda^I{}_a}{E\big(u'(c_s^1)\big)} = \beta E(f'(x)) + \frac{cov(f'(x), \;\; u'(c_s^1))}{E\big(u'(c_s^1)\big)}. \qquad (4.9)$$

When farmers are not credit constrained, $cov(f'(x), \;\; u'(c_s^1))$, and λa = 0 suggests that the implication of fundamental risk is to reduce investment in inputs, x. A second implication is that risk reduces the demand for credit: In an unconstrained case (where λa = 0), we know that input use is lower in period 1 and hence that marginal utility of consumption in period 1 is lower at any given borrowing choice a. Therefore, first-order condition (4.7) implies that farmers must reduce their consumption in period 1 as well, which is accomplished by borrowing less. This model lays out a clear priority for research. Credit constraints and risk can both reduce the adoption of new technologies, and the presence of risk further reduces the demand for credit. However, a good risk management behavior of farmers may qualify these theoretical expectations. A lot of studies currently focus on farmers' risk perceptions and managements (Smit, McNabb and Smithers 1996; Smit and Pilifosova 2003; Finger, Hediger and Schmid 2011; Bryan et al. 2009; Huang et al. 2015). Therefore, accounting for various risk management strategies of farmers is central to understanding technology adoption.

In the case of limited information, Magruder (2018) observed that the absence of full information on inputs emerges as an additional uninsured risk. Therefore, incomplete information will have a similar influence on technology adoption and on demand for credit just as climatic risks. As previously noted, information related uncertainty may be reduced at farm household level through different channels such as farmer organization, extension services, and education. We may expect also that inputs purchased from cooperatives or government recommended shops may be of better quality.

For the empirical part of this study, two main issues are being investigated: (i) the drivers of risky investment, and (ii) the impact of risky investment decisions on farm household outcomes. We considered two outcomes: agricultural profit per hectare and food production (in calories) per adult-equivalent per day. The first outcome measures the economic return of investment in crop production, whereas the second outcome tends to measure a household's self-sufficiency in food production. The latter is very important for households and for policymakers since most farm households in Senegal are involved in staples production and that they only sell a marginal part of produced food crops. As argued by Kassie et al. (2015), food productivity is a good proxy for food security since for most farmers in Sub-Saharan Africa 'the availability of food – and access to food – is crucially determined by the production of basic staples at the household level due to pervasive market weaknesses, poverty, and subsistence orientation'.

4.3.1. The Heckman selection model

From the theoretical model, it is clear that the level of investment in risky inputs depends on a set of factors such as production risks, credit constraints, information on inputs, and other factors including risk management strategies, and farm households' characteristics. On the other hand, all farm households in the sample do not buy risky inputs. Based on market participation literature, the decision to purchase inputs is genuinely linked among others to various transaction costs (Goetz 1992; Staal, Delgado and Nicholson 1997; Key et al. 2000; Alene et al. 2008; Barrett 2008; Asfaw, Lipper, et al. 2012). Therefore, a Heckman model is commonly used to explain in the first step the binary decision to buy risky inputs, in our case, then accounting for selection bias, a regression model is used to identify drivers of the level of investment made.

Since individuals self-select in a group (those who invest and those who do not), there is a latent variable $\mathrm{D}_{\mathrm{i}}^{*}$ that dictates the decision to invest. Assume U_1 and U_0, the expected utilities related to the decision to invest or not. We define $D_i^* = U_1 - U_0$, the difference between the expected utilities. D_i^* cannot be directly observed, since it is a latent variable, we express it as a function of observable elements in the following latent variable model.

$$D_i^* = \mathbf{Q}'_{1,i}\gamma + u_i,\ u_i \sim N(0,1) \qquad (4.10)$$

Individual i decides to invest in inputs if the utility derived from the investment is higher than the utility obtained when he/she does not invest. Thus, the decision to invest in risky inputs D_i is defined according to D_i^*:

$$D_i = \begin{cases} 1 & \text{if} \quad D_i^* > 0 \\ 0 & \text{if} \quad D_i^* \leq 0 \end{cases} \qquad (4.11)$$

Once the decision to purchase risky inputs is made, the corresponding investment level (**X**) is modeled as follow:

$$X_i = \mathbf{Z}'_{1i}\,\beta + \varepsilon_i \qquad (4.12)$$

Where Q_i is a non-stochastic vector of observed farm and non-farm characteristics determining adoption, Zi represents a vector of exogenous variables thought to influence the level of the risky investment. Equations (4.11) and (4.12) are simultaneously estimated using the Maximum Likelihood method with the assumption that the two error terms follow a bivariate normal distribution with ρ as the covariance between the two distributions:

$$(u_i, \varepsilon_i) \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & \sigma \end{pmatrix}\right] \qquad (4.13)$$

The existence of a selection bias between the two decisions depends on the covariance ρ. If ρ is significantly different from zero, we conclude that there is a selection bias, otherwise, either the selection equation is misspecified or there is no selection bias. For the Heckman model to be identified, it is important to have at least one variable in the selection equation (4.11) that is not included in the intensity equation (4.12). As instruments, we considered three factors. The first one is the farmer's self-report need for extension services on agricultural best practices. The second instrument considered is the farmer's self-report need for insurance. The last one is the distance to the nearest market. All these factors have a direct effect on the decision to buy risky inputs but do not directly affect the level of investment.

One common issue related to this kind of estimation is the problem of endogeneity of some explanatory factors such as farmer organization, access to extension services, access to credit, and the participation in the off-farm activity. For all these factors, it is possible to think of a scenario of reverse causality between these factors and the decision to invest in agricultural inputs. To account for this endogeneity, we used the control function approach as exposed in Wooldridge (2015). For binary endogenous variables, the correction is made by adding the generalized residuals as an additional factor in the selection equation. This additional factor is computed from a standard probit model where each potential endogenous variable is the dependent variable[9]. In the absence of obvious instruments for each of these endogenous variables, we considered as instruments the department level average of the following factors: (i) farmer organization membership, access to extension services, access to credit, off-farm activity dummy, the expressed extension services need, and that of agricultural insurance. The average is computed as the total number of farmers with a value 1 for the selected dummy minus one divided by the number of farmers in the department. This gives the share of other farmers with a value of 1 for a selected factor.

4.3.2. The endogenous switching regression model

Endogenous Switching Regression (ESR) model is commonly used to assess the impact of treatment when especially experimental data are not available (Di Falco, Veronesi and Yesuf 2011; Asfaw, Shiferaw, et al. 2012; Abdulai and Huffman 2014; Khonje et al. 2015; Abdulai 2016). Consider the following model, which describes the welfare outcome of households with two regression equations, and a criterion function Ii that determines which regime the household faces:

$$\mathrm{I}_\mathrm{i}^{*}=\mathbf{Q}_{2,\mathrm{i}}'\gamma+\epsilon_\mathrm{i} \tag{4.14}$$

Regime 1: $$\mathrm{Y}_{1\mathrm{i}}=\mathbf{Z}_{2\mathrm{i}}'\beta_1+\mathrm{u}_{1\mathrm{i}} \quad \text{if} \quad \mathrm{Ii}=1 \tag{4.15a}$$

Regime 2: $$\mathrm{Y}_{2\mathrm{i}}=\mathbf{Z}_{2\mathrm{i}}'\beta_2+\mathrm{u}_{2\mathrm{i}} \quad \text{if} \quad \mathrm{Ii}=0 \tag{4.15b}$$

where $\mathrm{I}_\mathrm{i}^{*}$ i is the unobservable or latent variable for risky input adoption, Ii is its observable counterpart, Q_i is a non-stochastic vector of observed farm and non-farm characteristics determining adoption, Y_i is welfare outcome of interest (agricultural profit per hectare or per adult food production in calories), **Regime 1** stands for adopters (buying risky inputs) and **Regime 2** for non-adopters, Z_i represents a vector of exogenous variables thought to influence the considered welfare outcome, and $\mathrm{u}_{1\mathrm{i}}$, $\mathrm{u}_{2\mathrm{i}}$ and ϵ_i are the error terms of the three equations

[9] The curious reader is referred to Wooldridge (2015, Pp. 427 - 428).

(14, 15a, 15b) and follow a trivariate normal distribution of zero mean and variance-covariance matrix specified as follows:

$$\mathrm{cov}(\epsilon_i, u_{1i}, u_{2i}) = \begin{pmatrix} 1 & . & . \\ \sigma_{1\varepsilon} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{pmatrix} \qquad (4.16)$$

The variance of ϵ_i is equal to 1, σ_1^2 and σ_2^2 represent the variance of the error terms u_{1i} and u_{2i}, $\sigma_{1\varepsilon}$ is the covariance of ϵ_i and u_{1i} and $\sigma_{2\varepsilon}$ is the covariance of ϵ_i and u_{2i}. The covariance of the error terms $u_{1i}$and u_{2i} (σ_{12} or σ_{22}) is not defined because of the two regimes Y_{1i} and Y_{2i} are not observed simultaneously. The selection equation is used to calculate the inverse Mills ratios λ_{1i} and λ_{2i} which are incorporated in equations (4.15a) and (4.15b) to correct for selection bias:

$$\lambda_{1i} = \frac{\phi(\mathbf{Q}'_{2,i}\gamma)}{\Phi(\mathbf{Q}'_{2,i}\gamma)} \text{ and } \lambda_{2i} = \frac{\phi(\mathbf{Q}'_{2,i}\gamma)}{1-\Phi(\mathbf{Q}'_{2,i}\gamma)} \qquad (4.17)$$

From the theoretical framework, factors included in Q_i and Z_i are production risks face by farmers, production structure (land allocation across crops), credit access, information on inputs (prices and origins), output prices, risk management strategies, and household characteristics (e.g., age, gender, family size, education, and other household composition indicators).

According to Lokshin and Sajaia (2004), given the joint normality of the error terms in equation 14 and equation 15a and 15b, to obtain robust standard errors, the model can be estimated using the Full Information Maximum Likelihood (FIML) which allows the parameters of the three equations to be estimated simultaneously. For identification purposes, one need to include at least one instrument (Lokshin and Sajaia 2004; Di Falco et al. 2011; Asfaw, Shiferaw, et al. 2012; Abdulai and Huffman 2014) which is expected to influence the adoption of risky inputs (equation 14) but not the welfare outcome of interest (equation 4.15a and 4.15b). The same identification strategy is used as explained in the previous section.

Conditional expectations, treatment, and heterogeneity effects

The previously estimated model allows us to calculate the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU). The estimations of the ATT and ATU is presented in Table 4- 1. The impact on adopters is measured by the ATT, which corresponds to the difference between the average predicted agricultural profit of investors in the situation where they invested (observed in the sample) and in the situation where they did not invest (unobserved, counterfactual). The ATU allows us to have the difference between the average predicted agricultural profit of non-investors in the situation where they invested (not observed in the sample, counterfactual) and in the situation where they did not invest (observed in the sample) (Di Falco et al. 2011; Khonje et al. 2015). Following Carter and Milon (2005) and Di Falco et al. (2011), one could also investigate "the effect of base heterogeneity" for the group of farm households within the same treatment decision. The first base heterogeneity (BH1) is the difference of predicted outcome of treated farmers in the treatment group and that in the untreated group in the situation where they invested (counterfactual). The second base heterogeneity (BH2) is the difference in the predicted outcome of treated farmers in the treatment group in the situation where they did not invest (counterfactual) and the untreated group. Finally, the difference between the ATT and the ATU measures the "transitional heterogeneity" (TH) which compares the effect of already adopters to not yet adopters of risky inputs.

Table 4- 1: Treatment effects

Sub-samples	Decision		Effects
	To buy risky inputs	To not buy risky inputs	
Investors	$E(y_{1i}\|I = 1; x) = x_{1i}\beta_1 + \sigma_{\varepsilon 1}\lambda_{1i}$ (a)	$E(y_{2i}\|I = 1; x) = x_{1i}\beta_2 - \sigma_{\varepsilon 2}\lambda_{1i}$ (c)	ATT=(a)-(c)
Non-investors	$E(y_{1i}\|I = 0; x) = x_{2i}\beta_1 + \sigma_{\varepsilon 1}\lambda_{2i}$ (d)	$E(y_{2i}\|I = 0; x) = x_{2i}\beta_2 - \sigma_{\varepsilon 2}\lambda_{2i}$ (b)	ATU=(d)-(b)
Heterogenous effects	BH1 = (a) – (d)	BH2 = (c) – (b)	TH = ATT - ATU

Source: Adapted from Di Falco et al. (2011)

The equations (a) and (b) in Table 4- 1 represent the situations observed in the sample: (a) would be the predicted outcome of investors who decide to buy risky inputs and (b) would be the predicted agricultural outcome if non-investors; ii) the counterfactual situations are expressed in equations (c) and (d) and allow to obtain respectively the predicted agricultural outcome if investors and non-investors had invested or not invested.

4.4. Data and descriptive summary

Data used in this study were collected under the PAPA[10] project, which is an initiative of the Government of Senegal funded by USAID-Senegal as part of the "Feed The Future" initiative implemented for a 3 years period (2015 - 2018) by the Ministry of Agriculture and Rural Equipment with the International Food Policy Research Institute (IFPRI) technical support.

[10] Official website of the project is http://www.papa.gouv.sn/.

A two-stage sampling method was used with the primary units being the census districts (CDs) as defined by the 2013 General Census of Population, Housing, Agriculture and Livestock (RGPHAE[11]) and the secondary units being agricultural households. The sample for rain-fed led agriculture is 4,533 farm households distributed across all the 42 agricultural departments of the country (except the urban departments of Dakar, Pikine, and Guediawaye).

Data collection took place between April and May 2017. After data cleaning, the final sample size for this analysis is 4,465 farm households. To control for influential observations, we remove from the analysis outcome values lower than its first centile (1%) or greater than the highest centile (99%).

The survey gathered information on household characteristics, input quantities, and prices, output quantities, and prices, experience of production (climatic) shocks, risk management strategies, as well as social and institutional characteristics.

Treatment variable. The treatment variable is based on the reported expenditure at the household level on at least one of the two main inputs in crop production: seeds and inorganic fertilizers. We created a binary variable equal to 1 if the total expenditure on these inputs is different from zero. The focus here is not on the quality of the input used, but on the presence of an investment. The objective being to identify factors that may increase input market participation in general and an increase in farm household's investment in agricultural investment. In our sample, the share of households that had purchased seeds (49.79 %) was higher than for inorganic fertilizers (35.30 %), while the number of households investing in both technologies at the same time was very low (4.97 %).

Outcome variables. To assess the benefits of investing in risky inputs (seeds and fertilizers), this study considered two outcomes: farm profit per hectare and food availability (in calories) per adult equivalent per day. The cropping profit per hectare, which measures the economic return of investment in crop production, which is computed as the value of crops produced per hectare net of the total production costs per hectare. The production is valued using the average crop-specific price received by farmers on the local market. On the other hand, the total cost includes expenditure on seeds, fertilizers, the wage paid, equipment rental cost, land rental cost, and other inputs cost reported. The second outcome measures the household level of self-sufficiency in food production. This indicator is very important for households and for

[11] Recensement Général de la Population, de l'Habitat, de l'Agriculture et de l'Élevage

policymakers since most farm households in Senegal are involved in staples production and that they only sell a marginal part of produced food crops. The food crops considered are cereals (millet, sorghum, maize, rice, and fonio) and cowpeas. Using the West African Food Composition Table (Stadlmayr and others 2012), we converted food crops production into calories (kcal). The total food available (kcal) was divided by total household size adjusted for adult equivalent using weights provided by Claro et al. (2010) and converted to daily food available by dividing by 365. The reference food requirement for an adult (men and women from 19 to 50 years of age) was 2550 kcal/day (Claro et al. 2010).

Table 4- 2 shows that households produced on average 1461 kcal of food per adult equivalent per day (AED). According to FAO (2010), the Senegalese population got about 62 percent of the energy requirement from cereals. Therefore, food crops considered here should provide more than 1600 kcal per AED. On average, households who invested in risky inputs were able to produce this required food while non-buyers produced only 1238 kcal/AED.

Explanatory variables. The choice of explanatory variables is based on both theoretical and empirical reasons. The most important factors include farm characteristics (farm size, crop diversification, etc.), production risks factors (rainfall standard deviation over the past years, number of risks events reported by households), the risk attitude of households (whether farmers reduced cultivated area or reoriented towards non-farm activities due to the production shocks experienced), and household characteristics (gender, age, and education of the household heads). Factors relative to services are considered, among which are farmer organization membership, access to extension services, access to credit. Farm mechanization (plow and tractor) dummy, as well as ownership of transportation equipment (cart), are considered in the model. Dummy variables accounting for other sources of income of the households are also included.

At the farm level, we considered the total cultivated area, the value of the farm equipment, the total number of crops produced, the share of the farm size allocated to cash crops to measure the market orientation of households, the quality of seeds and that of fertilizers. We assume here that inputs purchased from parastatal agencies or farmer organizations are of better quality. We also controlled for regional heterogeneity and differences by including in the model regional dummies.

Table 4- 2: Descriptive summary of selected variables used in estimations

Variable	Variable description	All sample	Investors	Non-investors	Difference
Treatment variable					
Treatment	1 if households spent on risky inputs, 0 otherwise	0.63			
Seed investment	1 if households invested in seeds, 0 otherwise	0.50	0.79		
Fertilizer investment	1 if households purchased fertilizers, 0 otherwise	0.35	0.56		
Joint investment	1 if households jointly purchased both inputs, 0 otherwise	0.22	0.34		
Risky investment	Value of the risky investment (1000 FCFA)	41.69	65.73		
Outcome variables					
Food availability		1461.96	1593.75	1238.49	355.27***
Profit per hectare		115.00	115.88	113.47	2.41
Household characteristics					
Gender	Household head is female (1=YES)	0.07	0.06	0.08	-0.02***
Household size	The household size in adult equivalence scale	8.91	9.34	8.17	1.16***
Age	Household head age (years)	53.07	53.33	52.61	0.72*
Age squared	Household head age (years), squared	2996.28	3027.53	2942.12	85.41*
Formal education	Household head received a formal education (1=YES)	0.24	0.25	0.22	0.03**
Extension services	Access to extension services (1=Yes)	0.10	0.12	0.08	0.04***
Organization	Membership of farmer organization (1=YES)	0.09	0.12	0.04	0.08***
Access to credit	Household received credit (1=YES)	0.03	0.04	0.01	0.03***
Livestock activity	Has a livestock income (1=YES)	0.33	0.35	0.28	0.08***
Off-farm activity	Has an off-farm income	0.27	0.25	0.30	-0.04***
Remittance	Has received remittances (1=YES)	0.09	0.10	0.08	0.02
Farm characteristics					
Farm size	Total cultivated area (hectare)	4.46	5.23	3.11	2.12***
Farm equipment value	Value of agricultural equipment (1000 FCFA)	106.75	130.46	65.65	64.8***
Number of crops	Number of crops produced	2.35	2.51	2.07	0.44***
Cash crops	Land share allocated to cash crops (%)	0.35	0.39	0.27	0.12***
Diversification index	Herfindahl–Hirschman Index of crop diversification	0.43	0.47	0.36	0.11***
Owned plough/tractor	Mechanization (1= if plough or tractor)	0.09	0.08	0.09	-0.01
Owned cart	Transportation equipment (1= if cart)	0.44	0.49	0.35	0.14***
Seed quality	Certified and subsidized seeds (1,0)	0.24	0.37	0.00	0.37***
Fertilizer quality	Fertilizers purchased from parastatal agencies	0.23	0.37	0.00	0.37***
Risk variables/indicators					
Risk events (count)	Number of risk events reported (past 5 years)	2.19	2.24	2.11	0.12**
Risk attitude	1 if household reduced cultivated area or reoriented in off-farm activities	0.47	0.46	0.48	-0.01
Rainfall 2010-2015 (std dev)	Monthly rainfall standard deviation over 2010-2015 in rainy season	93.17	88.42	101.39	-12.97***
Rainfall 2016	Annual rainfall observed in 2016 during the rainy season	675.37	644.77	728.42	-83.65***

Instrument variables					
Distance	Distance to the nearest market (km)	13.62	12.46	15.63	-3.17***
Best practices	1 if farmers reported to need support on farming best practices, 0 otherwise	0.49	0.53	0.42	0.11***
Insurance need	1 if farmers reported to need agricutural insurance, 0 otherwise	0.38	0.41	0.32	0.09***
Organization2	Share of farmers members of farmer organization at department level	0.08	0.09	0.06	0.03***
Ext. services need	Share of farmers that need extension services supports at the department level	0.72	0.73	0.71	0.02***
Best practices2	Share of farmers that need supports on best practices at the department level	0.48	0.49	0.45	0.05***
Ext. services2	Share of farmers that received extension services at department level	0.10	0.10	0.08	0.03***
Credit2	Share of farmers that received credit at department level	0.02	0.02	0.02	0.01***
Off-farm activity2	Share of farmers involved in off-farm activities at department level	0.26	0.24	0.30	-0.06***
Insurance need2	Share of farmers that need insurance products at department level	0.37	0.38	0.34	0.03***
Regional dummies					
Dakar	Dakar	0.01	0.01	0.00	0.01***
Ziguinchor	Ziguinchor	0.08	0.03	0.16	-0.14***
Diourbel	Diourbel	0.09	0.09	0.09	0
Saint-Louis	Saint-Louis	0.03	0.05	0.01	0.04***
Tambacounda	Tambacounda	0.10	0.08	0.13	-0.04***
Kaolack	Kaolack	0.09	0.12	0.05	0.07***
Thies	Thies	0.07	0.08	0.06	0.02***
Louga	Louga	0.08	0.09	0.06	0.03***
Fatick	Fatick	0.06	0.05	0.08	-0.03***
Kolda	Kolda	0.10	0.10	0.09	0.01
Matam	Matam	0.04	0.01	0.10	-0.09***
Kaffrine	Kaffrine	0.12	0.15	0.06	0.09***
Kedougou	Kedougou	0.05	0.05	0.05	0
Sedhiou	Sedhiou	0.08	0.08	0.07	0.01
Observation	Sample size	4133.00	2621.00	1512.00	0***

Source: Authors from PAPA data (2017). Note: FCFA = XOF is the local currency in Senegal and most of the West African countries. 1 USD is approximatively equal to 550 FCFA.

Instrument variables. The identification of the different models estimated required to find some instruments variables that may directly affect the decision to invest in seeds or fertilizers but will not directly influence various outcomes. As explained in the methodology section, we consider distance to the nearest market, farmer’s willingness to receive extension services on farming best practices, and that to access to insurance products. Regarding the issue of endogeneity raised, we used the average of various indicators at the department level.

4.5. Results and discussion

Investment in risky inputs

Table 4- 3 shows the results from the Heckman model of the decision to buy risky inputs (improved seeds and fertilizers) and the corresponding level of investment. For each model, the coefficient estimates as well as the standard error (see Equations (4.2) and (4.3)) are presented. Heteroskedasticity-corrected standard errors using a cluster approach at the census district are displayed. The Wald test (Table 4- 3 and Table 4- 4) of the hypothesis that all regression coefficients are jointly equal to zero is highly rejected. Similarly, the Wald test of the hypothesis that there is no selection bias (rh0=0) is highly rejected. Therefore, the Heckman model is appropriate in modeling investment on risky inputs. The exogenous test for potential endogenous variables (farmer organization, extension services, access to credit, and off-farm activity) reveals that only farmer organization and off-farm activity participation are not exogenous in the model. Therefore, the final model corrected that for these two variables. The same specification is used in the endogenous switching regression model.

The decision to invest in risky inputs is linked to household and farm characteristics, risk factors, and access to services. We find that household size, household head age and educational level, membership of farmer-based organizations and having livestock income sources positively and significantly drives the decision to invest in risky inputs. The effect of the household head age on the decision to invest in risk inputs is positive but very small. Conversely, we find that access to extension services and participation in off-farm activities is negatively related to the decision to invest in risk inputs. Both results here are a bit surprising, but the negative effect of extension access on risky inputs investment decisions can be modulated by the need for extension services which is positively and significantly related to the investment decision. Hence farmers that have a need for extension services are more likely to invest in risky inputs. Furthermore, since access to information can be obtained through farmer-based organizations, we find that membership of farmer-based organizations is positive and significantly correlated to the decision to invest in risky inputs. This modulating effect is supported by many empirical studies (Conley and Udry 2010; Isham 2002; Abdulai 2016; Hailu, Cao and Yu 2017; Husen, Loos and Siddig 2017).

The gender of the household head, credit access, and remittance do not significantly affect the decision to invest in risk inputs. The results obtained here are congruent with some studies in the empirical literature. For instance, Asfaw et al. (2012b) found the education level of a household head to drive the adoption of Pigeonpea in Tanzania. Muzari et al. (2012) also find gender-related differences in technology adoption in Sub-Saharan Africa. Due to gender inequalities in sub-Saharan Africa, women have less access to production resources such as land, lower access to education and information on new technologies (Muzari et al. 2012). In addition, women are sometimes disadvantaged in terms of access to credit (Muzari et al. 2012) that reduces their financial ability to have higher levels of investment in risky inputs compared to their male counterparts.

We find that farm-related variables including size, number of crops grown, and the share of land allocated to cash crops correlates positively to the decision to invest in risky inputs. The effects are also highly significant. At the same time, the value of farm equipment and ownership of a plow or tractor is negatively related to the decision to invest in risky inputs although the effect is not significant. The standard deviation of rainfall was found to negatively correlate to the decision to invest in risky inputs and the effect is significant. Hence as rainfall becomes more and more variable, farmers are less likely to invest in risky inputs.

Our regional fixed effect variables are all significant at 1%, implying that the location of a farmer likely influences their decision to invest in risk. The estimates for the potential endogenous variables[12], membership of a farmer-based organization and participation in an off-farm activity are significant, meaning that endogeneity was indeed present and well controlled for in the model.

[12] We do not include the residuals of the other potentially endogenous variables, credit access and extension because they were not statistically significant. They are however available on request

Table 4- 3 : Drivers of investment on risky inputs, Heckman model results

	Selection equation		Log input investment	
	Estimate	SE	Estimate	SE
Household characteristics				
Gender	0.132	0.085	-0.339***	0.112
Household size (adult equivalent)	0.018***	0.006	0.006	0.006
Age	-0.013	0.01	0.027**	0.012
Age squared	0.000*	0	-0.000**	0
Formal education	0.091*	0.055	0.04	0.056
Extension services	-0.232***	0.087	0.248***	0.089
Organization	1.599***	0.256	0.113	0.095
Access to credit	0.113	0.14	0.089	0.115
Livestock activity	0.300***	0.056	-0.157***	0.054
Off-farm activity	-0.573***	0.206	0.032	0.058
Remittance	0.064	0.077	-0.136	0.086
Farm characteristics				
Farm size (log, ha)	0.082**	0.038	0.605***	0.044
Farm equipment value (log)	0	0.012	0.039***	0.014
Number of crops	0.122**	0.053	-0.291***	0.057
Cash crops (% of farm size)	0.340***	0.098	0.645***	0.13
Diversification index	0.076	0.204	0.567**	0.25
Owned plough/tractor	-0.022	0.085	-0.108	0.097
Owned cart	0.059	0.052	-0.007	0.062
Risk variables/indicators				
Risk events (count)	0.012	0.016		
Risk attitude	0.06	0.043		
Std. rainfall 2010-2015	-0.363***	0.133		
Instruments used				
Distance to market (log)	-0.003	0.019		
Extension services need	0.159***	0.037		
Insurance need	0.036	0.043		
Organization (RES)	-0.678***	0.133		
Off-farm activity (RES)	0.357***	0.123		
Regional fixed effects				
Ziguinchor	-0.418***	0.142		
Diourbel	-0.352***	0.063		
Tambacounda	-0.627***	0.075		
Louga	-0.317***	0.086		
Fatick	-0.423***	0.084		
Kolda	-0.438***	0.076		

Matam	-1.381***	0.237		
Constant	1.551**	0.635	2.663***	0.332
rho	-0.929		-0.929	
Wald chi2 (1) for rho = 287.2***	287.2		287.2	
Wald chi2 (18) = 405.1***	405.1		405.1	
Number of clusters	945		945	
Sample size	4,133		4,133	

Note: Bootstrapped standard errors are reported. **rho** denotes the correlation coefficient between the error term of the selection equation and the error term of the outcome equations. Organization (RES) and Off-farm (RES) denote the generalized residuals from the first-stage regressions farmer organization membership and off-farm activity participations, respectively. Significance: *** p<0.01, ** p<0.05, * p<0.1. Source: Authors from PAPA data (2017).

Results of the second stage estimation show that the gender of the household head, age, extension access, and livestock income sources significantly drive the levels of investment in risky inputs. We, however, find the effect of gender and livestock ownership to be negative. Hence, female-headed households invest less in seeds and fertilizers compared to male-headed households. Furthermore, households that have livestock income sources invest less in risky inputs. On the contrary, the effect of a household's head age on the level of risky input investments decreases with increasing age. Extension access is related to increasing levels of investment in risky inputs. The effect of remittance is, however, negative which implies that households that receive remittances reduce the level of investment in risky inputs.

Farm characteristics including size, equipment value, the share of land allocated to cash crops and diversification are significant and positively correlated to investment levels of risky inputs. On the contrary, despite being significant, the number of crops grown decreases the level of investment in risky inputs. We also find that ownership of farm equipment (plow/tractor and cart) decreases investment levels in risky inputs but the effect is not significant.

In summary, we find the age of a household head, extension access, having livestock income sources, farm size, the number of crops grown and the share of land allocated to cash crops to simultaneously affect the decision to invest in risky inputs and the level of investment in these inputs. Extension access, on the other hand, has an opposing effect, it reduces the probability of investing in risky inputs but increases the level of investment. The effect of livestock income sources and the number of crops grown has the opposite effect of extension access. The presence of livestock income sources and the number of crops grown increases the probability of investing in risky inputs but decreases the level of investment. Farm size and the share of land allocated to cash crops have a consistently positive effect across the decision to invest in risky inputs and the levels of investment. They both significantly increase the probability of investing in risky inputs and the level of investment in risky inputs.

Household welfare impacts

Since the drivers of agricultural profit are not the main interest of this study, we directly discussed the impact of the decision to invest in risky inputs. Detailed results of the model are presented in the Supplementary materials section. Table 4- 4 shows the predicted welfare outcomes of risky investments under actual and counterfactual conditions for Senegal.

The results showed that investment in risky inputs (fertilizers and/or seeds) has a positive and significant impact on the profit per hectare and on food produced per AED. The treatment effect on the treated was estimated at 24 000 FCFA[13] per hectare for the profit and 238 kcal per AED for food availability. This is equivalent to a 44 percent increase in the profit per hectare and a 24 percent increase in food availability per AED relative to the expected outcome if they did not purchase risky inputs. Moreover, if non-buyers had purchased risky inputs, their average profit per hectare and food availability per AED would have increased by 150 percent and 107 percent, respectively. Therefore, investment in risky inputs increases household welfare measured in terms of crop profit per hectare or food availability.

Table 4- 4: Predicted outcomes and treatment effects

	Decision stage		Treatment effects
	To invest	Not to invest	
(Outcome 1): Profit per hectare (1000 FCFA)			
Farm households who invested	(a) 79.5 (0.7)	(c) 55.4 (0.5)	ATT = 24.2*** (0.5)
Farm households who did not invested	(d) 218.9 (2.4)	(b) 87.7 (1)	ATU = 131.2 (1.6)
Heterogeneity effects	BH1 = -139.3*** (2.1)	BH2 = -32.3*** (1)	TH = -107*** (1.4)
(Outcome 2): Food availability (Kcal/AED)			
Farm households who invested	(a) 1219.1 (16.6)	(c) 980.7 (12.8)	ATT = 238.4*** (7.7)
Farm households who did not invested	(d) 2038.4 (40.3)	(b) 987.1 (17.6)	ATU = 1051.3*** (25.1)
Heterogeneity effects	BH1 = -819.3*** (37.7)	BH2 = -6.4 (21.5)	TH = -812.9*** (21.7)

Note: Standard errors in parentheses. Significance: *** p<0.01, ** p<0.05, * p<0.1. Source: Authors from PAPA data (2017).

[13] FCFA = XOF is the local currency in Senegal and most of West African countries. 1 USD is approximatively equal to 550 FCFA.

However, surprisingly, results also reveal that the treatment effect is higher for non-buyers than for actual buyers. De Janvry et al. (2010) stated that such a situation may occur if technology adoption increases risks. In the absence of a perfect insurance market, poor farmers will not be able to adopt, unlike richer farmers who can adopt the technologies even if their expected gain is low. Therefore, the treatment effect on the untreated may exceed the treatment effect on the treated. On the other hand, the transitional heterogeneity effect for the two outcomes is negative; that is the effect is lower for farm households that did invest compared to the ones that did not invest.

Table 4- 5: OLS regression of the differential impact

	Profit equation		Food equation	
	Estimate	Std. Err	Estimate	Std. Err
Land share to groundnut (%)	14.139***	4.850	-986.701***	62.827
Land share to Maize (%)	6.188	5.545	4.744	64.552
Land share to Millet (%)	10.147**	4.650	310.568***	55.513
Land share to Rice (%)	32.391***	5.014	-185.241***	60.114
Farm size (Ha)	-7.931***	0.562	59.309***	6.440
farm size, squared	0.196***	0.020	-0.788***	0.231
Extension services (0,1)	24.297***	3.423	348.713***	39.472
Credit (0,1)	-17.245***	6.114	231.101***	69.648
farmer organization (0,1)	18.148***	3.764	163.236***	43.454
Value of agric. Equipment (1000 FCFA)	-0.001	0.002	-0.051**	0.024
Owned cart	1.788	2.085	113.262***	23.981
Mechanization (0,1)	15.457***	3.630	186.260***	41.636
Number of crops	6.917***	1.228	-15.515	14.587
Education	4.658**	2.345	46.771*	26.919
Gender (1=Female)	-23.824***	3.977	-217.998***	46.446
Age	0.141*	0.074	0.649	0.847
Constant	50.228***	6.002	412.322***	71.682
Observations	4,133		3,863	
R-squared adjusted	0.120		0.168	

Note: Robust standard errors are reported. Significance: *** p<0.01, ** p<0.05, * p<0.1. Source: Authors from PAPA data (2017).

To gain further understanding of results, we also examined the differential impact of investing in risky inputs by running an OLS estimation on a set of factors where our interest is on the production structure (share of the total cultivated area allocated to millet, maize, rice, and groundnut). **Table 4- 5** shows results from this simple OLS regression.

Table 4- 6: Comparison of mean of yield and land allocation across groups

	Yield (kg/ha)			land size share (%)		
	Adopters	Non-adopters	T-Stat	Adopters	Non-adopters	T-Stat
Groundnut	604.65	639.31	-1.25	0.35	0.25	12.17***
Millet	447.80	478.28	-1.87*	0.28	0.32	-5.06***
Maize	614.38	550.92	1.73*	0.12	0.13	-0.46
Rice	1664.36	1120.93	4.34***	0.08	0.14	-7***

Results show that the most influential crops are groundnut, millet, and rice. A test of differences between the yield and the land size share allocated to these crops across the groups reveals that the most important yield gap between adopters and non-adopters is present in rice production with an average gap of 543 kg/ha. In addition, non-adopters had allocated more land area to that crop (14%) than adopters (7%). This finding clearly explains why the expected profit for non-adopters is clearly higher than for adopters. Regarding the food production gap observed, it is explained by the fact that adopters had allocated less land size to millet than non-adopters. Moreover, there is no yield gap for millet between the two groups (see Table 4- 6).

4.6. Conclusion and policy recommendations

Using recent data of rain-fed agriculture in Senegal, this study provides an analysis of the investment decision of farm households in Senegal on “risky inputs”. More than half of the households in the sample had bought either inorganic fertilizers or seeds during the campaign of interest. However, the level of spending on these inputs is quite low. There is, thus, a need to investigate the drivers of the investment decision, the level of investment, and the potential impact of the household’s welfare in order to convince farmers to adopt and policymakers to use results to design appropriate interventions.

In summary, we find the age of a household head, extension access, having livestock income sources, farm size, the number of crops grown and the share of land allocated to cash crops to simultaneously affect the decision to invest in risky inputs and the level of investment in these inputs. Farm size and the share of land allocated to cash crops have a consistently positive effect across the decision to invest in risky inputs and the levels of investment. They both significantly increase the probability of investing in risky inputs and the level of investment in risky inputs.

The main drivers of the decision to purchase risky inputs are household size, education of household heads, membership in a farm organization, access to credit, farm size, the number of crops and existence of livestock income. On the other hand, results reveal gender, farm size, the number of crops grown and the share of land allocated to cash crops, crop diversification, the value of agricultural capital, rainfall variability, and extension services as the determinants of the level of investment on risky inputs. In terms of impact, results show a positive effect of risky investment on farm profit per hectare, and food produced per adult equivalent per day. This positive effect is higher for current non-adopters. This greater expected impact on non-adopters is explained by their cropping patterns. Most of them are involved in rice production which is found to be more sensitive to inputs investment.

Our results highlight that efforts made so far to encourage investments in inputs need to be strengthened through the revision of government interventions' strategy to ensure public expenditure efficiency and substantial impacts on beneficiaries of the promotion of private (farm) investment in terms of adoption and investment intensity. Private investments could be promoted through several complementary channels that affect both the decision to invest and the amount invested. Access to information can play an important role in the decision to invest in agricultural activity, particularly in improved inputs. The sources of information identified here are membership of a farm organization, access to advisory support, possession of means of transportation that allow households to access information. Another source of information would be climate information systems. Since liquidity constraints hinder agricultural investment, any policy that promotes access to credit could generate important returns. Efforts to ease access to credit would have to be accompanied by measures to manage agricultural risks.

Interventions along the lines proposed above could reduce the impact of agricultural risks and increase farmers' willingness to invest to increase their well-being. In addition, based on the positive effect of the use of risky inputs on farm profit per hectare, food availability, private operators may be interested to support public efforts to improve technology adoption and poverty reduction.

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Supplementary materials

Table A4- 1: Determinants of per hectare farm profits and Food produced (endogenous switching regression model)

	Log farm profit (1000 FCFA/ha)				Log Food produced (Kcal/adult/day)			
	(1)		(0)		(1)		(0)	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Household characteristics								
Gender	-0.070	0.080	-0.249***	0.091	0.036	0.076	-0.107	0.086
Household size (adult equivalent)	0.006	0.006	0.003	0.005	-0.090***	0.007	-0.079***	0.004
Age	0.004	0.010	0.003	0.009	-0.006	0.010	0.001	0.008
Age squared	-0.000	0.000	-0.000	0.000	0.000	0.000	0.000	0.000
Formal education	-0.092	0.058	-0.044	0.048	-0.075	0.061	0.014	0.044
Extension services	0.293***	0.098	0.274***	0.083	0.261***	0.074	0.338***	0.073
Organization	-0.016	0.111	0.087	0.082	0.002	0.100	0.063	0.073
Access to credit	-0.304*	0.181	-0.305***	0.101	-0.358*	0.196	-0.097	0.094
Livestock activity	-0.021	0.047	-0.042	0.045	-0.002	0.048	-0.027	0.041
Off-farm activity	-0.116**	0.050	-0.006	0.049	-0.045	0.053	0.035	0.046
Remittance	-0.075	0.076	0.007	0.071	-0.023	0.076	-0.102*	0.059
Farm characteristics								
Farm size (log, ha)	-0.396***	0.038	-0.368***	0.039	0.571***	0.042	0.545***	0.040
Farm equipment value (log)	0.031***	0.012	0.026**	0.011	0.028**	0.012	0.035***	0.010
Number of crops	0.110***	0.039	0.167***	0.040	0.074*	0.042	-0.014	0.036
Cash crops (% of farm size)	0.462***	0.103	0.207*	0.112	-1.259***	0.123	-1.656***	0.107
Diversification index	0.289*	0.164	-0.204	0.204	0.207	0.183	0.408**	0.194
Owned plough/tractor	0.328***	0.076	0.220***	0.067	0.257***	0.079	0.250***	0.067
Owned cart	0.083	0.052	0.077	0.052	0.053	0.051	0.047	0.045
Rainfall 2016 (log, total)	0.382***	0.074	0.351***	0.091	0.600***	0.077	0.223***	0.085
Seed quality			0.042	0.043			0.004	0.039
Fertilizer oquality			0.249***	0.045			0.334***	0.042
Other model parameters								
Constant	1.257**	0.519	2.112***	0.665	3.164***	0.547	5.857***	0.601
lnsigma0	-0.271***	0.041			-0.324***	0.029		
lnsigma1	0.026	0.036			-0.146***	0.039		
rho0	-0.354**	0.161			-0.110	0.202		
rho1	-0.935***	0.126			-0.742***	0.138		
Wald chi2 (2) for rho = 55.41***	55.41							
Wald chi2 (19) = 388.0***	388.0							
Number of clusters	945		945		927			
Sample size	4,133		4,133		3,863			

Note : (1) risk takers, (0) No risk takers. Regression with robust standard errors clustered at the Census District was used. Significance : *** p<0.01, ** p<0.05, * p<0.1.

Table A4- 2: Results of probit models for the control function

	Farmer organization		Extension services		Access to credit		Off-farm activity	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
organisation	.	.	0.912***	0.094	0.662***	0.126	-0.062	0.091
appui_conseil	0.903***	0.094	.	.	-0.087	0.151	0.020	0.086
credit_recu	0.784***	0.144	-0.114	0.172	.	.	-0.045	0.147
dinc_off	-0.042	0.082	0.067	0.077	0.002	0.118	.	.
Age	0.019	0.018	0.015	0.016	0.020	0.025	-0.020*	0.011
age2	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000
Gender	0.011	0.153	0.000	0.140	0.156	0.213	0.144	0.091
hsize_aduleq	0.012	0.007	-0.011	0.007	-0.009	0.011	0.005	0.005
formal_educ	0.278***	0.079	0.223***	0.077	0.265**	0.108	0.127**	0.057
dinc_live	0.097	0.075	0.073	0.069	0.223**	0.100	0.501***	0.050
dinc_remit	0.018	0.121	0.343***	0.101	-0.099	0.180	-0.201**	0.082
Lsuptot	0.104*	0.055	0.144***	0.049	0.120	0.078	-0.093***	0.036
Lcap	0.020	0.020	0.007	0.018	0.028	0.027	-0.040***	0.013
plough_tractor	-0.004	0.118	0.021	0.112	0.118	0.164	0.230***	0.086
transport_char	-0.043	0.093	0.037	0.085	-0.096	0.122	0.121*	0.062
N_crop	-0.049	0.072	-0.023	0.069	0.087	0.091	-0.012	0.049
cash_crop	0.263**	0.131	0.271**	0.121	0.139	0.194	0.054	0.089
HHI_div	0.128	0.311	-0.292	0.284	-0.333	0.423	0.221	0.204
risk_count_5y	0.030	0.024	0.138***	0.021	0.020	0.031	0.061***	0.017
risk_averse_strategy	-0.007	0.073	0.076	0.067	0.214**	0.100	0.362***	0.049
lrain_sd	0.276	0.232	0.525**	0.220	-0.088	0.346	0.018	0.159
ldistmark	-0.023	0.037	0.117***	0.038	-0.026	0.048	-0.009	0.024
extension_bestpractices	0.130*	0.077	0.322***	0.072	0.061	0.105	0.054	0.051
insurance_need	0.346***	0.078	0.180**	0.075	0.291***	0.110	-0.209***	0.054
reg_organization	5.787***	0.625	-1.157**	0.588	-0.653	0.910	0.785*	0.444
reg_ext_need	0.037	0.438	-0.126	0.436	0.001	0.708	0.030	0.269
reg_ext_best	-0.219	0.343	-0.319	0.314	-0.291	0.542	0.035	0.221
reg_ext_access	-1.672***	0.515	5.611***	0.458	0.499	0.858	-0.702**	0.325
reg_credit_access	-0.113	2.166	1.715	1.870	13.653***	3.094	-0.963	1.449
reg_offfarm_access	0.230	0.326	-0.494*	0.291	-0.243	0.459	2.755***	0.214
reg_insur_need	-0.403	0.267	-0.170	0.256	-0.043	0.362	0.116	0.164
REG2	-0.017	0.189	0.023	0.189	0.283	0.321	0.010	0.131
REG3	-0.614**	0.301	0.323*	0.182	-0.317	0.385	-0.032	0.117
REG5	-0.033	0.170	0.116	0.144	-0.242	0.232	0.035	0.107
REG6	-0.102	0.169	0.247	0.156	-0.059	0.206	-0.094	0.132
REG7	-0.113	0.198	0.223	0.147	-0.151	0.303	0.126	0.108
REG8	-0.388	0.243	0.256	0.161	-0.060	0.251	0.171	0.118
REG9	-0.254	0.215	-0.165	0.252	-0.537	0.428	0.093	0.115

REG10	-0.108	0.128	0.217*	0.121	0.064	0.180	-0.121	0.099
REG11	-0.065	0.327					0.143	0.155
Constant	-3.975***	1.193	-5.701***	1.076	-2.907*	1.672	-1.423*	0.788
Observations	4,133		4,133		4,133		4,133	
Pseudo R-squared	0.325		0.299		0.193		0.178	
Log-Likelihood Ratio (Chi2)	795.4		823.4		198.9		857.1	

Note : Significance : *** p<0.01, ** p<0.05, * p<0.1.

Chapter 5

5. Market Participation Regimes and Rural Household's Welfare in Senegal: *Evidence using a Multinomial Treatment Endogenous Framework*

Authors

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5.1. Introduction

Agricultural market participation is widely recognized as a key determinant of structural transformation in developing countries (Alene et al. 2008; Barrett 2008; Poole 2017). The reasons that call for such a view are i) market participation is a way for poor smallholders to generate higher income and therefore to increase their welfare (Poole 2017), ii) it improves access to new technology[14] that can generate a shift upward of total factor productivity increasing the production of marketable surplus (Barrett 2008; Asfaw et al. 2012).

There is a large body of literature on determinants of market participation since the seminal work by Goetz (1992), which suggests that transaction costs (transportation and search costs), productive assets endowment (land, labor, machinery and transport equipment), or socio-economic characteristics of households farmers (age of head, gender of head, education), are the main drivers of farmer's decisions to participate and supply in agricultural market (Goetz 1992; Staal et al. 1997; Key et al. 2000; Alene et al. 2008; Barrett 2008; Ouma et al. 2010; Asfaw et al. 2012; Burke et al. 2015; Olwande et al. 2015).

With exception of Alene et al. (2008) and Asfaw et al. (2012), most empirical studies emphasize output market participation, while there may be important transaction costs in inputs (fertilizers/ seeds) markets, preventing farmers to get access to new technologies. As a consequence, this can jeopardize the intensification process and mitigate the production of marketable surplus (Winter-Nelson and Temu 2005; Camara 2017). While Alene et al. (2008) studied the determinants of maize supply and fertilizer demands, Asfaw et al. (2012) analyzed participation in pigeonpea and seed markets, and their implications for household welfare. However, some elements can be raised as limitations of these studies. First, they analyze output market participation distinctly from input market participation; therefore, they might hide important heterogeneities among participants either in output market or input market. For example, a buyer of fertilizer may (not) sell a surplus of production because he/she faces specific low (high) costs-information and search costs (i.e. time spent to find a better price or a buyer- when trading in output market) can affect the intensity of participation in the fertilizer market and the production of marketable output surplus. The point we make here is that buyers in input market may have idiosyncratic factors creating considerable differences in transactions costs when deciding (not) to participate in output market; therefore, it is possible to observe

[14] use of fertilizer, improved seed or mechanization

different profiles of farmers based on their overall market strategies[15]. Thus, a joint analysis of input and output markets might be more insightful as it allows for better profiling of farmers and a better formulation of targeted policies aiming at improving households' welfare.

Studies by Alene et al. (2008), and Asfaw et al. (2012) are applied in specific regions in Kenya and pay attention to specific crops markets (maize, or pigeonpea) or analyze specific input market (fertilizer or seed), whereas the determinants of output market participation depend on the context and the nature of crop, and farmers' demands for inputs may include both fertilizers and seeds. On the other hand, Teklewold (2016) modeled simultaneously the decisions to adopt technology and to participate in output market. This study was very similar to ours, however, it only focused on the correlation between decisions (using a multivariate probit model) instead of the analysis of the determinants of the choice of a specific market participation regime.

This study pays attention to the above gaps. More specifically, we seek to answer the following questions: (i) What is the most gainful market regime when both input and output markets are simultaneously considered? (ii) Is this regime invariant across crops? The main objective of this study is to draw a joint analysis of participation in both output and input markets and find the market participation regimes that lead to the highest net revenue per hectare at the household level. Contrary to previous studies, we rely on a recent representative survey of Senegalese rainfed agriculture with more than 4,000 farm households and consider both fertilizers and seed as inputs and pay attention to both staple and cash crops.

From an econometric standpoint, we account for selection bias that may affect market participation by using the multinomial endogenous treatment effects model (Deb and Trivedi 2006a, b). The main advantages of this approach are that it accounts for selection bias due to both observed (through farm or household characteristics) and unobserved (via latent variables) heterogeneity in an impact evaluation setting.

The next section gives a description of the conceptual framework and the empirical strategy used. Section 3 presents the data and a descriptive summary of the variables used in the analysis. Results are presented and discussed in section 4. The last section provides conclusions and implications.

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[15] A farmer may buy inputs (fertilizers) because he/she wants to be self-sufficient regarding food crops, or to increase food surplus in order to sell that surplus. Therefore, farmer's behavior on output market may have its origin on the inputs choices and depends on the household-specific final objective. Thus, when considering simultaneously both markets, a set of four regimes of market participation emerge.

5.2. Conceptual framework and empirical strategy

5.2.1. Conceptual framework

The theoretical framework builds on the work by Alene et al. (2008), who analyzed the effects of transaction costs on both output and input market participation. Unlike these authors, this study supports that the decision to buy input is likely correlated with that of participating in the output market, thus revealing the strategic behaviors of farmers under transaction costs. A similar argument was made by Teklewold (2016) who modeled jointly the decisions to adopt crossbreeding technology (input side) and to participate in milk and milk products marketing (output side). Using a multivariate probit model, these authors found that input-side technology adoption decision was not independent of that to participate in the output market.

The analysis is based on a static farm household model where a decision-maker maximizes its utility that is a function of net revenue (5.1) under production technology constraint (5.2)

$$Max_{\{X\}}U(R) = U\{\hat{p}Q - \widehat{w}X - tcw_b^f(z) - tcq_s^f(z)\} \qquad (5.1)$$

$$Q = G(X, A) \qquad (5.2)$$

$$\hat{p} = p - tcq_s^v(z) \qquad (5.3)$$

$$\widehat{w} = w + tcw_b^v(z) \qquad (5.4)$$

$$Q = S + \bar{C} \qquad (5.5)$$

$$X = X_b + \bar{X}_o \qquad (5.6)$$

$$\partial U/\partial R > 0;\ \partial^2 U/\partial^2 R < 0\ ; \partial Q/\partial X > 0;\ \partial^2 Q/\partial^2 X < 0$$

$\hat{p}$ is the specific price that the decision-maker gets when he/she decides to sell in the output market. This price is equivalent to market price p minus incurred variable transaction costs such as transportation costs $tcq_s^v(z)$ (3). Q is the production which can be sold (S) or consumed at home $(\bar{C})$ (5). Similarly, $\widehat{w}$ is the specific price that farmer faces when buying input X; this price is equivalent to market price w plus variable transaction costs $tcw_b^v(z)$ (4). A farmer can buy input in the market X_b or relies on his/her own resources[16] $\bar{X}_o$ (6). $tcw_b^f(z),\ tcq_s^f(z)$ stand for fixed transactions when buying input and/or selling output. Fixed transaction costs include information and research costs and are not directly observable in surveys. However, they can

[16] For fertilizer, farmer only relies on market.

be expressed in terms of observable variables z at the household level. A stands for fixed factors.

The optimization problem and the associated Lagrange $\mathcal{L}$ function can be rewritten as:

$$Max_{\{s,x_b\}}U(R) = U\{(p - tcq_s^v)S + p\bar{C} - (w + tcw_b^v)X_b - w\bar{X}_o - tcw_b^f - tcq_s^f\} \quad (5.1')$$

$$\text{S/C} \qquad S + \bar{C} = G(X_b + \bar{X}_o, A) \quad (5.2')$$

$$\mathcal{L} = U\{(p - tcq_s^v)S + p\bar{C} - (w + tcw_b^v)X_b - w\bar{X}_o - tcw_b^f - tcq_s^f\} + \lambda\{G(X_b + \bar{X}_o, A) - S - \bar{C}\} \quad (5.7)$$

Due to the existence of fixed transactions costs that influence the decisions to participate in markets, there is a discontinuity when maximizing over $S \text{ and } X_b$. The literature suggests, first to determine the first-order condition (FOC) under each regime and second to retain one that gives the highest utility level (Alene et al. 2008; Ouma et al. 2010).

FOC 1: **Seller in the output market and buyer in the input market** ($S > 0$ *and* X_b*>0; j=3).*

$$\{S\}:\ U'(\cdot)(p - tcq_s^v) - \lambda = 0 \qquad (5.8)$$

$$\{X_b\}:\quad -U'(\cdot)(w + tcw_b^v) + \lambda G'(\cdot) = 0 \qquad (5.9)$$

Combining (5.8) and (5.9) ➔ $w + tcw_b^v = G'(\cdot)(p - tcq_s^v)$ (5.10)

Equation (5.10) shows that for farmers who decide to sell a part of their production and buy inputs, the unit cost including transaction costs in the input market must be equivalent to marginal productivity value net of incurred transaction costs when selling output. This reveals the rationale underlying the behavior of this group of farmers. More specifically, higher transaction costs in the output market tcq_s^v compared to those existing in the input market tcw_b^v impose a reduction of the quantity bought in the input market, thus increasing marginal productivity. Similarly, when transaction costs are relatively higher in the input market, rational behavior imposes a reduction of output sales as the farmer could reduce the output volume because he/she may decrease the quantity bought in the input market. Thus, for this group, an idiosyncratic shock affecting transaction costs when selling output may result in a considerable gap between transaction costs incurred in output and input markets; the consequence is an adjustment in the quantities traded in the input market. Under this condition, public policies focusing on input (output) market only may not be enough to significantly affect the household's participation.

***FOC 2*: Only seller in the output market** ($S > 0$ *and* X_b*=0; j=2).*

Under this regime, equation (5.8) remains valid only if the farmer relies on his/her own input, which we suppose is exogenous $\bar{X}_o$. The rationale behind this equation is that the relative opportunity cost of selling $(\lambda/p - tcq_s^v)$ must be equivalent to the marginal utility. Thus, higher transaction costs increase the relative opportunity cost, therefore, a rational farmer should reduce output sales in order to maintain the same utility level. So far, for this group, variable transaction costs are added to the fixed transaction costs that households could face before deciding (or not) to participate in the input market. As they are already non- participants in the input market, they could stay in that position if there are high costs of marketing.

***FOC 3*: Only buyer in the input market** ($S = 0$ *and* X_b*>0; j=1).*

In this regime, only equation (5.9) remains valid and households buy input to increase farm productivity in order to meet home consumption needs $\bar{C}$ (exogenous). The underlying rationale here is that the relative opportunity costs $(\lambda/(w + tcw_b^v))$ of output is equivalent to relative marginal utility. In this case, an increase in transaction costs reduces relative opportunity cost; and a rational behavior suggests that a farmer should increase the marginal productivity by reducing the quantities bought in the input market. Similarly, to the previous case, a farmer who belongs to this regime could not be a participant in the output market as long as input market conditions are not good enough to allow him/her to produce a marketable surplus.

***FOC 4*: Autarky** ($S = 0$ *and* X_b*=0; j=0).*

In this regime, equations (5.8) and (5.9) are not valid. The farmer relies on his/her production to meet household consumption needs and depends exclusively on his/her own input to produce. To focus on market participation process, we assume that these quantities $\bar{C}$ and $\bar{X}_o$ are exogenous.

As the choice of the regime is based on the comparison of utilities U_j derived from above FOCs (see **Figure 5- 1**), conditional on crop choice, the representative farm household would choose a regime *k* if:

$$U_k > U_j \ , \qquad k \neq j$$

$$U(\pi_k) > U\left(\pi_j\right) , \qquad k \neq j$$

The utility function is monotone and strictly increasing; therefore $\pi_k > \pi_j$ and the potential welfare gain related to regime k is $\Delta U = U(\pi_k) - U(\pi_j)$. As transaction costs play a critical role in determining the utility level associated with each market regime, we investigate empirically their effects on market regime choices and the implications for household's income.

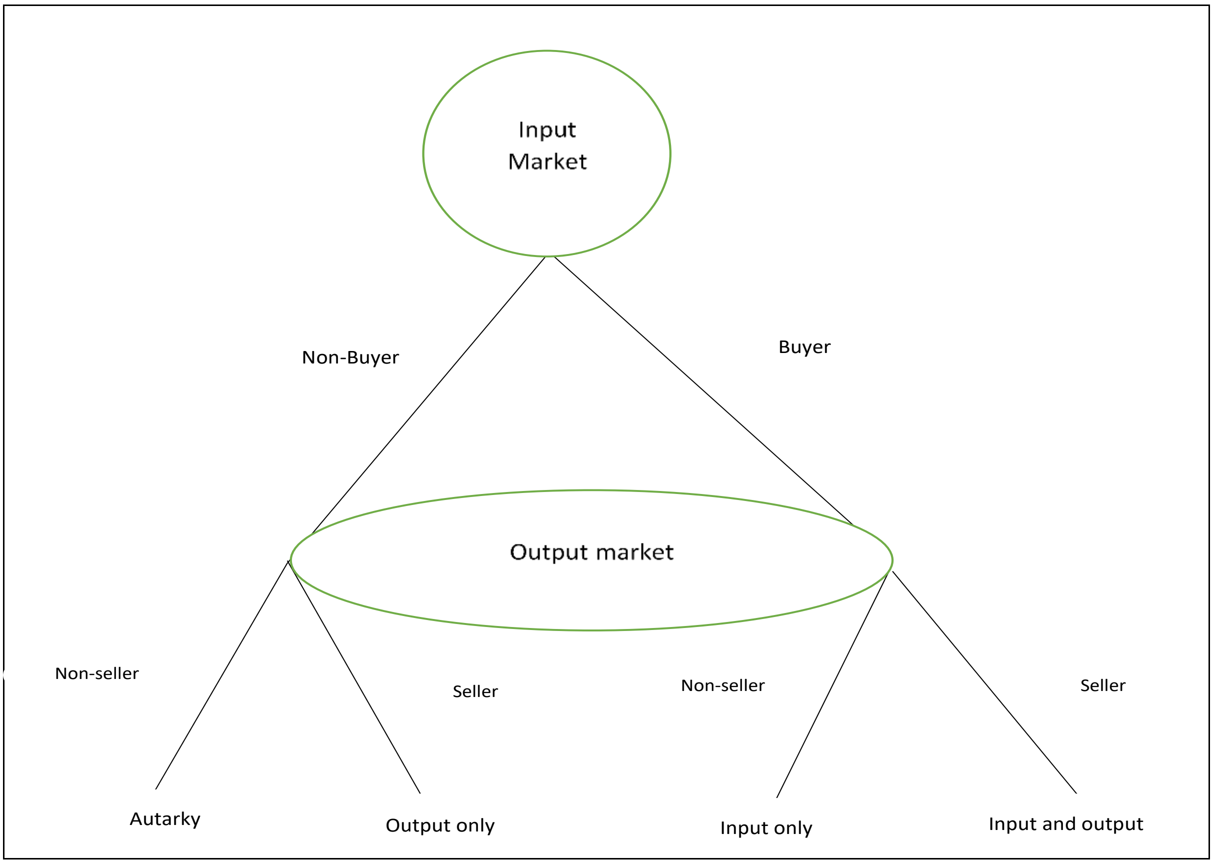

Figure 5- 1: Market participation regimes

5.2.2. Empirical framework

Following the conceptual framework, four groups of farmers may exist when we analyze both markets jointly: (i) no market participation at all (autarky), (ii) farmers buy inputs, but don't sell their production (input), (iii) farmers don't buy any inputs, but sell part of their production (output), (iv) farmers buy inputs and sell part of their crop production (joint).

As we have more than two groups, the standard propensity score approach or the endogenous switching model is not appropriate. Furthermore, in a multivalued treatment framework, efficient-influence function estimator (EIF) by Cattaneo (2010) could be a good candidate to be applied for the analysis. However, this method relies on a strong assumption of Conditional

Independence which implies, in our case, that the market choice regime is random once one can control for farmers' characteristics. Therefore, we adopt a more flexible modeling framework.

We model a farmer's choice between the four options and its impact on outcome variables in a multinomial endogenous treatment effect model as proposed by Deb and Trivedi (2006a, b). This framework simultaneously models the treatment equation (multinomial mixed logit model) and the outcome equation. The main advantages of this approach are that it accounts for selection bias due to both observed (through farm or household characteristics) and unobserved (via latent variables) heterogeneity in an impact evaluation setting.

Let d_{it} be binary variables representing the observed market choice (treatment) by farmer i.

$$d_{it}(T_i) = \begin{cases} 1, & if\ T_i = t \quad (\mathrm{t} = 0,1,2,3) \\ 0, & otherwise \end{cases}$$

The probability of treatment can be represented as:

$$Pr[d_{it}|z_i, l_i] = z'_i\alpha_t + \sum_{k=1}^{T} \delta_{tk} l_{ik} + \varepsilon_{it} \quad (5.11)$$

ε_{it} error term, and $Pr[d_{it}|z_i, l_i]$ is supposed to be a multinomial logistic function g, *z* denotes exogenous covariates with associated coefficients α_t, l_{ik} stands for unobserved characteristics (unobserved heterogeneity) common to individual *i*'s choice and outcome such as motivation or level of information. l_{ik} are assumed to be independent of ε_{it}. We assume that *t* = 0 denotes the control group (autarky).

For the model to be identified, a set of restrictions are imposed. First, we impose $\delta_{tk} = 0\ \forall\ t \neq k$, i.e. each market regime choice is affected by a unique unobserved factor. In addition, we assume that $\delta_{tt} = 1$, which implies that the scale of effects of an unobserved factor is normalized and equal to 1 in the treatment equation (Deb and Trivedi 2006a, b).

The outcome (net revenue per hectare) equation is as follows:

$$y_i = x'_i\beta + \sum_{t=1}^{T} \theta_t d_{it} + \sum_{t=1}^{T} \pi_t l_{it} + \epsilon_i \quad (5.12)$$

ϵ_i error term, y_i is supposed to follow a normal density distribution *f*, *x* denotes exogenous covariates with associated coefficients β, θ_t are the treatment effects relative to the control. The outcome y_i is affected by unobserved characteristics l_{it} that affect selection into treatment. If π_t is positive (negative), treatment and outcome are positively (negatively) correlated through unobserved characteristics, i.e., there is positive (negative) selection.

In practice, l_{it} are non-observed. Following Deb and Trivedi (2006a, b) we assume that they are *i.i.d* and drawn from a normal distribution and their joint distribution h can be integrated out of the joint density distribution of selection and outcome variables as follows:

$$\boldsymbol{\omega}(y_i, d_{it}|x_i, z_i) = \int \{\boldsymbol{f}(y_i, |x_i, d_{it}, l_{it}) * \boldsymbol{g}(z_i, l_i)\}\, \boldsymbol{h}(l_{it}) dl_{it} \qquad (5.13)$$

For a given specification of *f*, *g* and *h*, the integral (13) does not have a closed-form solution.

Then, the full estimation of equations 11 and 12 is based on a simulated-based estimation framework. This method finds the values of parameters that maximize the simulated log-likelihood function associated with a joint density distribution of selection and outcome variables (equation 13). For a large number of simulations (*S*), the maximization of the simulated log-likelihood is equivalent to maximizing the log-likelihood (Train 2009).

The simulated log-likelihood function of $\boldsymbol{\omega}(y_i, d_{it}|x_i, z_i)$ is:

$$\boldsymbol{ln\, L}(y_i, d_{it}|x_i, z_i) = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{ln\hat{\omega}}(y_i, d_{it}|x_i, z_i) = \sum_{i=1}^{N} ln\left(\frac{1}{S}\sum_{s=1}^{S}\{\boldsymbol{f}\left(y_i, |x_i, d_{it}, \hat{l}_{its}\right) * \boldsymbol{g}\left(z_i, \hat{l}_{its}\right)\}\right)$$

Where $\hat{l}_{its}$ is the s^{th} draw (from a total S draws) of a pseudo-random number from the density *h*.

Since our outcome variable is a continuous variable, we assume that it follows a normal (Gaussian) distribution function. The resulting model was estimated using a Maximum Simulated Likelihood (MSL) approach using the Stata command ***mtreatreg*** proposed by Deb (2009).

5.3. Data and Pre-estimation Analysis

Data used in this study were collected under the PAPA[17] project, which is an initiative by the Government of Senegal funded by USAID-Senegal as part of the "Feed The Future" initiative. PAPA has a 3 years implementation period (2015 - 2018) and is being carried out jointly by the Ministry of Agriculture and Rural Equipment and the International Food Policy Research Institute (IFPRI).

[17] Official website of the project is http://www.papa.gouv.sn/.

A two-stage sampling method was used with the primary units being the census districts (CDs) as defined by the 2013 General Census of Population, Housing, Agriculture and Livestock (RGPHAE[18]), and the secondary units being agricultural households. The sample for rain-fed agriculture is 4,533 farm households distributed across all the 42 agricultural departments of the country (except the urban departments of Dakar, Pikine, and Guediawaye). Data collection took place between April and May 2017. After data cleaning, the final sample size for this analysis is 4,160 farm households.

Regarding other income sources, about 33 % of households in the sample received income from livestock activities, 27 % from off-farm activities, while only 9 % of households had received transfers from migrants. Regarding the overall household wealth indicator, households in different subsamples have very close scores (3 over 6).

Table 5- 1 shows the socio-demographic characteristics of the households in our sample per main crop groups (staples, groundnut, and other crops). In the staples group, crops included are millet, sorghum, maize, rice, fonio, and beans. The "Other" group is composed of crops that are not included in the first two groups. The sample is mainly composed of households with, on average, 10 individuals. Household heads are mainly older (53 years old on average) and males (93%). This table also shows that few household heads (36.4%) are literate. In terms of crop choices, results show that about 94 % of households are involved in grain or beans production, while around 69 % of the total households produced groundnut, which is the main cash crop in Senegal. Other crops are produced by less than 10 % of households. About 70 % of staple food producers also produced groundnut, while almost all groundnut producers also produced staple foods (92%).

Only a few farm households have access to extension services (11%), to credit (3%), and are members of farmer organizations (9%). Surprisingly, households involved in staples production had more access to extension services and farmer organizations than households that produced groundnut. However, it is important to note that the staples group is a very broad group with about six individual crops.

Many households owned transport means (carts) and relied on animal traction tools. As groundnut is the major crop in the country, households seemed to allocate about half of their

[18] Recensement Général de la Population, de l'Habitat, de l'Agriculture et de l'Élevage

total farm size to its production. All staple crops occupied 2.7 ha of land on average. The net crop production value (profit) per household is around 447,000 CFA[19]. For staples producers, the average profit from crops is 213,000 CFA per household and for groundnut producers, the average profit from crops is about 292,000 CFA. The few households that are involved in other crop production earned higher net income. It is worth noting that the crop profit is computed as the total production value net of the total production cost (fertilizer, seed, wage paid, land and equipment rental cost, and other costs). The production is valued using the observed average crop marketing price in the sample for each crop. In terms of crop profit per hectare, the highest is observed for other cash crops (209, 000 CFA) followed by staples production (74, 000 CFA) and groundnut production (60, 000 CFA).

In terms of market participation, as expected, almost half staples producers (45%) do not participate in any market. About 36 % of these households bought inputs during the campaign but they did not sell any of their harvests. Only 13 % of staples households had purchased inputs and had sold part of their production. So far, only 14 % of groundnut producers intervened neither in the input market nor in the output market -autarky-. About 24 % of groundnut producers had participated only in the output market, while 17 % were present only in the input market during the season of interest. About half of groundnut producers (45%) had bought inputs and sold part of the produced groundnut. Therefore, market participation depends on crop choices. Finally, food producers had sold less than 25 % of the total value of food produced, while groundnut producers had sold about 70 % of the total production in value.

Regarding other income sources, about 33 % of households in the sample received income from livestock activities, 27 % from off-farm activities, while only 9 % of households had received transfers from migrants. Regarding the overall household wealth indicator[20], households in different subsamples have very close scores (3 over 6).

[19] CFA is the local currency in Senegal. 1 USD ≈ 550 CFA.

[20] The wealth index is computed as a count of a selected dummy variables related to household's assets. The formula used is: $WI = \sum_{i=1}^{6} D_i$, where D is a dummy variable, i stands for various dimensions considered. The dimensions included are : use of running water for cooking and drinking, access to electricity or solar power for light, quality of the roof (1 if the material used for the roof is either cement, tile, slate or metal sheet, 0 otherwise), quality of the wall (1 if the wall is made of cement, 0 otherwise), quality of the floor (1 if the floor is tiled, cement, or carpet, 0 else) and number of rooms available for household's members (1 if the ratio of household size to the number of rooms is less than or equal to 2, zero otherwise).

Table 5- 1: Descriptive statistics

	Staple crops producers (N= 3880)	Groundnut producers (N=2917)	Other crops producers (N=329)	Total (N=4157)
HH gender (1 male, 0 female)	0.936	0.948	0.933	0.935
HH age (year)	53.104	53.151	54.410	53.132
HH education (1=yes; 0=non)	0.362	0.364	0.435	0.363
Size of Household	9.932	10.419	10.529	9.887
Farmer organization (1=yes; 0=non)	0.085	0.073	0.164	0.086
Extension services (1=yes; 0=non)	0.107	0.090	0.134	0.107
Access to credit (1=yes; 0=non)	0.027	0.032	0.046	0.027
Received livestock income (1=yes)	0.335	0.341	0.347	0.328
Received off-farm income (1=yes)	0.266	0.245	0.264	0.266
Received remittances (1=yes)	0.094	0.098	0.097	0.092
Wealth index (0/6)	3.023	3.038	3.377	3.080
Cart ownership (1=yes; 0=non)	0.442	0.496	0.465	0.443
Farm machinery ownership (1=yes; 0=non)	0.088	0.089	0.073	0.087
Produced staples (1=yes)	1.000	0.923	0.796	0.933
Produced groundnut (1=yes)	0.694	1.000	0.653	0.702
Produced other crops (1=yes)	0.068	0.074	1.000	0.079
Total cultivated area (ha)	2.820	2.482	1.176	4.467
Labor costs ('1000)	4.936	3.207	4.778	7.235
Fertilizer costs (rent) ('1000)	12.764	9.254	6.232	18.900
Seed costs (rent) ('1000)	2.547	32.590	7.793	25.863
Other inputs costs ('1000)	5.803	4.846	4.631	9.183
Agricultural profit ('1000)	213.035	292.268	543.107	446.910
Agricultural profit per hectare ('1000)	74.282	60.614	209.055	130.034
Total crop sale value ('1000)	40.794	200.581	474.665	216.392
Market participation: None	0.445	0.140	0.064	0.206
Market participation: Input only	0.355	0.168	0.070	0.202
Market participation: Output only	0.072	0.243	0.319	0.155
Market participation: Both markets	0.128	0.449	0.547	0.438
Distance to the nearest road (km)	10.244	7.950	8.809	10.070
Distance to the nearest market (km)	13.598	12.409	13.353	13.540
Distance to the regional city (km)	46.395	43.851	45.962	45.929
AEZ: Agro Sylvo Pastorales	0.114	0.091	0.009	0.110
AEZ: Groundnut Basin	0.504	0.609	0.526	0.502
AEZ: Senegal River	0.046	0.015	0.021	0.045
AEZ: Littoral and Niayes	0.007	0.010	0.082	0.014
AEZ: Sylvo-pastoral of Ferlo	0.081	0.047	0.125	0.083
AEZ: Casamance	0.248	0.229	0.237	0.246

Number of observations	3880	2917	329	4157

Source: Authors from PAPA data (2017). Note: CFA is the local currency in Senegal. 1 USD ≈ 550 CFA.

Our theoretical model shows the central role of transaction costs in market decisions, especially for smallholder farmers in developing countries. Since these costs are directly collected and are even difficult to collect or empirically computed, we follow the standard approach in the literature, which is to use some observed factors that explain or mitigate transaction costs (Alene et al. 2008; Teklewold 2016). Factors considered in this study due to data availability are distance to the nearest market; distance to the nearest road; distance to the regional city; ownership of animals used for transportation (cart); and membership in farmers' organization. Distance variables were computed for each household using its GPS coordinates.

Table 5- 2: Mean comparison of crop profit per hectare across market choice ('000 CFA)

	Staples	Groundnut
input vs Autarky	-11.73 (4.24)**	-21.72 (5.89)***
output vs Autarky	7.48 (7.57)	21.44 (5.47)***
Joint vs Autarky	49.9 (5.98)***	14.65 (4.99)**
output vs input	19.2 (7.7)*	43.15 (5.17)***
Joint vs input	61.62 (6.14)***	36.37 (4.66)***
Joint vs output	42.42 (8.78)***	-6.78 (4.1)

Note: "Autarky" if a farm household does not buy any inputs and does not sell any crop groups; "Input" if a farm household only buys inputs for production and does not sell any crop produced; "output" if the farmer does not buy an input, but sells part of crop production; "joint" if the farm household participates into the two markets (input/output).

Our theoretical model shows the central role of transaction costs in market decisions, especially for smallholder farmers in developing countries. Since these costs are directly collected and are even difficult to collect or empirically computed, we follow the standard approach in the literature, which is to use some observed factors that explain or mitigate transaction costs (Alene et al. 2008; Teklewold 2016). Factors considered in this study due to data availability are distance to the nearest market; distance to the nearest road; distance to the regional city; ownership of animals used for transportation (cart); and membership in farmers' organization. Distance variables were computed for each household using its GPS coordinates.

Table 5- 2 shows the mean comparison for crop profit per hectare across market choice (4 categories). Results show that for staples production, the largest positive gap is observed between the group "Joint" and the group "Input". This suggests that farmers that are present on the two markets for staples production earned about 62, 000 CFA of profit per hectare more than farmers that only purchased inputs. Moreover, the latter choice is even less profitable than

being in autarky for staples production. For all other choices, being more involved in market participation is positively correlated with higher profit in staples production. For groundnut production, results show that buying inputs associated with autarky in the output market is worse than being completely in autarky. On the other hand, there is no significant difference in profit per hectare between farmers connected in the two markets and those that participated in the output market. Therefore, it seems that input market participation for groundnut production does not significantly increase groundnut productivity.

5.4. Estimation results

We estimate the econometric framework presented above using two sub-samples: staple food producers and cash crop producers (groundnut). We chose these two groups for two reasons: i) their importance in terms of cultivated areas in the context under analysis, ii) the optimal market regime may be crop-specific (cash or staples crops).

5.4.1. Market participation regimes

The full estimation of equations (5.11) and (5.12) for both sub-samples is presented in

Table 5- 3. Columns 1-6 present estimation results for treatment equations for both types of crops; the autarky regime is overlooked as it stands for the control group; the last 2 columns present results for the two outcome equations. The likelihood-ratio test for exogeneity of treatment, which is a test for the joint hypothesis that coefficients associated to the latent factors (unobserved heterogeneities) are jointly equal to zero, shows that the null hypothesis is rejected in both cases; therefore, unobserved heterogeneities are critical when explaining market choice and its linkage with a farm's net revenue.

For the market choice decisions, results (columns 1-6) suggest that these decisions are quite distinct and that the factors driving the participation decision across groups are different. This suggests that analyzing participation as we have done may bring more insights than the common approach of market participation that separately analyzed input market participation and output market participation. In addition, results are quite different between staples producers and groundnut producers, thus revealing the critical role played by the crop selection.

Ownership of transport means (cart) has a positive and significant effect on market participation regimes. Households that owned carts had fewer constraints to transport purchased inputs (products to sell) from (to) local markets to farms. In addition, in rural

Senegal, these households may rent their owned assets to other households, thus allowing them to generate more income. Alene et al. (2008) and Teklewold (2016) found similar results.

Membership in farmer organizations increases the probability that staple food producers intervene in the inputs market and in the two markets. For groundnut producers, being a member of a farmer organization has a positive effect on the probability to sequentially participate in both input and output markets. In general, farmer organizations increase market access for their members by reducing search and information costs or by increasing their bargaining power (Holloway et al. 2000; Teklewold 2016). For example, Burke et al. (2015) showed that the presence of milk cooperative in the village is likely to increase milk market participation in Kenya; and Fan and Salas Garcia (2018) revealed that being a member of an association increases farmers' market participation in Peru.

Other proxy variables for transaction costs are the distance from the household's location to some infrastructures such as market, road, and regional city. Results show that distance to the nearest market has a strong negative effect on groundnut input market participation. A similar result is found for Ethiopia by Woldeyohanes et al. (2017). Regarding distance to the nearest paved road, results are a bit ambiguous. A positive correlation is found for staples input market participation, groundnut joint market participation, while a negative and significant effect is observed for staples output and joint market participation. Distance to the regional city is found to have a very limited impact on market participation regimes. These ambiguous results may be due to the fact that agroecological zone dummies may already account partly for regional accessibility effects.

Access to extension service is found to decrease the probability to be connected to output market participation for staples food. Opposite results were found by Alene et al. (2008). Education (literacy rate) improves the bargaining power of farmers, therefore it increases the probability of intervention in the input market, and both markets for staple food producers. Household heads' gender and age seem to not have significant impacts on market choice decisions for farmers in the sample. Access to credit helps to relieve financial constraints for cash crop producers who are connected to both markets; therefore, it positively affects market participation. In the milk sector in Kenya, Burke et al. (2015) found similar results. The impact of credit is very limited in the case of staples crops, the associated coefficient is positive and significant at a 10 percent level.

Table 5- 3: Estimation results based on the mixed multinomial logit model

	To buy inputs		To sell output		Joint participation		Net crop revenue per hectare	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Treatment: Input							0.348	-27.705***
							(11.919)	(4.674)
Treatment: Output							-0.284	38.140***
							(7.179)	(5.755)
Treatment: Joint							69.959***	13.934***
							(14.376)	(4.568)
HH gender (1=Female)	0.037	-0.129	-0.324	0.458	0.459	0.473*	7.096	5.175
	(0.178)	(0.286)	(0.281)	(0.304)	(0.307)	(0.285)	(7.239)	(6.786)
HH age (years)	0.013	-0.051	0.026	-0.041	0.031	-0.024	-0.930	1.282**
	(0.022)	(0.038)	(0.035)	(0.036)	(0.031)	(0.034)	(0.860)	(0.637)
HH age squared	-0.000	0.001	-0.000	0.000	-0.000	0.000	0.012	-0.011*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.006)
HH education	0.283***	-0.234	0.189	-0.170	0.260*	0.122	-1.796	3.948
	(0.097)	(0.167)	(0.157)	(0.156)	(0.134)	(0.146)	(3.656)	(3.821)
Organization membership	0.787***	0.515	-0.205	0.240	1.366***	0.874**	38.783***	0.659
	(0.189)	(0.388)	(0.407)	(0.377)	(0.204)	(0.341)	(10.638)	(5.179)
Extension services	-0.018	0.459	-0.743**	-0.069	0.225	0.342	77.885***	12.331*
	(0.165)	(0.283)	(0.349)	(0.283)	(0.210)	(0.255)	(11.013)	(6.297)
Access to credit	0.092	0.527	-0.234	0.876	0.620*	1.832***	-24.976***	-10.696**
	(0.300)	(0.724)	(0.536)	(0.706)	(0.341)	(0.651)	(7.653)	(4.620)
Livestock income dummy	0.415***	0.160	0.088	-0.043	0.636***	0.342**	4.105	8.793**
	(0.098)	(0.170)	(0.161)	(0.160)	(0.138)	(0.149)	(3.955)	(4.396)
Off-farm income dummy	-0.254**	-0.128	-0.445**	-0.410**	0.015	-0.026	-0.632	-5.419
	(0.106)	(0.183)	(0.190)	(0.174)	(0.153)	(0.159)	(4.120)	(3.469)
Remittances income dummy	0.086	-0.023	0.341	-0.302	-0.286	-0.535**	-19.136***	15.334
	(0.155)	(0.240)	(0.235)	(0.238)	(0.225)	(0.224)	(5.194)	(9.881)
Wealth index (0/6)	0.129***	0.113**	0.066	0.024	0.219***	0.066	4.360***	1.679*
	(0.029)	(0.050)	(0.048)	(0.047)	(0.040)	(0.044)	(0.988)	(0.949)
Transport equipment	0.355***	-0.321**	0.711***	0.173	0.522***	0.552***		
	(0.096)	(0.160)	(0.148)	(0.153)	(0.135)	(0.143)		
Mechanization	0.092	-0.412	0.394	-0.587**	-0.399	-0.278	24.611***	16.039***
	(0.176)	(0.289)	(0.287)	(0.257)	(0.277)	(0.240)	(6.555)	(4.621)
Land holding (ha)	0.080***	0.097***	0.063***	0.126***	0.155***	0.174***	-4.770***	-2.006***
	(0.016)	(0.033)	(0.020)	(0.032)	(0.019)	(0.033)	(0.402)	(0.364)
distance to market, KM	0.001	-0.042***	0.012	-0.007	-0.002	-0.009		
	(0.004)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)		
distance to road, KM	0.017***	0.019*	-0.018**	-0.005	-0.010**	0.019**		
	(0.004)	(0.010)	(0.008)	(0.010)	(0.005)	(0.009)		
Distance to city	0.003	0.002	-0.002	0.005*	-0.000	0.001		

	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)		
Produced also staples		-1.809***		-1.104***		-1.646***		-54.429***
		(0.352)		(0.359)		(0.338)		(13.670)
Produced also groundnut	0.111		-0.384**		-0.245		-63.177***	
	(0.120)		(0.195)		(0.166)		(4.285)	
Produced also other cash crops	-0.029	0.095	0.590**	0.569*	0.310	0.484	-18.037***	-12.110*
	(0.197)	(0.371)	(0.262)	(0.337)	(0.245)	(0.330)	(4.797)	(6.234)
AEZ: Agro Sylvo Pastorales	0.249	0.453	2.084***	-0.168	1.523***	0.057		
	(0.163)	(0.350)	(0.319)	(0.340)	(0.271)	(0.346)		
AEZ: Groundnut Basin	-0.108	0.409	1.649***	0.755***	1.069***	1.950***		
	(0.135)	(0.296)	(0.311)	(0.280)	(0.230)	(0.289)		
AEZ: Senegal River	0.054		0.514		2.835***			
	(0.344)		(0.680)		(0.355)			
AEZ: Littoral and Niayes	3.097***		-37.634***		5.001***			
	(1.146)		(1.113)		(1.164)			
AEZ: Sylvo-pastoral of Ferlo	-1.897***		1.388***		1.033***			
	(0.255)		(0.409)		(0.322)			
AEZ: Casamance		-0.027		2.630***		2.536***		
		(0.362)		(0.315)		(0.321)		
lnSigma							4.587***	4.423***
							(0.049)	(0.156)
Lambda (Input)							-8.548	4.981***
							(13.985)	(0.694)
Lambda (Output)							25.251***	-18.215***
							(4.691)	(5.105)
Lambda (Joint)							-20.396	7.086***
							(12.686)	(1.330)
Constant	-2.133***	2.219*	-4.430***	0.623	-5.813***	-0.330	115.483***	59.388***
	(0.618)	(1.156)	(1.021)	(1.079)	(0.925)	(1.030)	(24.128)	(17.889)
Observations	3,880	2,917	3,880	2,917	3,880	2,917	3,880	2,917
LR test for treatment exogeneity (Lambdas=0)							13.43***	15.73***
Log-Likelihood							-27661	-20461
Number of simulations							5000	5000

Notes: ***P < 0.01, **P < 0.05, *P < 0.1. Robust standard errors in parentheses. AEZ refers to agroecological zones. Note: HH stands for household head.

Farm size is a critical determinant of market participation for both types of producers. This finding is common in the literature on market participation (Alene et al. 2008; Burke et al. 2015). Farmers with larger farms show a greater propensity to participate in markets. The largest coefficients are associated with the joint market participation. This suggests that increased farm size has a great impact on joint market participation.

Households that received income from livestock activities seem to be more integrated into markets, especially the input market for staples producers, and both markets for groundnut and staples producers. Therefore, a complementarity may exist between livestock and crop production as livestock activities help farmers to produce organic fertilizer (manure), thus increasing crop productivity. This finding is in line with results by Woldeyohanes et al. (2017). However, being involved in off-farm activity is shown to reduce the propensity to participate in the input market for staples food and output market for both groundnut and staples. Participating in off-farm activities is likely to reduce the time allocated to farming and thus, may reduce the productivity and likelihood to sell output. Farmers that received remittances similarly tend to reduce their joint participation in the two markets. The overall household wealth index is positively correlated with market participation, especially input market participation for both products, and the joint market participation for staples producers. This confirms that financial constraints may seriously reduce market choice in rural Senegal.

Finally, results show that staples producers that also produce groundnut appear to participate less in markets for staples. On the other hand, when groundnut producers also produce staples, they commercialize less on the groundnut output market. This suggests that market participation regimes depend on the crop under consideration and also on the mix of crops produced.

5.4.2. Effects of market participation regimes

Columns 7-8 in

Table 5- 3 display results of the outcome equation for staples and groundnut production. Before analyzing the impact of market participation regimes on net production value per hectare, a brief look at other explanatory variables is worth it. Results reveal that crop profit per hectare is heterogeneous across farmers. For staples producers, their profit per hectare is positively and significantly associated, among others, with farmer organizations, extension services, wealth index, and mechanization. On the contrary, the following factors display a negative correlation with staples profit per hectare: access to credit, access to remittances, and farm size. Regarding groundnut profit per hectare, farmer’s access to livestock income and mechanization have a positive effect, while access to credit and farm size seem to decrease groundnut profit.

In terms of impacts of the treatment variable, results reveal that once one controls for farm household characteristics and agroecological zones, a strong and positive effect is observed for joint market participation choice in the context of staples producers. Ceteris paribus, staples producers that decided to participate in input and output markets will earn around 70,000 CFA more profit per hectare than staples producers in complete autarky. Conversely, any other choice of participation in the markets, ceteris paribus, is unprofitable compared to autarky for food crops.

For groundnut production, the impact of market participation regimes is more nuanced. In fact, all else being equal, the purchase of inputs for self-consumption production generates a loss of nearly 28,000 CFA per hectare compared to households that remain self-sufficient. On the other hand, production intended for sale but without buying inputs generates a profit gain of 38,000 CFA, whereas when the farmer buys inputs and sells part of the harvest (joint participation), he obtains a net gain of about 14,000 CFA per hectare on average.

5.4.3. Discussions

From the results presented in the previous section, we found that the most gainful market participation regimes depend on the crop under consideration, as far as profit per hectare is concerned. For staples producers, the only strategic choice to maximize net cropping income per hectare is to buy inputs (fertilizer and/or seeds) in order to increase production for marketing. The average treatment effect (ATE) associated with this choice is about 70,000 CFA per hectare. In the case of groundnut production, the most profitable choice is to avoid purchasing inputs (especially seeds) but to sell products. The associated ATE is estimated at 38,000 CFA per hectare of groundnut farm. The second-best choice for groundnut production is to jointly participate in the two markets (buy inputs and sell groundnut), with an ATE of 14,000 CFA.

When looking at production cost structure, we note that for staples producers, the main inputs from markets are inorganic fertilizers, which account for about 83% of the total seed-fertilizer cost. On the other hand, most groundnut producers spent around 88 percent of their input costs (seeds and inorganic fertilizers) on seeds. This suggests that fertilizers are more important for cereals and other staples crops than for groundnut production. Moreover, farmers may use seeds from their previous production, which in turn will lower the production cost. Therefore, it is not surprising that staples producers rely more on markets to meet their input needs than groundnuts producers. In addition, we do not note any yield gap between groundnut producers that bought seeds and those who used their groundnut stock.

Previous discussions were on the most profitable market choice if farmers produced one of the two crops under consideration. However, as stated in the data description section, about 70 percent of staple food producers also produced groundnut, while almost all groundnut producers also produced staple foods (92%). Therefore, it is interesting to see which choice is the most profitable at the household level, summing the two profits.

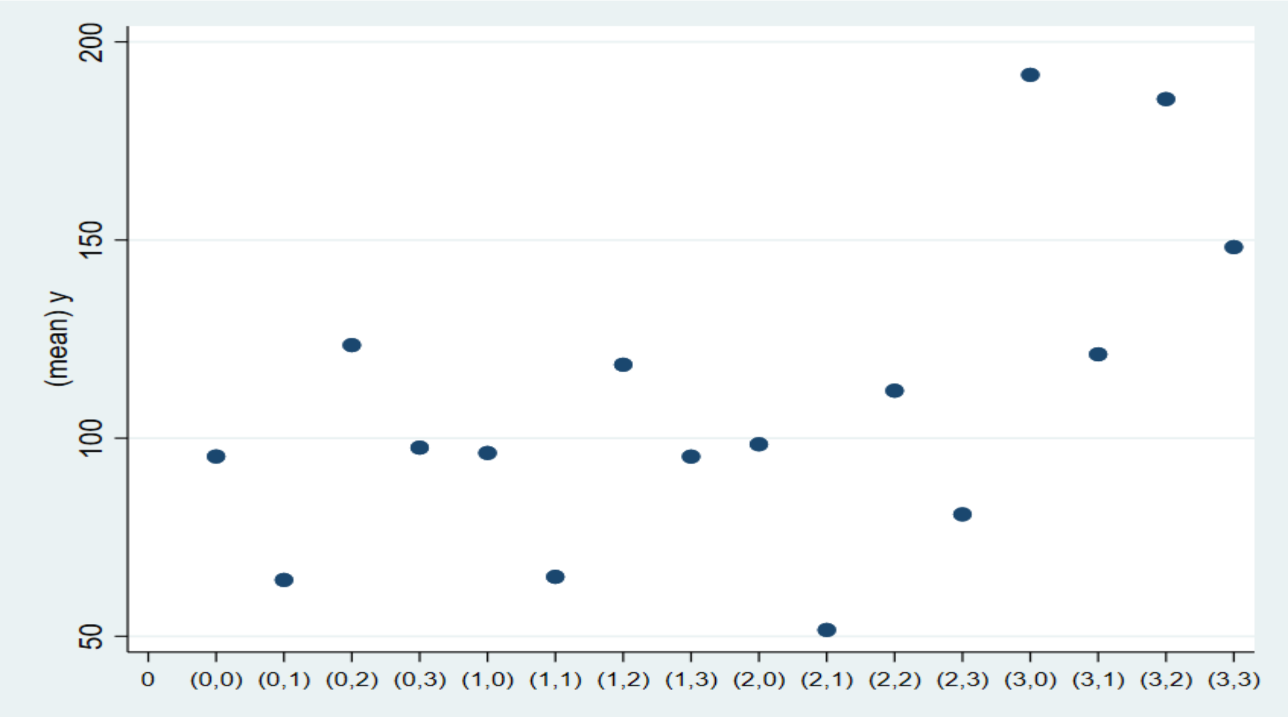

Figure 5- 2: Comparison of predicted household level profit for producing the two groups of products by market regimes

Notes: On the X-axis, labels are related to market regimes per household regarding the two value chains (staples and groundnut). The first digit is related to the participation regime adopted for food crops, while the second digit is the one for groundnut production. Example: "00" autarky for both products; "13" input market participation for staple food production combined with input and output market participation for groundnut production.

Figure 5- 2 displays the average profit per hectare from the two farming activities for households that were involved in both. Results show that the top 3 strategies of crop diversification and market regimes choice are: (i) being in autarky for groundnut and fully integrated in the staples input/output markets; (ii) being fully integrated in staples markets and participate in the groundnut output market; and (iii) being fully integrated in the two segments (staples and groundnut). Among the three most profitable choices, the best one is the first choice: being fully integrated for staples production and autarky for groundnut production. The main lesson

from this finding is that to maximize farming profit per hectare in rainfed agriculture in Senegal, farm households need to invest in inputs for staples production, and to produce staples for marketing. Results also reveal that is not enough to get access to inputs for staples production. A marketing target for staples production seems to be the key to better welfare gain. Therefore, policymakers should find a way to increase access to inputs for producers, especially those involved in staples production. On the other hand, any policy that facilitates access to the output market should complement input side policies.

5.5. Conclusion

Agricultural commercialization is a critical pathway to stimulate a structural transformation in developing countries, as it allows poor smallholders to generate more income for better welfare. Analyses of determinants of market participation have focused on identifying factors influencing participation in the output market. However, transaction costs--i.e information and search costs, may exist in the input market -fertilizers/seed-and may be highly different from those existing in the output market; this can result in jeopardizing the production of marketable surplus. In addition, technology adoption (input side) has a great impact on farm productivity and thus on the propensity to market products (Teklewold 2016). A few studies (Alene et al. 2008; Asfaw et al. 2012) have included determinants of input market participation when analyzing output market participation. However, these studies suffer from some limitations: i) they analyze output market participation distinctly from input market participation; and therefore, they might hide important heterogeneities among participants either in the output market or the input market; ii) they are located in specific regions in Kenya and pay attention to specific crops markets (maize, or pigeonpea) or analyze specific input market (fertilizer or seed), while the determinants of output market participation depend on the context and the nature of crop, and farmers' demands for inputs may include both fertilizers and seeds. To the best of our knowledge, the only paper that jointly analyzed technology adoption (input side) and output market participation was Teklewold (2016). Nevertheless, he only focused on that joint modeling and did not analyze the impact of such strategic choices on farm household's welfare.

This study goes beyond these limitations. Specifically, we jointly model the market participation regimes and their impact on farm profit per hectare. The theoretical model is applied to an agriculture representative survey conducted in Senegal in 2017. Using a multinomial endogenous treatment effects model, results show that the transaction costs drive market participation decisions. We also find that the drivers of the choice of market participation regimes depend on the crop under study. More importantly, we find that the most gainful market participation regime for staples producers is the joint participation in both input and output markets, while for groundnut producers, the most profitable regime is to market their products without a need to purchase inputs. Finally, when farmers choose to produce both groundnut and staples, the efficient market choice combination is to be fully integrated into the two markets for staples production and being in autarky for groundnut production.

As policy implications of our findings, it is important to promote market access for farm households to increase their livelihood. Especially, it is not enough to provide inputs to producers, there is a need to find the right policy to connect them to both input and output markets. Especially, this study shows that staple crops are more responsive to joint market participation than groundnut which is the most common cash crop in Senegal. Therefore, special attention to the staples sector is required. Such a policy would increase farming profit per hectare and also reduce food insecurity in the country.

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Chapter 6

6. Final Remarks

6.1. Main findings

Adoption of new and profitable technologies is crucial for smallholder farmers to increase their productivity (yield), and then their production, which in turn will allow them to move from subsistence farming towards market-oriented production. However, the level of adoption of agricultural technologies is still low in African countries. In Senegal, there is very little up-to-date data on the technologies adopted by small-scale farmers. Thus, this thesis aims to provide more information on the level of technology adoption and to identify the drivers and impacts of agricultural technology adoption in Senegal.

Using the most recent survey data, collected in 2017, results show a two-tier agricultural economy in terms of technology adoption. In the irrigated agriculture dominated by rice production, almost all farmers adopt the most advanced technologies (certified seeds and chemical fertilizers), with an average intensity of chemical fertilizer use of more than 300 kg per hectare. On the other hand, in the rain-fed agriculture characterized by a lack of financial resources and climatic variability, only a few farmers use improved agricultural inputs. For example, in this rain-fed agriculture, less than 30 kg of chemical fertilizer per hectare is used in the survey year (the 2016/2017 season).

In Chapter 2, we explore the determinants of joint adoption of certified seeds and inorganic fertilizers in rainfed agriculture in Senegal using a flexible bivariate probit model in a context of production risk. The proposed framework is applied to study the joint adoption of certified seeds and inorganic fertilizers in rice and groundnut sectors in Senegal. Results show a heterogeneous correlation between the two decisions under consideration for rice, while for groundnut technology adoptions, a homogeneous correlation is found. For both sectors, the decision to adopt certified seeds and that to apply inorganic fertilizers were dependent. Production risk measured by the partial moments of agricultural profit per hectare has a significant effect on technology adoption in Senegal. For the rice sector, profit variance has a significant and positive influence on the correlation parameter of the joint distribution. For in the groundnut sector, profit variance has a positive impact on both marginal distributions. Therefore, production risk has an unobserved effect on the joint adoption of rice technologies, while it has a direct and positive effect on the probability to adopt individual technologies and their joint adoption for groundnut. Other drivers of technology adoption identified include cooperative membership, access to extension services, access to credit, education, family size, and farm size.

Based on findings from Chapter 2, we assess the impact of joint technology adoption on the rice sector. It is worth noting that rice is the main staple in the country. Three main rice technologies are considered: irrigation, rice certified seeds, and inorganic fertilizers. Data description shows that the rice irrigated system is the most productive in terms of rice produced per hectare. The metafrontier framework reveals that different rice production frontiers are present in the rice sector. The estimated technical efficiency is very low (about 50%), suggesting that with the right policies the country rice production could double without any additional investment on inputs. Across groups, the traditional rice system is the most efficient. A huge technological gap is also observed, especially for farmers that partially adopt improved inputs (certified seeds or inorganic fertilizer). Therefore, there is an important knowledge gap regarding advanced technologies. In terms of impact on rice yield, results show that the most productive technology choice is the joint adoption of certified seeds and inorganic fertilizers in both systems of production (rain-fed and irrigated). We also find that the most impactful technology between certified seeds and inorganic fertilizers is the use of the latter.

In chapter 4, we model the decision to invest in inputs (seeds and inorganic fertilizers) under uncertainty. A Heckman model is used to study the main drivers of the investment decision and the level of investment, while an endogenous switching regression model is applied to analyze the causal effect of the risky investment on agricultural profit and food security. Results show that the main drivers of the decision to purchase risky inputs include household composition, farmer organization, farm size, access to livestock income, and crop diversification. Drivers of the level of investment in risky inputs are gender, extension services, farm size, agricultural capital, and cropping patterns. On the other hand, results reveal a positive impact of risky investment on agricultural profit per hectare and food security measured as total food crops produced per capita. The expected impact for non-adopters is found to be higher than that for adopters. In addition, the heterogeneity effect shows that for each treatment level, current adopters perform less than current non-adopters.

In chapter 5, we model the choice of market participation regimes for both input and output markets and the corresponding welfare effect. Using a farm household model, we show that transaction costs have a strong impact on the choice of a market participation regime. Empirically, a multinomial treatment effects model, that combines a multinomial logistic regression and an outcome equation, is used. The framework is applied to study the cases of groundnut and staples crops. The driving factors of the market choices identified are very distinct across value chains and market regimes. This suggests that analyzing participation as done here brings more insights, revealing more heterogeneities among farmers. Regarding the impact of market participation regimes on agricultural profit per hectare, being integrated into the two markets displays the highest staples profit per hectare, whereas participating only in the output market is the best choice for groundnut producers, as far as profit per hectare is concerned. For farmers who are involved simultaneously in the production of food crops and groundnut, the most profitable alternative is to be fully integrated for staples production and to be in autarky for groundnut production.

6.2. Policy implications

Based on our results, several policy implications are obvious. Firstly, the adoption of a given technology is not an isolated fact and takes into account the existence of complementary and non-complementary technologies. Thus, a comprehensive vision to promote complementary technology packages is required. Secondly, in some contexts, the most obvious combination of technologies is not necessarily the most efficient or productive choice. For example, results show, among other things, that the adoption of certified rice seed does not particularly improve the yield of irrigated rice. In this context, the adoption of chemical fertilizers is largely sufficient. This result shows the usefulness of identifying the best choice of technologies adapted to each crop and agroecological zone, hence the importance of the work of extension agents in advising producers. Therefore, to better assist producers, the government must provide good training to the agents supplying advisory support services. Thirdly, results show that investment in inputs such as seeds and chemical fertilizers is generally profitable in Senegal and even the expected return for those who have spent nothing is even higher when they would make that decision. This suggests that the government and the private sector should pay more attention to the agricultural sector since the sector is profitable and remains the basis for structural transformation. Fourth, production risks and climate shocks are found to impact the choice and performance of agricultural technologies. Thus, the development of contract farming and agricultural insurance are serious options to be explored by the different actors in the sector (cooperatives, government, and the private sector). Finally, results have shown that the option that provides the maximum profit per hectare for the food sector is agriculture that buys inputs and sells part of the production. In other words, market-oriented food agriculture gives the best welfare to farm households. Thus, policies to facilitate access to inputs only are no longer sufficient to bring the desired structural transformation. Above all, it is necessary to develop joint policies for access to markets for both inputs and products. This calls for a thorough review of the current policies and for structural reforms in the agricultural sector.

6.3. Future research

The current research has focused on the analysis of technology adoption, market participation, and their impacts on farm profit or food security in Senegal. One possible extension of this work would be to consider more than two improved technologies in order to find the best technology combination that generates the most welfare effects for farm households. Another interesting direction in the technology adoption literature would be to extend our flexible bivariate probit using the copula framework. This extension will be useful to study the drivers of joint decisions in a higher dimension. Finally, since transaction costs are so central in the literature of technology adoption and market participation, it would be important to find an empirical strategy to estimate them. One approach would be to use the Bayesian framework (data augmentation approach) to solve this issue of missing data.

Appendix

A. Summary

Essays on Technology Adoption in Senegal

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African agriculture is characterized by very low average productivity. This results in a very high yield gap, i.e. the average yields achieved by farms are up to 90% below the yields that can be achieved by applying proven best-practice technologies. A central problem of low agricultural productivity is, therefore, technology adoption, i.e. the question of why farms do not apply available best-practice technologies. In this context, this dissertation investigates the mechanisms of technology adoption using a unique farm data set of more than 4000 farms in Senegal and innovative econometric methods. A first descriptive analysis reveals dual Senegalese agriculture with a small percentage of farms using modern technologies, i.e. irrigation, use of mineral fertilizers and pesticides and improved seeds, and a majority of farms using traditional extensive farming without the use of purchased inputs and irrigation. For example, the use of N-fertilizer in the majority of traditional farms is less than 30kg/ha while modern farms use more than 300kg/ha. While a shift from traditional to modern agriculture at the macro level has a clear positive effect on food security and rural development, the question arises as to the key micro-level barriers that prevent traditional farms from using modern technologies. While the potential obstacles have been identified from the theoretical literature, i.e. transaction costs in credit, labor, goods, and insurance markets as well as imperfect technological knowledge of farmers, for practical agricultural policy the question arises as to which are the central causes in a specific empirical case. This is particularly important because the efficient agricultural policy measures to reduce these obstacles differ significantly depending on the specific obstacle. In this interesting and highly relevant area of agricultural policy, the present study makes central contributions by applying innovative econometric methods for the microeconomic analysis of technology adaptation, i.e. the concrete obstacles to the application of modern agricultural technology at the farm level. In total, the dissertation comprises 4 contributions. In the first contribution, a flexible bivariate probit model is applied to analyze the joint use of certified seed and mineral fertilizer in rice and peanut production. While the flexible versus the standard probit model is theoretically and statistically preferable, both approaches lead to the same key policy implications. The second paper analyzes the

impact of multiple technology decisions on technical efficiency and yield using rice production as an example. On a methodological level, the paper combines a metafrontier approach with a multinominal treatment-effects model to take into account the heterogeneity in rice production and potential selection bias in the choice of technologies. A remarkable result of the analyses is the identification of significant knowledge gaps as a central obstacle for the use of modern inputs. The third paper examines the importance of yield risk for the use of modern inputs and its significance for the income and food security of agricultural households. Methodologically, an endogenous switching regression model is used to adequately analyze the treatment effects of modern input use. In the fourth paper, an interdependent farm household model is used as a theoretical approach to analyzing participation in relevant agricultural input and output markets. Transaction costs are a central determinant of the market participation of agricultural enterprises. Since transaction costs can be specific for different input and output markets, different market regimes result, including complete self-sufficiency, selective participation in specific output or input markets, and complete market participation. Methodologically, a multinomial endogenous treatment effects model is applied to empirically analyze the market participation decisions of individual farm households. Interestingly, farms participate selectively in output and input markets. This implies market-specific transaction costs, which cannot be explained by general factors such as infrastructure and market distance, but rather, for example, by specific social network structures that determine selective access to markets.

B. Zusammenfassung

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Die afrikanische Landwirtschaft ist durch eine sehr geringe durchschnittliche Produktivität gekennzeichnet ist. Dabei ergibt sich ein sehr hohes *Yield-GAP*, d.h. die von den landwirtschaftlichen Betrieben durchschnittlich erzielten Erträge liegen bis zu 90% unter den Erträgen, die bei der Anwendung bewährter *best practice* Technologien erzielt werden können. Ein zentrales Problem der geringen landwirtschaftlichen Produktivität ist somit *Technology Adoption*, d.h. die Frage, warum landwirtschaftliche Betriebe verfügbare *best practice* Technologien nicht anwenden. In diesem Zusammenhang untersucht die vorliegende Arbeit anhand eines einmaligen landwirtschaftlichen Betriebsdatensatzes von über 4000 Betrieben im Senegal mit Hilfe innovativer ökonometrischer Methoden die Mechanismen des *technology adapotion*. Eine erste deskriptive Analyse ergibt eine duale senegalische Landwirtschaft mit einem kleinen Anteil an Betrieben, der moderne Technologien, d.h. Bewässerung, Einsatz von mineralischem Dünger und Pestiziden sowie verbessertem Saatgut, verwendet und einer Mehrheit an Betrieben, die eine traditionelle extensive Landwirtschaft ohne Einsatz zugekaufter Inputs und Bewässerung betreibt. Zum Beispiel beläuft sich der Einsatz von N-Dünger in der Mehrheit der traditionell wirtschaftenden Betriebe auf unter 30kg/ha während der modern wirtschaftenden Betriebe über 300 kg/ha einsetzten. Während ein Wechsel von der traditionellen zu der modernen Landwirtschaft auf der Makroebene einen klar positiven Effekt auf die Nahrungsmittelsicherheit und die ländliche Entwicklung ausübt, stellt sich die Frage nach den zentralen Hindernisse auf der Mikroebene, die traditionell wirtschaftenden Betriebe davon abhalten, moderne Technologien anzuwenden. Während die potentiellen Hindernisse klar aus der theoretischen Literatur herausgearbeitet worden sind, dies sind im Wesentlichen Transaktionskosten auf Kredit-, Arbeits-, Güter- und Versicherungsmärkten sowie unvollkommenes technologisches Wissen der Farmer, stellt sich für die praktische Agrarpolitik die Frage, welches jeweils die zentralen Ursachen in einem konkreten empirisch Fall sind. Dies ist insbesondere deshalb von Bedeutung, da sich die effizienten agrarpolitischen Maßnahmen zum Abbau dieser Hindernisse je nach konkretem Hindernis signifikant unterscheiden. In diesem interessanten und agrarpolitisch hoch relevantem Bereich leistet die vorliegende Arbeit zentrale Beiträge, in dem diese innovative ökonometrische Verfahren zur mikroökonomischen Analyse von *technology adaption*, d.h. der konkreten Hindernisse der Anwendung moderner

landwirtschaftlicher Technologie auf Betriebsebene, anwendet. Insgesamt umfasst die Dissertation 4 Beiträge. Im ersten Beitrag wird ein flexibles bivariates Probitmodell zur Analyse des gemeinsamen Einsatzes von zertifiziertem Saatgut und mineralischem Dünger in der Reis- und Erdnussproduktion angewendet. Während das flexible gegenüber dem Standard-Probit-Model theoretisch und statisch zu präferieren ist, führen beide Ansätze zu den gleichen zentralen Politikimplikationen. Im zweiten Beitrag wird die Bedeutung von multiplen Technologieentscheidungen auf die technische Effizienz und den Ertrag am Beispiel der Reisproduktion analysiert. Auf methodischer Ebene kombiniert der Beitrag einen *Metafrontier*-Ansatz mit einem *multinominalen treatment-effects-Modell* um die Heterogenität in der Reisproduktion sowie potentielle Selektionsverzerrungen bzgl. der Auswahl der Technologien zu berücksichtigen. Ein bemerkenswertes Ergebnis der Analysen ist die Identifikation von signifikanten *knowledge-gaps* als zentrales Hindernis für den Einsatz moderner Inputs. Der dritte Beitrag untersucht die Bedeutung des Ertragsrisikos für den Einsatz von modernen Inputs und deren Bedeutung für das Einkommen und die Nahrungsmittelsicherheit landwirtschaftlicher Haushalte. Methodisch wird ein *endogenous switching regression* Modell verwendet, um Treatment Effekte des Einsatzes modernen Inputs adäquat zu analysieren. Im vierten Beitrag wird ein interdependentes Farm-Haushalts-Modell als theoretischer Ansatz verwendet, um die Partizipation in relevanten landwirtschaftlichen Input- und Outputmärkten zu analysieren. Zentrale Determinante der Markteilnahme landwirtschaftlicher Betriebe sind Transaktionskosten. Da diese spezifisch für unterschiedliche Input- und Outputmärkte ausfallen können, ergeben sich unterschiedliche Marktregimes, die eine komplette Autarkie, eine selektive Teilnahme an speziellen Output- bzw. Inputmärkten sowie eine komplette Marktteilnahme umfassen. Methodisch wird ein *Multinomial endogenous treatment effects model* angewendet, um die Marktpartizipations-Entscheidungen individueller Farm-Haushalte empirisch zu analysieren. Interessant ist, dass Betriebe durchaus selektiv an Output- und Inputmärkten teilnehmen. Dies impliziert marktspezifische Transaktionskosten, die nicht durch generelle Faktoren wie Infrastruktur und Marktdistanz erklärt werden können, sondern z.B. durch spezielle soziale Netzwerkstrukturen, die einen selektiven Zugang zu Märkten determinieren.