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Abstract

The adoption of certified seeds and chemical fertilizers is central for African agriculture which is characterized by very low productivity. This paper analyzes the technology adoption of certified seeds and inorganic fertilizers for two central crops in Senegal: rice and groundnut. The joint adoption of these two technologies is modeled in the presence of production risk using a flexible bivariate probit model. A recent agricultural survey, representative country-wide, collected in 2017 is used for our application. Descriptive statistics confirm the low rate of agricultural technology adoption. In the rainfed system, the average inorganic fertilizer used is about 28 kg/ha. The analysis reveals that in rural Senegal decisions to adopt certified seeds and inorganic fertilizers are interrelated for both rice and groundnut systems. For the rice system, a heterogeneous dependency is revealed, while for groundnut technology adoptions, a homogeneous correlation is found. Production risk is found to have a significant impact on technology adoption. We also found that determinants of individual technologies and their joint adoption vary widely across crops. However, the main determinants of technology adoption in rainfed agriculture in Senegal include cooperative membership, access to extension services, access to credit, education, family size, and farm size.

Keywords: *Fertilizer use, certified seeds, joint technology adoption, rainfed agriculture, Senegal*

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 et al., 2006) According to Dethier and 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 et al., 2014; Teklewold et al., 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. 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 et al., 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 more education and 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 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.

3 Methodology

3.1 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 et al. (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 and 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 and Chavas, 2009). Moreover, Antle (1987) and Kim and 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

$$q = f(x, z, e) \tag{1}$$

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

$$\pi = q - wx \tag{2}$$

Where $\mathbb{E}$ is the expectation operator, $U(.)$ is the von Neumann-Morgenstern utility function. Let note the expected gross income from farming activities $\mu_1 - wx > 0$.

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

$$\max_x V[\mu_1(x), \eta_2(x), \varphi_2(x), \eta_3(x), \varphi_3(x)] \tag{3}$$

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 3 in the elasticity form is as follow:

$$\mu_1^\star - \frac{wx}{\mu_1} = s_2(V_{2\eta}\eta_2^\star - V_{2\varphi}\varphi_2^\star) + s_3(V_{3\eta}\eta_3^\star - V_{3\varphi}\varphi_3^\star) \tag{4}$$

where $s_j = \mu_j/(\mu_1(\mu_1 - wx)^{j-1})$, $\eta_j^\star = \partial \ln \eta_j / \partial \ln x$, $\varphi_j^\star = \partial \ln \varphi_j / \partial \ln x$, $\mu_1^\star = \partial \ln \mu_1 / \partial \ln x$, $V_{j\eta} = -(\mu_1 - wx)V_{\eta_j}/V_{\mu_1}$, $V_{j\varphi} = -(\mu_1 - wx)\frac{V_{\varphi_j}}{V_{\mu_1}}$. 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 $\eta_j^\star = \varphi_j^\star$. In the empirical investigation, we compared results using partial moments (η_j, φ_j) with that from the full moments (μ_j).

From equation 4, an input use is a function of its cost, expected profit, partial moments of profit, and farm and household characteristics. Therefore, the adoption of productivity-enhancing technology such as inorganic fertilizers or improved seeds will depend on expected technology return, 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).

$$\mathbb{E}[U(\mu_1 - wx - R)]_{k,t=1} - \mathbb{E}[U(\mu_1 - wx - R)]_{k,t=0} > VI_{t=1} \tag{5}$$

3.2 Empirical model

From equation (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 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 (). 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.

$$\pi_i = g(x_i) + z_i'\gamma + u_i \tag{6}$$

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 x, 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

$$\log[(\pi_i - \hat{u}_i)^2] = g'(x) + z_i'\gamma + u_i' \tag{6'}$$

where $\hat{u}_i$are the residuals from an OLS estimation of equation (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

$$\mu_i^j = g'(x_i) + z_i'\gamma_j + u_i^j \tag{7}$$

$$\eta_i^j = g'(x_i) + z_i'\gamma_{j,\eta} + u_i^{j,\eta} \tag{8}$$

$$\varphi^j = g'(x_i) + z_i'\gamma_{j,\varphi} + u_i^{j,\varphi} \quad \text{if} \quad u_i^{GLS} > 0 \tag{9}$$

Equation (7) represents the full higher-order moments' specification, equations (8) and (9) are for partial moments. Equation (8) and (9) are combined in a kind of threshold regression for their joint estimation. The dependent variable in equation (7) is the residuals u_i^{GLS} raised to the power j (2,3), while the dependent variables in (8) and (9) are the absolute residuals u_i^{GLS} raised to the power j. For the variance specification (2^{nd} moment) of (7) and for all partial moments, a log transformation is preferred in order to preserve the positivity of predicted moments. Equations (7) to (9) were estimated using OLS corrected for heteroscedasticity following MacKinnon and 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; Feder and Onchan, 1987; 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:

$$\begin{aligned} y_1^\star &= x_1'\beta_1 + \epsilon_1 \quad \text{if } y_1^\star > 0 \text{ and } 0 \text{ otherwise;} \\ y_2^\star &= x_2'\beta_2 + \epsilon_2 \quad \text{if } y_2^\star > 0 \text{ and } 0 \text{ otherwise;} \end{aligned}$$

$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} |(x_1, x_2) \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{10}$$

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), x_1 et 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 Y_1 and Y_2 given X is not constant, but depends on the 'value of the conditioning variable explicitly'. Interested readers are referred to Vatter (2016) for the 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.

$$\rho = \frac{\exp(x_3'\beta_3) - 1}{\exp(x_3'\beta_3) + 1} \tag{11}$$

where β_3 are the parameters of interest. Readers interested in non(semi)-parametrical specification of the correlation equation (11) are referred to Ieva et al. (2014); Marra and Radice (2017, 2013, 2011); McGovern et al. (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 et al., 2017; Vatter and Nagler, 2018; Vatter, 2016).

4 Data and descriptive summary

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 and the implementation for a period of 3 years (2015 - 2018) by the Ministry of Agriculture and rural facilities with 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. 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 5207 farm households. We remove all households that have a very small land size (less than 0.1 hectares, a total of 33 households).

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.

4.1 Certified seeds and fertilizer adoption in Senegal

This section discusses the joint adoption of certified seeds and chemical fertilizers at crop level. Figure 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 (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

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

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

33 percent had adopted certified seeds for at least one crop, while 45 percent of them had used inorganic fertilizers.

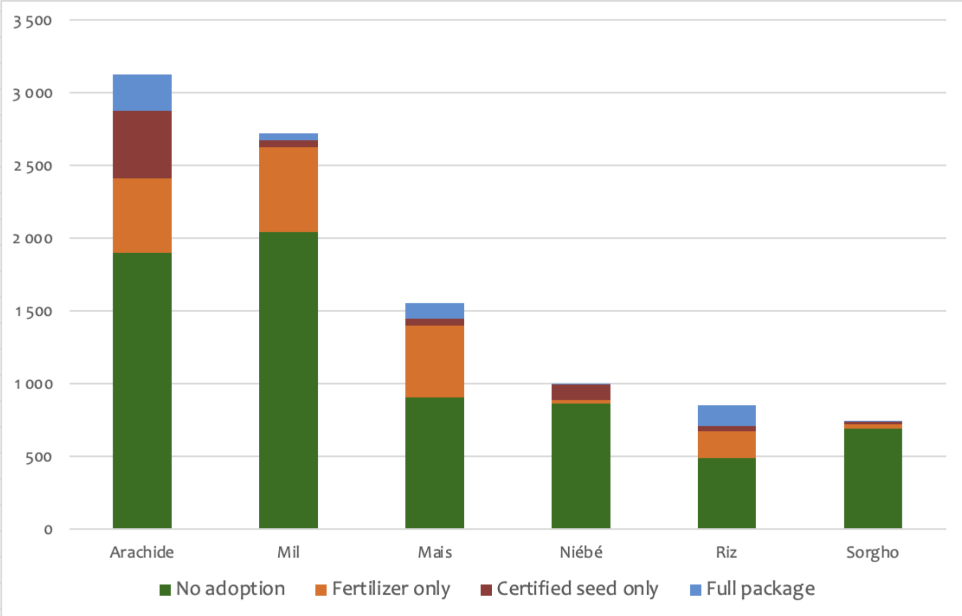

Figure 1: Multiple technology adoption across crops in Senegal. Source: PAPA data (2017).

One key statistic of technology adoption is the intensity of chemical fertilizer use. Table (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.

[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.

Table 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, 2017.

From Figure 1 we know that not all technologies are of equal importance across crops. Table 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: 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	312.27	529.99	489.48	445.46
	(393.19)	(301.22)	(406.05)	(422.27)	(397.65)
Sorghum	522.93	464.27	499.78	1777.22	525.41
	(576.08)	(323.59)	(323.59)	(1191.35)	(572.74)
Maize	559.84	458.16	788.04	771.65	647.57
	(718.48)	(497.91)	(826.18)	(692.63)	(756.57)
Rice	1152.94	595.42	2010.28	3347.88	2254.31
	(1647.23)	(508.79)	(2105.68)	(2463.43)	(2332.57)
Cowpeas	212.05	260.83	316.38	128.7	219.57
	(305.26)	(307.33)	(600.43)	(19.71)	(315.42)
Groundnut	583.85	570.56	728.2	586.84	605.33
	(753.37)	(835.19)	(663.5)	(545.55)	(739.97)

Source: PAPA, 2017.

4.2 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 et al., 1993; Feder et al., 1985; Gebremedhin and Swinton, 2003; Isham, 2002; Kassie et al., 2011, 2013; Lee, 2005; Marenya and Barrett, 2007; Neill and 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 3.

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

	Variable	Description	Rice producers Mean	Rice producers Std dev.	Groundnut producers Mean	Groundnut producers 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 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.

[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).

5 Results and discussion

This section presents results based on our econometric specification. As presented in section 3.2, 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 A1 and Table A2). 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 and for agricultural insurance. Results from these probit models are presented in the appendix (Table A3).

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 and Radice (2017) under the free statistical software R (Team and Others, 2013).

5.1 Joint adoption of rice certified seeds and chemical fertilizers

Table 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 and Mundlak, 1991; Ogada et al., 2014; Singh and 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.

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 5 reports the marginal effects of covariates on marginal technology adoptions and joint technology adoption.

Table 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

Table 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.

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 et al. (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, 2008; Wollni et al., 2010; Teklewold et al., 2013).

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

5.2 Joint adoption of groundnut certified seeds and chemical fertilizers

Table 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.

Table 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.

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 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.

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.

Table 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.

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).

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.

6 Conclusion and policy implications

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.

References

Abay, Kibrewossen Kibrom A. Kibrewossen, Guush Berhane, Alemayehu Seyoum Taffesse, Kibrewossen Kibrom A. Kibrewossen Abay, Bethelhem Koru, Alemayehu Seyoum, Kibrewossen Kibrom A. Kibrewossen Abay, Bethelhem Koru, Alemayehu Seyoum Taffesse, Kibrewossen Kibrom A. Kibrewossen Abay, and Bethelhem Koru, "Estimating input complementarities with unobserved heterogeneity: Evidence from Ethiopia," *Journal of Agricultural Economics*, 2018, *69* (2), 495–517.

Antle, John M, "Testing the stochastic structure of production: a flexible moment-based approach," *Journal of Business & Economic Statistics*, 1983, *1* (3), 192–201.

_ , "Econometric estimation of producers' risk attitudes," *American Journal of Agricultural Economics*, 1987, *69* (3), 509–522.

Antle, John M., "Asymmetry, partial moments, and production risk," *American Journal of Agricultural Economics*, 2010, *92* (5), 1294–1309.

Antle, John M and W J Goodger, "Measuring stochastic technology: The case of Tulare milk production," *American Journal of Agricultural Economics*, 1984, *66* (3), 342–350.

Crawford, Eric Winthrop, Thomas S Jayne, and Valerie Auserehl Kelly, *Alternative approaches for promoting fertilizer use in Africa*, Agriculture & Rural Development Department, World Bank Washington, DC, 2006.

Dethier, Jean-Jacques and Alexandra Effenberger, *Agriculture and development: A brief review of the literature*, The World Bank, 2011.

Di Falco, Salvatore and Jean Paul Chavas, "On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia," *American Journal of Agricultural Economics*, 2009, *91* (3), 599–611.

Dorfman, Jeffrey H, "Modeling multiple adoption decisions in a joint framework," *American Journal of Agricultural Economics*, 1996, *78* (3), 547–557.

D'souza, Gerard, Douglas Cyphers, and Tim Phipps, "Factors affecting the adoption of sustainable agricultural practices," *Agricultural and Resource Economics Review*, 1993, *22* (2), 159–165.

Feder, Gershon, "Adoption of interrelated agricultural innovations: Complementarity and the impacts of risk, scale, and credit," *American Journal of Agricultural Economics*, 1982, *64* (1), 94–101.

— **and Tongroj Onchan**, "Land ownership security and farm investment in Thailand," *American Journal of Agricultural Economics*, 1987, *69* (2), 311–320.

— **, Richard E Just, and David Zilberman**, "Adoption of agricultural innovations in developing countries: A survey," *Economic development and cultural change*, 1985, *33* (2), 255–298.

Filippou, Panagiota, Giampiero Marra, and Rosalba Radice, "Penalized likelihood estimation of a trivariate additive probit model," *Biostatistics*, 2017, *18* (3), 569–585.

Gebeyehu, Mulat Goshu, "The Impact of Technology Adoption on Agricultural Productivity and Production Risk in Ethiopia: Evidence from Rural Amhara Household Survey," *OALib*, 2016, *03* (02), 1–14.

Gebremedhin, Berhanu and Scott M Swinton, "Investment in soil conservation in northern Ethiopia : the role of land tenure security and public programs," 2003, *29*, 69–84.

Gerhart, John, *The diffusion of hybrid maize in western Kenya*, CIMMYT, 1975.

Greene, W A, *Econometric Analysis, 7th Edn., Harlow*, Pearson, 2012.

Ieva, Francesca, Giampiero Marra, Anna Maria Paganoni, and Rosalba Radice, "A semiparametric bivariate probit model for joint modeling of outcomes in STEMI patients," *Computational and Mathematical Methods in Medicine*, 2014, *2014* (April).

IPAR, *Subventions des intrants agricoles au Sénégal : Controverses et Réalités*, Initiative Prospective Agricole et Rural (IPAR) Annual Publication, 2015.

Isham, Jonathan, "The effect of social capital on fertiliser adoption: Evidence from rural Tanzania," *Journal of African economies*, 2002, *11* (1), 39–60.

Kassie, Menale, Bekele Shiferaw, and Geoffrey Muricho, "Agricultural technology, crop income, and poverty alleviation in Uganda," *World Development*, 2011, *39* (10), 1784–1795.

— **, Moti Jaleta, Bekele Shiferaw, Frank Mmbando, and Mulugetta Mekuria**, "Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania," *Technological forecasting and social change*, 2013, *80* (3), 525–540.

—, Precious Zikhali, Kebede Manjur, and Sue Edwards, "Adoption of organic farming technologies: Evidence from semi-arid regions of Ethiopia," *rapport nr.: Working Papers in Economics 335*, 2008.

Kim, Kwansoo and Jean-Paul Chavas, "Technological change and risk management: an application to the economics of corn production," *Agricultural economics*, 2003, *29* (2), 125–142.

Koundouri, Phoebe, Céline Nauges, and Vangelis Tzouvelekas, "Technology adoption under production uncertainty: theory and application to irrigation technology," *American Journal of Agricultural Economics*, 2006, *88* (3), 657–670.

Lee, David R, "Agricultural sustainability and technology adoption: Issues and policies for developing countries," *American journal of agricultural economics*, 2005, *87* (5), 1325–1334.

MacKinnon, James G and Halbert White, "Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties," *Journal of econometrics*, 1985, *29* (3), 305–325.

Marenya, Paswel P and Christopher B Barrett, "Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya," *Food policy*, 2007, *32* (4), 515–536.

Marra, G and R Radice, "GJRM: generalised joint regression modelling," *R package version 0.1-1*, 2017.

Marra, Giampiero and Rosalba Radice, "Estimation of a semiparametric recursive bivariate probit model in the presence of endogeneity," *Canadian Journal of Statistics*, 2011, *39* (2), 259–279.

— and —, "A penalized likelihood estimation approach to semiparametric sample selection binary response modeling," *Electronic Journal of Statistics*, 2013, *7* (1), 1432–1455.

McGovern, M E, T Bärnighausen, G Marra, and R Radice, "On the Assumption of Bivariate Normality in Selection Models: A Copula Approach Applied to Estimating HIV Prevalence.," 2015, pp. 1–31.

McGuirk, Anya and Yair Mundlak, *Incentives and constraints in the transformation of Punjab agriculture*, Vol. 87, Intl Food Policy Res Inst, 1991.

Neill, Sean P and David R Lee, "Explaining the adoption and disadoption of sustainable agriculture: the case of cover crops in northern Honduras," *Economic development and cultural change*, 2001, *49* (4), 793–820.

Ogada, Maurice J., Germano Mwabu, and Diana Muchai, "Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions," *Agricultural and food economics*, 2014, *2* (1), 12.

Olwande, John, Geophrey Sikei, and Mary Mathenge, "Agricultural technology adoption: A panel analysis of smallholder farmers' fertilizer use in Kenya," 2009.

Rahim, Afaf H, Ruerd Ruben, and Ekko C van Ierland, "Adoption and abandonment of gum Arabic agroforestry in Sudan," in "AFTA 2005 Conference proceedings" 2005, p. 13.

Seck, Abdoulaye, "Fertiliser subsidy and agricultural productivity in Senegal," *The World Economy*, 2017, *40* (9), 1989–2006.

Singh, Nirvikar and Deepali Singhal Kohli, "The green revolution in Punjab, India: The economics of technological change," *Journal of Punjab Studies*, 2005, *12* (2), 285–306.

Team, R Core and Others, "R: A language and environment for statistical computing," 2013.

Teklewold, Hailemariam, Menale Kassie, and Bekele Shiferaw, "Adoption of multiple sustainable agricultural practices in rural Ethiopia," *Journal of agricultural economics*, 2013, *64* (3), 597–623.

Thuo, Mary, Boris E Bravo-Ureta, Ibrahima Hathie, and Patrick Obeng-Asiedu, "Adoption of chemical fertilizer by smallholder farmers in the peanut basin of Senegal," *African Journal of Agricultural and Resource Economics*, 2011, *6* (311-2016-5558).

Thuo, Mary W., Boris E. Bravo-Ureta, Kofi Obeng-Asiedu, and Ibrahima Hathie, "The Adoption of Agricultural Inputs by Smallholder Farmers: The Case of an Improved Groundnut Seed and Chemical Fertilizer in the Senegalese Groundnut Basin," *The Journal of Developing Areas*, 2014, *48* (1), 61–82.

Vatter, Thibault, "Generalized Additive Modeling For Multivariate Distributions." PhD dissertation, Université de Lausanne, Faculté des hautes études commerciales 2016.

_ **and Thomas Nagler**, "Generalized Additive Models for Pair-Copula Constructions," *Journal of Computational and Graphical Statistics*, 2018, *27* (4), 715–727.

Wollni, Meike, David R Lee, and Janice E Thies, "Conservation agriculture, organic marketing, and collective action in the Honduran hillsides," *Agricultural economics*, 2010, *41* (3-4), 373–384.

Wooldridge, Jeffrey M, "Control function methods in applied econometrics," *Journal of Human Resources*, 2015, *50* (2), 420–445.

Yu, Li, Terrance Hurley, James Kliebenstein, Peter Orazem, Li Yu, Terrance Hurley, James Kliebenstein, and Peter Orazem, "A test for complementarities among multiple technologies that avoids the curse of dimensionality," *Economics Letters*, 2012, *116* (3), 354–357.