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Anatole Goundan
Amy Faye
Christian Henning
Peron A. Collins-Sowah
Department of Agricultural Economics
University of Kiel

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About the authors:
Anatole Goundan is senior associate scientist at Akademiya2063 (Senegal). He studied statistics, economics, agricultural economics, and physics. He earned a PhD in agricultural economics from the University of Kiel (Germany). His main areas of specialization are applied economics, agricultural trade, time series, social network analysis.
Amy Faye is a Post-doctoral Researcher at the Center for Development Research (ZEF).
Christian Henning is professor and chair of agricultural economics, University of Kiel (Germany). He studied economics, agricultural economics, sociology, political science and mathematics. He earned a PhD in economics, in agricultural economics and in political science. His main areas of specialization are applied political economy and applied economic modeling of agricultural policies.
Peron A. Collins-Sowah is PhD candidate at University of Kiel.
Corresponding author: agoundan@akademiya2063.org

Abstract

While the productivity effects of the application of modern inputs, such as improved seeds or inorganic fertilizer, are well known, farmers in Sub-Saharan Africa tended to underinvest in purchased inputs. This underinvestment appears related to the unpredictable nature of agricultural production that is subject to risks and shocks. Farmers make production decisions before climatic and other shocks are realized. They, therefore, have no certainty about the outcome of their decisions. This makes investments in agricultural inputs very risky. This paper uses recent data for Senegal to identify the main drivers of the decision to purchase risky inputs (seeds and/or fertilizers), the level of investment and to quantify the impact of the use of risky inputs on household welfare. Using a Heckman model, 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. Using an endogenous switching regression, we find a positive impact on the adoption of risky inputs on farm profit per hectare, and food available from production. The expected impact for non-adopters is found to be higher than that for adopters because they are involved in rice production (which is more responsive to inputs use) and in millet production (which is central for food security).

Keywords: *Risky inputs, purchased fertilizers, purchased seeds, household welfare, Senegal*

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 et al., 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 (Rosenzweig and Udry, 2013; Karlan et al., 2014) 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, at least in theory, to manage this risk. The literature identifies several strategies for managing production risks. Some of these include diversification (Bezabih and Di Falco, 2012; Bezabih and Sarr, 2012; Di Falco et al., 2010; Obiri et al., eds, 2017; Birthal and Hazrana, 2019; Ullah and Shivakoti, 2014), formal insurance products such as index-based products (Velandia et al., 2009; Enjolras et al., 2012; D'Alessandro et al., 2015; Obiri et al., eds, 2017; Wang et al., 2016), agronomic practices such as conservation farming practices, mulching, sustainable land management (Liniger et al., 2011; Obiri et al., eds, 2017; Choudhary et al., 2016) and adoption of risk-reducing inputs or technologies8 such as improved and high yield seeds, fertilizer, pesticides, and irrigation (Barnett et al., 2008; Kahan, 2008; Obiri et al., eds, 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 (Ribeiro and Koloma, 2016; Sall, 2015; CIAT and BFS/USAID, 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 et al., 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.

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 et al., 2003; Gillespie et al., 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 et al., 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 et al., eds, 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 et al., eds, 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; Bank, 2005; Barnett et al., 2008; Kahan, 2008; Chetaille et al., 2011; Obiri et al., eds, 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 et al., 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 US77(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.

3 Conceptual framework and estimation strategies

Risky inputs investment decision and household welfare

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 production 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. The risky nature of these expenditures is exacerbated by their high opportunity cost in a context where liquidity constraints are severe.

We model the 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. Two periods 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, $s \in S$. This state of the world occurs with probability π_s and affects the production that a farmer can anticipate realizing 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). Indeed, in addition to rainfall variability faced by farmers, the quality of inputs is crucial for its potential productivity under different 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 nutrient is missing in fertilizer, and hybrid maize seed is estimated to contain less than 50% authentic seeds. However, various instruments may be used by farmers to reduce this risk. Farmer organization, and extension services allows farmers to get more information on inputs and the most reliable input providers. Thus, information emerges in the model as an additional dimension of the state space, $t \in T$.

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:

$$u(c^0) + \beta \sum_{t,s \in T\text{x}S} \pi_t \pi_s u(c_{t,s}^1) \tag{1}$$

Subject to budget constraints:

$$c^0 = y - x - a \tag{2}$$

$$c_{t,s}^1 = f_{t,\ s}(x, z) + Ra \tag{3}$$

$$x \geq 0 \tag{4}$$

$$a \geq \bar{a} \tag{5}$$

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 which has a return R in the next period.β is the discount factor. $f_{s,t}(x)$ is a state-specific production function.

Constraint (5) represents a constraint on borrowing. Thus, this model incorporates all three constraints: Credit is constrained by $\bar{a}$, risk is generated through the realization of s, and incomplete information enters through the realization of t.

At 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 $s \in S = \{g, b\}$. In the absence of incomplete information issue, 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 $f_s(x)$, farmers solving this problem realize the following first-order conditions:

$$u'(c^0) = \beta \sum_{s \in S} \pi_s f_s'(x) u'(c_s^1) \tag{6}$$

and

$$u'(c^0) = \beta R \, \mathbb{E} \, u'(c_s^1) + \lambda_a \tag{7}$$

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 λ_a^I, the multiplier associated with full insurance, then the two first-order conditions point out that:

$$\beta R + \frac{\lambda_a^I}{\mathbb{E}\left(u'(c^{1I})\right)} = \beta \, \mathbb{E}\left(f_s'(x)\right) \tag{8}$$

In contrast, absent perfect insurance, we know that for some λ_a ,

$$\beta R + \frac{\lambda_a^I}{\mathbb{E}\left(u'(c_s^1)\right)} = \beta \, \mathbb{E}\left(f_s'(x)\right) + \frac{cov(f'(x), u'(c_s^1)}{\mathbb{E}\left(u'(c_s^1)\right)}. \tag{9}$$

When farmers are not credit constrained, $cov(f'(x), u'(c_s^1)$, and $\lambda_a = 0$ 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 $\lambda_a = 0$), 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 λ_a. Therefore, first-order condition 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 (Huang et al., 2015; Finger et al., 2011; Smit and Pilifosova, 2003; Bryan et al., 2009). Therefore, accounting for various risk management strategies of farmers is central to understanding technology adoption.

Regarding now the limited information case, according Magruder (2018), the absence of full information on inputs emerges as an additional uninsured risk. Therefore, incomplete information will have similar influence on technology adoption and on demand for credit as with climatic risks. As said previously, 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 shop may be of better quality.

For the empirical part of this study, two main issues will be investigated: (i) the drivers of risky investment, and (ii) the impact of risky investment decision of farm household outcomes. We considered two outcomes which are 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 tend to measure household's self-sufficiency in food production. The latter is very important for households and for policy makers 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".

3.1 Heckman selection model

From the theoretical model, it is clear that the level of investment on risky inputs depends on a set of factors such as production risks, credit constraint, 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 (Asfaw et al., 2012b; Barrett, 2008; Alene et al., 2008; Key et al., 2000; Goetz, 1992; Staal et al., 1997). 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 D_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 that is not observed because we do not observe the expected utilities.

$$D_i^* = \mathbf{Q}'_{1,i}\gamma + u_i, u_i \sim \ N(0,1) \tag{10}$$

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^*:

$$D_i = \begin{cases} 1 & \text{if } \ D_i^* > 0 \\ 0 & \text{if } \ D_i^* \leq 0 \end{cases} \tag{11}$$

Once the decision to purchase risky inputs is made, the corresponding investment level ($\mathbf{X}$) is modeled as follow:

$$X_i = \mathbf{Z}'_{1i}\beta + \varepsilon_i \tag{12}$$

Where $Q_{1,i}$ are non-stochastic vectors of observed farm and non-farm characteristics determining adoption, Z_i represents a vector of exogenous variables thought to influence the level of risky investment. Equations (11) and (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 covariance between the two distributions:

$$(u_i, \varepsilon_i) \sim N[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \ \begin{pmatrix} 1 & \rho \\ \rho & \sigma \end{pmatrix}] \tag{13}$$

The existence of a selection bias between the two decisions depends of the covariance ρ. If ρ is significantly different from zero, we conclude that there is a selection bias, otherwise, either the selection equation is mispecified 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 (11) that is not included in the intensity equation (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[1]. 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.

3.2 Endogenous switching regression model

Endogenous Switching Regression (ESR) model is commonly used to assess the impact of a treatment when especially experimental data are not available (Abdulai, 2016; Khonje et al., 2015; Abdulai and Huffman, 2014; Asfaw et al., 2012a; Di Falco et al., 2011). 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:

$$I_i^* = \mathbf{Q}_{2,i}'\gamma + \epsilon_i \tag{14}$$

$$\text{Regime 1:} \quad Y_{1i} = \mathbf{Z}_{2i}'\beta_1 + u_{1i} \quad \text{if} \quad Ii = 1 \tag{15}$$

$$\text{Regime 2:} \quad Y_{1i} = \mathbf{Z}_{2i}'\beta_2 + u_{2i} \quad \text{if} \quad Ii = 0 \tag{16}$$

where I_i^* i is the unobservable or latent variable for technology adoption, Ii is its observable counterpart, $Q_{2,i}$ are non-stochastic vectors of observed farm and non-farm characteristics determining adoption, Y_i is either agricultural profit per hectare or per adult food production in calories, **Regimes 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 u_{1i}, u_{2i} and ϵ_i are the error terms of the three equations (14, 15, 16) and follow a trivariate normal distribution of zero mean and variance-covariance matrix specified as follows:

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

$$\text{cov}(\epsilon_i, u_{1i}, u_{2i}) = \begin{pmatrix} 1 & . & . \\ \sigma_{1\varepsilon} & \sigma_1^2 & . \\ \sigma_{2\varepsilon} & . & \sigma_2^2 \end{pmatrix} \tag{17}$$

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 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 (15) and (16) to correct the selection bias:

$$\lambda_{1i} = \frac{\phi(\mathbf{Q}'_{2,i}\gamma)}{\Phi(\mathbf{Q}'_{2,i}\gamma)}, \quad \text{and} \quad \lambda_{2i} = \frac{-\phi(\mathbf{Q}'_{2,\ i}\gamma)}{1 - \Phi(\mathbf{Q}'_{2,i}\gamma)} \tag{18}$$

From the theoretical framework, factors include in Q_i and Z_i are production risks face by farmers, the production structure (land allocation across crops), credit constraint, 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 equations 15 and 16, 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 et al., 2012a; Abdulai and Huffman, 2014) which is expected to influence the adoption of risky inputs (equation 14) but not the welfare outcome of interest (equations 15 and 16). The same identification strategy is used as explained in the previous section.

3.3 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 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); 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 1: Treatment effects

Sub-samples	Decision				Effects
	To buy risky inputs		Not to buy risky inputs		
Investors	$\mathbb{E}\left(y_{1i} \mid I=1; x\right) = x_{1i}\beta_1 + \sigma_{\varepsilon 1}\lambda_{1i}$	(a)	$\mathbb{E}\left(y_{2i} \mid I=1; x\right) = x_{1i}\beta_2 - \sigma_{\varepsilon 2}\lambda_{1i}$	(c)	ATT=(a)-(c)
Non-investors	$\mathbb{E}\left(y_{1i} \mid I=0; x\right) = x_{2i}\beta_1 + \sigma_{\varepsilon 1}\lambda_{2i}$	(d)	$\mathbb{E}\left(y_{2i} \mid I=0; x\right) = x_{2i}\beta_2 - \sigma_{\varepsilon 2}\lambda_{2i}$	(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 1 represent the situations observed in the sample: (a) would be the predicted outcome of investors if they decide to buy risky inputs and (b) would be the predicted agricultural outcome if non-investors do not invest; 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 not invested.

4 Data and descriptive summary

Data used in this study were collected under the PAPA[2] 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[3]) 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).

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

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

Data collection took place between April and May 2017. After data cleaning, the final sample size for this analysis is 4465 farm households. In order 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 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 (millet, sorghum, maize, fonio, rice, and beans) 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 2 shows that households produced on average 1461 kcal of food per adult equivalent per day (AED). According to FAO (2010), Senegalese population got about 62 percent of the energy requirement from cereals. Therefore, food crops considered here should provide more 1600 kcal per AED. On average, households who invested on risky inputs were able to produce this required food while non-buyers produced only 1238 kcal/AED.

Table 2: Variables definition and summary

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***

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.

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.

5 Results and discussion

5.1 Investment in risky inputs

Table 3 shows the results from the Heckman model of the decision to buy risky inputs (seeds and fertilizers) and the corresponding investment. For each model, the coefficient estimates as well as the standard error (see Eqs. (11) and (12)) are presented. Heteroskedasticity-corrected standard errors using cluster approach at district of census are displayed. The Wald test 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, 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 et al., 2017; Husen et al., 2017).

Table 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).

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. (2012a) 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[4], 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.

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,

[4]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.

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.

5.2 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 shows the predicted welfare outcomes of risky investments under actual and counterfactual conditions for Senegal.

Table 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).

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[5] 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.

[5]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 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 5 shows results from this simple OLS regression.

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 6).

Table 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***

6 Conclusions

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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