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Risk management under climate change and its implication on technical efficiency: Evidence from Senegal

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Abstract

Using empirical data from a nationally representative farm household survey in Senegal, this study evaluated the impact of different risk management strategies employed by farm households on technical efficiency (TE). The findings of the study suggest that risk management has implications for TE. We find that the use of ex-post risk management strategies is associated with relatively higher technical efficiencies with respect to the meta-frontier compared to other risk management strategies. Households employing only ex-ante risk management strategies were observed to be the least technically efficient in comparison to households employing other risk management strategies. The findings also suggest that managing production risks using multiple strategies does not necessarily result in the highest TE gain compared to the use of single strategies. The findings underscore the need to evaluate the trade-offs and likely consequences of risk management approaches used by farm households to provide countermeasures to deal with any adverse related effects.

Keywords: Climate change, Risk management, Sample selection, Meta-frontier, Efficiency, Technology gap.

JEL codes: D13, G32, Q12

1 Introduction

Does risk management under climate change have adverse effects on farm households' technical efficiency (TE)? Studies that have attempted to answer this question have been rather scanty. Because risk exposure is an inherent feature of agricultural production systems, risk management, therefore, plays a very important role in helping farm households deal with risk. Risk reduction is particularly often much more important for smallholder producers than productivity increases per se (Kraaijvanger and Veldkamp 2015). However, the management of risks can also withdraw resources from the production activity, resulting in a likely negative impact on overall farm productivity and efficiency (Vigani and Kathage 2019). Concurrently, previous studies have found considerable efficiency losses associated with risk management strategies such as risk mitigation (see Rosenzweig and Binswanger 1993; Morduch 1995; Kurosaki and Fafchamps 2002). For instance, crop diversification, which is a well-known risk management strategy, could imply that farmers shift the share of land use under high-value crops such as cash and permanent crops, and this reallocation can have a detrimental effect on productivity, production cost, income, and farm efficiency (Morduch 1995; Salazar-Espinoza et al. 2015; Vigani and Kathage 2019).

Additionally, the use of formal risk management instruments in the form of insurance has also been observed to lower investments in inputs and productivity-enhancing technologies (Smith and Goodwin 1996; Giné and Yang 2009; de Nicola 2015), reduce labour and land productivity (Spörri et al. 2012), and reduce the use of complementary risk management strategies such as diversification (Nigus et al. 2018; Matsuda et al. 2019). While the literature has extensively investigated the use and drivers of these risk management strategies (see Ullah and Shivakoti 2014; Wang et al. 2016; Saqib et al. 2016), their corresponding impacts on household welfare outcomes (Di Falco and Veronesi 2013; Kassie et al. 2014; Birthal and Hazrana 2019) and input use (Goodwin et al. 2004; Mieno et al. 2018; Hill et al. 2019), it has not provided adequate definitive answers on the link between risk management and efficiency.

Simultaneously, risk in agricultural production has been acknowledged to widely shape farmers' technology adoption (Gillespie et al. 2004; Yang et al. 2005; Liu 2013) and investment decisions (Mude et al. 2010; Clarke and Dercon 2015; McCarthy et al. 2018). For instance, risk and uncertainty can force households to select less risky technology portfolios that generate lower returns (Cavatassi et al. 2011; Dercon and Christiaensen 2011; Gebregziabher and Holden 2011; Lien et al. 2022). Particularly in developing regions of the world, smallholder producers are often exposed to a wide range of risk factors that negatively affect not just output and input prices but also household income and wealth. At the same time, climate change has been widely acknowledged to have increased the intensity and frequency of risk factors such as erratic rainfall, drought, flooding, and pests and diseases. Beyond input and resource allocation effects, risk management by farm households has also been observed to be mostly incomplete, suboptimal, and mitigates only a small part of the overall risk (Siegel and Alwang 1999; Dercon 2002; Alderman 2008; Barnett et al. 2008; Deressa et al. 2010). Although much attention in the literature has been devoted to identifying the strategies used by farm households to deal with risks and their potential drivers, the link between risk management and TE remains relatively unexplored.

Some studies (Roco et al. 2017; Khanal et al. 2018; Imran et al. 2019; Torres et al. 2019; Vigani and Kathage 2019) have tried to address this link with a limited scope. At the same time, the results have been contentious. For example, studies by Larochelle and Alwang (2013) and Vigani and Kathage (2019) have found that in the case of diversification, the cost of employing this risk management strategy is reflected by an increase in technical inefficiency. Other studies (Khanal et al. 2018; Imran et al. 2019; Vigani and Kathage 2019) have largely found a positive effect of risk management on TE. Since farm households use risk management strategies simultaneously, a major limitation of the literature exploring the link between risk management and TE is the failure to account for the simultaneous adoption of several risk management instruments and also the potential selectivity biases associated with adoption. This might likely lead to biased results and inadequate policy recommendations.

Building on the past and rather limited studies linking risk management, productivity, and efficiency, this study investigates the implication of risk management under climate change on farm household TE in Senegal. To achieve this, the study uses empirical data from a nationally representative farm household survey in Senegal, a sample selection stochastic production frontier, and a meta-frontier approach. The paper contributes to the literature in twofold: First, quantifying the TE implications of farm household risk management is critical for understanding the costs and benefits of climate change adaptation. Furthermore, quantifying the TE implications of risk management highlights the need for making trade-offs between various future adaptation strategies. Secondly, this study provides new knowledge to assist farmers and policymakers in Senegal to identify more effective adaptation strategies and minimize or remedy any negative effects of adaptation. The rest of the paper is organized as follows. The next section describes the conceptual framework. Section 3 formally presents the econometric strategy. Section 4 describes the data used and the risk management strategies evaluated for the study. In Section 5, the empirical results and discussions are presented, and finally, in Section 6, the conclusion is presented.

2 Conceptual framework

In anticipation of production-related risks and shocks, farm households are known to employ different risk management strategies to reduce the effects of shocks such as drought, erratic rainfall, flooding, pest and disease outbreaks, and price volatility for inputs and outputs. The presence of production-related shocks affects farm households in three main ways. First, they influence households' decisions to adopt productivity-enhancing inputs and impose ex-ante barriers to their use (Di Falco and Chavas 2009; Dercon and Christiaensen 2011; Amare et al. 2018). Secondly, they reinforce changes in production portfolio towards farm enterprises that are less vulnerable to shocks, but at the same time may also be less remunerative compared to others (Birthal and Hazrana 2019). Thirdly, they cause potential deviations between expected and real outcomes (Schaffnit-Chatterjee 2010; Obiri and Driver 2017). Concurrently, actions taken by farm households herein risk management strategies could lead to inefficient resource use or allocations that may have adverse consequences for farm productivity. For instance, by trying to evade shocks, farm households could diversify production, which could potentially shift land resources from high-value crops to staple crops. Additionally, off-farm strategies to deal with climate shocks reduce the amount of household labour for farm work, and this can have severe consequences for production efficiency. Selling productive assets such as livestock could also potentially mean a loss of animal power, in cases where households rely on livestock for farm work such as ploughing. This can have negative consequences for farm productivity.

The main motivation of this study is to investigate the impact of different risk management strategies employed by Senegalese farm households on farm TE. In doing so, our study is underpinned by the empirical work of Hayami (1969) and Hayami and Ruttan (1970, 1971), who introduced the meta-frontier production function. The meta-frontier production function is based on the idea that all producers in the various production groups have differential access to an array of production technologies. The choice of a particular technology may be driven by several factors, such as regulation, production environments, resources, relative input prices, etc. According to Huang et al. (2014), the presence of these factors inhibits producers in some groups from choosing the best technology from the array of potential technology sets. Estimation of the meta-production frontier, which envelopes the group-specific frontiers, is assumed to be the most optimal, hence allowing for the estimation of technology gap ratios (TGRs), which is the difference between the optimal or 'best' technology and the chosen sub-technology. Employing this approach offers us the opportunity to compare the impact of the various risk management strategies employed by farm households on productivity and TE by providing a common technology of reference for both adopters and non-adopters of the various risk management strategies.

3 Econometric strategy

3.1 Sample selection stochastic frontiers approach

Farm households' decisions to adopt the various risk management strategies may not be random, and as such, they may endogenously self-select into adoption or non-adoption. As shown in previous studies (Villano et al. 2015; Rahman et al. 2018; Azumah et al. 2019), selectivity effects exist in technology adoption. Farm households may therefore endogenously self-select adoption or non-adoption, making such decisions to be likely influenced systematically by both observed and unobservable characteristics that may be correlated with the outcomes of interest, herein TE. Hence, the inability to capture these unobservable characteristics may lead to selection bias. In acknowledging the presence of selectivity biases, earlier studies (see Bradford et al. 2001; Sipiläinen and Lansink 2005; Solís et al. 2007) attempted to address this issue by relying on the Heckman approach. However, as argued by Greene (2010), the Heckman approach is unsuitable for non-linear models such as the stochastic production frontier. To control for selection bias and disentangle the pure effects of risk management, we model farm households' choice of risk management strategies and their impacts on TE by adopting the framework developed by Greene (2010) that extends Heckman's approach to consider sample selection in a stochastic frontier framework assuming that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier. The sample selection SPF model by Greene (2010) is specified as follows[1]:

$$\text{Sample selection: } t_j = 1\left[\beta' X_j + \varepsilon_j > 0\right],\ \varepsilon_j \sim N(0,\ 1), \tag{1}$$

$$\text{Stochastic frontier model: } y_j = \gamma'\ W_j + \epsilon_j,\ \epsilon_j \sim\ N\left(0,\ \sigma_\epsilon^2\right),\ \ \epsilon_j =\ \nu_j - \upsilon_j, \tag{2}$$

where y_j and W_j are observed only when $t_j = 1$, $\nu_j = \sigma_\nu V_j$ with $V_j \sim N(0, 1)$, $\upsilon_j = |\sigma_\upsilon U_j| = \sigma_\upsilon |U_j|$ with $U_j \sim N(0, 1)$, and $(\varepsilon_j, \nu_j) \sim N_2[(0, 1), (1, \rho\sigma_\nu, \sigma^2{}_\nu)]$. Also, y_j denotes the value of crop output in CFA[2] of farm household j, W_j is a vector of logarithmic input quantities, t_j is a binary dummy variable that equals 1 for adopters of a particular risk management strategy (see Table 4) and 0 otherwise, and X_j is a vector of covariates in the sample selection equation. The coefficients β and γ are parameters to be estimated, ϵ_j is the composed error term of the stochastic frontier model that includes the conventional error (ν_j) and inefficiency term (υ_j), and ε_j is the error term. The inefficiency term υ_j is assumed to follow a half-normal distribution with the dispersion parameter σ_υ, whereas ε_j and ν_j follow a bivariate normal distribution with variances of 1 and $\sigma^2{}_\nu$, respectively. The correlation coefficient, $\rho\sigma_\nu$ if statistically significant, indicates evidence of selectivity bias implying that estimates of the standard stochastic frontier model would be inconsistent (Greene 2010). The standard errors of the parameters are adjusted using the approach by Murphy and Topel (2002) and estimated using the Broyden–Fletcher–Goldfarb–Shanno approach, and asymptotic standard errors are obtained by employing the Berndt–Hall–Hall–Hausman algorithm estimator.

The specification described earlier allows us to estimate separate selectivity-corrected stochastic frontier models for each risk management strategy. From these estimated stochastic frontier models, we derive the group-specific TE estimates, $\text{TE}_{ji} =\ E[e^{-\upsilon_{ji}},\ i\ =\ 1,\ 2\ldots.4]$. The estimated technical efficiency scores allow us to compare how adopters of specific risk management strategies are closer to their respective group production frontiers. However, as stated earlier, farm households could have potential access to an array of production technologies, yet, specific barriers prevent households in one group from choosing the best technology from the array of the potential technology set. Hence, the estimated group-level technical efficiencies do not account for technology differences (O'Donnell et al. 2008). Additionally, a direct comparison of technical efficiencies between adopters of the various risk management strategies is not possible because these scores are relative to each group's own frontier (González-flores et al. 2014). To address this issue, we estimate a meta-frontier that envelopes the risk management-specific frontiers and allows for the comparison among the risk management strategies.

3.2 Meta-frontier analysis

Following the approach outlined by O'Donnell et al. (2008), we estimate a meta-frontier[3] that envelops the production frontiers of the risk management-specific group frontiers. The deterministic meta-frontier model for farm households adopting the various risk management strategies can be expressed as follows:

$$Y_i^* = f(X_i, \beta^*) = e^{X_i\beta^*}, \quad (3)$$

where Y^* is the meta-frontier output, and β^* denotes the vector of parameters of the meta-frontier function such that $X_j\beta^* \geq X_j\beta_i$ and β_i are parameters obtained from the risk management-specific group frontiers. We estimate the parameters of the meta-frontier function (β^*) in equation (3) by minimizing the sum of the absolute differences between the meta-frontier and the respective group-specific frontier at all observations, while the meta-frontier may not be below any of the group-specific frontiers at any observation:

$$\min_{\beta^*} \sum_{j=1}^{N} |(\text{In } f(X_j, \beta^*) - \text{In } f(X_j, \hat{\beta}_i)| \quad (4)$$

$$\text{s.t. In } f(X_j, \beta^*) \geq \text{In } f(X_j, \hat{\beta}_i).$$

Based on the parameters of the meta-frontier function (β^*), we can calculate the gaps between the meta-frontier and the individual risk management-specific group frontiers, termed the meta-TGR. As suggested by Issahaku and Abdulai (2020), a comparatively high average meta-TGR for a particular technology group indicates a lower technology gap between farm households in that group compared with all available sets of production technologies represented in the all-encompassing production frontier. For any given level of inputs, the meta-technology ratio is calculated as the ratio of the highest attainable group output to the highest possible meta-frontier output and is, therefore, an index lying between zero and unity, defined as follows:

$$\text{TGR}_j^i = \frac{e^{X_j\hat{\beta}_i}}{e^{X_j\beta^*}}. \quad (5)$$

Subsequently, the TE with respect to the meta-frontier production technology (MTE) is determined as follows:

$$\text{MTE}_i = \text{TGR}_i \times \text{TE}_i. \quad (6)$$

It is also necessary to identify whether all the group-level data were generated from a single production frontier. As noted by Battese et al. (2004), there would be no good reason for estimating the TE of farmers relative to the meta-frontier if all the data were generated from a single production frontier. Hence following the aforementioned authors, we applied the likelihood-ratio test of the null hypothesis that there is no difference between the risk management group-specific sample selection stochastic frontiers for all farm households. By pooling data from adopters of the four risk management strategies, the likelihood-ratio test of the null hypothesis that the group-specific stochastic frontiers are the same for all farm households was tested. The likelihood-ratio test is defined by $\lambda = -2[L(H_p) - (L(H_0) + L(H_1) + L(H_2) + L(H_3))]$, where $L(H_p)$ is the value of the log-likelihood function for stochastic frontiers estimated by pooling data for all farm households, and $L(H_0)$, $L(H_1)$, $L(H_2)$, and $L(H_3)$ are the value of the sum of all the log-likelihood functions for the no-risk management strategy adopters, ex-ante risk management strategy adopters, ex-post risk management strategy adopters, and both ex-ante and ex-post risk management strategy adopters, respectively.

3.3 Empirical model specification

Because estimation results may be sensitive to different model specifications (Wang 2003; Liu and Myers 2009), the selection among alternative competing models was based on careful examination both on a theoretical and an empirical level considering also the type of data available and the context of the study. Based on a review of traditional and popular literature, Griffin et al. (1987) identified twenty functional forms of production functions. However, the two most common functional forms used for production frontiers in efficiency studies, the Cobb–Douglas and transcendental logarithmic, also known commonly as the translog[4] (Bravo-Ureta et al. 2007; Seymour 2017), were evaluated in our study. However, the Cobb–Douglas production is preferred for several reasons. The Cobb–Douglas production function is a simpler functional form and imposes certain restrictions such as unitary elasticity of substitution that the more flexible translog production function avoids. Bokusheva and Hockmann (2006) argue that functional forms such as translog and linear-quadratic provide poor estimates and do not fulfil the axiom of monotonicity and quasi-concavity. Additionally, other researchers (Laureti 2008; Mayen et al. 2010; Larochelle and Alwang 2013) have observed the Cobb–Douglas functional form to be less susceptible to loss of degrees of freedom and multicollinearity issues, especially between inputs and the interaction terms as in the case of the translog production function. Furthermore, the Cobb–Douglas production function involves the estimation of fewer parameters than the translog functional form, which facilitates the ease of results interpretation (Benedetti et al. 2019). Others (see Felipe 1998; Johnes and Johnes 2009) have also argued that the presence of quadratic and interaction terms, as in the case of the translog functional form, complicates results interpretation. Furthermore, the choice of the functional form is connected to the shape, values of the elasticities of factor demand, and factor substitution; hence, the Cobb–Douglas production function is widely used because it has universally smooth and convex isoquants (Fried et al. 2008). For this study, the technology for crop production by farm households is represented by a Cobb–Douglas production frontier that can be specified as follows:

$$\ln\left(y_j\right) = \beta_0 + \sum_{k=1}^{4} \beta_k \ln W_{jk} + \sum_{k=1}^{4} \delta_k D_{kj} + v_j - u_j, \tag{7}$$

where y_j denotes the log of the value of crop output of farm household j; W_{jk} is the quantity of the kth input of the jth household; D represents the dummy variable for input subsidy access, improved seed use, irrigation, and fertilizer use; β and δ denote unknown parameters to be estimated; and v and u are the elements of the composed error term, ϵ. Following the approach of Battese (1997), the inclusion of the dummy variable for fertilizer use helps to account for zero values of fertilizer in the model, such that the logarithm of the inputs with zero values is taken only if it is positive and zero otherwise. This ensures that unbiased and efficient parameter estimates of the model are obtained. The input vectors include labour in man-days/acre, landholding in acres, and fertilizer and seed quantities used in kilograms. A summary of the variables and their definitions used in the analysis are presented in Table 1. The detailed summary statistics of variables across the various risk management portfolios are presented in Table S1 of the supplementary information.

3.4 Method for addressing endogeneity in the model

An issue that needs to be addressed in the estimation of equation (1) is the potential endogeneity problem that may arise. This is particularly important because the presence of reverse causality and endogeneity in models can make the identification of causal effects difficult due to biased estimates. A potential source of endogeneity identified in the empirical literature comes from the risk attitude of a farmer, membership in farmer-based organizations, extension, and credit access. The risk attitude of a farmer may influence the choice

Table 1. Variables definition.

Name	Variable description
Household characteristics	
Age	Age of household head in years
Gender	=1 if the household head is male
Education	=1 if the household head has formal education
Household size	Total number of people in the household
HWI[a]	Household welfare index
Remittance	=1 if the household receives remittances
Institution variables	
Extension	=1 if accessed extension service
Membership	=1 if a member of a farmer-based organization
Credit	=1 if access to credit
Subsidy	=1 if access to both subsidized fertilizer and seeds
Farm-related characteristics	
Cash crop	Share of land under cash crops (Per cent)
Improved seeds	=1 if a household uses improved and high-yielding seeds
Irrigation	=1 if the household uses irrigation
Fertilizer use	=1 if the household did not use fertilizer
Risk variables	
Risk attitude	=1 if the household is risk-taking
Risk count	Number of risks experienced by household
Loss count	Number of risk-related losses experienced by household
Location variable	
Distance	Distance to a major city in km
Input variables for stochastic frontier model	
Labour	Total quantity of labour used in man-days/acre
Land	Total land holding of household in acres
Fertilizer	Fertilizer quantity used in kg (Log)
Seeds	Seed quantity used in kg (Log)
Output variables for stochastic frontier model	
Crop output	Value of crop output in CFA (Log)
Instruments for endogeneity control	
Storage	=1 if household use metal silos for storage
Contracts	=1 if access to production contracts
Support needs	=1 if farmer has support needs
Location	=1 if the household is located in a highly populous region

[a]We computed a household welfare index (a proxy for household wealth) using principal component analysis (PCA) based on farm household access to basic amenities such as water, electricity, toilet, the type of roof, wall, and floor material, and the number of sleeping rooms in the household.

of risk management strategy; therefore, risk management strategies employed by a farmer can be potentially correlated to his or her risk attitude (see Ullah et al. 2015; Meraner and Finger 2017; Asravor 2019). Since some of the risk management strategies employed by farmers are technologies and management practices-oriented, farm households' membership in farmer-based organizations may encourage the adoption of some risk management strategies such as index-based insurance and diversification. At the same time, access to extension and credit may influence the adoption of certain risk management strategies and not others. For example, farmers with extension access may be encouraged to subscribe to agricultural insurance or adopt crop diversification as a risk management strategy. At the same time, farm households with credit access may subscribe to agricultural insurance and avoid costly risk management strategies such as the sale of productive assets.

We control for the potential endogeneity of these variables using the control function approach developed by Wooldridge (2015). Due to the dichotomous nature of the four variables, we employed a probit regression specification of the potential endogenous variable (i.e. risk attitude, membership in farmer-based organizations, extension, and credit access) as a function of all other variables used in the selection equation (i.e. equation (1)). We incorporated both potential endogenous variables and the estimated residuals predicted from the probit equation into the selection equation (1) to account for endogeneity. One important consideration in the control function approach is the inclusion of instruments that are expected to influence the potentially endogenous variable but not the adoption decision of risk management strategies in equation (1). We employed the storage technology used by farm households as instruments to control for potential endogeneity of risk attitude and the access to production contracts as an instrument to control for membership in farmer-based organizations. Similarly, support needs and location were employed as instruments to control for extension and credit access, respectively. These instruments are expected to influence their respective endogenous variables but not the choice of risk management strategy adoption. We test for the admissibility of the selected instruments by using a falsification test suggested by Di Falco and Veronesi (2013). Furthermore, Wooldridge (2015) observed that if the coefficient on the estimated generalized residual is statistically significant, then there is a need to adjust the standard errors for the two-step estimation by bootstrapping.

4 Data sources

4.1 Farm household survey

The data used in the study come from a farm household survey as part of the larger Senegalese 'Projet d'appui aux politiques agricoles (PAPA)' or the Agricultural Policy Support Project, which was funded by the United States Agency for International Development under the 'Feed The Future' initiative. The survey was conducted between April and May 2017. The survey covered all the fourteen administrative regions of Senegal and all the departments except for the departments of Dakar, Pikine, and Guédiawaye due to a lack of agricultural activities. In total, forty-two agricultural departments were included in the survey. A general census of population and housing, agriculture, and livestock conducted in 2013 showed that ~755,532 agricultural households practised agriculture, with ~61 per cent (458,797) of the farming households practising rainfed agriculture. The survey design, therefore, included a global sample of 6,340 farm households in 1,260 rural census districts and 42 agricultural departments. The sample represented a survey rate of 1.4 per cent, which is about one household out of every seventy-two. The sample distribution considered the overall survey rates and the agricultural weight of the stratum. The survey was focused on cereals, horticultural, and fruit and vegetable value chains.

The survey design was a two-stage, nationally based random survey that included rural census districts as the primary units and farm households as the secondary units. The method consisted of first dividing the statistical population (i.e. agricultural households) into the primary units so that each of them was unambiguously related to a well-defined primary unit. Then, samples were drawn in two stages. In the first stage, a sample of rural census districts was drawn, and in the second stage, a sample of agricultural households was selected at the level of each primary unit. In rural census districts where rainfed agriculture was practised and localized crops were grown, such as the Senegal River Valley and the Niayes Market Gardening Zone, stratification of the rural census districts was done before agricultural households were selected. The collected data covered the main agricultural season of 2016–7 and included information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit access, input use and cost, agricultural insurance, risks, adaptation strategies, subsidy access, household consumption, access to amenities, non-farm and livestock revenue, and remittance.

Table 2. Risks often faced by farm households in the past 5 years.

Risk	Frequency	Per cent
Insufficient rains[a]	2,481	48.61
Early rains stop[b]	1,579	30.94
Pause rainfall[c]	1,298	25.43
Damage by animals (livestock)	1,047	20.51
Granivorous birds	567	11.11
Drought	543	10.64
Plant disease	469	9.19
Theft of draft animals	324	6.35
Other pests	304	5.96
Flood	271	5.31
Harvest theft	233	4.57
Bush fire	203	3.98
Locust invasion	175	3.43
Late rains[d]	160	3.13
Fluctuation of product prices	78	1.53
Motor pump failure	32	0.63
Weakness of river flow	20	0.39
Total household	5,104	

[a]Not enough rain for crops during the whole growing season.
[b]Rain stops before the plant completes its maturation process.
[c]Rain pauses once or multiple during the growing season. This could also happen at any phase of the development cycle of plants and therefore can hamper the normal growth of crops.
[d]Rain starts late, and this delays the sowing period.

4.2 Risks and risk management strategies

In the survey, farm households were asked three different questions related to risks faced in production. These were related to risks often faced during the last 5 years, risks faced during the past cropping season (campaign), and a general list of risks and constraints experienced by farm households. Descriptive statistics showed that the order of importance of the observed risks does not change across the three questions. For this study, the focus was on risks often faced during the last 5 years. In the survey, seventeen production risks were evaluated, and this is presented in Table 2. In the context of this study, however, we only considered production risks related to the climatic shocks—drought, erratic rainfall, and flooding—and biological shocks—pest and disease outbreaks—experienced by farm households. This is because most of the adaptation or risk management strategies (see Table 3) employed by farm households were to address these related risks.

Climatic-related shocks were widely experienced by many farm households compared to biological shocks. Furthermore, price-related shocks, equipment breakdowns, and hydrology-related issues appear to have been experienced in isolated cases (see Table 2). Besides the shocks experienced by farm households, strategies employed to deal with the risks in Table 2 were solicited (see Table 3). In the presence of production shocks, diversification of agricultural activities was the largest (39.7 per cent) strategy employed by farm households to deal with risk. This is subsequently followed by an orientation to non-agricultural activities, which is employed by 30.2 per cent of the surveyed households. Reduction of land areas under cultivation as a risk management strategy is employed by 20.6 per cent of the surveyed households. After risks have occurred, measures related to the sale of livestock are employed by 20.4 per cent of the surveyed households. The sale of grain stocks and properties is used as a risk management strategy by 9.4 and 8.8 per cent of farm households, respectively. Based on the empirical literature (see World Bank 2001, 2005; Lilleor et al. 2005), we aggregated the risk management strategies employed by farm households based

Table 3. Risk management strategies employed by farm households.

Risk management strategies	Frequency	Per cent
Ex-ante strategies		
Diversify agricultural activities	2,026	39.7
Reduce the area under cultivation	1,053	20.6
Orientation to non-agricultural activities	1,539	30.2
Rent land to others	118	2.3
Subscribe to agricultural insurance	169	3.3
Ex-post strategies		
Sell grain stocks	482	9.4
Sell property	450	8.8
Sale of animals	1,041	20.4
Exchange/swap clothes or jewels for food	78	1.5
Total	5,104	100.0

Table 4. Risk management portfolios available to farm households.

Risk management portfolio	Portfolio ID	Frequency	Per cent
No-risk management	RMP0	261	5
Ex-ante risk strategy only	RMP1	3,119	62
Ex-post risk strategy only	RMP2	987	19
Ex-ante and ex-post strategy	RMP3	737	14
Total		5,104	100

on the point at which the reaction to risk takes place into two broad typologies; ex-ante and ex-post risk management strategies, as shown in Table 3.

Ex-ante strategies refer to those actions taken before the realization of a risky event to lower the probability of a risky event. On the other hand, ex-post strategies are those actions taken after a risk event has occurred and are also synonymous to risk coping strategies. They are used in response to the variation in farm income. Since evidence from the empirical literature (Velandia et al. 2009; Ullah and Shivakoti 2014; Ullah et al. 2015) suggests these risk management approaches are used simultaneously or in combinations, we assume that in a multiple risk management strategies adoption setting, farm households' simultaneous use of these two strategies leads to four (2^2) possible combinations or portfolios of strategies that farm households could choose from Table 4.

Based on these risk management portfolios, ~62 per cent of farm households are observed to employ ex-ante risk management strategies. This is followed by ex-post risk management strategies, which are employed by ~19 per cent of farm households, while ~14 per cent of farm households employ both ex-ante and ex-post measures. About 5 per cent of farm households employ no-risk management strategy.

5 Empirical results

In this section, the results from the empirical approaches used in the study are presented. We first present the results of the second-stage sample selection stochastic frontier model and also examine the appropriateness of using the sample selection stochastic production frontier model. Secondly, we provide and discuss the estimates of the TE scores, TGRs, and risk management-specific technical efficiencies with respect to the meta-frontier (MTE). The results of the first stage of the sample-selection stochastic frontier model and its ancillary model (control function specification) are presented in Tables S3 and S2 of the supplementary information, respectively, but in the interest of brevity, we do not discuss the results. We find that the control-function approach for the correction of endogeneity in the first stage of the model was necessary. The coefficients of membership in a farmer-based organization, extension access, and credit access residual terms (see Table S3) are statistically significant in three of the risk management portfolios, implying the presence of endogeneity of membership in a farmer-based organization, extension access, and credit access. Thus, accounting for the endogeneity of these variables using the control function approach as we did in this study was appropriate.

5.1 Production frontier estimates

In this section, we present and discuss the second-stage results of the sample selection stochastic production frontier model. Results of the risk management-specific stochastic frontiers are presented in Table 5. We find that the selectivity parameter (Rho (w v)) of the sample selection production frontier models is negative and statistically significant for ex-ante risk management strategies and both ex-ante and ex-post risk management strategy production frontiers. This suggests that a farmer who adopts either ex-ante risk management strategies or both ex-ante and ex-post risk management strategies obtains a higher value of crop output and TE compared to a randomly chosen farmer in our sample. This suggests the presence of selectivity bias; thus, unobserved factors that affect the adoption of risk management strategies are correlated with the idiosyncratic error term of the stochastic frontier model. The results, therefore, strongly support the use of the sample selectivity framework and are congruent to similar studies (Villano et al. 2015; Rahman et al. 2018; Azumah et al. 2019) that have shown that selectivity effects exist in technology adoption.

For all risk management-specific stochastic production frontier models, the results show that the inefficiency dispersion parameters Sigma (u) are significant, suggesting that inefficiency is an important contributor to crop output variability. Furthermore, the results show that Sigma (u) is much larger for farmers not managing risks, followed by farmers adopting ex-ante risk management strategies. This suggests that non-risk managing farmers and ex-ante risk management strategy adopting farmers are more affected by inefficiency than farmers adopting ex-post risk management strategies in isolation or in combination with ex-ante risk management strategies. Additionally, we tested the null hypothesis that there is no difference between the pooled (meta)-frontier model and the four risk management-specific stochastic frontiers. With a generalized likelihood ratio test statistic $\chi^2(37) = 52.192$ ($P < 0.01$), the null hypothesis is rejected suggesting significant technology differences between the frontiers for the various risk management strategies. Thus, the estimation of separate frontiers for each group is justified.

Results show that the input vectors are positive and significant, hence implying that these inputs contribute to moving farm productivity to the frontier. However, for the no-risk management and ex-ante risk management strategy frontiers, the results suggest that labour has a negative effect. However, the effect is not statistically significant in the case of no-risk management strategy group frontier, while for the ex-ante risk management strategy group frontier, it was observed to be significant. Because the Cobb–Douglas coefficients have an elasticity interpretation, the value of the parameters can be taken as a measure of the percentage contribution of each input vector to a percentage change in the value of crop output. The production elasticity estimates indicate that land has the highest contribution in moving farm productivity to the frontier in all the risk management-specific frontiers. The input subsidy access dummy variable was observed to have a negative effect across all the risk management-specific frontiers. The effect is however statistically significant only for ex-ante risk management and both ex-ante and ex-post risk management strategy group frontiers. This suggests that input subsidy access moves farm productivity away from the frontier. Improved seed use dummy variable has a positive across all risk

Table 5. Parameter estimates for sample selection stochastic production function models and meta-frontier.

Variable	RMP0 Coefficient	RMP0 Standard error	RMP1 Coefficient	RMP1 Standard error	RMP2 Coefficient	RMP2 Standard error	RMP3 Coefficient	RMP3 Standard error	Meta-frontier Coefficient	Meta-frontier Standard error
Constant	10.027***	2.157	10.116***	0.150	9.045***	0.317	10.458***	0.349	10.882***	1.147
Ln labour	−0.052	0.108	−0.056***	0.018	0.029	0.032	0.091*	0.051	0.042	0.055
Ln land	0.721***	0.190	0.384***	0.033	0.462***	0.056	0.469***	0.067	0.663***	0.200
Ln fert	0.338***	0.085	0.271***	0.018	0.210***	0.038	0.140***	0.034	0.295***	0.091
Ln seed	0.174**	0.075	0.316***	0.014	0.383***	0.026	0.240***	0.032	0.218***	0.075
Subsidy	−0.029	0.272	−0.127***	0.048	−0.053	0.069	−0.185**	0.082	0.063	0.133
Improved seed	0.120	0.324	0.220***	0.040	0.054	0.063	0.142*	0.073	0.221*	0.172
Irrigation	1.175***	0.393	0.073	0.047	0.130	0.091	0.163	0.111	0.871**	0.522
Fertilizer use	1.148*	0.588	0.787***	0.097	0.614***	0.207	0.121	0.189	0.910**	0.518
Sigma (u)	0.965***	0.270	0.886***	0.075	0.665***	0.104	0.715***	0.141		
Sigma (v)	0.822*	0.491	0.856***	0.051	0.671***	0.042	0.744***	0.054		
Rho (w v)	−0.541	0.831	−0.613***	0.074	0.249	0.210	−0.206*	0.120		
Returns to scale (RTS)	1.18		0.92		1.08		0.94		1.22	
Log-likelihood	−1033.050		−5670.984		−2701.221		−2099.903			
N	261		3,119		987		737		5104	

Notes: RMP0—denotes no-risk management strategy, RMP1—denotes ex-ante risk management strategy, RMP2—denotes ex-post risk management strategy, and RMP3—denotes both ex-ante and ex-post risk management strategy. ***, **, and * represent 1 per cent, 5 per cent, and 10 per cent significance levels, respectively.

Table 6. Summary statistics of efficiency measures across risk management strategies.

Risk management portfolio	Mean	SD	Min	Max
No-risk management				
TE	0.498	0.143	0.051	0.864
TGR	0.934	0.015	0.874	0.976
MTE	0.465	0.133	0.047	0.819
Ex-ante strategies				
TE	0.518	0.135	0.073	0.900
TGR	0.894	0.021	0.821	0.931
MTE	0.463	0.121	0.064	0.782
Ex-post strategies				
TE	0.603	0.112	0.095	0.849
TGR	0.857	0.020	0.787	0.890
MTE	0.517	0.097	0.078	0.741
Ex-ante and Ex-post strategies				
TE	0.580	0.113	0.118	0.830
TGR	0.890	0.018	0.810	0.941
MTE	0.516	0.102	0.109	0.765
Pooled				
TE	0.542	0.133	0.051	0.900
TGR	0.888	0.027	0.787	0.976
MTE	0.481	0.117	0.047	0.819

management-specific group frontiers. The effect is however significant for ex-ante and both ex-ante and ex-post risk management strategies frontier.

Irrigation use has a significant effect on the frontier of no-risk management, suggesting it moves farm productivity towards the frontier. In the stochastic meta-frontier estimates (Table 5), we observe that all the input vectors except labour have a significant and positive effect in moving farm productivity to the meta-frontier. All three dummy variables, input subsidy access, improved seeds use, and irrigation use, are positive, suggesting that they move farm productivity towards the meta-frontier. However, the effect of improved seed use and irrigation use was found to be statistically significant. At the risk management-specific frontiers, returns to scale were found to be 1.18 for no-risk management strategy, 0.92 for ex-ante risk management strategy, 1.08 for ex-post risk management, and 0.94 for both ex-ante and ex-post risk management strategies. This implies that farm households not managing production risks and those managing risks ex-post shocks are operating under increasing returns to scale. Hence, holding all else constant, a 1 per cent joint increase in all inputs will bring about more than a unit increase in the value of crop output for non-risk managing and ex-post risk managing households. On the contrary, households employing ex-ante risk management strategies in isolation and, also in combination with ex-post risk management strategies are operating under decreasing returns to scale. This implies that if the households jointly increased all productive inputs by 1 per cent, then the value of crop output would increase by <1 per cent.

5.2 Technical efficiencies and TGRs

The estimated TE scores, meta-TGRs, and TE with respect to the meta-frontier (MTE) are presented in Table 6. At the risk management-specific frontiers, the average TE of farm households employing ex-post risk management strategies was the highest (60.3 per cent) followed by both ex-ante and ex-post risk management strategies (58 per cent) and ex-ante risk management strategies (51.8 per cent). Farm households employing no-risk management strategies were the least efficient (49.8 per cent). The results here are congruent to some related studies that have found that household adaptation to climatic risk improves productivity and efficiency. For instance, in Nepal, Khanal et al. (2018) observed that farm households with a higher adaptation index were on average 13 per cent more efficient than those with a lower adaptation index. Torres et al. (2019) also arrive at a similar conclusion in their study of farmers' preference for mitigation and adaptation actions against climate change in Mexico. They find that the most efficient farmers adopt adaptation actions. In Chile, Roco et al. (2017) found that the use of adaptive practices had a significant and positive effect on the productivity of annual crops. Similarly, Imran et al. (2019) found that cotton farmers in Pakistan adopting climate-smart agriculture used inputs more efficiently compared to their counterparts who did not adopt climate-smart agriculture practices.

As stated earlier, the results of the group-level technical efficiencies are not directly comparable because of the assumption of differential technology adoption. To make a more reasonable comparison across the various risk management portfolios, the derived gaps between the stochastic meta-frontier and the risk management-specific frontiers provide a better comparison. According to Huang et al. (2014), a higher TGR for any particular group is an indication of the adoption of the best available production technology. From Table 6, farm households not adopting any risk management are slightly more efficient in adopting the best available technology, which is reflected by a high mean TGR of 0.93, followed by households adopting ex-ante risk management strategies (0.89). Households employing ex-post risk management strategies were observed to have the lowest mean TGR (0.86). It is worth noting that although different risk management strategies have been assumed in this study, the actual technology driving the production functions of these risk management regimes are production inputs—land, labour, fertilizer, and seeds. Households not managing risks use the largest quantities of labour, fertilizers, improved seeds, and irrigation compared to households using the other risk management strategies (see Table S1 of the supplementary information). This likely explains the relatively high TGRs for households not managing production risks.

Subsequently, the study also evaluated how technically efficient Senegalese farm households employing the various risk management strategies are in terms of their operations with respect to crop output as captured by the MTEs. The study finds low meta-technical efficiencies across all the risk management strategies employed by households. The results show that, in general, farm households employing only ex-post risk management strategies are more technically efficient in their operations with respect to overall crop production (51.7 per cent) followed by households employing both ex-ante and ex-post risk (51.6 per cent). Furthermore, households employing no-risk management strategy are 46.5 per cent technically efficient, while those employing only ex-ante risk management strategies are the least technically efficient (46.3 per cent). As discussed previously, risk management is related to changes or allocation in scarce production resources, and these allocations have implications for the TE of farm households. To get a better understanding of the TE results, we refer back to Table 3 to evaluate the consequences of the strategies. For example, diversification of agricultural activities, which is a very popular risk management strategy under ex-ante measures, could lead to shifts or reallocation of land for staple crops. This can particularly harm crop output when a household's income is largely dependent on the sale of high-value crops and yields for high-value crops are lower relative to staple crops (Morduch 1995; Salazar-Espinoza et al. 2015).

The survey data suggest that farm households using ex-ante risk management strategies allocate about 50 per cent of their cultivated lands towards staple crop production and only ~26 per cent towards cash crops. As shown in previous studies (see Skees et al. 2002; Larochelle and Alwang 2013), diversification hinders important gains that could be obtained from specialization. Renting land to third parties, intuitively also has implied opportunity costs related to the loss of farm income and hence production efficiency. Such opportunity costs can have substantial effects on production. For example, Soullier (2017) estimated the opportunity cost of labour in the Senegalese rice value chain to be about CFA

Table 7. Determinants of technical efficiency.

Variable	Efficiency model	
	Coefficient	Standard error
Constant	0.463***	0.008
Extension	0.027***	0.005
Credit	−0.014*	0.008
Membership	−0.009*	0.005
Subsidy	−0.003	0.003
Market integration	0.000	0.003
Risk management strategy		
RMP1	−0.002	0.007
RMP2	0.053***	0.008
RMP3	0.052***	0.008
Log-likelihood	3840.000	
LR $\chi^2(8)$	281.230***	
N	5,104	

Notes: RMP1—denotes ex-ante risk management strategy, RMP2—denotes ex-post risk management strategy, and RMP3—denotes both ex-ante and ex-post risk management strategy. *** and * represent 1 per cent and 10 per cent significance levels, respectively.

500 (US $0.93) per day during the production season. Orientation to non-agricultural activities potentially presents two effects: an income effect and a labour effect. Income earned by farm households from non-agricultural activities may be used to purchase inputs or invested in farm production, which has implications on incomes and TE. Additionally, engaging in non-agricultural activities might lead to a loss of farm labour for farm work related to planting, weeding, and harvesting, and this can also affect production efficiency. The use of agriculture insurance in the form of index-based insurance also presents implications for TE. Recent findings on the impact of insurance on farm efficiency (see Vigani and Kathage 2019) suggest that insurance positively affects farm efficiency. Intuitively, transferring risk to third parties in the form of insurance should allow farm households to use and invest more in productivity-enhancing inputs; however, as the empirical literature (Smith and Goodwin 1996; Goodwin 2001; Goodwin et al. 2004) shows, moral hazard problems can rather influence effort expended in production or reduce investment in such productivity-enhancing inputs. Other studies (see Nigus et al. 2018; Matsuda et al. 2019) suggest a crowding-out effect of insurance related to the use of other risk management strategies such as diversification, and this can have implications on farm productivity. Although ex-post risk management strategies (Table 3) do not have direct resource use or allocations as in the case of ex-ante risk management strategies, the sale of productive assets might not be entirely used for household consumption but part might be re-invested into production in terms of inputs. Hence, the use of ex-post risk management strategies might also have 'input use effects', which can affect production efficiency as observed from the results of this study. Additionally, for a farm household to be able to continuously sell grain stocks or livestock ex-post shocks, they must be able to produce enough to have a surplus to sell. This might also likely have a positive effect on household TE. However, it is worth noting that the use of ex-post risk management strategies is costly, especially for very poor households. In the long run and with persistent risk situations, poorer households might be unable to recover the loss of productive assets ex-post shock (Bhandari et al. 2007; Barnett et al. 2008; Amare et al. 2018).

The study also explored the influence of some institutional variables on TE by regressing the TE scores with respect to the meta-frontier on these variables, using a Tobit model. The results presented in Table 7 show a positive and significant relationship between extension access and TE, suggesting that farmers with lower extension access tend to be less efficient compared to those with extension access. The result is congruent with previous studies (see Abdulai and Abdulai 2016; Yang et al. 2016, 2018; Imran et al. 2019) that have found extension access to have a positive and significant effect on TE. In addition, the results reveal a negative and significant relationship between membership in farmer-based organizations and credit access, suggesting that farmers who are members of farmer-based organizations and with access to credit tend to be less efficient. Previous studies (see Theriault and Serra 2014; Azumah et al. 2019) have arrived at a similar result. The results also suggest that input subsidy access might harm TE, although the effect is not statistically significant. The finding is consistent with previous studies (Bojnec and Ferto 2013; Latruffe et al. 2017; Alem et al. 2018) that have also found a negative effect of subsidies on TE. The results also suggest that compared to households not adopting risk management strategies, the adoption of ex-ante risk management strategies reduces TE by ~0.2 per cent, although the effect is not statistically significant. Adopting ex-post risk management strategies either in isolation or in combination with ex-ante risk management strategies significantly increases TE by ~5.3 and 5.2 per cent, respectively. The results here confirm the results discussed previously.

6 Conclusion

This study investigated the TE implications of risk management, using data from a nationally representative farm household survey in Senegal, a sample selection stochastic production frontier, and a meta-frontier approach. The findings suggest that although managing production risks have implications for farm households' TE, beyond risk management, technical inefficiencies are still high. The use of ex-post risk management strategies is associated with relatively higher technical efficiencies with respect to the meta-frontier compared to other risk management strategies. At the same time, households employing both ex-ante and ex-post risk management strategies appear to be more technically efficient compared to households not managing risk or employing only ex-ante risk management strategies in isolation. Households employing ex-ante risk management strategies were observed to be the least technically efficient. The study also finds that households, not managing risks are relatively more efficient in adopting the best available technology. This paper contributes to our understanding of other welfare dimensions of risk management beyond income, food security, and productivity. Evaluating the impacts of various risk management strategies helps both farm households and policymakers to identify maladaptation consequences of risk management that can worsen the already weaker adaptive capacities of farm households. Identifying such maladaptation-related effects can help in the design of context-specific and sustainable adaptation strategies for farm households.

The findings from this study have some policy implications. First, it highlights some important trade-offs that have to be made in adapting to climate shocks. For example, ex-post risk management strategies appear to result in higher technical efficiencies relative to the other risk management strategies; however, using ex-post risk management strategies might deepen the poverty status of resource-poor households. Secondly, because access to extension appears to reduce technical inefficiency, effective extension services through the provision of information on inputs application can be instrumental in enhancing the technical capacity of farm households. Furthermore, complementing the provision of technical information on input use should be done in combination with soil testing services and fertilizer recommendations to help farmers to use appropriate amounts of fertilizer, which can go a long way to minimize input costs and help them better adapt to climate variability.

There are some important caveats to be considered for this study. Because the scope of risk management strategies employed by farm households is multifarious, aggregating the various risk management strategies into two broad typologies helped us to capture only aggregate effects. This approach obscures or fails to evaluate individual risk management-specific effects on TE. Future research can therefore focus on more localized and isolated risk management strategies and their impacts on TE. Additionally, TE across the evaluated risk management strategies might have both temporal and spatial effects that our study fails to capture. Access to long-term data, such as panel or longitudinal data, can provide answers to these temporal and spatial TE effects of risk management strategies. As already established in the paper, risk management under climate change has implications for the optimal allocation of resources, and this is particularly relevant for determining household allocative efficiency. This study was unable to study the allocative efficiency implication of risk management for two main reasons. First, we do not have sufficient price data for inputs and outputs. A considerable number of households in our sample reported using to some extent their own seeds and owning their cultivated lands. Without specific information on the type of seeds, the quality, and the location of farmlands, we were unable to assign appropriate prices to seeds or a rental cost to land. Secondly, looking at allocative efficiency would have restricted us to only looking at crop-specific enterprises because one cannot aggregate different output prices for different crop commodities grown by households. Additionally, a considerable number of farm households did not use mineral fertilizers or plant protection inputs for the commonly grown crop commodities. Identifying such allocative efficiency implications of risk management in future studies can help to identify possible adverse effects (costly adaptation or maladaptation) that can worsen the already weaker adaptive capacities of poor farm households in developing regions of the world.

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Supplementary material

Supplementary data are available at *Q Open* online.

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Conflict of interest

The authors declare none.

Data availability

Data and replication code are available here: https://doi.org/10.5281/zenodo.7787196

End Note

1 The model of Greene (2010) is limited to dichotomous treatments, and since the risk management evaluated in this study is a polytomous choice and mutually exclusive, the choice of one risk management strategy implies rejection of the others. Hence in the specification in equation (1), each t_j is a binary variable, and, thus, equation (1) is actually a system of m probit equations ($m = 4$ in this case). In most cases, regression estimates from a multinomial logit or probit regression model could be replicated through a set of simple logit or probit models. As shown by Begg and Gray (1984), the asymptotic

relative efficiencies of the individual parameter estimates are generally high, as are the efficiencies of predicted probability estimates and, to a somewhat lesser extent, joint tests of parameters from different regressions.

2 This is the currency used in Senegal and other France former colonies in West and Central Africa.

3 The meta-frontier was estimated in R using the lpSolve package.

4 The estimated translog model suffered from both convergence and multicollinearity problems, which meant that we were unable to estimate the coefficients of the model precisely.

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