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Farm household adaptation to climate shocks in Senegal: A microeconometric analysis of strategies and welfare impacts

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dem Internet geladen werden.

Dedication

This work is dedicated to my dad and the memory of my mom. I also dedicated it to my wife, daughter, siblings, and to all knowledge seekers out there who want to make our societies a better place.

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Abstract

Climate change threatens food production systems and the livelihoods of agriculture-dependent populations, particularly in developing countries. Farm household's exposure to weather changes such as prolonged drought, late start of rains, and shifting rainfall patterns causes greater loss of incomes and threatens food security. Particularly in Sub-Saharan Africa, farm households mostly have limited access to formal risk management instruments to deal with the myriad of production-related risks that they face. Therefore, they mostly rely on a range of traditional risk management strategies to avoid or minimize these production-related losses. However, these traditional or informal risk management strategies are mostly incomplete, suboptimal, and mitigate only a small part of overall risk. Additionally, each of these risk management strategies is associated with different cost and resource use or allocation implications. This PhD research, therefore, sought to explore the impact of various risk management strategies employed by Senegalese farm households across multiple outcomes including, agriculture incomes and dispersions around income, technical efficiency, and food security. In doing so, the study sought to provide context-specific information to guide farmers and policymakers to better manage production-related risks by selecting the right portfolio or mix or risk management strategies. The PhD research which is a collection of 5 papers employed several econometric analyses using a nationally representative farm household survey data collected in 2017.

The first paper examined the impact of climate change in the form of rainfall variability on inter-household income inequality, daily food calorie availability, and agricultural labour productivity in Senegal, and the role of adaptation strategies. It employed the recently developed model-averaging techniques (Weighted Average Least Squares) to address model uncertainty and the Gini decomposition approach. The result showed that rainfall variability negatively affects income equality by increasing the Gini elasticity of agriculture incomes. Particularly for agriculture incomes, the study found that the Gini elasticity increases for every deviation in rainfall. Because agriculture income sources constitute the largest share and contributor to household income inequality, any shocks to the sector will largely be responsible for any observed increases in income inequality. The study also finds that rainfall variability decreases household daily food calorie availability and agricultural labour productivity. The study also finds varying impacts of adaptation strategies on household outcomes, however, insurance (risk transfer) use appeared to be more effective in addressing rainfall variability impacts.

The second paper evaluated the adoption effect of different risk management strategies employed by farm households on agriculture income and dispersions around incomes. To achieve this, the study employed a Multinomial Endogenous Switching Regression model to control for potential selectivity bias problems and a Moment-Based Approach. The empirical results showed that the use of ex-ante risk management strategies significantly reduces agriculture incomes while the use of ex-post strategies either in isolation or in combination with ex-ante risk management strate-

gies significantly increases agriculture incomes. All the risk management strategies employed by households significantly reduce dispersions around agriculture incomes, however, ex-post strategies produce the largest dispersion reduction effect.

The third study analysed the technical efficiency implications of the risk management strategies employed by farm households. The study employed a sample selection stochastic production frontier to control for potential self-selectivity biases in adoption together with a meta-frontier model to evaluate the impact of risk management strategies on technical efficiency. The empirical results showed that risk management has implications on farm household's technical efficiency. The results also revealed that farm households adopting ex-post risk management strategies appear to have a relatively higher technical efficiency with respect to the meta-frontier compared to the other risk management strategies. Households, adopting ex-ante risk management strategies were observed to be the least technically efficient compared to households not managing risks or those employing ex-post risk management strategies in isolation or in combination with ex-ante risk management strategies. The results also suggested that managing risks using multiple strategies does not necessarily result in the highest technical efficiency gain compared to the use of single or isolated strategies.

The fourth study assessed the complementary impact of productivity-enhancing technologies (mineral fertilizer and improved seeds) with insurance adoption on technical efficiency by comparing two distinct farm households – one adopting fertilizer and improved seeds with insurance and the other fertilizer and improved seeds without insurance. The study employed a sample selection stochastic production frontier with a meta-frontier model, propensity score matching (PSM) approach, and an endogenous switching regression model to control for potential biases. The results showed that households that adopted productivity-enhancing technologies without insurance tend to be more technically efficient on average compared to those that adopted productivity-enhancing technologies with insurance. Nonetheless, the technology gap ratios of productivity-enhancing technologies with insurance adopting households were significantly higher than households adopting productivity-enhancing technologies without insurance, suggesting that productivity-enhancing technologies with insurance adopters appear to be slightly more efficient in adopting the best available technology. The study also finds that adopting productivity-enhancing technologies with insurance appears to decrease the technical efficiency of productivity-enhancing technologies with insurance adopters by about 50.17% at the meta-frontier. Conversely, adopting insurance with productivity-enhancing technologies could potentially increase the mean technical efficiency of productivity-enhancing technologies only adopters by about 37.44%. The results suggest that lower observed technical efficiencies for productivity-enhancing technologies with insurance adopters may be driven by unobserved effort or behavioural biases of farmers which can be an important source of heterogeneity in the observed treatment effects.

The last paper assessed the joint welfare impacts of managing climatic risk through the adoption of risk-reducing technologies and insurance by comparing three distinct farm households: 1) non-adopters of mineral fertilizer, improved seeds and insurance, 2) mineral fertilizer and improved seeds adopters without insurance and 3) mineral fertilizer and improved seeds adopters with insurance. To achieve the objective of the study, a Multinomial Endogenous Switching Regression model was employed to control for potential selectivity bias problems. The results showed that the adoption of mineral fertilizer and improved seeds with or without insurance is associated with significant increases in household food calorie availability and crop income per capita. However, complementing the adoption of mineral fertilizer and improved seeds with insurance leads to higher household welfare outcomes compared to adopting mineral fertilizer and improved seeds without insurance. The findings of this study are important not only in helping farm households to refine their risk management decisions but also in selecting the optimum set of strategies when faced with risky situations. Additionally, the identified optimal risk management strategies provide useful information to policymakers to better design, target, and scale up intervention programs and appropriate risk management policies.

Zusammenfassung

Der Klimawandel bedroht die Lebensmittelproduktionssysteme und die Lebensgrundlagen der von der Landwirtschaft abhängigen Bevölkerung, insbesondere in den Entwicklungsländern. Die Gefährdung der landwirtschaftlichen Haushalte durch Wetterveränderungen wie anhaltende Dürre, verspäteten Regenbeginn und veränderte Niederschlagsmuster führt zu größeren Einkommensverlusten und bedroht die Ernährungssicherheit. Vor allem in den afrikanischen Ländern südlich der Sahara haben die landwirtschaftlichen Haushalte nur begrenzten Zugang zu formellen Risikomanagementinstrumenten, um mit den unzähligen produktionsbezogenen Risiken umzugehen, denen sie ausgesetzt sind. Daher verlassen sie sich meist auf eine Reihe traditioneller Risikomanagementstrategien, um diese produktionsbedingten Verluste zu vermeiden oder zu minimieren. Diese traditionellen oder informellen Risikomanagementstrategien sind jedoch meist unvollständig, suboptimal und mindern nur einen kleinen Teil des Gesamtrisikos. Darüber hinaus ist jede dieser Risikomanagementstrategien mit unterschiedlichen Kosten und Auswirkungen auf die Ressourcennutzung oder -zuweisung verbunden. Im Rahmen dieser Doktorarbeit wurde daher versucht, die Auswirkungen verschiedener Risikomanagementstrategien, die von senegalesischen landwirtschaftlichen Haushalten eingesetzt werden, auf verschiedene Ergebnisse zu untersuchen, darunter landwirtschaftliche Einkommen und Einkommensstreuungen, technische Effizienz und Ernährungssicherheit. Auf diese Weise sollte die Studie kontextspezifische Informationen liefern, die Landwirten und politischen Entscheidungsträgern dabei helfen, produktionsbezogene Risiken durch die Auswahl des richtigen Portfolios oder Mixes von Risikomanagementstrategien besser zu bewältigen. Die Doktorarbeit, die aus fünf Beiträgen besteht, verwendet mehrere ökonometrische Analysen unter Verwendung von Daten einer national repräsentativen landwirtschaftlichen Haushaltserhebung aus dem Jahr 2017.

Die erste Arbeit untersuchte die Auswirkungen des Klimawandels in Form von Niederschlagsvariabilität auf die Einkommensungleichheit zwischen Haushalten, die tägliche Verfügbarkeit von Nahrungskalorien und die landwirtschaftliche Arbeitsproduktivität im Senegal sowie die Rolle von Anpassungsstrategien. Dabei wurden die kürzlich entwickelten Modellmittelungstechniken (Weighted Average Least Squares) zur Berücksichtigung von Modellunsicherheiten und der Ansatz der Gini-Zerlegung verwendet. Die Ergebnisse zeigen, dass die Niederschlagsvariabilität die Einkommensgleichheit negativ beeinflusst, indem sie die Gini-Elastizität der landwirtschaftlichen Einkommen erhöht. Insbesondere für die landwirtschaftlichen Einkommen ergab die Studie, dass die Gini-Elastizität bei jeder Abweichung der Niederschlagsmenge zunimmt. Da die landwirtschaftlichen Einkommensquellen den größten Anteil an der Einkommensungleichheit der Haushalte haben, sind Schocks in diesem Sektor weitgehend für den beobachteten Anstieg der Einkommensungleichheit verantwortlich. Die Studie zeigt auch, dass die Variabilität der Niederschläge die tägliche Verfügbarkeit von Nahrungsmittelkalorien und die landwirtschaftliche Arbeitsproduktivität der Haushalte verringert. Die Studie zeigt auch unterschiedliche Auswirkungen der Anpassungsstrategien auf die Ergebnisse der Haushalte, wobei die Nutzung von Versicherungen (Risikotransfer) bei der Bewältigung der Auswirkungen von Nieder-

schlagsschwankungen effektiver zu sein scheint.

In der zweiten Studie wurde die Auswirkung verschiedener Risikomanagementstrategien, die von landwirtschaftlichen Haushalten eingesetzt werden, auf das landwirtschaftliche Einkommen und die Einkommensstreuung untersucht. Zu diesem Zweck wurden in der Studie ein multinomiales endogenes Switching-Regressionsmodell zur Kontrolle möglicher Selektivitätsverzerrungen und ein augenblicksbasierter Ansatz verwendet. Die empirischen Ergebnisse zeigen, dass der Einsatz von Ex-ante-Risikomanagementstrategien die landwirtschaftlichen Einkommen signifikant reduziert, während der Einsatz von Ex-post-Strategien entweder isoliert oder in Kombination mit Ex-ante-Risikomanagementstrategien die landwirtschaftlichen Einkommen signifikant erhöht. Alle von den Haushalten angewandten Risikomanagement-Strategien verringern die Streuung der landwirtschaftlichen Einkommen erheblich, wobei die Ex-post-Strategien die größte Streuungsreduzierung bewirken.

In der dritten Studie wurden die Auswirkungen der von den landwirtschaftlichen Haushalten angewandten Risikomanagementstrategien auf die technische Effizienz analysiert. In der Studie wurde eine stochastische Produktionsgrenze für die Stichprobenauswahl verwendet, um potenzielle Verzerrungen durch Selbstselektion bei der Annahme zu kontrollieren, sowie ein Meta-Frontier-Modell, um die Auswirkungen der Risikomanagementstrategien auf die technische Effizienz zu bewerten. Die empirischen Ergebnisse zeigten, dass das Risikomanagement Auswirkungen auf die technische Effizienz der landwirtschaftlichen Haushalte hat. Die Ergebnisse zeigten auch, dass landwirtschaftliche Haushalte, die Ex-post-Risikomanagementstrategien anwenden, im Vergleich zu den anderen Risikomanagementstrategien eine relativ höhere technische Effizienz in Bezug auf die Meta-Grenze zu haben scheinen. Haushalte, die Ex-ante-Risikomanagementstrategien anwenden, waren im Vergleich zu Haushalten, die kein Risikomanagement betreiben, oder zu Haushalten, die Ex-post-Risikomanagementstrategien isoliert oder in Kombination mit Ex-ante-Risikomanagementstrategien anwenden, am wenigsten technisch effizient. Die Ergebnisse deuten auch darauf hin, dass ein Risikomanagement mit mehreren Strategien nicht unbedingt zu den höchsten technischen Effizienzgewinnen im Vergleich zur Anwendung einzelner oder isolierter Strategien führt.

Die vierte Studie untersuchte die komplementären Auswirkungen produktivitätssteigernder Technologien (Mineraldünger und verbessertes Saatgut) in Verbindung mit der Einführung von Versicherungen auf die technische Effizienz, indem sie zwei verschiedene landwirtschaftliche Haushalte miteinander verglich - einen, der Dünger und verbessertes Saatgut mit Versicherungen einsetzt, und einen, der Dünger und verbessertes Saatgut ohne Versicherungen einsetzt. In der Studie wurde eine stochastische Produktionsgrenze mit einem Meta-Frontier-Modell, einem Propensity-Score-Matching-Ansatz (PSM) und einem endogenen Switching-Regressionsmodell verwendet, um mögliche Verzerrungen zu kontrollieren. Die Ergebnisse zeigen, dass Haushalte, die produktivitätssteigernde Technologien ohne Versicherung einsetzen, im Durchschnitt technisch effizienter sind als Haushalte, die produktivitätssteigernde Technologien mit Versicherung einsetzen. Dennoch waren die Technologieabstände der Haushalte, die produktivitätssteigernde Technologien mit Versicherung anwandten, signifikant höher als die der Haushalte, die produktivitätssteigernde Technologien ohne Versicherung anwandten, was darauf hindeutet, dass Haushalte, die produktivitätssteigernde Technologien mit Versicherung anwandten, offenbar etwas effizienter bei der Anwendung der besten verfügbaren Technologie sind. Die Studie zeigt auch, dass die Einführung produktivitätssteigernder Technologien mit Versicherung die technische Effizienz der Anwender produktivitätssteigernder Technologien mit Versicherung an der Metagrenze um etwa 50,17% verringert. Umgekehrt könnte die Einführung von Versicherungen in Verbindung mit produktivitätssteigernden Technologien die durchschnittliche technische Effizienz derjenigen, die nur produktivitätssteigernde Technologien einsetzen, um etwa 37,44% erhöhen. Die Ergebnisse deuten darauf hin, dass die beobachteten niedrigeren technischen Effizienzen für produktivitätssteigernde Technologien mit Versicherungsabschluss auf unbeobachteten Aufwand oder Verhaltensverzerrungen der Landwirte zurückzuführen sein könnten, die eine wichtige Quelle für Heterogenität bei den beobachteten Behandlungseffekten sein können.

Im letzten Beitrag wurden die gemeinsamen Wohlfahrtseffekte des Managements von Klimarisiken durch den Einsatz von risikomindernden Technologien und Versicherungen bewertet, indem drei verschiedene landwirtschaftliche Haushalte verglichen wurden: 1) Haushalte, die Mineraldünger, verbessertes Saatgut und Versicherungen nicht einsetzen, 2) Haushalte, die Mineraldünger und verbessertes Saatgut ohne Versicherung einsetzen und 3) Haushalte, die Mineraldünger und verbessertes Saatgut mit Versicherung einsetzen. Um das Ziel der Studie zu erreichen, wurde ein multinomiales endogenes Switching-Regressionsmodell verwendet, um mögliche Selektivitätsverzerrungen zu kontrollieren. Die Ergebnisse zeigten, dass die Einführung von Mineraldünger und verbessertem Saatgut mit oder ohne Versicherung mit einer signifikanten Steigerung der Verfügbarkeit von Nahrungsmittelkalorien und des Pro-Kopf-Einkommens verbunden ist. Die Ergänzung des Einsatzes von Mineraldünger und verbessertem Saatgut durch eine Versicherung führt jedoch zu höheren Wohlfahrtsergebnissen für die Haushalte im Vergleich zum Einsatz von Mineraldünger und verbessertem Saatgut ohne Versicherung. Die Ergebnisse dieser Studie sind nicht nur wichtig, um den landwirtschaftlichen Haushalten dabei zu helfen, ihre Risikomanagemententscheidungen zu verfeinern, sondern auch, um in Risikosituationen die optimalen Strategien auszuwählen. Darüber hinaus liefern die ermittelten optimalen Risikomanagement-Strategien nützliche Informationen für politische Entscheidungsträger, um Interventionsprogramme und geeignete Risikomanagement-Maßnahmen besser zu konzipieren, auszurichten und auszuweiten.

List of abbreviations

ADB	Asian Development Bank
AE	Adult Equivalents
ADW	Angular-Distance Weighting
ANACIM	Agence Nationale de l'Aviation Civile et de la Météorologie
ANSD	Agence Nationale de la Statistique et de la Démographie
ATT	Average Treatment effect on Treated
ATU	Average Treatment effect on Untreated
BMA	Bayesian Model Averaging
CFA	Communauté Financière Africaine
CO_2	Carbon Dioxide
CRU	Climatic Research Unit
CSA	Climate Smart Agriculture
DEA	Data Envelopment Analysis
EMAP	Etude et Management du Projets
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GIIF	Global Index Insurance Facility
HHI	Herfindahl-Hirschman Index
HWI	Household Welfare Index
IFAD	International Fund For Agricultural Development
IFPRI	International Food Policy Research Institute
IIA	Independence of Irrelevant Alternatives
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
ISRA	Institut Sénégalais de Recherches Agricoles

ISRIC	International Soil Reference and Information Centre
MDS	Minimum Data Set
MSE	Mean Squared Error
MTE	Meta-Technical Efficiency
OLS	Ordinary Least Squares
PAPA	Projet d'Appui aux Politiques Agricoles
PCA	Principal Component Analysis
PET	Productivity-Enhancing Technologies
PSM	Propensity Score Matching
QGIS	Quantum Geographic Information System
RDA	Recommended Dietary Allowance
SDGs	Sustainable Development Goals
SFA	Stochastic Frontier Analysis
SMF	Stochastic Meta-Frontier
SQI	Soil Quality Index
TE	Technical Efficiency
TGR	Technology Gap Ratio
UNDESA	United Nations Department of Economic and Social Affairs
USAID	United States Agency for International Development
WALS	Weighted-Average Least Squares
WHO	World Health Organization
WFP	World Food Programme
WMO	World Meteorological Organization
WTO	World Trade Organization

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Chapter 1
General introduction

1.1 Background

The agricultural sector is one of the most important sectors experiencing the effect of climate change. Several studies (e.g., Parry *et al.*, 2009; Hertel *et al.*, 2010; IPCC, 2014; FAO *et al.*, 2018; Hoffman *et al.*, 2018) have shown that Sub-Saharan Africa will be the region largely impacted by climate change due to its heavy reliance on agriculture for livelihoods. In Senegal, climate-sensitive sectors such as agriculture, livestock, and fisheries are highly vulnerable to natural disasters and the effects of climate change (USAID, 2017). With agriculture being predominantly rain-fed, more than 95% of the total cropped area in Senegal depends on rain-fed systems, and most farmers practise subsistence agriculture (Khouma *et al.*, 2013). Simultaneously, growing evidence suggests that climate change is already affecting agriculture and food security in Senegal. The country in recent years is experiencing erratic rainfall patterns and rising sea levels which are increasing the rates of soil erosion, salinization in agricultural soils, and destruction of critical infrastructure (ANACIM *et al.*, 2013; IFAD, 2019).

The subject of farm household adaptation to climate change in developing countries are well known and studied. Most empirical studies (e.g., Di Falco and Veronesi, 2013; Kassie *et al.*, 2015; Roco *et al.*, 2017; Teklewold *et al.*, 2017; Gorst *et al.*, 2018; Khanal *et al.*, 2018; Birthal and Hazrana, 2019; Torres *et al.*, 2019) have been devoted to understanding the impact of mostly agronomic adaptation strategies on household welfare outcomes. Some other studies have also provided important insights into the channels of climate change impacts and weaknesses of several adaptation or risk management approaches. The empirical literature for instance identifies four important channels through which climate shocks impact farm households. 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 and investment 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 deviation between expected and real outcomes (Schaffnit-Chatterjee, 2010; Obiri and Driver, 2017). Fourthly, climate shocks drive household poverty through the destruction of livelihood assets, increases in food prices and reductions in consumption (Hallegatte *et al.*, 2016; Hertel *et al.*, 2010).

The impact of farm household adaptation to climate change is highly contentious because the continuum nature of risks in agriculture implies that different instruments are best suited to address different risks. Simultaneously, because it is virtually impossible to address all climate change-related risks at once, it is necessary to prioritize interventions based on evaluating trade-offs between changes in risk, expected returns, and other variables. Building farm household's resilience to climate-related shocks thus requires an understanding of the effectiveness and impact of risk management measures (adaptation) across several outcomes. Although a significant body of research in existence have assessed the impact of climate change on agriculture, further research is needed to identify the impact of adaptation or risk management strategies on multiple outcomes. Particularly for the study country Senegal, large empirical research gaps exist on the subject of adaptation and its impact on farm households. The available literature on Senegal only provides anecdotal evidence at best. Motivated by these research gaps, this PhD research sought to explore the impact of climate change and various adaptation strategies herein risk management strategies across multiple outcomes including, agriculture incomes and dispersions around income, technical efficiency, and food security of Senegalese farm households.

Globally, cognizance of the impacts of climate-related shocks has led to an increased focus on reducing smallholder farmers' exposure and increasing the resilience of production systems and livelihoods to adverse impacts (World Bank, 2016). Because risks faced by farmers are both numerous, complex, and interconnected, they vary in their levels of frequency and severity and have profound short-term and long-term impacts on both income and livelihoods. This means that a singular blueprint for risk management is not feasible. Farmers especially in developing countries when facing climate-related shocks have heavily relied on several traditional or informal risk management tools to deal with such shocks largely due to limited access to formal risk management instruments such as insurance or credit. Farm households use these risk management tools simultaneously or in combinations to deal with agricultural risks (Harwood *et al.*, 1999; Makki *et al.*, 2001; Flaten *et al.*, 2005; Velandia *et al.*, 2009; Ullah and Shivakoti, 2014; Ullah *et al.*, 2015; World Bank, 2016). In most cases, they are assumed to select a combination of risk management strategies that, for example, maximize expected net returns subject to the degree of risk they are willing to accept (Harwood *et al.*, 1999; Tomek and Peterson, 2001).

Traditional or informal strategies employed by households usually include agronomic adaptation practices such as conservation farming practices, mulching, sustainable land management (World Bank, 2016; Baiyeri and Aba, 2017; Obiri and Driver, 2017), diversifying income sources through multiple farm enterprises or off-farm activities (Kijima *et al.*, 2006; Matsumoto *et al.*, 2006; Barnett *et al.*, 2008; Di Falco and Chavas, 2009; Di Falco *et al.*, 2010; Tangermann, 2011; Bezabih and Di Falco, 2012; Ullah and Shivakoti, 2014; Birthal and Hazrana, 2019), household coping strategies such as labour market participation, reduced consumption, and sales of assets (Rosenzweig and Wolpin, 1993; Fafchamps, 1999; Dixon *et al.*, 2001; Belay *et al.*, 2005; Demeke *et al.*, 2016; World Bank, 2016). Other strategies include producing lower risk outputs (Rosenzweig and Binswanger, 1993; Carter and Barrett, 2006; Barnett *et al.*, 2008), informal risk-sharing arrangements such as share tenancy contracts, traditional money-lending, and risk-sharing within extended families and other community networks (Zeuli, 1999; Anderson, 2001; Barnett *et al.*, 2008), informal insurance such as dependence on relatives and neighbours for material and moral support (World Bank, 2005a,b, 2016), and employing risk-reducing inputs or technologies (Holzmann and Jørgensen, 2001; World Bank, 2005b; Barnett *et al.*, 2008). Beyond these, recent innovations in formal insurance in the form of index-based risk transfer products (Deng *et al.*, 2007b,a; Huirne *et al.*, 2007; Barnett *et al.*, 2008; Velandia *et al.*, 2009; Wang *et al.*, 2016; World Bank, 2016)and production and market or sales contracts (Makus *et al.*, 1990; Harwood *et al.*, 1999; World Bank, 2005b) are increasingly playing an important role in helping households better manage climate-related risks.

However, the reliance on these largely traditional risk management strategies to avoid or minimize losses are mostly incomplete, suboptimal and mitigate only a small part of the overall risk (Siegel and Alwang, 1999; Dercon, 2002; Alderman, 2008; Barnett *et al.*, 2008; Deressa *et al.*, 2010; Kouamé, 2010). For example, covariate agriculture shocks often affect entire regions, thus, local mutual insurance schemes can break down (Hazell, 1992; Dercon, 1996, 2002; Rosenzweig and Binswanger, 1993; Townsend, 1994; Zimmerman and Carter, 2003). Traditional or household-level risk-management strategies are mostly ineffective (Skees *et al.*, 2002; World Bank, 2005a) because they only achieve partial risk coverage at a very high cost and are in some cases localized and limited in scope. In addition, informal risk transfer measures such as socially constructed reciprocity obligations within various social networks, semi-formal microfinance, rotating savings, and credit marginalize the most vulnerable and have high hidden costs (World Bank, 2001a,b, 2005a,b). Empirical evidence (see Platteau, 1997; Jalan and Ravallion, 1999; Santos and Barrett, 2006) also suggest that access to these informal risk transfer measures are positively related to social factors such as existing wealth, meaning this can prevent reciprocity obligations and hence the poorest of the poor have little to gain from such arrangements. At the same time, such arrangements are fragile, inequitable, and untimely and can leave individuals exposed to risk while at the same time creating a dependency that has dire consequences (Carter, 1997; World Bank, 2005a).

Furthermore, there is an implied risk premium or cost for all of these risk management strategies which can be very high (Rosenzweig and Binswanger, 1993; Morduch, 1995; Zimmerman and Carter, 2003; Deressa *et al.*, 2010; World Bank, 2016). For instance, the implied risk premium for self-insurance strategies employed by farm households such as diversification, producing lower risk outputs, or employing risk-reducing inputs or technologies is either the direct or the opportunity cost of undertaking the strategy. According to Kahan (2008), the cost could be expressed by the amount of resources tied up in order for a farm household to manage their risks more effectively. Such implied costs are easy to identify in some instances, while in others, the cost is less recognisable. At the same time, some of these risk management strategies can potentially generate adverse external effects. Dercon (1996), Skees *et al.* (2002), and Barrett and Swallow (2006) for instance observed pecuniary externalities in the case of distress asset sales following covariate shocks. For example, mass selling of livestock during a major shock such as drought can drive livestock prices down in situations where covariate risks have impacts across large regions, hence bringing no increased income gains for households. Furthermore, some authors (see Rosenzweig and Binswanger, 1993; Zimmerman and Carter, 2003) also tend to suggest the occurrence of such impacts even in the case of localized adverse shocks if markets for the asset are not spatially integrated.

Some empirical studies (see Rosenzweig and Binswanger, 1993; Morduch, 1995; Kurosaki and Fafchamps, 2002) have found considerable efficiency losses associated with risk mitigation, typically due to lack of specialization and the need for farmers to make trade-offs between income variability and profitability. Skees *et al.* (2002) also observed that ex-post risk management strategies involving coping measures such as reduced consumption and sales of assets are costly. Some studies (see Bhandari *et al.*, 2007; Barnett *et al.*, 2008; Amare *et al.*, 2018) suggest that farm households that use risk coping mechanisms are unable to recover the loss of assets ex-post the shock. Hence, liquidating productive assets may also not be a viable risk management option for the poorest of the poor (Barnett *et al.*, 2008) with empirical evidence (see Zimmerman and Carter, 2003; Kazianga and Udry, 2006) suggesting that extremely poor households recognize the danger of such sales of assets and thus choose to waive consumption (e.g. reduced expenditures on school fees, health care, and food consumption) rather than further liquidating assets. Waiving household consumption also has severe implications mostly through reductions in the value of human assets, further presenting not only a barrier to poverty alleviation but also reinforcing poverty (Hoddinott and Kinsey, 2001; Dercon and Hoddinott, 2003; Thomas *et al.*, 2004; Hoddinott, 2006; Kouamé, 2010). The need of households to smooth consumption against idiosyncratic and correlated shocks which they do through coping strategies, also comes at a serious cost in terms of production efficiency and reduced profits, thus lowering the overall level of household consumption (World Bank, 2005b).

Diversification, as a risk management strategy, can hinder development since gains are possible when households specialize (Skees *et al.*, 2002). Furthermore, diversification may not actually spread certain types of risk, in particular, weather events that cause widespread losses. Implying that when covariate risks occur, it may impact a variety of sources of income such as own farm, agricultural labour, and non-farm income hence diversification may not necessarily be an effective strategy (Skees *et al.*, 2002). Furthermore, diversification could imply 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 not only on agriculture income but also allocative and technical efficiency. Furthermore, diversification can reduce the yields of cash crops relative to staple crops, and potentially increase the level of staple crops planted (Mullins *et al.*, 2018). This is because farmers devote a larger share of land to safer, traditional varieties or staple crops than to riskier high-yielding varieties or high-value crops (Morduch, 1995; Salazar-Espinoza *et al.*, 2015). In the nutshell, farmers tend to use resources sub-optimally leading to less productivity on average than other strategies that farmers could have followed if the risk could be ignored for instance (Anderson, 2001). Other studies (see Purdy *et al.*, 1997; Barry *et al.*, 2001; Poon and Weersink, 2011) have also shown that farm enterprise diversity does not always lower farm income volatility, suggesting that encouraging a wider mix of enterprises is not always an effective strategy to reduce fluctuations in farm income. For instance, Schoney *et al.* (1994) found that despite several crops typically having a risk-reducing effect, these benefits were typically offset by the lower gross incomes linked with such levels of diversification.

Index-based insurance products in agriculture serve two main purposes, reducing vulnerability by compensating producers for the economic losses suffered from insured events and increasing productivity through increased investment by securing credit in case of loan default due to insurable events (Barnett *et al.*, 2008; Kouamé, 2010; D'Alessandro *et al.*, 2015). However, despite index-based insurance products being a powerful ex-ante instrument to address risk before it materializes, one significant limitation is the existence of basis risk (Miranda and Vedenov, 2001; World Bank, 2005b; Barnett *et al.*, 2008; Hazell *et al.*, 2010; Jensen and Barrett, 2017; Jensen *et al.*, 2018). As suggested by the World Bank (2005b) and Schaffnit-Chatterjee (2010), the presence of basis risks implies that a farm household can experience a loss and yet receive no payment. Conversely, it is also possible that the household will not experience a loss and yet receive a payment. Basis risk occurs because the index upon which the insurance is developed is not perfectly correlated with farm-level losses (Barnett *et al.*, 2008).

The effectiveness of index-based insurance as a risk management tool is therefore dependent on how positively farm-level losses are correlated with the underlying index (World Bank, 2005b). Barnett *et al.* (2008) argue that index-based insurance products can be a highly effective risk management tool if basis risk is relatively small and ineffective if basis risk is large. Some studies have also found contradictory impacts of insurance. For example, Giné and Yang (2009) find index insurance contracts to significantly reduce investment in a new agricultural opportunity. de Nicola (2015) finds that in cases where single, low-technology options are available, insurance tends to reduce total input investments, and it weakens farmers' precautionary motives to overinvest. Farrin and Murray (2014) report a negative effect of insurance on wealth, as in good years farmers pay a premium but do not receive an indemnity payment. Giné *et al.* (2010) also observed that index-insurance products could only improve welfare if other risk-sharing mechanisms employed by households are insufficient. Dercon *et al.* (2014) argue that index insurance is particularly beneficial to groups that are able to hedge idiosyncratic risks in an informal manner.

Some insurance schemes have also been observed to reduce the use of production diversification or, reduce and even eliminate the demand for other formal risk hedging/transfer products (Schaffnit-Chatterjee, 2010; Nigus *et al.*, 2018; Matsuda *et al.*, 2019). Supplementary to risk management strategies employed by farm households, public risk-management strategies targeting farm households also have limitation in terms of coverage, weak institutional linkages among stakeholders who deal with risk management, poor early warning mechanisms, and dependence on foreign sources (World Bank, 2005a; Devereux and Guenther, 2007).

1.2 Research objectives

The general objective of this PhD research is to assess farm household adaptation to climate shocks in Senegal and its impact on several welfare indicators. Specifically, the PhD research:

1. Examined the impact of climate change in the form of rainfall variability on inter-household inequality, food security, and labour productivity
2. Evaluated the impact and effectiveness of risk management strategies on household agricultural incomes and dispersions around agriculture incomes
3. Analysed the implication of risk management under climate change on farm household technical efficiency
4. Assessed the complementary impact of productivity-enhancing technologies (PET) with insurance adoption on technical efficiency.
5. Assessed the welfare impacts of managing climate risk through the joint adoption of risk-reducing technologies and insurance

1.3 Relevance of the study

The PhD research study contributes to the existing literature in several ways. First, the study empirically contributes to our understanding of how current moisture stress-related climatic events, shape Senegalese farm household outcomes today. The study contributed to the current understanding of how climate change in the form of rainfall variability can drive income inequality and agricultural labour productivity. Secondly, this study contributed to the current understanding of the effectiveness of various risk management strategies employed by households in terms of reducing dispersion around agriculture incomes. This helps farm households to not only refine their decisions but also select the optimum set of strategies when faced with risky situations. Besides farm households, the identified optimal risk management strategies provide useful information to policymakers to better design, target, and scale up intervention programs and appropriate risk management policies. At the same time, the holistic analysis of this study confirmed the results of existing studies that have emphasized the importance of insurance in risk management in terms of unlocking demand and increasing investments in productivity-enhancing technologies, and also improving general household welfare outcomes. However, the present study also identified a new form of moral hazard problems with insurance that has not yet been emphasised in the existing literature. Understanding the impact of risk management strategies employed by households on technical efficiency is also important for designing performance-improvement programs that can help farmers better optimize the returns on the use of these risk management strategies.

1.4 Data

The data used in the study comes 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 (USAID) under the "Feed The Future" initiative. The survey was conducted between April and May 2017. The survey covered all the 14 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, 42 agricultural departments were included in the survey. A general census of population and housing, agriculture and livestock conducted in 2013 showed that about 755,532 agricultural households practised agriculture, with about 61% (458,797) of the farming households practising rainfed agriculture. The survey design, therefore, included a global sample of 6,340 farm households in 1260 rural census districts and the 42 agricultural departments. The sample represented a survey rate of 1.4%, i.e., about 1 household out of every 72. 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 vegetables 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 is 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 Senegal River Valley and Niayes Market Gardening Zone, stratification of the rural census districts was done before agricultural households were selected.

The agricultural survey was geared towards estimating the level of the main agricultural production of family farms. The survey provided information on the physical characteristics of cultivated plots (geolocation and area) and major investments made at their level (agricultural inputs, cultural operations, soil management, and restoration), level of agricultural equipment, agricultural income, agricultural risks, and adaptation strategies[1]. Specifically, the data collected in the survey included information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit and extension access, membership of farmer-based organizations, inputs use and cost, family and hired labour, sales volumes, and processing of agricultural produce. Others included household consumption, access to amenities, non-farm and livestock revenue, remittance, agricultural insurance, risks, and production-related constraints and risk adaptation strategies, input subsidies access, and their perceptions.

1.5 Thesis structure

This PhD study is a collection of five papers. The first paper which is presented in Chapter 2 was a general opening to the subject of my PhD research. In this paper, I examined the impact of climate change in the form of rainfall variability on inter-household income inequality, daily food calorie availability, and agricultural labour productivity in Senegal and the role of adaptation strategies. The study employed the recently developed model-averaging techniques that address issues related to model uncertainty and controlled for household vulnerability factors. The empirical results revealed that rainfall variability negatively affects income inequality, and decreases household daily food calorie availability and agriculture labour productivity. Adaptation strategies produced varying effects across the three household welfare

[1] The survey specifically asked farm households about the adaptation strategies they employ when faced with risk. These strategies are in the nutshell meant to manage production and climate-related risks. Thus, these are risk management strategies, hence throughout this thesis, risk management strategies is used. Readers are however to note that in this context, adaptation strategies and risk management strategies are one and the same since they are meant to reduce risk exposure or mitigate the adverse impacts of risks.

outcomes, but risk transfer (insurance) use was found to better help households deal with rainfall variability related shocks.

In Chapter 3, the study evaluated the effect of different risk management strategies employed by farm households on agriculture income and dispersions around incomes. The study employed a Multinomial Endogenous Switching Regression model to control for potential selectivity bias problems and a Moment-Based Approach. The study found that the use of ex-ante risk management strategies significantly reduces agriculture incomes while the use of ex-post strategies either in isolation or in combination with ex-ante risk management strategies significantly increases agriculture incomes. In general, all the risk management strategies significantly reduced dispersions around agriculture incomes with ex-post strategies however producing the largest effect.

Chapter 4 of the study broadly analysed the technical efficiency implications of risk management strategies employed by farm households. Because the adoption and use of risk management strategies are non-random and farm households self-select into adopting or not adopting, the study addressed potential biases by employing a sample selection stochastic production frontier together with a meta-frontier model to evaluate the impact of risk management strategies on technical efficiency. The study finds that risk management has implications on farm household's technical efficiency. The result also showed a relatively higher technical efficiency for households adopting ex-post risk management strategies compared to the other risk management strategies. At the same time, farm households employing only ex-ante risk management strategies were observed to be the least technically efficient compared to households not managing risks or employing ex-post risk management strategies either in isolation or in combination with ex-ante risk management strategies.

Complementary to Chapter 4, the more specific study of Chapter 5 assessed the complementary impact of productivity-enhancing technologies (fertilizer and improved seeds) with insurance adoption on technical efficiency by comparing two distinct farm households: one adopting fertilizer and improved seeds with insurance and the other fertilizer and improved seeds without insurance. The study employed a sample selection stochastic production frontier with a meta-frontier model and an endogenous switching regression model to control for potential biases. The study finds that households that adopted productivity-enhancing technologies with insurance tend to have higher levels of investment in inputs, however, households that adopted productivity-enhancing technologies without insurance tend to be more technically efficient on average. At the meta-frontier, the study finds that complementing the adoption of fertilizer and improved seeds with insurance reduces the technical efficiency of fertilizer and improved seeds with insurance adopting households. On the contrary, the study finds that if households adopting fertilizer and improved seeds without insurance were to have adopted with insurance, their technical efficiency would significantly increase. The finding suggests that behavioural biases might be the underlying reason for the heterogeneous treatment effects observed.

To better evaluate the influence of insurance on household welfare, Chapter 6, assessed the joint welfare impacts of managing climatic risk through the adoption of risk-reducing technologies and insurance by comparing three distinct farm households; non-adopters of mineral fertilizer, improved seeds, and insurance, mineral fertilizer and improved seeds adopters without insurance and mineral fertilizer and improved seeds adopters with insurance. The study employed a multinomial endogenous switching regression model to control for selection bias stemming from both unobserved and observed factors. The study finds that complementing the adoption of mineral fertilizer and improved seeds with insurance leads to higher household welfare outcomes in terms of food calorie availability and crop income per capita compared to households adopting mineral fertilizer and improved seeds without insurance.

Finally, Chapter 7 presents the main conclusions of the PhD research, offers relevant policy implications of the study, discusses some caveats related to the study, and offers recommendations for future research.

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Chapter 2

The impact of climate change on inter-household inequality, food security and labour productivity: Evidence from Senegal

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Abstract

Changing precipitation patterns caused by climate change are expected to have major impacts on economic inequality, food security and labour productivity in the agriculture sector of developing countries. This study examines the impact of climate change in the form of rainfall variability on inter-household income inequality, daily food calorie availability and agricultural labour productivity in Senegal using a nationally representative household survey data. Using the recently developed model-averaging techniques that address issues related to model uncertainty and controlling for household vulnerability factors, we show that the inequality impacts of climate-induced shocks will be highly dependent on the income source composition of households. We find that the Gini elasticity of agriculture income increases for every deviation in rainfall whiles in the case of nonfarm income it decreases for every deviation in rainfall. Because agriculture income sources constitute the largest share and contributor to household income inequality, any shocks to the sector will largely be responsible for any observed increases in income inequality. Additionally, we find that rainfall variability decreases household daily food calorie availability and agricultural labour productivity. Lastly, we find that risk transfer, irrigation use, subsidies access and the adoption of productivity-enhancing technologies (fertilizer and improved seeds) are important instruments to help households deal with rainfall variability related shocks.

Keywords: Climate change, rainfall variability, weighted-average least squares, income inequality, food security, labour productivity

JEL Codes: D63, Q18, Q54, Q12

2.1 Introduction

As one of the most dominant economic sectors in many poor Sub-Saharan African countries, agriculture is the mainstay of rural economies and the livelihoods of its rural residents. The sector plays a multi-dimensional role in the development process through direct and indirect linkages such as stimulating growth in other parts of the economy, creating employment opportunities, reducing poverty, lowering income disparities, ensuring food security, delivering environmental services and providing foreign exchange earnings (World Bank, 2007; Odusola, 2017). Particularly in the context of poverty reduction and inequality some studies (Bourguignon and Morrisson, 2002; Thirtle *et al.*, 2003; Christiaensen *et al.*, 2006; Ravallion and Chen, 2007; World Bank, 2007; Imai and Gaiha, 2014; Odusola *et al.*, 2017) strongly show that agriculture growth is the most efficient and powerful tool to accelerate a reduction in poverty and income inequalities in developing countries. At the same time, accumulating evidence suggests that due to the dependence of agriculture on climate, it is one of the sectors where climate change impacts are expected to hit hardest (Dixon *et al.*, 2001; InterAcademy Council, 2004; Hertel *et al.*, 2010; Hallegatte *et al.*, 2016). Particularly in Sub-Saharan Africa, the influence of climate on production and livelihoods is both strongest and most complex, primarily due to a heavy reliance on rainfed agriculture which makes rural populations more vulnerable to the effects of climate change (Neely *et al.*, 2009; Molnar, 2010; FAO *et al.*, 2018). These vulnerabilities are due to several interlinking factors such as low level of technological progress (e.g. irrigation, improved and high yielding varieties of crops and improved breeds of livestock adoption), and lack of resources to mitigate the adverse effect of climate change on agriculture (UNDESA, 2020).

In recent years, there has been renewed interest in the effects of climatic variability on agriculture. Although accumulating evidence suggests that agricultural production is affected by climate change in Senegal, there remains little quantitative understanding of how these agricultural impacts would affect livelihoods and welfare. At the same time, a growing consensus exists within the literature that differential ability to cope with extreme weather events exacerbates existing inequalities and power disparities within societies (IPCC, 2014). While some few studies have provided empirical evidence that climate-related risks increase inequality (Bui *et al.*, 2014; Thiede, 2014; Silva *et al.*, 2015; Narloch and Bangalore, 2018; Warr and Aung, 2019), food insecurity (Codjoe and Owusu, 2011; Murali and Afifi, 2014; Weldearegay and Tedla, 2018; Kinda and Badolo, 2019) within countries, a large part of the literature only provide anecdotal evidence at best. Furthermore, empirical work on the effects of such climate-related risk events on within-country inequality at the subnational level in less developed countries remains relatively limited (Leichenko and Silva, 2014; Islam and Winkel, 2017). Although model-based studies such as those by Parry *et al.* (2009), Hertel *et al.* (2010), Biewald *et al.* (2015), Havlík *et al.* (2015), IFPRI (2017), Popp *et al.* (2017), Hasegawa *et al.* (2018) and Diffenbaugh and Burke (2019) provides important insights into climate change impacts on inequality and food security, they obscure or fail to capture other important factors and spatial variations that drive these observed social and economic impacts. Furthermore, the impacts of climate change are a function of the three dimensions (exposure, sensitivity and adaptive capacity) of vulnerability. Such existing studies fail to account for these dimensions of vulnerability and therefore gives little guidance to decision-makers on groups in particular that gain or lose the most from climate change. Additionally, the physical, social and economic landscape of climate risk is uneven across countries. This makes subnational level analysis particularly relevant because of heterogeneous vulnerability, thus the effects of climate change is not experienced by everyone in the same way due to differences in exposure, susceptibility to the damage caused by climate change, and the ability to cope with the effects and recover. The implication is that such heterogeneous vulnerabilities will change the relative status, or distribution of affected households with respect to social and economic outcome. Furthermore, while prior studies have largely focused on the likely direct climate impacts on crop yields and agricultural output, they neglected a vast majority of potential economic impacts of climate change on agriculture such as agricultural labour productivity (Hertel and De Lima, 2020).

The purpose of this paper is therefore to explore the impact of climate change in the form of rainfall variability on inter household income inequality, food calories availability and agricultural labour productivity using a nationally representative survey data from Senegal. Studying the effect of climate change on the agricultural sector of Senegal is of particular interest for several reasons. First, the country is a food-deficit country with coverage rates of its cereal needs through domestic production being varied between 30% and 65% over the past 10 years (Hathie, 2019). Some estimates suggest that the country imports approximately 60% of its cereal requirements, mostly rice (USAID, 2017). This leads the country to rely on imports to meet domestic demand which exposes the country to global food price shocks. Food insecurity at the national level is estimated to be about 7.2% while malnutrition is about 8.2% (WFP, 2020). However, over 15% of rural households and over 8% of urban households are considered food insecure (WFP, 2012; IMF, 2013; USAID, 2017). Under climate change, per capita, food consumption (kg per capita per year) is projected to decrease by 4.4% and 9% in 2030 and 2050 respectively (IFPRI, 2019). Secondly, the agriculture sector is a key policy target of the government in its poverty reduction strategies effort (IMF, 2013). Poverty in Senegal remains essentially a rural phenomenon, with about 57.3% of the population being poor and about 70% of the rural population depending on rainfed subsistence farming (IFAD, 2019). Thus, excessive and recurrent climatic shocks will affect most of these rural households through losses in assets and food insecurity. This will reverse any gains made and further deepen poverty and inequality.

Our study is relevant for several reasons. Firstly, the study provides a better understanding of how current moisture stress-related climatic events, shape household outcomes today. Secondly, investigating the inequality implications of climate-related risks among farm households in Senegal is important because inequality is expected to affect progress toward the achievement of the Sustainable Development Goals (SDGs), thus quantifying the impacts of climate will help direct where, when, and how adaptation should proceed. Thirdly, because labour productivity is directly linked to improved standards of living for farm households, knowledge of the impacts of rainfall variability on agricultural labour productivity indirectly offers important cues relating to the climate-poverty nexus within households. The rest of the paper is organized as follows. In Section 2.2, we provide an overview of climate change impacts in Senegal. Section 2.3 provides a review of the literature on the channels and pathways by which climate change affects inequality, food security and labour productivity. Using the information from Section 2.3, we present the conceptual framework and empirical strategy in Section 2.4. We discuss the data used and variables measurement in Section 2.5 and the empirical specification in Section 2.6. In Section 2.7, we present the empirical results and discussions and finally, Section 2.8, concludes and offers some policy recommendations.

2.2 Climate-related shocks in Senegal

In Senegal, climate-sensitive sectors such as agriculture, livestock and fisheries are highly vulnerable to natural disasters and the effects of climate change (USAID, 2017). With agriculture being predominantly rain-fed, more than 95% of the total cropped area in Senegal depends on rain-fed systems, and most farmers practise subsistence agriculture (Khouma *et al.*, 2013). Like most countries in the Sahel region, Senegal's agricultural sector faces highly variable rainfall and is highly vulnerable to the effects of climate change. Simultaneously, growing evidence shows that climate change is already affecting agriculture and food security in Senegal. The country in recent years is experiencing erratic rainfall patterns and rising sea levels which are increasing the rates of soil erosion, salinization in agricultural soils, and destruction of critical infrastructure (ANACIM *et al.*, 2013; IFAD, 2019). Historically, climate change in Senegal is linked to persistent drought in the 1970s and the 1980s (ANACIM *et al.*, 2013). Since the 1960s, average temperatures have been observed to increase by 0.9°C, with higher rates of warming in the northern part of the country and more pronounced between October and December (USAID, 2017). Average annual rainfall has diminished since 1970 and is predicted to continue to diminish across Senegal (Ministère de l'Environnement et de la Protection de la Nature, 2010; Jalloh *et al.*, 2013; Ministère de l'Environnement et du Développement Durable, 2015). Rainfall declines of about 15% below the long-term average have also been observed and with the most significant rainfall declines in the southern region of Senegal during the wet season between June and September. Between 1970 and 2000, the country suffered prolonged droughts that contributed to a rural exodus (USAID, 2017). Similarly, documented accounts of these droughts and flooding events in Senegal over the past several decades have been reported in several studies (Braman *et al.*, 2013; Lo, 2013; WFP, 2014).

Persistent drought in the 1970s and 1980s severely affected the natural and managed ecosystems of the climatologically drier northern regions of the country (Gonzalez *et al.*, 2012). In the period 1986 to 2003, the average annual rainfall in many départments[1] in Senegal was observed to be considerably lower than the long term average (World Bank, 2009). Major droughts in 2002 and 2007 led to significant losses in total crop production values by 35% and 25% respectively (World Bank, 2009). The drought in 2002 was projected to have affected about 284,000 people (ANACIM *et al.*, 2013). The causes of loss as identified during an annual crop yield surveys indicated that drought was the primary cause of crop loss for almost 30% of rain-fed farmers, followed by locust infestation which was reported by 16% of farmers (EMAP, 2004). A major drought event in the 2011/2012 cropping season led to drought-induced food insecurity followed by subsequent floods in 2012 (ANACIM *et al.*, 2013). This was projected to have affected about 850,000 people (GIIF, 2017). In the year 2007, the World Bank (2009) reported a general decrease in agricultural production compared to the previous season, mainly due to drought. The drought event decreased cereal and groundnut production by 12% and 7% respectively compared to the previous year. More recently, a low and delayed rainfall was observed in 2013 and 2014 raining season affecting agriculture productivity (GIIF, 2017).

[1] These are administrative subdivisions in Senegal

Based on an analysis of available quantitative and qualitative data, D'Alessandro *et al.* (2015) identified drought, locusts, price volatility, crop pest and diseases as the most important climatic related risks facing Senegal's agricultural sector. Specifically, weather-related factors that relate to moisture stress caused either by erratic rainfall, early cessation of rains, delayed onset of rains, or extended drought are particularly prominent. Despite these identified risk events occurring in isolation, multiple and overlapping shocks are observed to have far greater impacts and higher associated losses (D'Alessandro *et al.*, 2015). Furthermore, more than 40% of the variation in crop yields in Senegal can be ascribed to the variation in annual rainfall amounts (D'Alessandro *et al.*, 2015). In the case of the country's most important cash crop, groundnut, rainfall levels are estimated to explain about 39% of the variability of yields (IMF, 2007). Empirical data provide strong evidence that environmental and climatic shocks related to floods and droughts have been highly correlated to production losses in the agricultural sector of Senegal (EMAP, 2004; World Bank, 2009; Régent *et al.*, 2011; D'Alessandro *et al.*, 2015). For instance, a macro-level analysis and estimates of the indicative value of losses, due to agricultural risks for 11 major crops between the period of 1980 to 2012 by D'Alessandro *et al.* (2015) shows that total losses from production risks in Senegal amounted to 4.82 million MT. In monetary equivalent, this is about US$1.38 billion, or about US$41.7 million per year, corresponding to about 3.9% of agricultural GDP on an average annual basis.

The analysis further showed that the highest crop losses coincided with major shocks to agricultural production. D'Alessandro *et al.* (2015) further observed that although the average annual impact of shocks on GDP is relatively modest, actual impacts when they occur potentially results in losses of the order of 10 to 20% of the agricultural sector GDP. Further analysis also shows that Senegalese agriculture is subjected to losses exceeding 10% of gross production value in one out of every five or six years on average due to unmanaged risks. The most significant cause of loss in Senegal is due to drought/erratic rainfall, and this accounts for approximately 50% of crop yield reductions, followed by pests and diseases, especially locusts, which accounts for about 25% of crop yield losses. Besides, maize production exhibits the highest level of vulnerability in terms of frequency of risk, whereas groundnuts production incurs the highest losses, accounting for nearly 45% of aggregate losses (D'Alessandro *et al.*, 2015). At the individual farm level, Régent *et al.* (2011) have estimated the cost of natural disasters damage to crop and livestock farmers in Senegal to average between US$474.55 to 596.48. In the long-term, climate change in Senegal is predicted to manifest as further declines in the amount of rainfall however with increased intensity, increased temperatures, and sea-level rise (Ministère de l'Environnement et de la Protection de la Nature, 2010; Braman *et al.*, 2013; Jalloh *et al.*, 2013; USAID, 2017).

2.3 Literature Review

A growing body of evidence has linked climate change to the extent and the persistence of rural poverty (Reardon and Taylor, 1996; Ahmed *et al.*, 2009; Hertel *et al.*, 2010; Olsson *et al.*, 2014; Abeygunawardena *et al.*, 2016; Hallegatte *et al.*, 2016; Tschakert, 2016; World Bank, 2016; Hallegatte and Rozenberg, 2017; Hansen *et al.*, 2019; WFP, 2020), inequality (Valentine, 1993; Bui *et al.*, 2014; IPCC, 2014; Thiede, 2014; Silva *et al.*, 2015; Hallegatte *et al.*, 2016; Narloch and Bangalore, 2018; Diffenbaugh and Burke, 2019; Warr and Aung, 2019; Sedova *et al.*, 2020; UNDESA, 2020) and food insecurity and malnutrition (FAO, 2008, 2010; Parry *et al.*, 2009; Ringler *et al.*, 2010; St.Clair and Lynch, 2010; Codjoe and Owusu, 2011; Havlík *et al.*, 2015; Popp *et al.*, 2017; FAO *et al.*, 2018; FSIN, 2018; Hasegawa *et al.*, 2018; Kinda and Badolo, 2019; WFP, 2020) in developing regions of the world. Thus, climate change will pose enormous threats to the achievement of key SDGs such as poverty reduction, zero hunger, good health and well-being, and reduced inequality. Recent research has identified pathways or channels through which climate change will impact these key SDGs.

For instance, pertaining to poverty, Hallegatte *et al.* (2016) argues that the impacts of climate change on agriculture affect poverty in two ways, first through prices and consumption, and secondly through farmers' incomes. They argue that higher food prices will reduce households' available income especially for those that spend a large share of household income on food products. At the same time, food price changes also affect farmers' incomes positively. A 15 country study by Hertel *et al.* (2010), shows that a climate-induced price rise increases extreme poverty by 1.8 percentage points. These price shocks are also directly linked to household food security and malnutrition. In Uganda, Hill and Mejia-Mantilla (2016) observed that a 10% reduction in water availability due to a lack of rainfall reduced crop income of farm households by an average of 14.5% and almost 20% for the poorest households. Similarly, they observed that a decrease in rainfall of about 10% results in a decline of about 4.8% in per capita consumption for the average household. Similarly, Charles *et al.* (2019) argue that the impacts of climate change on poverty occur through two channels. The first channel is directly through changes in the biophysical environment and any associated market responses. In the second channel which is indirect, biophysical changes can alter other factors (economic, political, cultural, and institutional) that are also linked to poverty and development.

Climate change is also expected to affect not only asset accumulation and investments in new assets but also the destruction of assets (Carter *et al.*, 2007; Dercon and Christiaensen, 2011; Verner, 2011; Abeygunawardena *et al.*, 2016; Hallegatte *et al.*, 2016; FAO *et al.*, 2018; Weldearegay and Tedla, 2018; Charles *et al.*, 2019; Steiner *et al.*, 2020; UNDESA, 2020) and trigger new vulnerabilities that can exacerbate poverty (Tschakert, 2016). Climate change thus directly impacts on assets and resources needed to earn a living and thereby harms climate-sensitive livelihoods (UNDESA, 2020), making it more difficult for poor people to increase their income leading to poverty traps (Hallegatte *et al.*, 2016). By disrupting livelihoods, climate change undermines access to income-earning opportunities. Similarly, related health shocks of climate change can result in loss of labour capacity and lost labour income (Hallegatte *et al.*, 2016; FAO *et al.*, 2018). Furthermore, climate change is expected to contribute to a decoupling of economic growth which will directly impact poverty through reduced income opportunities, thereby making it even harder to eradicate poverty (Abeygunawardena *et al.*, 2016; Hallegatte *et al.*, 2016). According to Hallegatte *et al.* (2016), the net effect of climate change on poverty, is a culmination of its impacts on productivity, consumer prices, and incomes.

The relationship between climate change, poverty, and income inequality is theoretically ambiguous (Reardon and Taylor, 1996; Beteille, 2003) however poverty and inequality affect each other directly and indirectly through their link with economic growth (Naschold, 2002). Nevertheless, climate change is expected to influence intra-household resource allocation and sectoral sources of income, hence the intensity of the shock can increase income inequality (Valentine, 1993; Reardon and Taylor, 1996). As shown by Thiede (2014), the influence of climate change on inequality may be reflected by changes in both asset loss and wealth or income accumulation. Furthermore, because households or individuals differ in their exposure, susceptibility and adaptive capacity to shocks, climate change could reduce income inequality by reducing income at the top of the distribution (Reardon and Taylor, 1996; Thiede, 2014) or exacerbate existing wealth inequalities (Abdullah *et al.*, 2016). For instance, in Ethiopia, Little *et al.* (2006) found evidence that households with relatively high levels of assets were more likely to experience shock-related decreases in assets than those with few assets. Therefore by affecting both the prevalence and depth of poverty, climate change contributes to inequality (UNDESA, 2020). Other studies in Africa (Mendelsohn, 2009; Nhemachena, 2014; Shumetie and Alemayehu, 2017) show that rainfall variability and higher average temperatures negatively affect households' income that comes from crops and livestock in Africa.

Climate change is projected to influence food insecurity and malnutrition via many channels. Because climatic factors such as rainfall and temperature are direct inputs for production, any change and variability in these variables are inevitably going to have significant effects on production, causing yield losses hence leading to food insecurity and escalating famine (Gregory *et al.*, 1999; Amthor, 2001; Fuhrer, 2003; Schmidhuber and Tubiello, 2007; Porter *et al.*, 2014; FAO, 2018; FAO *et al.*, 2018; FSIN, 2018; Weldearegay and Tedla, 2018; UNDESA, 2020). Modelling studies by Nelson *et al.* (2014), Biewald *et al.* (2015), and Havlík *et al.* (2015) all suggest that climate change could result in global crop yield losses as large as 5% in 2030, 17% in 2050 and 30% in 2080, even after accounting for adaptive behaviours. Estimates by Thornton *et al.* (2011) shows that climate change has already reduced agricultural production by 1-5% per decade compared to production levels expected with no climate change. Particularly, in sub-Saharan Africa, a region with the lowest global crop yields, increasing temperatures reduced yields for principal crops such as maize, sorghum and groundnuts (Hoffman *et al.*, 2018). Parry *et al.* (2009) also project that global cereal production will decrease by between 1-7%, depending on the General Circulation Model scenario adopted by 2060. Additionally, the largest negative changes, which is estimated to average between 9-11% will occur in developing countries. At the same time, Vogel *et al.* (2019) observed that growing season climate factors including mean climate as well as climate extremes explains between 20-49% of the variance of yield anomalies. Climate extremes, in particular, explain between 18-43% of this variance depending on the crop type. Among the climate extremes, droughts are known to cause more than 80% of the total damage and losses in agriculture, especially for the livestock and crop production subsectors (FAO *et al.*, 2018).

Climate change will not only reduce agricultural production but also increase food prices due to lower agricultural production which will intensify the risk of hunger and malnutrition, poverty and reduce food access (Parry *et al.*, 2009; Hertel *et al.*, 2010; Abeygunawardena *et al.*, 2016; Hallegatte *et al.*, 2016; FAO, 2018; FAO *et al.*, 2018; Kinda and Badolo, 2019; UNDESA, 2020). For example, Hertel *et al.* (2010) suggests that climate-induced crop yield changes will increase prices for major staples between 10-60% by 2030. Similarly, Nelson *et al.* (2014) estimate that yield shocks due to future climate change will increases market prices of agricultural commodities by

20% and reduces related consumption by 3% by 2050. Parry *et al.* (2009) observed that decreases in production by 2060 will lead to about 25-150% increases in prices and 10-60% increases in hunger involving 350 million people. The number of people at risk of hunger most of which will be in sub-Saharan Africa is projected to increase by 10-20% by 2050 as a consequence of climate change (Parry *et al.*, 2009). In fact, FAO *et al.* (2018) projects that 59 million people in 24 countries in Africa will require urgent humanitarian action due to climate shocks and stressors. At the same time a modelling framework by Hertel *et al.* (2010) shows that climate-induced rise in food prices could increase poverty rates of non-agricultural households by 20-50% in parts of Africa and Asia. Furthermore, climate change will increase the risks of hunger by affecting all four components of food security: food availability, food accessibility, food utilization and food stability (FAO, 2018; FAO *et al.*, 2018; Charles *et al.*, 2019).

Through production losses, climate change is expected to reduce food calorie availability. For instance, Havlík *et al.* (2015) estimate that global average calorie losses will be about 6% and 14% by 2050 and 2080 respectively. Hasegawa *et al.* (2018) also project average global food calorie availability to be lower by 45-110 kcal per person per day by 2050. Similarly, IFPRI (2017) shows that global per capita food consumption (kcal per capita per day) will decrease by 2% in 2030 and 4% in 2050 with climate change. Climate change will also lead to malnutrition and lower nutritional levels in crops. Parry *et al.* (2009) estimate a 26% increase in the number of malnourished children in sub-Saharan Africa by 2050 due to climate change. Studies by Yamano *et al.* (2005), Alderman *et al.* (2006), Ringler *et al.* (2010) and Dercon and Porter (2014) shows that asset-poor households in Sub-Saharan Africa typically provide children with lower-quality nutrition following weather shocks. Climate changes also impact heavily on nutrition by impairing nutrient quality and dietary diversity of foods produced and consumed (FAO, 2018; FAO *et al.*, 2018).

Recent studies by Myers *et al.* (2014), Medek *et al.* (2017) and Smith and Myers (2018) show that higher CO_2 concentrations reduce the protein, zinc, and iron content of crops. Smith and Myers (2018) observe that elevated CO_2 could cause an additional 175 million people to be zinc deficient and an additional 122 million people to be protein deficient by 2050. Poor households that are dependent on plant sources for their nutrition will be largely impacted. Climate variability via erratic rainfall and higher temperatures also affects the quality and safety of food (Shelby *et al.*, 1994b,a; Magan *et al.*, 1997). Climate change in terms of higher rainfall intensity can lead to the occurrence of some strains of toxins producing microbes, such as aflatoxins on field crops (Cotty and Jaime-Garcia, 2007; Unnevehr and Grace, 2013; Benkerroum, 2020), that can lead to stunting among children (Lombard, 2014).

Beyond poverty, inequality and food security, climate change is projected to impose health and disease risks (WHO and WMO, 2012; Smith *et al.*, 2014; Hallegatte *et al.*, 2016; FAO *et al.*, 2018; Steiner *et al.*, 2020; UNDESA, 2020). Indirectly through health, climate change is expected to not only affect poverty as previously discussed but also labour productivity. There is mounting evidence that global warming will sharply reduce labour capacity particularly with outdoor workers exposed to solar radiation. According to Heal and Park (2016) temperature stress may affect workers in at least two immediate ways; through direct physical or psychological discomfort and reduction of task productivity. These two immediate channels may in turn affect labour productivity, labour supply (hours worked), and labour effort. Climate-related impacts via occupational heat exposure can undermine workers performance in both physical and mental tasks but also "slowing down" work and other activities (Ramsey, 1995; Kjellstrom *et al.*, 2009b,a; UNDESA, 2020). Loss of labour capacity particularly due to extreme heat and other related health risks such as malaria can have important implications for agricultural wage labour and thus reduce labour productivity (FAO *et al.*, 2018).

Evidence from the empirical literature suggests that increasing temperatures or heat stress will negatively affect labour productivity. For instance, in accounting for the impact of heat stress on outdoor labour productivity, Watts *et al.* (2018) estimated global labour capacity diminished by 5.3% between 2000 and 2016, with a dramatic decrease of more than 2% between 2015 and 2016. In a recent review of the rapidly evolving literature on heat stress and labour productivity, Dell *et al.* (2014) suggest that estimates of labour productivity impacts of heat stress appear to converge to around 1% to 3% normalized decline per degrees Celsius above room temperature. Existing literature has also demonstrated that labour productivity losses due to heat stress have stronger impacts in regions that are already hot today than in cooler regions (Kjellstrom *et al.*, 2009b,a). However, in many developing regions such as Sub-Saharan Africa, beyond heat stress, rainfall variability will perhaps have the single most important effect on agriculture labour productivity. As rightly argued by Hertel and De Lima (2020), ignoring the impacts of combined heat and humidity on labour capacity paints a very distorted picture of how climate change affects agriculture.

In summary multiple and interreacting factors influence income inequality, food security and labour productivity and the impact of climate change on these household welfare outcomes are partly dependent on the vulnerability of households in terms of exposure, sensitivity and adaptive capacity to climatic shocks.

2.4 Empirical Framework

2.4.1 Conceptual Framework

From the literature review in section 2.3, we developed a conceptual framework that guides our empirical analysis (Figure 2.1). In this framework, we assume that the vulnerability of households to the effects of rainfall variability on welfare outcomes is not homogeneous due to inter-households differences in exposure, susceptibility (sensitivity) to the damage caused by climate change, and the ability to cope with the effects and recover. The interactions between these dimensions explain the level or degree of vulnerability of a household to rainfall variability and the magnitude of impacts. Thus, to estimate the impact of rainfall variability on inter-household income inequality, food security and labour productivity, we account for these dimensions – exposure, sensitivity and adaptive capacity by using pseudo-vulnerability[2] indicators.

In the literature (see for example Moss *et al.*, 2001; Tubiello and Rosenzweig, 2008) exposure has been used to characterize the biophysical impacts of climate change on agroecological systems. It also includes the spatial and temporal dimensions of climate variability, such as droughts and floods, and also the magnitude and duration of weather events. While we do not have data on all these aspects of exposure, we rely on the deviations of rainfall from 30 years mean rainfall to capture any spatial dimensions of exposure to rainfall variability. Additionally, we use reported data of farm households relating to the most recurring rainfall variability related climatic events in the past 5 years as an indicator for the magnitude of rainfall variability.

As defined in the IPCC's Fourth Assessment Report (IPCC, 2007), sensitivity is the "degree to which a system is either adversely or beneficially affected by climate variability or change". Sensitivity is rather a complex concept to measure because

[2]Vulnerability as a concept is complex and empirically difficult to measure, so we rely on some indicators of the three dimensions reported in the literature to control for vulnerability in our modelling framework. Because these are not widely universally acknowledged indicators, we choose to call them pseudo-vulnerability indicators.

the responsiveness of a system can be influenced by both intrinsic characteristics and degrees of external manipulation (ADB and IFPRI, 2009). Nevertheless, some indicators exist to identify the sensitivity of a system. In the case of agriculture, Tubiello and Rosenzweig (2008) suggest that the characteristics of the agricultural system such as rural population density, irrigated land, and agricultural employment can provide useful insights about sensitivity. For example, water-stressed areas that have no irrigation infrastructure will be most sensitive to rainfall variability in terms of drought. Additionally, farm households practising solely rainfed agriculture without access to irrigation will be more sensitive to rainfall variability compared to those who have access to or practice solely irrigated farming. We, therefore, use the information on irrigation use and the type of farming system to control for household's sensitivity to rainfall variability. The adaptive capacity of a system, which is the last dimension of vulnerability according to Tubiello and Rosenzweig (2008) can be viewed as the full set of system skills i.e., technical solutions available to farmers to respond to climate stresses as determined by the socio-economic and cultural settings, plus institutional and policy contexts, prevalent in the region of interest. As argued by Tubiello and Rosenzweig (2008), adaptive capacity as a concept is a theoretical one, and it is not easily measurable. However, actual adaptation responses can be measured and evaluated to make inferences about adaptive capacity. In layman's term, adaptive capacity can be seen as actions taken by individuals or household to avoid potential damage, to take advantage of opportunities, or to cope with the consequences of change. In this regards, we use the information on adaptation strategies (mitigation, transfer and coping) used by farm households when faced with rainfall variability shocks to control for differences in adaptive capacities.

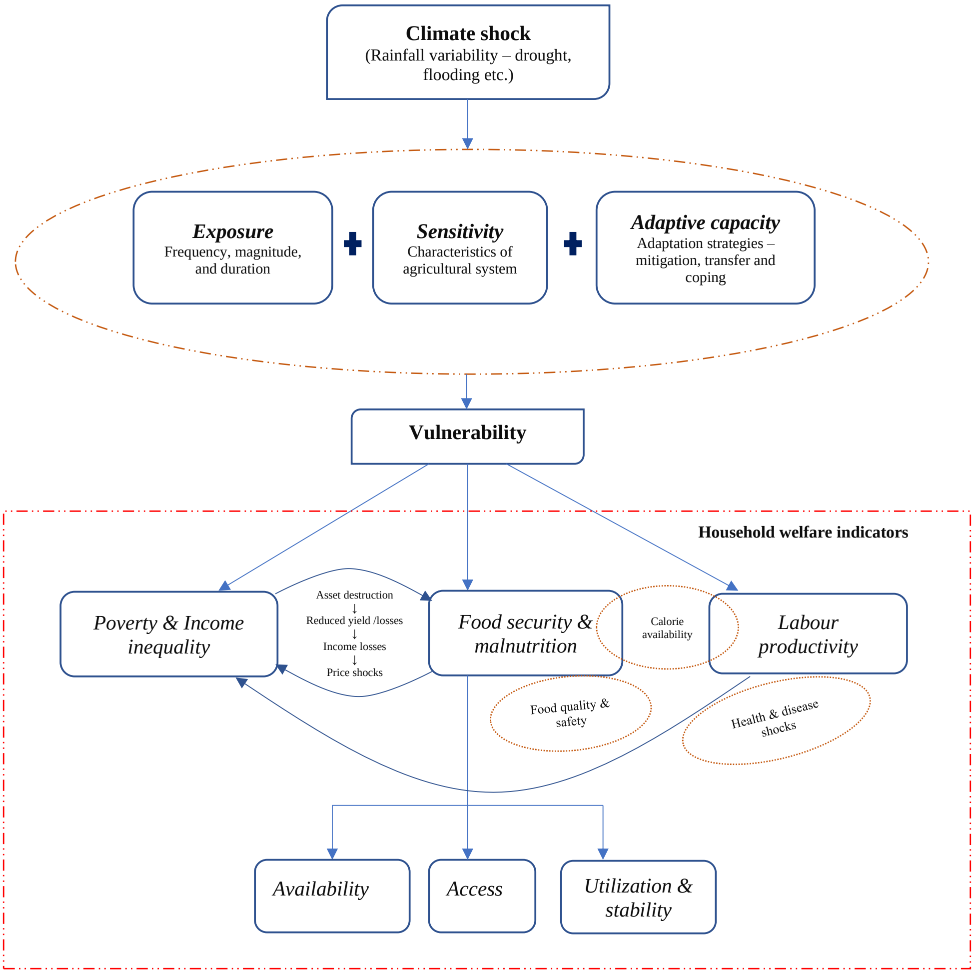


Figure 2.1: Conceptual framework of the impact of climate change on household welfare

The effect of rainfall variability on economic inequality and food security occurs through interrelated pathways. These pathways are related to asset destruction or accumulation, reduced yields or losses, income losses and price shocks. Although the biophysical impact of higher temperatures and declining labour productivity is well documented, less well understood are the effects of rainfall variability particularly on agricultural labour productivity. In the context of farming households in tropical regions, rainfall variability can affect agricultural labour productivity in at least two ways (See figure 2.1). Firstly, rainfall variability can impose health and disease-related impediments mostly through vector-borne diseases, such as malaria and dengue fever which can directly affect labour productivity. Secondly, through food production losses, rainfall variability will reduce food calorie availability to farm households and thus the physiological function of food in terms of providing energy for growth, development, and work will be impeded. Our study investigates the latter channel.

2.4.2 Empirical Strategy

As argued by De Luca and Magnus (2011) economic theory provides some information about empirical model specifications but offers little guidance about how to specify the exact data-generating process for the outcome of interest. At the same time, the lack of a one-to-one link between theory and empirical model specification generates uncertainty regarding, for example, which explanatory variables must be included in the model, which functional forms are appropriate, or which lag length captures dynamic responses. In econometrics, these problems are known as problems of model uncertainty (De Luca and Magnus, 2011). The key feature behind model uncertainty is the existence of a wide range of functional forms and explanatory variables without much consensus concerning which canonical model is appropriate. The implication of this is that empirical researchers need to choose among a set of possible model specifications. In such cases, empirical results will typically be influenced by the inclusion or omission of specific variables.

Depending on the model selection procedure, different researchers may arrive at different conclusions even when using the same data (De Luca and Magnus, 2011). As shown by Magnus and Durbin (1999), Wang (2003), Danilov and Magnus (2004) and Liu and Myers (2009), estimation results may be sensitive to different model specifications. Model averaging alleviates such inconsistencies by comparing the robustness of regression coefficients over the entire model space. Model uncertainty is particularly relevant when examining the drivers of income inequality and labour productivity, where theory is even less settled (Furceri and Ostry, 2019). At the same time, examining drivers of food security involves uncertainties regarding which explanatory variables to include. While economic theory suggests a wide range of potential drivers, there is little consensus regarding the most relevant ones. Furthermore, when estimating the drivers of income inequality there are a potentially large number of endogenous variables that have to be controlled for. One approach to address the endogeneity of variables is the control function approach (Wooldridge, 2015) but this generates further auxiliary variables in the model. With several possible explanatory drivers for our outcomes on interest, identifying their relative importance and robustness is tenuous. A common practice will be to focus on a handful of variables selected based on their priors. But as previously argued, different results may be obtained.

In this paper, we attempt to advance our understanding of the impact of rainfall variability on the drivers of income inequality, food security and labour productivity by employing the recently developed model-averaging techniques. The basic idea of model-averaging estimators is that one first estimates the parameters of interest conditional on each model in the model space and then compute the unconditional estimate as a weighted average of these conditional estimates (De Luca and Magnus, 2011). This approach has been employed recently by Furceri and Ostry (2019) and a spatial variant has also been used by Hortas-rico and Rios (2019) to investigate the drivers of income inequality. Specifically, we adopt the weighted-average least squares (WALS). As discussed by Magnus *et al.* (2010) and De Luca and Magnus (2011), WALS is theoretically and practically superior to the standard Bayesian model averaging (BMA). It is theoretically superior because the prior is 'neutral' and the risk properties of the estimator are close to those of the minimax regret estimator (Magnus *et al.*, 2010). Additionally, it is also practically superior because the space over which model selection is performed increases linearly rather than exponentially with size. WALS unlike BMA relies on preliminary orthogonal transformations of the auxiliary regressors and the parameters. Thus the computational burden required to obtain an exact WALS estimate is lower compared to BMA (De Luca and Magnus, 2011). Also, the choice of the prior distribution on parameters is independent on prior information availability as in the case of BMA. Although WALS addresses model uncertainty and endogeneity concerns related to omitted variable bias, it does not solve reverse causality issues (Furceri and Ostry, 2019).

Our model framework to assess the drivers of income inequality, food security and labour productivity is a linear regression model of the reduced form:

$$y_i = \alpha + \beta' X_i + \varepsilon_i \tag{2.1}$$

where X is a vector of k covariates reflecting rainfall variability, pseudo-vulnerability indicators, access to institutional elements and characteristics of household i, and y is a measure of the outcomes of interest (income inequality, food security and labour productivity). As previously mentioned, the estimation of this model is plagued with two important econometric challenges. Firstly, a large number of potential explanatory factors and the correlation among them and secondly the lack of a priori 'true' statistical model to test these potential drivers. The weighted-average least squares (WALS) approach addresses these challenges by (i) running the maximum combination of possible models and (ii) providing estimates and inference results that take into account the performance of the variable not only in the final 'reported' model but over the full set of possible specifications. In practice, these two steps consist of estimating a parameter of interest conditional on each model in the model space and computing the unconditional estimate as a weighted average of conditional estimates. Formally, assuming that we are faced with M different models and that β^x is the coefficient related to the variable X, the final estimate of this coefficient is computed as $\beta^x = \sum_{i=1}^{M} w_i \beta_i^x$ where the weights W_i denote a measure of goodness of fit of each model.

We apply the WALS techniques developed by Magnus *et al.* (2010). Compared to the Bayesian Model Averaging (BMA) which uses a Gaussian distribution prior for the auxiliary parameters, the WALS uses a Laplace distribution which reduces the risk of the prior influencing heavily the final estimates (Magnus *et al.*, 2010). Besides, the WALS relies on the preliminary orthogonal transformation of the auxiliary regressors and their parameters. This consists of computing an orthogonal $k \times k$ matrix P and a diagonal $k \times k$ matrix Δ such that $P^\top X^\top M X P = \Delta$, for each model M. The key advantage of this transformation is that the space over which model selection is performed increases linearly rather than exponentially in size as in the case of BMA.

Denoting $\bar{t}$ the Laplace estimator of the vector of theoretical t-ratios of the auxiliary regressors ($t = [t_1, t_2, ..t_{k2}]$), the WALS estimators of the coefficients β in equation 2.1 is given by:

$$\beta = sP\Delta^{-1/2}\bar{t} \tag{2.2}$$

In determining whether a given auxiliary regressor is a robust determinant of the outcome of interest, Magnus *et al.* (2010) suggest an absolute value of the t-ratio greater than 1 for a variable to qualify as robust. This choice is motivated by the fact that including a given auxiliary regressor variable increases the model fit as measured by the adjusted R^2 and the precision of the estimators of focus regressors which is measured by a lower mean squared error (MSE) is met if and only if the t-ratio of the additional auxiliary regressor is in absolute value greater than 1. Finally, it should be noted that while the WALS addresses model uncertainty and endogeneity concerns related to omitted bias, it does not address reverse-causality issues. In this regards, Furceri and Ostry (2019) suggest that such reverse-causality issues are best taken up through event-study type of analysis. In our study, however, we address the issue of reverse-causality using the control function approach by Wooldridge (2015).

In estimating the impact of rainfall variability on inter-household income inequality in equation 2.1, some of the control explanatory variables such as education, landholding, extension access, credit access, membership of farmer organizations, market information access and subsidy access are potentially endogenous. As shown in several empirical studies, access to assets such as land and institutional factors such as credit, extension, credit etc. are highly correlated to income inequality. Furthermore, despite rainfall variability potentially affecting agricultural labour productivity through food calorie availability, it might also be that households with high labour productivity have generally high food calories available, thus making food calories availability potentially endogenous. Addressing issues related to endogeneity 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. To address the potential endogeneity of these variables we used the control function approach proposed by Wooldridge (2015). The approach involves the specification of the potential endogenous variable as a function of explanatory variables influencing the outcome variable (in our case income inequality and labour productivity), together with a set of instruments in a first stage probit regression[3]. The employed instruments here should strongly influence the given potential endogenous variables but not the outcome of interest (income inequality and agriculture labour productivity).

Finding true instruments in empirical work is very challenging and sometimes impossible. The difficulty arises with finding an instrument that is strongly correlated with the endogenous variable of interest and that satisfies the exclusion restriction i.e., having no direct effect on the outcome of interest. For our study, gender ratio, the share of household labour, support needs, the main occupation of the household head, occupation with known unions or memberships, sale of raw farm produce, rural population per region of household residence and the adoption of traditional granaries were used as identifying instruments for education, landholding, extension access, credit access, membership of farmer organizations, market information access, subsidy access and food calorie availability respectively. Following Di Falco and Veronesi (2013), we establish the admissibility of the selected instruments by performing a simple falsification test: the selected or valid instruments are required

[3]The probit regression specification (see Wooldridge, 2015, Pp. 427 – 428), was for the binary variables – education, extension access, credit access, membership of farmer organizations, market information access and subsidy access. On the other hand, an OLS regression (see Wooldridge, 2015, Pp. 424) was used for the continuous variables land holding and food calorie availability.

to significantly influence the potentially endogenous variable but have no significant effect on the outcome variable. The "generalized residuals" predicted from a first-stage regression are included as covariates in the outcome model. As suggested by Wooldridge (2015), the approach leads to a robust, regression-based Hausman test for the endogeneity of the suspected variables. If the coefficient of the residual term is statistically significant, it shows that endogeneity was indeed present and also well controlled for in the model (Gibson *et al.*, 2010; Ricker-Gilbert *et al.*, 2011; Amankwah *et al.*, 2016; Harris and Kessler, 2019; Katengeza *et al.*, 2019; Ogutu *et al.*, 2019). Furthermore, Wooldridge (2015) observed that if the coefficient on the estimated generalized residual is statistically significant, there is a need to adjust the standard errors for the two-step estimation by bootstrapping.

2.5 Data and variable measurement

2.5.1 Farm household survey

The data used in the study comes from a farm household survey as part of the larger Senegalese "Projet d'appui aux politiques agricoles (PAPA)" or the Agricultural Policy Support Project funded by USAID under the "Feed the Future" project. The implemented project focused on several value chains such as dry cereals, irrigated rice, horticulture, and inputs value chains such as seeds and fertilizers. The Senegalese National Agricultural Research Institute (ISRA) conducted the survey, with the support of the International Food Research Institute (IFPRI) between April and May 2017 across all the 14 administrative regions of Senegal and all the departments except the departments of Dakar, Pikine and Guédiawaye. A total of 42 agricultural departments were included in the survey. 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 primary units so that each of them is 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 rain-fed agriculture was practice and localized crops were grown such as Senegal River Valley and 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 2016-2017 and include information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit, inputs use and cost, family and hired labour, sales volumes, and food processing. Others included household consumption, access to amenities, non-farm and livestock revenue, remittance, agricultural insurance, risks and adaptation strategies, perception of subsidized inputs, and membership of farmer-based organizations.

2.5.2 Measuring rainfall variability

A high-resolution (0.5 x 0.5 degree) gridded time-series data (version 4.04) which covers month-by-month variations in climate over the period 1901-2019 and produced by Harris *et al.* (2020) at the Climatic Research Unit (CRU), University of East Anglia was obtained to estimate rainfall variability for farm households. The data covers several climatic variables including cloud cover, diurnal temperature range, frost day frequency, wet day frequency, potential evapotranspiration (PET), precipitation, daily mean temperature, monthly average daily maximum and minimum temperature, and vapour pressure for the period January 1901 - December 2019. The data were produced using angular-distance weighting (ADW) interpolation based on monthly observational data calculated from daily or sub-daily data by National Meteorological Services and other external agents. Using farm households' geographical coordinates data and QGIS, we extracted monthly rainfall data from 1988 to 2017 for each household. We used 30 years preceding the farm household survey because climate change takes place over decades or centuries. This helps us to capture both long term and shorter-term rainfall variations in the form of extremes drought and floods. Rainfall variability was measured for each household as the standard deviation from the long term mean for the period 1988 to 2017. We also included a self-reported experience of recurring rainfall related shocks in the last 5 years preceding the survey as an additional control for rainfall variability shocks.

2.5.3 Measuring income inequality

We use the Gini index as the baseline measure of income inequality in this study, mainly because it is the ubiquitous standard in the inequality literature. Also known as the Gini coefficient or Gini ratio, it is a measure of statistical dispersion that is used to represent the income or wealth distribution of a population. It does so by comparing the cumulative proportions of the population against cumulative proportions of income they receive. The coefficient ranges between 0 in the case of perfect equality and 1 in the case of perfect inequality. In our study, we estimated an income Gini from three main household income sources: agriculture income which consists of crops and livestock incomes, nonfarm income and remittances. We calculate the Gini coefficient at the regional level as our income inequality measure. This index is defined as:

$$G\left(y\right) = 1 - 2\int_0^1 L(p;y)\mathrm{d}p \tag{2.3}$$

where the Lorenz curve of income L(p; y) at such p-values of ranked relative cumulated-population (so that, p ∈ (0, 1)) can be defined mathematically by the expression:

$$p = F(q) \Rightarrow L\left(p;y\right) = \int_0^q yf(y)\frac{\mathrm{d}y}{\mathrm{d}\mu_y} \tag{2.4}$$

where p is a percentile function; *F(q)* is the distribution function measuring the proportion of individuals of the population having incomes below or equal to q, and μ_y denotes the average total household income. *G(y)* takes values between 0 (perfect equality) and 1 (complete inequality).

Gini decompositions

Beyond, identifying the impact of rainfall variability on income inequality, we were interested in exploring the impact of rainfall variability on the Gini elasticity of agriculture income and nonfarm income. This is particularly important because the impact of rainfall variability on inequality may depend on where a household earns most of its income. For example, a household that earns most of its income from nonfarm sources that are not climate-sensitive will be less affected by rainfall variability compared to a household that solely depends on agriculture for income. On the contrary, if the nonfarm income source is somehow indirectly climate dependent (e.g. sale of production inputs such as fertilizer, seeds and agrochemicals), the impact of rainfall variability on income can be substantial through either increase or decrease demand. Hence the impact of climate change will be uneven across income sources, thus examining the income-source specific changes effects on Gini elasticity provides an important step in identifying how rainfall variability drives income inequality. Investigating the Gini decompositions by source also provides important cues as to how changes in particular income sources will also affect overall income inequality. To estimate the Gini decompositions by income source we follow the approach introduced by Shorrocks (1982) and extended by Lerman and Yitzhaki (1985) and Stark *et al.* (1986) for a static decomposition of the Gini index. Because the decomposed income inequality by different income sources is observed at a particular moment in time, the approach is a static one. Nevertheless, by taking the derivative for a small percentage change in income from a particular income source, Lerman and Yitzhaki (1985) and Stark *et al.* (1986) analysed the effect of a marginal change in an income source on the overall Gini index at that point in time, holding all other income sources constant. Following Lerman and Yitzhaki (1985) and Stark *et al.* (1986), the overall Gini index G_0 can be given as follows:

$$G_0 = \sum_{k=1}^{K} R_k * G_k * S_k \tag{2.5}$$

where S_k and G_k are the share and the Gini index of income component k, respectively. The Gini index of income component k is estimated using equation 2.3. R_k represents the Gini correlation of component k with total household income. It shows similar characteristics to Pearson's and Spearman's correlation coefficients. According to Hundenborn *et al.* (2018) Equation 2.5 allows the examination of three important concepts. First, the share of the respective income source in overall household income, S_k. Secondly, the inequality within the different income sources, G_k and lastly the Gini correlation R_k between income component k and total household income. The share of an income source in overall household income S_k and the Gini index of any income source G_k are always positive and ranges between 0 and 1. Similarly, Hundenborn *et al.* (2018) suggest that the Gini correlation R_k, on the other hand, will be positive when an income source contributes positively to the overall Gini index, i.e. when y_k is an increasing function of total income y_0. Similarly, R_k will be negative when income source y_k is a decreasing function of total income y_0. Thus, R_k is bounded by -1 $\leq R_k \geq 1$ and will be equal to zero when y_k and y_0 are uncorrelated. Additionally, we are interested in assessing how a small change in any one of the income components k affects the overall Gini index. We want to get a better understanding of the impact of rainfall variability on the Gini elasticity of agriculture and nonfarm income. If we assume that an exogenous change in any income source j by a factor e occurs, then the income from j is assumed to change according to $y_j(e) = (1 + e)y_j$ and

$$\frac{\partial G_0}{\partial e} = S_j(R_j * G_j - G_0) \tag{2.6}$$

The partial derivative[4] which simulates a marginal change in a particular income source while holding income from other sources constant is shown in equation 2.6. Dividing equation 2.6 by G_0 yields:

$$\frac{\partial G_0/\partial e}{G_0} = \frac{S_j * R_j * G_j}{G_0} - S_j \tag{2.7}$$

Accordingly, the change in overall inequality due to a small change in income source j is equal to the initial share of j in total inequality less the share of source j in total household income (Stark *et al.*, 1986). Given the characteristics of R_j, this produces two possible outcomes for the overall Gini index. If income source j has a negative or zero correlation between j and total household income y_0, an increase in income from source j will have an equalizing effect, thereby lowering inequality. This is because the share of income from source j (S_j), as well as the Gini index for j and total income, G_j and G_0, are always positive. The other possible outcome is when R_j represents a positive Gini correlation. Assuming that $G_j > G_0$, then $\frac{R_k * G_k}{G}$ which leads to an increase in inequality associated with component j. $G_j > G_0$ is a necessary condition for an inequality-increasing effect of income component j, given that R_j is always smaller or equal to 1. The sum of relative marginal effects across all income sources is zero. At the same time, multiplying all income sources by e leaves the overall Gini index unchanged.

2.5.4 Measuring food calorie availability

In measuring household food security, the study focused on only the first dimension of food security which is related to food availability, i.e. the supply of foodstuffs in a household from production. Thus, the focus here was on household food production only. We used the daily per adult-equivalent food availability as an indicator of a household's food security because it helps determine the capacity of each household to provide proper food energy to its members during a whole calendar year. The total quantity of food calories produced per equivalent adult per day or a household daily food calories availability was estimated using staple food crops grown by

[4]The prove that the derivative of the overall Gini with respect to a uniform percentage change in income source j is equation 2.6 is provided in the Appendix

households. A total of 9 staple crops were used in estimating household food calorie availability. This includes 5 cereal staples (maize, rice, millet, sorghum, and fonio), 2 legumes (groundnut[5] and cowpeas), 1 oilseed crop (sesame) and 1 root tuber crop (cassava). According to Hathie (2019), Senegal has food traditions, both in urban and rural, based on the consumption of cereals (rice, millet, maize, and sorghum) as staple foods, and these constitute about 40% of households' food budget. Furthermore, rice, millet/sorghum, wheat, and maize are the foundations of the Senegalese diet with Senegalese deriving about 60% of their calories from grain consumption. Household food calorie availability was computed using the gross household production of these 9 crops. We first, estimated available food crop by multiplying the farm-gate production of each crop by the appropriate post-harvest losses ratios[6]. Subsequently, the derived available food crops were converted into calories (kcal) available using the crop-specific energy ratios and edible portions conversion factors from the West African Food Composition[7] table by Stadlmayr *et al.* (2012).

For each household, we estimated the total adult equivalent following Claro *et al.* (2010)[8] by considering the gender and age composition of family members. Household adult equivalents (AE) for each household member is obtained by dividing the Recommended Dietary Allowance (RDA) for the energy of each household member, according to the specific age and gender, by the average energy RDA reference value of 2,550 kcal (Claro *et al.*, 2010). The sum of all of the individual adult equivalents within a household was further computed to obtain the household adult equivalent (AE) value. This approach is particularly important because some family members such as children might have distinct energy needs which differ from adults. We subsequently divided the calories available at the household level by the households' total adult equivalents (AE) to make the values comparable. Finally, the obtained values were divided by 365 to have the daily food available per adult equivalent.

[5] As reported in D'Alessandro *et al.* (2015) despite considered as an important cash crop, groundnut is also grown for household consumption

[6] The postharvest losses ratios used were obtained from the African Postharvest Losses Information System (APHLIS), Affognon *et al.* (2015) and Tomlins *et al.* (2016) are provided in Table 2.5 in the Appendix

[7] Conversion ratios for edible fractions and energy equivalence (kilo calories) are presented in Table 2.6 in the Appendix

[8] The Adult-equivalent conversion factors for estimated calorie requirements according to age and gender are presented in Table 2.7 in the Appendix

2.5.5 Measuring labour productivity

Household agricultural labour productivity was measured as the total value of crop output of households measured in CFA divided by the number of household labour. The estimation of agricultural labour productivity was restricted to crop production because we only have household labour use for this sector. Because some household employ labour (hired) we only considered the part of labour productivity attributed to household labour only. As shown in the study of Taylor and Adelman (2003) in developing countries, family and hired labour may not be perfect substitutes. Since the observed crop output for each household is from a combination of household labour and hired labour, we tried to disentangle the part of labour productivity associated with household labour only. We achieved this by accounting for the share of household labour in total labour used for crop production. Finally, this share was multiplied by the total agricultural labour productivity to obtain the part of labour productivity associated with household agriculture labour.

2.6 Empirical specification

The specification of our empirical models was based on economic theory and other empirical studies that have similarly investigated the topics of concern. Although economic theory suggests a wide range of potential determinants of income inequality, there is little consensus regarding the most relevant ones (Furceri and Ostry, 2019). Similarly, Odusola *et al.* (2017) argue that the drivers of inequality are neither homogeneous nor universal. Nonetheless, the literature identifies a myriad of factors affecting income inequality some of these include education (Odusola *et al.*, 2017; Hortas-rico and Rios, 2019), access to capital and markets (Odusola *et al.*, 2017), household size or the age-dependency ratio (Guvenen *et al.*, 2015; Ouedraogo and Ouedraogo, 2015; Odusola, 2017; Odusola *et al.*, 2017; Furceri and Ostry, 2019), access to institutions (Ostry *et al.*, 2018), technological change (Jaumotte and Buitron, 2015; Dabla-Norris *et al.*, 2015; UNDP, 2013), type of income distribution (UNDP, 2013; Odusola, 2017) and farm size (Odusola, 2017). Particularly in Senegal spatial pattern of poverty is explained by factors such as market access and transportation connectivity (ANSD, 2016). Other factors including tax systems, distribution of public investments and expenditures, globalisation and structural transformation etc. could affect inequality but are not suited for our study. This is because the local dimension of income inequality based on cross-sectional data is likely to be different from national-level income inequality. After all, they may not respond to the same factors.

A wide range of factors has been found in the empirical literature to drive household food security or insecurity. These factors operate on both the demand and supply side. Some of these include sociodemographic factors such as age of household head, household size and composition, education, gender of household head, migration, asset ownership, income (Garrett and Ruel, 1999; Iram and Butt, 2004; Idrisa *et al.*, 2008; Maxwell *et al.*, 2008; Gbetibouo, 2009; Pankomera *et al.*, 2009; Davis *et al.*, 2010; Fekadu and Muche, 2010; Mallick and Rafi, 2010; Kassie *et al.*, 2012; Aidoo *et al.*, 2013; Frimpong and Asuming-Brempong, 2013; Abafita and Kim, 2014; Kakota *et al.*, 2015; Agidew and Singh, 2018; Alpízar *et al.*, 2020), farm characteristics such as improved technologies adoption, farming system, agro-ecological zones, farm size, and land quality (Feleke *et al.*, 2005; Kidane *et al.*, 2005; Fekadu and Muche, 2010; Van der Veen and Tagel, 2011), climatic shocks such drought, shortage of rainfall, crop diseases (Feleke *et al.*, 2005; Abafita and Kim, 2014; Agidew and Singh, 2018), access to market and credit (Feleke *et al.*, 2005; Pankomera *et al.*, 2009; Kassie *et al.*, 2012; Aidoo *et al.*, 2013; Frimpong and Asuming-Brempong, 2013), and access to government intervention programs such as food assistance or food-for-work program, subsidies (Sharkey *et al.*, 2011; Van der Veen and Tagel, 2011).

Similarly, sociodemographic factors such as age, education, household size, savings, land ownership (Okoye *et al.*, 2008; Anyaegbunam *et al.*, 2010; Shittu *et al.*, 2010; Obike *et al.*, 2017; Nuttee *et al.*, 2019), farm characteristic such as farm size, improved technologies adoption such as fertilizer, improved planting materials, tractor, irrigation etc. (Okoye *et al.*, 2008; Anyaegbunam *et al.*, 2010; Shittu *et al.*, 2010; Obike *et al.*, 2017; Shanmugan and Baria, 2019), and access to credit (Okoye *et al.*, 2008) have been identified to influenced agriculture labour productivity.

In Table 2.1, we present the definition and summary statistics of all variables used in the analysis.

Table 2.1: Variables definition and summary statistics

Name	Variable description	Mean	Std. Dev.
Dependent variables			
Gini index	Income inequality	0.556	0.088
Daily calorie	Log of food calorie per adult equivalent per day	6.266	2.147
Labour productivity	Log of the value of crop production per household labour	11.006	1.957
Socio-demographic characteristics			
Age	Age of household head in years	53.013	13.272
Gender	=1 if household head is male	0.923	0.267
Education	=1 if the household head has formal education	0.382	0.486
Household size	Total number of people in the household	9.766	5.262
Dependency	Dependency ratio of household (%)	87.132	73.659
Agriculture	Share of agriculture income (%)	85.116	27.243
Storage	=1 adoption of advanced storage technology	0.170	0.376
Market integration	=1 if household is integrated into markets	0.559	0.497
AII[a]	Agriculture implement index	-0.014	1.274
Institutional factors			
Extension	=1 if accessed extension service	0.152	0.359
Membership	=1 if member of farmer-based organization	0.131	0.338
Credit	=1 if access to credit	0.044	0.206
Subsidy	=1 if access to subsidized inputs	0.506	0.500
Road	Log of distance to the nearest all-weather road in km	3.597	0.875
Market	Log of distance to the nearest market in km	3.962	0.455
Market info	=1 if access to market information	0.503	0.500
Farm-related characteristics			
Land	Total land holding of household in hectares	5.425	8.203
Staple crop	Share of land under staple crops	0.489	0.351
PET	=1 if household adopts productivity enhancing technologies	0.230	0.421
Mixed	=1 if household practices mixed farming	0.315	0.465
Pseudo-vulnerability indicators			
Std Rainfall	The standard deviation of annual rainfall in mm (1988 – 2017)	120.153	28.556
Rainfall shock	=1 if household experienced rainfall shock in past 5 years	0.759	0.428
Farming system	=1 if household practices rainfed subsistence agriculture	0.857	0.350
Irrigation use	=1 if household uses irrigation	0.191	0.393
Mitigation[b]	=1 if household adopts risk mitigation strategies	0.739	0.439
Transfer[c]	=1 if household adopts formal insurance	0.034	0.180
Coping[d]	=1 if household adopts risk coping strategies	0.334	0.472

[a] This is an index computed using principal component analysis (PCA) based on the number of agricultural equipment owned by a household.

[b] These are ex-ante measures taken by households before the occurrence of a shock. These include diversifying agricultural activities, reducing cultivation areas, shifting to non-agricultural activities, and renting land

[c] Refers to the use of formal insurance products such as livestock, crop or index-based insurance.

[d] These are ex-post measures taken after the occurrence of a shock. They include selling grain stocks, livestock, properties and exchanging or swapping clothes or jewels for food

Table 2.1: Variables definition and summary statistics(*continued*)

Name	Variable description	Mean	Std. Dev.
Agro-ecological factors			
Rainfall	Log of mean annual rainfall in mm (1988 – 2017)	6.507	0.480
BasinAra	=1 if agro-ecological zone is Bassin Arachide	0.425	0.494
RiverVall	=1 if agro-ecological zone is River Valley	0.136	0.343
SylvFerlo	=1 if agro-ecological zone is Ferlo Sylvo-pastoral	0.073	0.260
Casamance	=1 if agro-ecological zone is Casamance	0.212	0.408
CentEast	=1 if agro-ecological zone is Center East	0.091	0.287
VallAnambe	=1 if agro-ecological zone is Valley Anambe	0.048	0.213
Instruments for endogeneity control			
Gender ratio	The ratio of men to women in the household	1.376	1.070
Household labour	Share of household labour in total labour use	0.144	0.866
Support needs	=1 if the household has support needs	0.755	0.430
Main occupation	=1 if the main occupation of the household head is agriculture	0.854	0.353
Union	=1 if household head is in occupations with known unions	0.083	0.276
Sale	=1 if household sells raw farm produce	0.548	0.498
Rural population	Rural population per region of household residence	6,393,600	2,659,060
Granaries	=1 if traditional granaries are adopted	0.291	0.454
Observations		**5,232**	

2.7 Results

2.7.1 Composition of income inequality

We first present the results of the Gini decomposition method by Lerman and Yitzhaki (1985) and Stark *et al.* (1986) in Table 2.2. As mentioned previously, households have several income sources, and the effects of the rainfall variability will be uneven across these income sources. Examining the income-source specific changes effects on Gini elasticity provides an important step in identifying how rainfall variability might drive income inequality. The results show that income from agriculture (crop and livestock) sources is the biggest contributor to household income inequality. Agriculture income contributes to about 93% of overall inequality. Furthermore, it is also the most strongly correlated (coefficient of 0.971) of all income sources with total household income. We also find that the second-largest contributor to inequality is nonfarm income, accounting for about 4.72% of overall inequality, and remittances having the least contribution, about 2.62% to overall inequality. At the same time, the finding reported in Table 2.2 shows that income from agriculture sources has a strongly dis-equalizing effect. This is shown by the elasticity reported in the last column of Table 2.2. Following equation 2.7, a 1%

change in income from agriculture leads to an absolute increase in the Gini index by 0.076. Nevertheless, the static decomposition suggests that the equalizing effects of nonfarm income and remittances can offset to some degree the dis-equalizing effect of agriculture income sources.

The marginal change analysis shows that nonfarm income and remittances have the potential to lower the Gini index. A 1% increase in nonfarm income and remittances would lead to a 0.060 and 0.016 decrease in inequality, respectively. The results here suggest that the inequality impacts of climate-induced shocks will be highly dependent on where a household earns its income from. The finding is congruent to that of Reardon and Taylor (1996) who suggested that weather shocks have greater unequalizing effects on income distributions in households with less diverse income sources. Our results strongly suggest that because agriculture in Senegal is highly dependent on climate, especially through rainfed production, and accounts for a large part of household incomes, any variability in climate can aggravate farm household income inequality. Nonetheless, we find evidence of the existence of a Kuznets curve relationship between Gini elasticity and the share of agriculture incomes. As the share of agriculture income in total household income increases, Gini elasticity may rise until a threshold is reached, after which inequality declines.

This can be seen in the inverted U-shape relationship in Figure 2.2a. Beyond what we observed in Figure 2.2a, the model results in Table 2.4 also support this finding. The results suggest that the share of agriculture income in total household income is robust and negatively associated with income inequality. This means that an increasing share of agriculture income in total household income will reduce the Gini index. From Figure 2.2b and 2.2c, we find an opposite relationship between Gini elasticity and the share of nonfarm and remittance income which exhibits a U-shape, suggesting an increasing share of these income sources in total household income may decrease Gini elasticity until a threshold is reached after which Gini elasticity increases. Thus, the finding here corroborates the general view and econometric evidence (see Bourguignon and Morrisson, 2002; Thirtle *et al.*, 2003; Christiaensen *et al.*, 2006; World Bank, 2007; Byerlee *et al.*, 2009; Imai and Gaiha, 2014; Odusola *et al.*, 2017) that agriculture remains a powerful tool to accelerate reductions in poverty and income inequalities in developing countries.

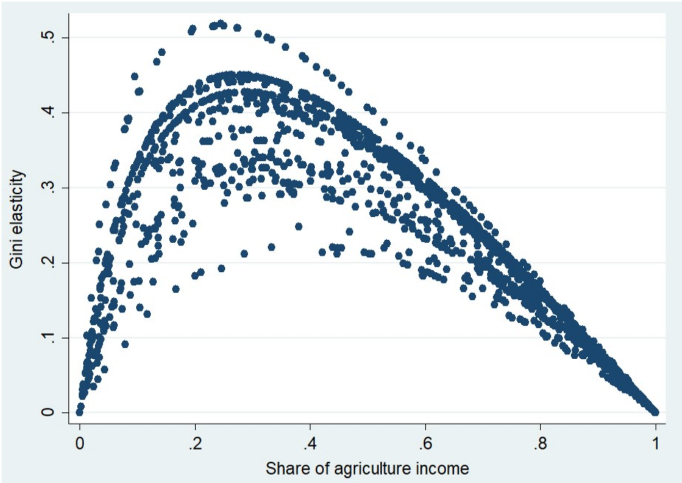
Table 2.2: Static decomposition of the Gini index by household income sources

	Income share (S_k)		**Gini correlation** (R_k)		**Gini index** (G_k)		**Contribution** (S_k*R_k*G_k)		**Percentage contribution** ($\frac{S_k * R_k * G_k}{G}$)		**Elasticity** ($\frac{\delta G / \delta e}{G_0}$)	
Income source	**Mean**	**Std. Err.**	**Mean**	**Std. Err.**	**Mean**	**Std. Err.**	**Mean**	**Std. Err.**	**Mean**	**Std. Err.**	**Mean**	**Std. Err.**
Agriculture	0.851	0.004	0.971	0.003	0.565	0.001	0.466	0.002	0.927	0.002	0.076	0.002
Nonfarm	0.107	0.003	0.153	0.026	0.547	0.001	0.009	0.000	0.047	0.002	-0.06	0.002
Remittances	0.042	0.002	0.271	0.042	0.579	0.001	0.007	0.000	0.026	0.002	-0.016	0.001
Total	1.000		1.000		0.481		0.481		1.000		-	

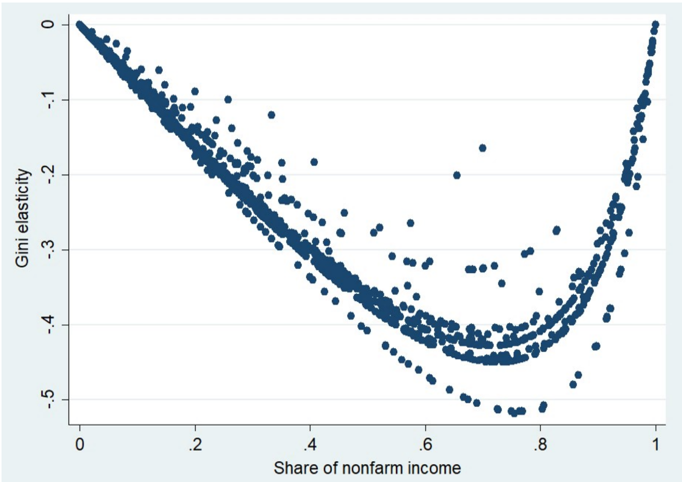
With the first results indicating that agriculture and nonfarm income accounts for a larger part of overall inequality, we also explored whether rainfall variability drives the observed Gini elasticities concerning these two income sources[9]. This is particularly important because the Gini elasticities we estimated earlier, on their own offer few immediate insights in identifying possible pathways by which climate change affects income inequality. As previously stated, differences in household income composition imply that households whose income sources are from non-climate dependent sectors, for instance, may be affected differently from those whose income sources are climate dependent. To address this, we use the estimated elasticities of agriculture and nonfarm income reported in the last column of Table 2.2 for each household and regress them on rainfall variability and a set of control variables. The WALS results which are presented in Table 2.3 show that rainfall variability is a robust driver of Gini elasticity concerning the two income sources. In the case of agriculture income, we find that rainfall variability is positively associated with the Gini elasticity while in the case of nonfarm income it is negatively associated. This suggests that the Gini elasticity of agriculture income increases for every deviation in rainfall while that of nonfarm income decreases for every deviation in rainfall. This is rather not surprising because agriculture income sources are highly dependent on climate, thus any shocks related to the climate might reduce agriculture incomes and this will increase the Gini elasticity with respect income.

Nonfarm incomes on the other hand might not be directly dependent on the climate and hence, climate shocks will not increase the Gini elasticity. It is however worth noting that mean rainfall decreases the Gini elasticity for agriculture income and increases the Gini elasticity for nonfarm income. The result strongly suggests that climate change is more likely going to increase Gini elasticity with respect to agriculture income, thereby plunging vulnerable households more into poverty.

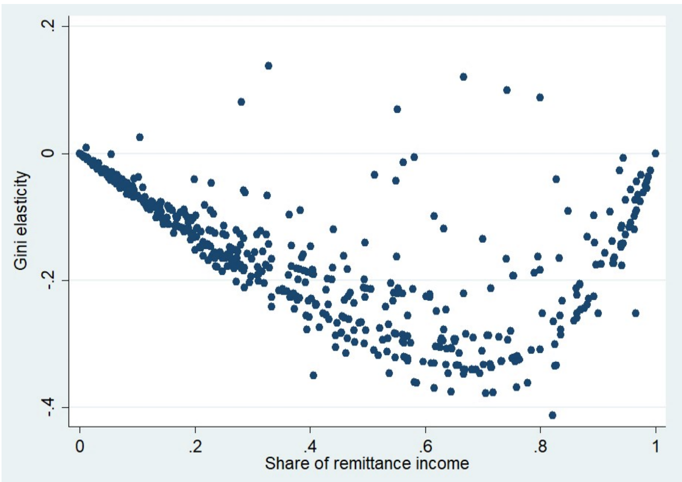
[9] We ignored remittances in the analysis because unlike the agriculture and nonfarm income sources, it is not highly correlated or dependent on the weather.



(a) Agriculture income



(b) Nonfarm income



(c) Remittance

Figure 2.2: Relationship between Gini elasticity with respect to the share of income by source

2.7.2 Impact of rainfall variability on inequality, food security, and labour productivity

Table 2.4 reports the WALS estimates of the most robust drivers of the outcomes of interest, estimated using equation 2.2. As pointed earlier, a regressor is considered to be robust if the value of the associated t-statistic in absolute terms is larger than 1. This choice is motivated by the fact that including a given auxiliary regressor variable increases the model fit as measured by the adjusted-R^2 and the precision of the estimators of focus regressors which is measured by a lower MSE is met if and only if the t-ratio of the additional auxiliary regressor is in absolute value greater than 1. The robustness of the five variables representing the residuals derived from the first-stage regressions for the potential endogenous variables (extension access – Resid ext, credit access – Resid cred, market information access – Resid mar, subsidy access – Resid sub and daily calorie availability – Resid food) indicates the presence of simultaneity bias, and hence a consistent estimation of these variables. The results of the control function approach are provided in Table 2.8 for the inequality model and Table 2.9 for the labour productivity model in the appendix. A falsification test (Table 2.12 and 2.13) and correlation test (Table 2.10 and 2.11) between the used instruments and the outcome variables also showed that all the instruments used were appropriate. In the spirit of brevity, we limit our discussions to the main variables of interest – mean rainfall, rainfall variability, experienced shocks, and the pseudo-vulnerability indicators of households.

Regarding income inequality, we find that several factors robustly drive differences in the level of income inequality at the inter-household level. We find that mean annual rainfall is negatively associated with income inequality, suggesting that a unit increase in mean rainfall reduces income inequality. On the contrary deviations from the mean annual rainfall and household experience with rainfall related shocks in the past 5 years are positively associated with income inequality. The result here supports our earlier finding that deviation in rainfall increases the Gini elasticity of agriculture income. With agriculture incomes accounting for about 85% of total household incomes, the net impact of rainfall variability on income inequality is clearly through agriculture incomes. Our findings here are congruent with previous studies such as Sedova *et al.* (2020) who show that adverse weather aggravates inequality by reducing consumption of poor rural farming households in India. In Mozambique, Silva *et al.* (2015) find that weather shocks exacerbate existing income and power disparities, although in some cases inequality and polarization declines

Table 2.3: Robust drivers of Gini elasticity with respect to income sources

	Gini elasticity of agriculture income			**Gini elasticity of nonfarm income**		
Variables	**Coef.**	**Std. Err.**	**t**	**Coef.**	**Std. Err.**	**t**
Constant	**0.262**	0.059	4.42	**-1.490**	0.110	-13.54
Age	0.000	0.000	-0.01	**0.001**	0.000	3.14
Gender	**-0.020**	0.007	-3.01	-0.009	0.012	-0.82
Education	**0.010**	0.004	2.85	**0.010**	0.007	1.47
Dependency	**0.000**	0.000	1.51	0.000	0.000	-0.93
Land	**-0.001**	0.000	-4.53	**0.003**	0.001	5.27
Extension	**0.013**	0.005	2.35	0.008	0.009	0.92
Credit	-0.001	0.009	-0.07	**-0.020**	0.017	-1.20
Membership	**0.007**	0.006	1.14	**-0.016**	0.010	-1.56
Subsidy	**0.012**	0.004	3.20	-0.002	0.007	-0.32
Market info	-0.002	0.003	-0.73	0.000	0.005	-0.02
PET	**-0.019**	0.005	-3.77	**0.026**	0.010	2.62
Rainfall	**-0.060**	0.012	-4.78	**0.259**	0.023	11.26
Std Rainfall	**0.001**	0.000	6.17	**-0.004**	0.000	-9.51
Rainfall shock	0.004	0.005	0.88	-0.007	0.011	-0.65
Farming system	**0.023**	0.009	2.65	**-0.019**	0.018	-1.04
Irrigation use	**0.050**	0.006	7.86	-0.008	0.010	-0.79
Mitigation	**0.026**	0.005	5.28	**-0.016**	0.008	-1.89
Transfer	**-0.041**	0.011	-3.67	**0.062**	0.026	2.38
Coping	**0.023**	0.005	5.00	0.004	0.007	0.56
N		5190			1401	

Note: A regressor is considered to be a robust driver of Gini elasticity if the associated t-statistic is in an absolute value larger than 1. In bold are those regressors that can be considered robust.

in the aftermath of an extreme event, or increase even in cases where the weather is relatively good. Similarly, Thiede (2014) show that rainfall deficits do not only have an equalizing effect on within-community livestock inequality in parts of Ethiopia but also at the regional level.

The distributional impacts of rainfall shocks depend critically on household vulnerability in terms of exposure, sensitivity, and adaptive capacity. We find varying effects of these pseudo-vulnerability indicators on income equality. Mitigation and risk transfer adaptive strategies are positively associated with inequality while coping strategies and farming system is negatively associated with income inequality. Mitigation strategies (reducing land areas, renting land, and moving to nonfarm activities) particularly affect resource allocations negatively. These negative resource allocations might have implications for income generation, and this might explain the positive association with inequality. The finding of Odusola (2017) provides a good insight into this. The author finds that a 1% shift of labour away from agriculture to other sectors leads to a 0.282% reduction in the rural poverty gap, but a 0.071% rise in rural poverty. Similarly, Silva *et al.* (2015) argue that low-return or low-skilled activities undertaken by households to offset poor agricultural productivity through shocks, for instance, maybe inequality-decreasing, while participation in high-return activities may increase inequality as wealthier households tend to have better access to these types of jobs. Risk transfer in the form of index-based insurance is also not accessible to poor households and it also requires substantial financial investments in the form of premia. The finding here is in line with the consensus that some adaptation measures are likely to increase inequality when they prioritize higher-income groups and economically valuable areas over low-income or marginalized neighbourhoods (Anguelovski *et al.*, 2016). Rainfed subsistence agriculture is generally a low input alternative and generates lower income opportunities compared to commercial farming the requires massive inputs in the form of fertilizers, seeds, pesticides, machinery, and irrigation, and generates higher incomes. The implication is that rainfed subsistence farming will be associated with lower levels of income inequality compared to commercial farming.

Just as expected, we find that mean annual rainfall is positively associated with household daily calorie availability. Deviations from the mean annual rainfall and experience with rainfall related shocks in the past 5 years are however negatively associated with household daily calorie availability. The finding here is congruent to the study of Kinda and Badolo (2019). In their study, they analysed the effect of rainfall variability on food security for 71 developing countries from 1960 to 2016 and they found that rainfall variability reduces food availability per capita and increases the percentage of total undernourished population in developing countries. In Ghana and Bangladesh, Cooper *et al.* (2019) found an association between precipitation shocks and household hunger. Other studies (Codjoe and Owusu, 2011; Abafita and Kim, 2014; Murali and Afifi, 2014; Abegaz, 2017; Agidew and Singh, 2018) have also found that weather-related shocks affect household food security. We find that risk transfer as an adaptive strategy is positively associated with daily food calorie availability. Risk transfer products are known to increase investments in productive inputs such as fertilizers, seeds, and pesticides (see Goodwin *et al.*, 2004; Mobarak and Rosenzweig, 2012; Berhane *et al.*, 2013; Karlan *et al.*, 2014; Cai *et al.*, 2015; Elabed and Carter, 2015; Delavallade *et al.*, 2015; Cole *et al.*, 2017; Hill *et al.*, 2019) and this can translate to higher household food production and thus daily food calorie availability.

Although not a robust driver of household daily food calorie availability, mitigation as an adaptive strategy is negatively associated with daily food calorie availability. As pointed out earlier, these strategies affect agriculture resource allocations, particularly land and labour and this can negatively affect household food production. Similarly, household coping strategies were found to be a robust driver and negatively associated with household daily food calorie availability. These strategies which involve sales of grain stocks and livestock assets can potentially reduce household food availability. As argued by Abeygunawardena *et al.* (2016), traditional coping mechanisms are backwards-looking and in the face of changing patterns of climate variability, their effectiveness may be significantly reduced.

Table 2.4: Robust drivers of inequality, food security, and labour productivity

	Gini index			**Daily calorie**			**Labour productivity**		
Variables	**Coef.**	**Std. Err.**	**t**	**Coef.**	**Std. Err.**	**t**	**Coef.**	**Std. Err.**	**t**
Constant	**1.404**	0.066	21.28	**4.402**	0.716	6.15	**1.354**	0.574	2.36
Age	**0.000**	0.000	2.14	0.001	0.001	0.70	**-0.002**	0.001	-2.17
Gender	0.004	0.006	0.76	**0.356**	0.058	6.18	**0.311**	0.052	5.97
Education	0.013	0.018	0.70	**0.054**	0.032	1.69	0.023	0.028	0.82
Dependency	**0.000**	0.000	-1.71						
Household size				**-0.061**	0.003	-20.17	**-0.011**	0.005	-2.43
Land	0.001	0.001	0.59	**0.038**	0.002	21.21	**0.023**	0.003	6.99
Extension	**0.051**	0.009	5.63	**0.181**	0.048	3.76	0.014	0.043	0.32
Credit	**-0.043**	0.019	-2.25	0.055	0.075	0.74	-0.062	0.067	-0.92
Membership	**0.039**	0.016	2.50	-0.015	0.053	-0.27	**0.054**	0.044	1.22
Agriculture	**0.000**	0.000	-5.74						
Subsidy	**-0.223**	0.014	-15.47	**0.173**	0.032	5.39	**0.101**	0.028	3.65
Road	0.001	0.001	0.95				**-0.056**	0.016	-3.48
Market	**-0.011**	0.002	-4.72				**0.169**	0.031	5.36
Market info	-0.002	0.002	-0.82				-0.011	0.025	-0.42
Market integration				0.008	0.030	0.27			
Rainfall	**-0.112**	0.013	-8.73	**0.561**	0.137	4.09	**1.346**	0.109	12.31
Std Rainfall	**0.000**	0.000	1.01	**-0.011**	0.002	-5.10	**-0.02**	0.003	-6.05
Rainfall shock	**0.005**	0.003	1.59	**-0.266**	0.048	-5.53	**0.064**	0.042	1.53
Mitigation	**0.007**	0.002	3.29	-0.041	0.044	-0.92	-0.007	0.038	-0.18
Transfer	**0.024**	0.004	5.58	**0.803**	0.089	8.99	**0.406**	0.090	4.51
Coping	**-0.004**	0.002	-1.52	**-0.048**	0.044	-1.10	**0.061**	0.034	1.81
PET	**0.076**	0.005	14.08	**0.411**	0.047	8.74	**0.231**	0.047	4.89
Farming system	**-0.044**	0.007	-6.45	**-1.20**	0.126	-9.51	**0.274**	0.080	3.42
Irrigation use	0.001	0.004	0.31	**0.162**	0.059	2.76	**0.266**	0.053	5.06
AII							**-0.203**	0.014	-14.08
Storage				**0.13**	0.042	3.09			
Daily calorie							**0.408**	0.068	5.96
Daily calorie × Std Rainfall							**-0.001**	0.000	-1.28
Staple crop				**0.859**	0.067	12.79			
Mixed				**0.153**	0.035	4.41			
BasinAra				**0.489**	0.211	2.31			
RiverVall				**0.339**	0.229	1.48			
SylvFerlo				**0.277**	0.220	1.26			
Casamance				**0.450**	0.224	2.01			
CentEast				**0.507**	0.225	2.25			
VallAnambe				**0.599**	0.259	2.31			
Resid edu	-0.002	0.011	-0.21						
Resid land	0.000	0.001	0.21						
Resid ext	**-0.011**	0.005	-2.40						
Resid cred	**0.027**	0.009	3.09						
Resid mem	0.001	0.008	0.07						
Resid mar	**0.004**	0.002	1.76						
Resid sub	**0.133**	0.009	15.00						
Resid food							**0.399**	0.061	6.52
N	5232			4862			4862		

Note: A regressor is considered to be a robust driver of Gini elasticity if the associated t-statistic is in an absolute value larger than 1. In bold are those regressors that can be considered robust.

We find that rainfed subsistence agriculture is negatively associated with household daily food calorie availability. This is expected because of its high dependence on rainfall and low input use. These two factors might largely explain the observed effect. Supplementing rainfed agriculture with irrigation use is positively associated with household daily food calorie availability. Intuitively, irrigation use will help a household to deal with rainfall related shocks such as droughts and allow households to produce crops all year round.

Lastly, we examined the robust drivers of agriculture labour productivity. Mean annual rainfall is positively associated with agricultural labour productivity. The implication is that sufficient rainfall can reduce production risk and entice farm households to increase cultivated land and use of more productivity-enhancing technologies. Such resource allocations might increase agriculture productivity. Our results suggest that land and the adoption of productivity-enhancing technologies – fertilizer and improved/high yielding varieties are positively associated with agricultural labour productivity. A key argument we made in this paper is that beyond, high temperatures, rainfall variability will affect agricultural labour productivity, through food production losses and reductions in food calorie availability. Reductions in food calories will impede on the important physiological function of food in terms of providing energy for growth, development, and work. We find that deviations from the mean annual rainfall are negatively associated with agricultural labour productivity. At the same time, food calorie availability is positively associated with agricultural labour productivity. We find that the correlation between daily food calorie availability and agricultural labour productivity is relatively high ($\mathrm{R} = 0.638$, $p < 0.05$).

As shown by the coefficient of the interaction term between food calorie availability and rainfall variability, the effect of food calorie availability on agricultural labour productivity decreases for every deviation in rainfall. Rather surprisingly, we find that household experience with rainfall related shocks in the past 5 years is positively associated with agricultural labour productivity. Exposure to such shocks may in the short term shift some household labour to high-return off-farm activities. This decrease in household labour force might push them to be more efficient. As suggested by Chavas *et al.* (2005) most farm households operate under decreasing returns to scale because household resources particularly the number of adults and land are ‘too large’ for the prevailing technology. A shift to off-farm employment opportunities can therefore elevate production into either a constant or increasing returns to scale. Although not a robust driver of agricultural labour productivity, mitigation as an adaptive strategy is negatively associated with agricultural labour productivity. Just as we argued in the case of income inequality and daily food calorie availability, mitigation potentially pulls resources or shifts them out of production, and this can ultimately lower labour productivity. We find that risk transfer and coping strategies are positively associated with agricultural labour productivity. As mentioned previously, risk transfer has an input use effect that may complement agriculture labour, hence potential increases in agricultural labour productivity. Similarly, coping strategies involving the sale of assets might have two effects – a food availability effect and/or an input use effect. Household supplementary foods obtained from purchases or exchange may provide physiological needs of food related to work. Furthermore, 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 which can help increase agricultural labour productivity. We find that the farming system and irrigation use are positively associated with agricultural labour productivity.

The study also assessed the robustness of the above estimates to various empirical model specifications. For income inequality, we specified a tobit model due to the censored nature of the variable (i.e. ranges between 0 and 1) and an OLS model was specified for both daily food calorie availability and agricultural labour productivity. The result which is presented in Table 2.14 in the appendix is in line with parameter estimates of interest in Table 2.4. The tobit model to determine the drivers of inequality shows that our results remain essentially unchanged both in terms of direction and robustness of the coefficients, except for risk transfer, which turned out insignificant though with a positive sign. Similarly, the OLS model results for the drivers of both daily food calorie availability and agricultural labour productivity also remain essentially unchanged both in terms of direction and robustness of the coefficients. However, coping strategies, turned out insignificant though it maintained the correct signs throughout both models. We also found that the sign, on experience with rainfall related shocks in the past 5 years and the interaction term between food calorie availability and rainfall variability were maintained in the OLS model but did not turn out significant.

2.8 Conclusion

This study investigated the impact of climate change in the form of rainfall variability on inter-household income inequality, food security, and agricultural labour productivity of Senegalese farm households. We employed the recently developed model-averaging techniques which address issues related to model uncertainty and controlled for potentially endogenous variables and household pseudo-vulnerability factors. Besides, we employed the Gini decomposition approach to identify key household income sources and the contribution of each source to overall inequality. The empirical results revealed that the inequality impacts of climate-induced shocks will be highly dependent on the income source composition of households. Our results suggest that the Gini elasticity of agriculture income increases for every deviation in rainfall while in the case of nonfarm income it decreases for every deviation in rainfall. Since agriculture income constitutes the largest source of income and contributor to household income inequality, any shocks to the sector will largely be responsible for any observed increases in income inequality. Nonetheless, we found evidence of the existence of a Kuznets curve relationship between Gini elasticity and the share of agriculture incomes. This suggests that even though incomes from agriculture is the biggest contributor to household income inequality, as the share of agriculture income in total household income increases, Gini elasticity may rise initially, after which inequality will decline.

Consistently we find that rainfall variability decreases household daily food calorie availability and agricultural labour productivity. Beyond the effect of temperature increases on labour productivity which has been well studied, we show that food calorie availability is positively associated with agricultural labour productivity. Furthermore, the effect of food calorie availability on agricultural labour productivity decreases for every deviation in rainfall. This suggests that climate change in the form of rainfall variability can affect labour productivity through changes in food availability. We also find that the pseudo-vulnerability indicators have varying effects on the three outcomes. However, risk transfer and irrigation use are positively associated with food calorie availability and agricultural labour productivity. Although both increase income inequality, they appear to be the best instruments in addition to subsidies and the adoption of productivity-enhancing technologies (fertilizer and improved seeds) to help households deal with rainfall variability related shocks.

The findings from the study have some policy implications. First, policymakers should scale up and offer subsidized index-based insurance products since they help the farm household better adapt to rainfall related shocks. Secondly, to achieve substantial reductions in inequality, improved food security and labour productivity, accelerated improvements in agricultural yields, through functioning markets for inputs such as fertilizers, seedlings, and tractors, as well as access to credit, irrigation, and post-harvest facilities, are key to limit future impacts of climate change. There are some important caveats to be considered for this study. Because our analysis is rather static, it obscures or fails to capture important spatial and temporal shifts in outcomes, that can provide critical thresholds to identify the impact of rainfall related shocks. Future research can therefore focus on using long-term data such as panel or longitudinal data on incomes, food production, and household labour to provide answers on the effect of these temporal and spatial shifts on household welfare.

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Appendix

Derivation of Equation 2.6

Following Stark *et al.* (1986), let G_0 be the Gini index before multiplying each household's income from source j by (I + e), and let G(e) be the Gini after the multiplication. As already shown in equation 2.5, the Gini index (G_0) is given by:

$$G_0 = \sum_{k=1}^{K} R_k * G_k * S_k \tag{2.8}$$

The multiplication of income source j by (I + e) does not affect G_k (k = I, ..., K). However, R_k is a function of the ranks of total income. The rank function is not well defined for incomes that are equal. In order to avoid the problem created in this case, we assume that incomes vary slightly across households (aside from households whose income from source j is zero). Then, R_k does not change for k = I, ..., K. Hence

$$G(e) = \sum_{k=1}^{K} R_k * G_k * S_k(e) \tag{2.9}$$

By definition,

$$S_k(e) \;=\; \frac{\mu_k}{\sum_{k\neq j} \mu_k + (1+e)\mu_j} \;=\; \frac{\mu_k}{\sum_{k=1}^{K} \mu_k + e\mu_j} \text{ for } k \neq j \tag{2.10}$$

while for source j,

$$S_k(e) \;=\; \frac{(1 \;+\; e)\mu_j}{\sum_{k=1}^{K} \mu_k + e\mu_j}\;. \tag{2.11}$$

Let us now evaluate:

$$\begin{aligned} G \;= G(e) - G_0 = \sum_{k=1}^{K} R_k * G_k * S_k(e) \;-\; G_0 = \sum_{k=1}^{K} R_k * G_k * S_k \\ \sum_{k=1}^{K} = [\,S_k(e) \;-\; S_k]\, R_k * G_k \end{aligned} \tag{2.12}$$

This simplifies to:

$$S_k(e) - S_k = \frac{-eS_kS_j}{1 + \; eS_j} \tag{2.13}$$

Now for $k = j$

$$S_j(e) - S_j = \frac{eS_j - eS_j^2}{1 + eS_j} \tag{2.14}$$

Substituting equations 2.13 and 2.14 into 2.12, we have:

$$\begin{aligned} G(e) - G_0 &= \sum_{k=1}^{K}[S_k(e) - S_k]R_k * G_k \\ &= \sum_{k \neq j} \frac{-eS_kS_j}{1 + eS_j} R_k * G_k + \frac{eS_j - eS_j^2}{1 + eS_j} R_j * G_j \\ &= \sum_{k=1} \frac{-eS_kS_j}{1 + eS_j} R_k * G_k + \frac{eS_j}{1 + eS_j} R_j * G_j \end{aligned} \tag{2.15}$$

Using equation 2.15, we can examine the derivative:

$$\begin{aligned} \lim_{e \to 0} \frac{G(e) - G_0}{e} &= -S_j \lim_{e \to 0} \sum_{k=1}^{K} \frac{S_k}{1 + eS_j} R_k * G_k + \lim_{e \to 0} \frac{eS_j}{1 + eS_j} R_j * G_j \\ &= -S_j \sum_{k=1}^{K} R_k * G_k * S_k + R_j * G_j * S_j \\ \frac{\partial G_0}{\partial e_j} &= S_j(R_j * G_j - G_0) \end{aligned} \tag{2.16}$$

Table 2.5: Post-harvest loss ratios per crop and region (%)

Region	Maize[a]	Rice[a]	Sorghum[a]	Millet[a]	Fonio[a]	Groundnut[b]	Sesame[c]	Cowpea[b]	Cassava[b]
Dakar	17.19	0.00	11.09	8.02	0.00	10.10	25.00	23.50	42.3
Diourbel	20.52	0.00	12.29	20.80	0.00	10.10	25.00	23.50	42.3
Fatick	20.45	11.09	12.29	8.69	0.00	10.10	25.00	23.50	42.3
Kaffrine	28.85	10.85	22.19	20.67	18.76	10.10	25.00	23.50	42.3
Kaolack	20.34	10.85	11.31	8.54	11.48	10.10	25.00	23.50	42.3
Kédougou	26.57	11.79	11.40	10.63	23.70	10.10	25.00	23.50	42.3
Kolda	26.57	22.69	12.49	22.60	23.55	10.10	25.00	23.50	42.3
Louga	17.19	10.85	11.31	8.34	0.00	10.10	25.00	23.50	42.3
Matam	17.19	11.25	11.20	8.12	18.76	10.10	25.00	23.50	42.3
Saint-Louis	17.19	11.37	11.31	8.46	0.00	10.10	25.00	23.50	42.3
Sédhiou	26.54	22.76	22.39	10.76	23.58	10.10	25.00	23.50	42.3
Tambacounda	17.19	11.05	22.23	8.34	11.48	10.10	25.00	23.50	42.3
Thiès	25.94	10.85	22.13	20.67	0.00	10.10	25.00	23.50	42.3
Ziguinchor	17.91	23.07	11.40	10.63	0.00	10.10	25.00	23.50	42.3

[a] Source: African Postharvest Losses Information System (APHLIS). `https://www.aphlis.net/en`
[b] Source: Affognon *et al.* (2015)
[c] Source: Tomlins *et al.* (2016)

Table 2.6: Conversion ratios for edible fractions and food energy equivalence

Crop	Edible conversion factor	Kcal/100g
Maize	1	349
Rice	1	353
Sorghum	1	344
Millet	1	348
Fonio	1	347
Cowpea	1	316
Groundnut	1	578
Cassava	0.84	153
Sesame	1	577

Source: Stadlmayr *et al.* (2012)

Table 2.7: Adult-equivalent conversion factors according to age and gender

Age (years)	**Calories (kcal)**	**Adult-equivalent conversion factor**
New-borns		
0-1	750	0.29
Children		
1-3	1,300	0.51
4-6	1,800	0.71
7-10	2,000	0.78
Men		
11-14	2,500	0.98
15-18	3,000	1.18
19-24	2,900	1.14
25-50	2,900	1.14
51+	2,300	0.90
Women		
11-14	2,200	0.86
15-18	2,200	0.86
19-24	2,200	0.86
25-50	2,200	0.86
51+	1,900	0.75

Source: Claro *et al.* (2010)

Table 2.8: Control function approach for potentially endogenous variables for income inequality model

	Education		**Land**		**Extension**		**Credit**		**Membership**		**Market info**		**Subsidy**	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	5.508***	0.625	-30.346***	3.739	-0.621	0.826	-5.060***	1.273	-2.762***	0.869	-0.664	1.185	-5.673***	0.750
Age	-0.015***	0.001	0.044***	0.008	0.004*	0.002	-0.003	0.003	-0.002	0.002	-0.001	0.003	0.002	0.001
Gender	0.676***	0.076	1.266***	0.420	0.036	0.093	-0.125	0.132	-0.096	0.095	0.050	0.136	0.154**	0.071
Education			1.037***	0.235	0.123**	0.051	0.122*	0.072	0.134**	0.053	0.043	0.075	0.031	0.039
Dependency	-0.001***	0.000	-0.003*	0.002	0.000	0.000	0.001**	0.000	0.000	0.000	-0.001	0.000	0.000	0.000
Land	0.010***	0.002			-0.004	0.004	0.009***	0.003	-0.001	0.004	-0.007**	0.004	0.020***	0.003
Extension	0.129**	0.056	-0.631*	0.339			-0.119	0.092	0.679***	0.062	-0.192*	0.108	0.345***	0.058
Credit	0.098	0.090	1.555***	0.555	-0.182*	0.107			0.563***	0.095	0.199	0.227	0.080	0.096
Membership	0.139**	0.060	-0.230	0.364	0.679***	0.064	0.492***	0.083			-0.035	0.123	0.338***	0.063
Subsidy	0.029	0.039	1.853***	0.233	0.179***	0.053	0.166**	0.075	0.289***	0.055	0.104	0.074		
Road	-0.110***	0.022	0.359***	0.134	-0.127***	0.029	-0.032	0.044	0.020	0.032	0.010	0.042	0.003	0.023
Market	0.019	0.042	-0.386	0.252	0.233***	0.060	0.040	0.081	0.043	0.059	0.12	0.077	-0.148***	0.043
Market info	0.057	0.036	-0.557**	0.218	-0.054	0.048	-0.037	0.069	0.006	0.051			0.016	0.037
Mitigation	-0.306***	0.083	0.301	0.506	0.015	0.107	0.238	0.160	-0.563***	0.094	-0.118	0.173	-0.052	0.085
Transfer	-0.137	0.142	0.292	0.876	0.399**	0.159	0.847***	0.195	-0.059	0.149	0.002	0.367	0.101	0.157
Coping	-0.278***	0.086	0.701	0.523	0.119	0.111	0.359**	0.165	-0.626***	0.099	-0.062	0.178	0.043	0.088
PET	0.140***	0.054	0.516	0.325	0.428***	0.062	0.368***	0.086	0.633***	0.061	0.152	0.109	0.851***	0.056
Agriculture	-0.002***	0.001	0.022***	0.004	-0.003***	0.001	0.001	0.002	0.000	0.001	0.001	0.001	-0.002***	0.001
Rainfall	-1.231***	0.127	5.890***	0.757	-0.283*	0.168	0.615**	0.264	0.236	0.176	-0.612***	0.236	1.205***	0.141
Std Rainfall	0.027***	0.002	-0.108***	0.013	-0.003	0.003	-0.010**	0.005	0.002	0.003	0.012***	0.004	-0.019***	0.002
Rainfall shock	0.081	0.054	0.844***	0.324	-0.153**	0.071	0.136	0.100	-0.416***	0.069	-0.022	0.105	-0.029	0.055
Farming system	-0.147*	0.089	3.673***	0.532	-0.083	0.104	-0.701***	0.140	-0.089	0.102	-0.827***	0.207	-0.116	0.093
Irrigation use	0.079	0.065	0.477	0.391	0.362***	0.079	0.012	0.114	0.079	0.080	-0.246*	0.126	-0.224***	0.069
Gender ratio	**-0.060*****	0.017												
Household labour			**0.652*****	0.127										
Support needs					**1.074*****	0.09								
Main occupation							**0.280****	0.123						
Union									**0.168***	0.09				
Sale											**4.969*****	0.294		
Rural population													***0.000*****	0
N							5232							

***, **, * represent 1%, 5%, and 10% significance level, respectively.

Table 2.9: Control function approach for potentially endogenous variables for labour productivity model

	Daily calorie	
Variables	**Coef.**	**Std. Err.**
Constant	3.019***	0.528
Age	-0.001	0.001
Gender	0.353***	0.061
Education	0.056*	0.033
Household size	-0.065***	0.003
Land	0.034***	0.002
Extension	0.247***	0.048
Credit	-0.022	0.078
Membership	0.047	0.052
Subsidy	0.104***	0.034
Road	0.013	0.019
Market	0.206***	0.036
Market info	0.000	0.031
PET	0.419***	0.046
Rainfall	0.745***	0.107
Std Rainfall	-0.011***	0.002
Rainfall shock	-0.334***	0.046
Farming system	-0.721***	0.076
Irrigation use	0.247***	0.055
AII	-0.133***	0.014
Mitigation	-0.055	0.043
Transfer	0.830***	0.093
Coping	-0.035	0.04
Granaries	**0.348*****	0.035
N	4862	

***, * represent 1%, and 10% significance level, respectively.

Table 2.10: Correlation test of instrumental variables used for income inequality model

Variable	**Gini index**	**Gender ratio**	**Household labour**	**Support needs**	**Main occupation**	**Union**	**Sale**	**Rural population**
Gini index	1.000							
Gender ratio	-0.005	1.000						
Household labour	0.022	-0.021	1.000					
Support needs	0.021	-0.019	0.063	1.000				
Main occupation	0.009	-0.001	0.010	0.048	1.000			
Union	-0.002	0.010	0.006	-0.022	-0.293	1.000		
Sale	0.001	0.000	0.001	0.002	-0.018	0.130	1.000	
Rural population	-0.013	0.013	-0.040	-0.040	-0.149	0.035	0.015	1.000

Table 2.11: Correlation test of instrumental variables used for labour productivity model

Variable	**Labour productivity**	**Granaries**
Labour productivity	1.000	
Granaries	0.002	1.000

Table 2.12: Test of the validity of instruments on inequality model

	Gini index		
Variable	**Coef.**	**Std. Err.**	**t**
Constant	**0.556**	0.003	172.83
Gender ratio	0.000	0.001	-0.35
Household labour	0.001	0.001	0.98
Support needs	0.002	0.002	0.96
Main occupation	0.001	0.002	0.24
Union	0.001	0.003	0.18
Sale	0.000	0.002	0.29
Rural population	0.000	0.000	-0.65
N	5232		

Note: A regressor is considered to be a robust driver of Gini elasticity if the associated t-statistic is in an absolute value larger than 1. In bold are those regressors that can be considered robust.

Table 2.13: Test of the validity of instruments on labour productivity model

	Labour productivity		
Variable	**Coef.**	**Std. Err.**	**t**
Constant	11.207	0.022	519.49
Granaries	0.002	0.029	0.08
N	4862		

Note: A regressor is considered to be a robust driver of Gini elasticity if the associated t-statistic is in an absolute value larger than 1. In bold are those regressors that can be considered robust.

Table 2.14: Model robustness check

	Gini index (Tobit model)		Daily calorie (OLS model)		Labour productivity (OLS model)	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	1.555***	0.086	4.339***	0.700	1.103*	0.600
Age	0.000	0.000	0.000	0.001	-0.002**	0.001
Gender	0.017**	0.007	0.398***	0.061	0.296***	0.055
Education	-0.048*	0.027	0.073**	0.034	0.021	0.028
Dependency	-0.000***	0.000				
Household size			-0.061***	0.003	-0.009	0.006
Land	0.001	0.001	0.040***	0.002	0.022***	0.004
Extension	0.071***	0.011	0.200***	0.049	0.004	0.045
Credit	-0.013	0.022	0.019	0.078	-0.06	0.068
Membership	0.004	0.017	0.008	0.053	0.052	0.044
Agriculture	-0.000***	0.000				
Subsidy	-0.233***	0.014	0.163***	0.034	0.098***	0.029
Road	-0.001	0.002			-0.055***	0.016
Market	-0.012***	0.002			0.158***	0.034
Market info	-0.001	0.002			-0.011	0.025
Market integration			-0.012	0.031		
Rainfall	-0.134***	0.016	0.560***	0.134	1.333***	0.118
Std Rainfall	0.001**	0.000	-0.011***	0.002	-0.019***	0.003
Rainfall shock	0.005*	0.003	-0.296***	0.047	0.067	0.046
Mitigation	-0.020***	0.005	-0.018	0.073	-0.014	0.037
Transfer	0.010	0.007	0.776***	0.124	0.415***	0.100
Coping	-0.027***	0.006	-0.005	0.076	0.053	0.032
PET	0.087***	0.006	0.408***	0.047	0.223***	0.052
Farming system	-0.045***	0.007	-1.235***	0.125	0.340***	0.088
Irrigation use	0.002	0.004	0.173***	0.058	0.263***	0.053
AII					-0.198***	0.016
Storage			0.146***	0.044		
Daily calorie					0.454***	0.093
Daily calorie×Std Rainfall					-0.001	0.000
Staple crop			0.923***	0.066		
Mixed			0.150***	0.036		
BasinAra			0.620***	0.200		
RiverVall			0.457**	0.217		
SylvFerlo			0.367*	0.209		
Casamance			0.605***	0.212		
CentEast			0.669***	0.214		
VallAnambe			0.817***	0.247		
Resid edu	0.035**	0.016				
Resid land	0.000	0.001				
Resid ext	-0.016***	0.005				
Resid cred	0.017*	0.010				
Resid mem	0.020**	0.009				
Resid mar	0.006**	0.002				
Resid sub	0.140***	0.009				
Resid food					0.370***	0.082
N	5232		4862		4862	

***, **, * represent 1%, 5%, and 10% significance level, respectively. The standard errors reported for the inequality and labour productivity model are the bootstrapped errors.

Chapter 3

How Effective are Risk Management Strategies? Empirical Evidence from Farm Households in Senegal[1]

Peron A.Collins-Sowah, Christian H. C. A. Henning

Abstract

Using empirical data from a nationally representative farm household survey in Senegal, this study evaluated the effect of different risk management strategies employed by farm households on agriculture income and dispersions around incomes. To achieve this, the study employed a Multinomial Endogenous Switching Regression model and a Moment-Based Approach. We find that the use of ex-ante risk management strategies significantly reduces agriculture incomes while ex-post risk management strategies adoption either in isolation or in combination with ex-ante significantly increases agriculture incomes. Ex-ante risk management strategies were observed to be associated with opportunity costs relating to income loss and likely inefficient resource allocations. Ex-post strategies on the contrary involve the sale of assets, hence it grants households the ability to smoothen household income ex-post shocks. The study also finds that all risk management strategies significantly reduce dispersions around agriculture incomes with ex-post risk management strategies producing the largest effect. The results suggest that ex-post risk management strategies appear to be the most effective in terms of helping households to maximize their objectives in terms of expected income and reductions in the variability of incomes. For wealthy households, ex-post risk management might be an effective strategy while for poor households it might not be optimal since it can plunge them deeper into poverty.

Keywords: Risk management, strategies, dispersion, multinomial, ex-ante, ex-post

JEL Codes: D13, G32, Q12

[1]Part of this chapter has been published as a working paper: An earlier version of this paper was published as the working paper title: *Risk management and its implications on household incomes*. Working Papers of Agricultural Policy, No. WP2019-05, Kiel University, Department of Agricultural Economics, Chair of Agricultural Policy, Kiel. `https://www.econstor.eu/bitstream/10419/213603/1/1689255315.pdf`. In this working paper a less aggregated risk management typology (risk mitigation, transfer and coping) was used.

3.1 Introduction

As pervasive and permanent fixtures of agricultural landscapes, risks are costly and if unchecked breeds uncertainty, stifle agricultural investments (D'Alessandro *et al.*, 2015), and impose ex-ante barriers to the use of technologies, which in turn affect agricultural productivity and economic growth (Binswanger and Sillers, 1983; Barnett *et al.*, 2008; Miller, 2008; Di Falco and Chavas, 2009; Kouamé, 2010; Dercon and Christiaensen, 2011; Demeke *et al.*, 2016; Poole, 2017; Amare *et al.*, 2018). The incidence of risks also has important spill-over effects on other rural households and businesses (Anderson, 2001). For instance, by lowering farm outputs, risks can also reduce turnover for agricultural merchants and agro-processors (Pannell and Nordblom, 1998). Additionally, agricultural risks potentially limit access to finance, increases the likelihood of farmers defaulting on loans and this restrains agriculture productivity (Yaron *et al.*, 1997; Demeke *et al.*, 2016). Particularly in developing regions of the world, smallholder producers are often exposed to a variety of climate risks that does not only adversely affect output and input prices but also household income and wealth.

Several empirical studies (see Newbery and Stiglitz, 1981; Harwood *et al.*, 1999; Fafchamps, 2000; Poole, 2017) suggests that farm households are not particularly concerned with uncertainty relating to agricultural output and prices, but rather to the variability of their incomes. Thus one of the most fundamental and complex decisions that farm households have to make, is the choice among probability functions of income stemming from different risk management strategies. In most cases, they are assumed to select a combination of risk management strategies that, for instance, maximize expected net returns subject to the degree of risk they are willing to accept (Harwood *et al.*, 1999; Tomek and Peterson, 2001). An optimal risk management decisions of farm households often rely on sound analysis of the entire portfolio of policies available to them. At the same time, empirical evidence also suggests that risk management approaches in which multiple approaches are considered simultaneously appear to be more efficient than single approaches (Huirne *et al.*, 2007). An important question that arises in the context of household risk management is how effective[2] these risk management strategies farm households employ are, and how

[2]The overall effectiveness of a risk management strategy typically requires the evaluation of trade-offs between expected returns and the associated costs (actual or opportunity costs). Effectiveness of a risk management strategy therefore calls for a balanced of costs against the achieved reduction or returns (dispersion around incomes). In this paper we only evaluate the effectiveness of risk management strategies from the returns perspective. Cost effectiveness is beyond the scope of this study. We use the associated standard deviation of households' agriculture incomes as proxy

large are the benefits? The available empirical evidence (see Howard and D'Antonio, 1984; Li and Vukina, 1996; Dhuyvetter and Kastens, 1997; Heifner and Coble, 1997; Berg, 2002; Kimura *et al.*, 2010; Vigani and Kathage, 2019) is largely concentrated on formal risk management instruments such as insurance and future contracts. A limited number of studies (see Kimura *et al.*, 2010; Birthal and Hazrana, 2019; Vigani and Kathage, 2019) have been focused on informal strategies such as crop and income diversification either in isolation or in combinations with formal instruments. For most of the informal risk management strategies employed by farm households in developing countries, the available empirical evidence is inadequate to provide definitive answers on their effectiveness.

Concurrently, agricultural risk management aims to find the risk-efficient combination of tools and instruments that maximizes household farm incomes and at the same time reducing the variability of incomes. Particularly in the study country Senegal, the use of traditional risk management strategies by households to deal with climate-related risk is well known and documented (see Evans, 2007; Tacoli, 2011; ANACIM *et al.*, 2013; Miller *et al.*, 2014). However, to date, no empirical study has been carried out to investigate the impact of these strategies on household incomes or their effect on dispersions around incomes. The purpose of this paper is to identify the optimal risk management strategies that allow households to maximize their income and reduce the variability of income. The study there seeks to investigate the effectiveness of the various risk management strategies employed by farm households to deal with climate shocks. By employing a multinomial endogenous switching regression that accounts for selectivity bias and a moment-based approach, the study examined the impact of two main risk management typology on agriculture incomes and its dispersions in a multinomial framework. This approach permits the evaluation and comparison of aggregate effects across these different risk management typologies and their simultaneous use.

Evaluating the effectiveness of risk management strategies on Senegalese farm households' agricultural incomes and dispersions around incomes is important for several reasons. First, because of limited access to formal risk management instruments, farm households most often have challenges managing the myriad risks they face. They therefore heavily rely on a range of traditional risk management strategies to avoid or minimize losses but these are mostly incomplete, suboptimal and mitigate only a small part of the overall risk (Siegel and Alwang, 1999; Dercon, 2002; Alderman, 2008; Barnett *et al.*, 2008; Deressa *et al.*, 2010; Kouamé, 2010). Secondly,

indicators for the return's effectiveness of a risk management strategies.

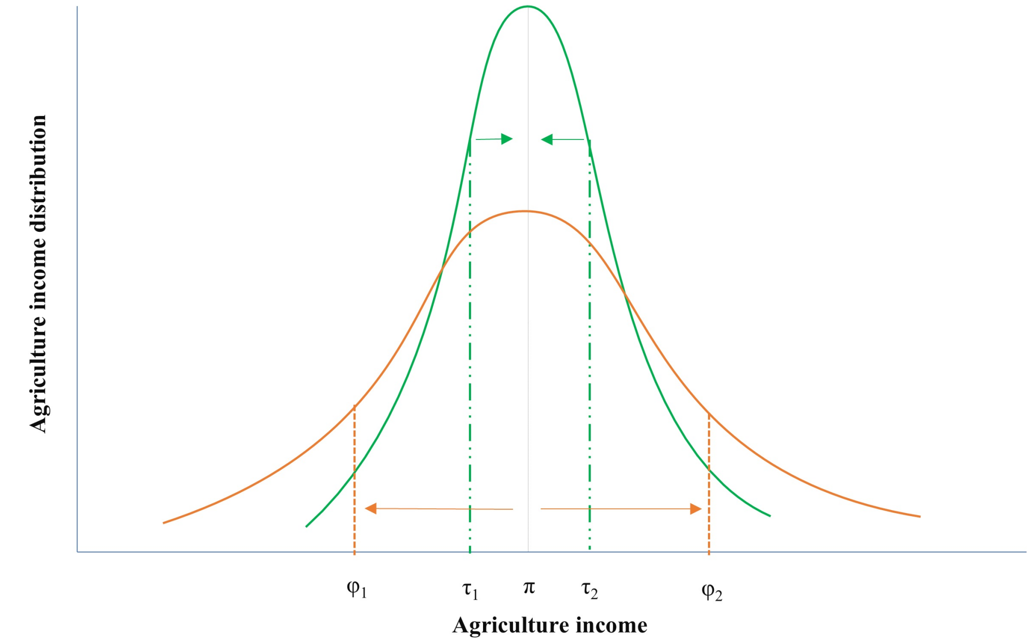
these traditional risk management strategies are not always widely available or prove ineffective for poor farm households and also come with associated costs (see Zimmerman and Carter, 2003; Barnett *et al.*, 2008; Kahan, 2008; Deressa *et al.*, 2010; World Bank, 2016) which can either be direct costs or the opportunity cost of undertaking a specific strategy. Thirdly, ineffective risk management strategies could potentially result in a vicious sequence of shock–partial recovery–shocks, which can undermine natural and capital resources and threaten the transition from subsistence to commercial agriculture (Cusmano, 2013; Demeke *et al.*, 2016; World Bank, 2016).

This study is important for several reasons. First, it highlights the need for a more targeted and systematic approach to agricultural risk management. Because good risk management decisions depend on accurate information, evaluating the effectiveness of different strategies and tools will help farm households to refine their decisions and select the optimum set of strategies when faced with risky situations. This is particularly important because fluctuations in farm incomes, due to risks may present difficult welfare problems for farmers. Optimal risk management tools also have implications for rural growth and poverty reduction. Furthermore, identifying optimal risk management strategies provides useful information for the design of appropriate risk management policies by policymakers. The rest of the paper is organized as follows. Section 3.2 and 3.3 presents the conceptual framework and empirical strategy, respectively. In Section 3.4, the survey data and variable measurements are presented. In Section 3.5, the empirical results and discussions are presented and finally, Section 3.6 offers conclusion and policy implications.

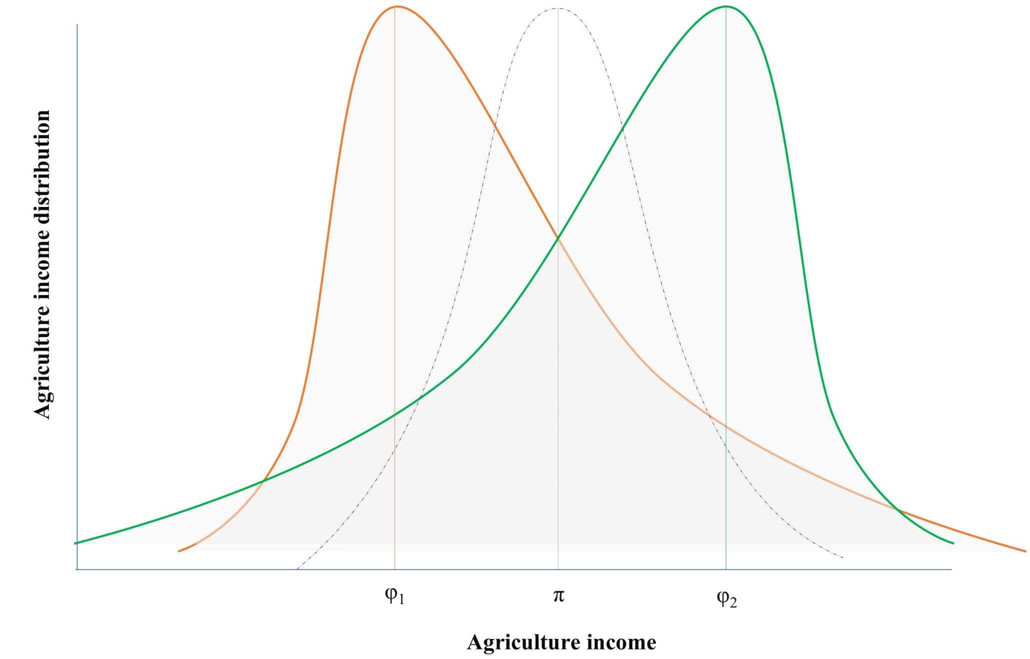
3.2 Conceptual framework

At the farm household level, one can assume that risk management strategies are aimed at enhancing expected returns while reducing volatility. Concurrently, farm households' when faced with production-related shocks must decide to adopt among a possible set of risk management strategies (Table 3.6) that can help them to offset the adverse effects of risk and income shortfalls. Following Kim and Chavas (2003), Koundouri *et al.* (2006), and Mukasa (2018) we model farm households' choice of risk management strategies in an expected utility framework. Just like farm households having to make production decisions before climatic and other risks are realized, the adoption of risk management strategies follows a situation where farm households are uncertain about the outcome of their decisions. Therefore, the adoption of risk management strategies is related to uncertain prospects, which one can reduce to a probability distribution over a domain of possible payoffs. Hence, decision-making by farm households, therefore, boils down to a choice between different possible probability distributions of returns, herein agricultural incomes and dispersions around incomes.

Households select from a finite set of risk management strategies (ex-ante, ex-post, or both) to maximize agriculture incomes but minimize dispersions around incomes. More importantly, as shown in figure 3.1, adoption of these risk management strategies is associated with different effects, herein dispersions around the means of agriculture income. From figure 3.1a, if we assume that agriculture incomes follow a normal distribution and π is the mean or average household agriculture income, then an adopted risk management strategy can; a) reduce the dispersion or variation around π – i.e., the areas between τ_1 and τ_2 or b) increase the dispersion or variation around π – i.e., the areas between ϕ_1 and ϕ_2. In the same fashion, risk management strategies could have different effects on the skewness distribution of household incomes (figure 3.1b). It could lead to a) negative skewness distribution – i.e., ϕ_1 or b) positive skewness distribution – i.e., ϕ_2.



(a) Variance effects



(b) Skewness effects

Figure 3.1: Dispersion effect of risk management strategies on incomes

Furthermore, adoption decisions on these risk management strategies are made without knowing which outcomes may result from such decisions, hence farm household decision making occurs under uncertainty. The risk management strategies in this finite set are also mutually exclusive, therefore the choice of one implies the rejection of the others. We assume that a farm household's decisions are based on whether or not to adopt any, some, or all of the risk management strategies, j available to them (j = 1,...., M). In light of this, it is assumed that farm households will choose risk management strategies that will result in the highest expected utility.

3.3 Empirical strategy

In a multiple risk management strategies adoption setting, farm households' simultaneous use of strategies leads to 4 possible combinations that farm households could choose from (Table 3.1). Because of the simultaneous use of these strategies, failing to account for the fact that farm households can adopt several risk management strategies simultaneously, can lead to biased estimates as the overall effect of adoption is not necessarily equal to the sum of the effects of adopting each strategy separately (Wu and Babcock, 1998). Farm households' decisions to adopt these strategies may not also be random and they may endogenously self-select into adoption or non-adoption. Therefore, the adoption decisions are likely to be influenced systematically by both observed and unobservable characteristics that may be correlated with the outcomes of interest (agriculture income and standard deviation of agriculture income). Such unobservable characteristics may include for example the innate managerial and technical abilities of the farmers in understanding and using risk management strategies or the types of social networks formed by farmers that are not captured, such as the kind of neighbours the farmer communicates with and whether such neighbours have adopted risk management strategies. The inability to therefore capture these unobservable characteristics may lead to selection bias.

Table 3.1: Risk management portfolios available to farm households

Risk Management Portfolio	**Portfolio ID**	**Frequency**	**Percent (%)**
No risk management	RMP0	279	5.38
Ex-ante risk strategy only	RMP1	3,172	61.18
Ex-post risk strategy only	RMP2	1,004	19.36
Ex-ante and Ex-post strategy	RMP3	730	14.08
Total		**5,185**	**100**

Hence, to disentangle the pure effects of adoption, we model the farm households' choice of risk management strategies and the impact of adoption in a multinomial endogenous switching regression framework. This approach is a selection-bias correction methodology based on the multinomial logit selection model developed by Bourguignon *et al.* (2007). The approach allows us to firstly, obtain both consistent and efficient estimates of the selection process and a reasonable correction for the outcome equations. Secondly, it allows us to evaluate both individual risk management strategies and combined strategies while capturing the interactions between the choices of alternative strategies. Estimation of the multinomial endogenous switching regression occurs simultaneously in two steps. In the first stage, farm households' choice of risk management strategy is modelled using a multinomial logit selection model, while recognizing the inter-relationships among the portfolios. The estimated parameters from the first stage and then used to calculate the selection-bias correction (or selectivity) terms.

In the second stage, the selection-bias correction terms together are incorporated as covariates into the outcome model to estimate the impacts of risk management strategies on agriculture income and the standard deviation of agriculture incomes using ordinary least squares (OLS). Following the studies of Di Falco and Veronesi (2013), Kassie *et al.* (2015), Teklewold *et al.* (2017), and Vigani and Kathage (2019), we describe the empirical econometric approach used in the study below.

3.3.1 Stage I: Multinomial Adoption Selection Model

Farm households are assumed to maximize their expected revenues by using a portfolio of risk management strategies. Let Y_{ij}^* be the latent variable that captures the expected net revenues from the use of a risk management strategy j (j=1...M) concerning implementing any other strategy k. We specify the latent variable as

$$Y_{ij}^* = X_i\varpi + \varepsilon_{ij} \tag{3.1}$$

Equation 3.1 includes a deterministic component, $X_i\varpi$, and an idiosyncratic unobserved stochastic component ε_{ij}. The deterministic component is a latent variable determined by observed household characteristics such as age, gender, and education of the household head, household size, asset ownership, farm size, soil fertility, etc. While the unobserved stochastic component captures all the variables that are relevant to the household's decision-maker but are unknown to the researcher such as skills or motivation. The utility obtained by farm households from choosing among the risk management strategies is not directly observable, but the adoption decision is observable. A farm household i will choose a risk management strategy j if it provides expected returns greater than any other portfolio if:

$$Y_i \begin{cases} 1 \quad \text{iff} \quad Y_{i1}^* > \max\limits_{k \neq 1}(Y_{ik}^*) \quad \text{or} \quad \varepsilon_{i1} < 0 \\ \vdots \qquad\qquad\qquad \vdots \qquad\qquad\qquad\qquad \vdots \\ M \quad \text{iff} \quad Y_{iM}^* > \max\limits_{k \neq M}(Y_{ik}^*) \quad \text{or} \quad \varepsilon_{iM} < 0 \end{cases} \quad \text{for all} \quad k \neq j \tag{3.2}$$

The formulation in equation 3.2 implies that the ith farm household will adopt a risk management strategy j to maximize their expected benefit if it provides greater expected utility than any other risk management strategy $k \neq j$, i.e., if $\varepsilon_{ij} = \max\limits_{k \neq 1}(Y_{ik}^*)$ < 0. It is assumed that the covariate vector X_i in equation 3.1 is uncorrelated with the idiosyncratic unobserved stochastic component ε_{ij}, i.e., $\mathrm{E}(\varepsilon_{ij} \mid X_i) = 0$. Under the assumption that ε_{ij} is identically and independently Gumbel distributed, the probability of the ith farm household with characteristics X choosing the jth risk management strategy can therefore be specified by a multinomial logit model (McFadden, 1974) as:

$$P_{ij} = P\left(\varepsilon_{ij} < 0 | X_i\right) = \frac{\exp\left(X_i \varpi_j\right)}{\sum_{k=1}^{M} \exp\left(X_i \varpi_k\right)} \tag{3.3}$$

The parameter estimates of the latent variable model can be estimated by maximum likelihood estimation. In our specification, the base category, non-adoption of any risk management portfolio (see Table 3.1), is denoted as $j = 1$. In the remaining portfolios ($j = 2, \ldots, 4$), at least one portfolio is used by a farm household.

3.3.2 Stage II: Multinomial Endogenous Switching Regression Model

In the second stage, we estimate a multinomial endogenous switching regression model to investigate the impact of each risk management strategy on agriculture income and the standard deviation of agriculture incomes by applying the Bourguignon *et al.* (2007) selection bias correction model. Our model implies that farm households face a total of M regimes (one regime per risk management strategy, where $j = 1$ is the reference category (no risk management). We assume that the vector of outcome variables is a linear function of explanatory variables. Hence, the stochastic function to evaluate agriculture income and the standard deviation of agriculture incomes implication of each risk management strategy for each regime j is given as:

$$\begin{array}{ll} \text{Regime 1}: & Q_{i1} = Z_i\beta_1 + \alpha_{i1}\overline{Z}_{i1} + \mu_{i1} \text{ if } A_i = 1 \\ \vdots & \qquad\qquad \vdots \qquad\qquad\qquad\qquad , \\ \text{Regime M}: & Q_{iM} = Z_i\beta_M + \alpha_{iM}\overline{Z}_{iM} + \mu_{iM} \text{ if } A_i = M \end{array} \tag{3.4}$$

where Q_{ij} is the outcome variable of farm household i in regime j, (j = 1,..., M), and Z_i represents a vector of inputs, and household's characteristics, such as the age of household head, household size, asset ownership, etc., included in X_i. β and α represent the corresponding vector of coefficients to be estimated. μ_{ij} represents the unobserved stochastic component, which verifies $\mathrm{E}(\mu_{ij} \mid Z_i, X_i) = 0$ and $\mathrm{V}(\mu_{ij} \mid Z_i, X_i) = \sigma_j^2$. In addition, to overcome the possible correlation of farm-invariant unobserved heterogeneity with observed covariates, we employed the approach of Mundlak (1978) and Wooldridge (2018) which has also been used by Di Falco (2014), Kassie *et al.* (2015), Teklewold *et al.* (2017) and Vigani and Kathage (2019)[3]. Controlling for unobserved heterogeneity is particularly important to help address farm or plot-specific unobservables as they may contain useful missing information regarding land quality (Kassie *et al.*, 2015) for instance.

Concurrently, if farm households obtain private information about unobservable effects such as how good the soil is on the plot or some shocks, they will adjust their factor input decisions accordingly (Fafchamps, 1993; Levinsohn and Petrin, 2003; Assunção and Braido, 2007). Hence, this approach allows us to exploit crop-level information to deal with the issue of the farm household's unobservable characteristics. Furthermore, crop-level information can potentially control for farm-specific effects. We exploit crop-level information and include the mean of crop varying $\overline{Z}$ explanatory variables, which include land holding, labour, fertilizer, and seed quantity to deal with the issue of unobserved heterogeneity. According to Teklewold *et al.* (2013), a Wald test of the null hypothesis that the vectors α are jointly equal to zero is required to indicate the relevance of crop-specific heterogeneity.

[3]In most of these studies, plot-variant variables were used to control for unobserved heterogeneity but due to the lack of plot-level data we use an alternative approach by using crop and farm household-variant variables since household produce multiple crops and we have crop-level data.

For each sample observation, Q_{ij} is observed if and only if one among the M dependent regimes is observed. When estimating an ordinary least squares (OLS) model, the outcomes of interest, agriculture income, and the standard deviation of agriculture income equations 3.4 are estimated separately. However, if the error terms of equation 3.1, ε_{ij} are correlated with the error terms μ_{ij} of the outcome model 3.4, then the expected values of μ_{ij} conditional on the sample selection are nonzero i.e., $\text{corr}(\varepsilon_{ij}, \mu_{ij}) \neq 0$, and the OLS estimates will be biased and inconsistent. To correct for the potential inconsistency, we employ the multinomial endogenous switching regression model by Bourguignon *et al.* (2007), which takes into account the correlation between the error terms ε_{ij} from the multinomial logit model estimated in the first stage and the error terms from each outcome equation μ_{ij}. Bourguignon *et al.* (2007) show that consistent estimates of β and α in the outcome equations 3.4 can be obtained by estimating the following selection bias-corrected agriculture income and the standard deviation of agriculture income equations:

$$
\begin{array}{rl}
\text{Regime 1}: & Q_{i1} = Z_i\beta_1 + \alpha_{i1}\overline{Z}_{i1} + \sigma_1\tau_{i1} + v_{i1} \text{ if } A_i = 1 \\
\vdots & \qquad\quad \vdots \qquad\qquad\qquad\qquad\qquad\qquad , \\
\text{Regime M}: & Q_{iM} = Z_i\beta_M + \alpha_{iM}\overline{Z}_{iM} + \sigma_M\tau_{iM} + v_{iM} \text{ if } A_i = M
\end{array}
\tag{3.5}
$$

where v is the error term with an expected value of zero, σ is the covariance between ε_{ij} and μ_{ij}, τ is the inverse Mills ratio computed from the estimated probabilities in equation 3.3 as follows:

$$
\tau_{ij} = \sum_{k \neq j}^{j} \rho_j \left[\frac{\hat{P}_{ki}\text{In}\left(\hat{P}_{ki}\right)}{1 - \hat{P}_{ki}} + \text{In}\left(\hat{P}_{ji}\right) \right] ; \rho
$$

where $\hat{P}$ represents the probability that farm household i chooses risk management strategy j as defined in equation 3.3, ρ_j is the correlation between ε_{ij} and μ_{ij}. The specification in equation 3.5 implies that the number of selection correction (bias) terms in each equation are equal to the number of multinomial logit choices M.

The specified model allows us to identify not only the direction of the bias related to the allocation of farm households in a specific strategy but also which choice among any two alternative strategies this bias stems from. For example, a positive bias correction coefficient related to alternative j selection equation in the alternative k outcome equation highlights higher outcomes of farm households who chose alternative k compared to farm households taken at random, due to the allocation of farm households with worse unobserved skills out of alternative k into the alternative j. In the nutshell, for each strategy-based outcome estimation, a negative (positive) selectivity coefficient related to any of the alternative strategies, indicates lower outcomes than those of randomly chosen farm households on account of the allocation of farm households with better (worse) unobserved characteristics out of the given strategy and into the respective alternative risk management strategy.

3.3.3 Estimating the standard deviation of agriculture incomes

Ideally in estimating dispersions around agriculture income, panel or longitudinal data will be the most appropriate to observe risk management strategies and dispersions around agriculture incomes over time. But since we only have cross-sectional data for this study, an alternative approach to observe dispersions around agriculture incomes was employed. In line with previous studies (Kim and Chavas, 2003; Koundouri *et al.*, 2006; Di Falco *et al.*, 2007; Di Falco and Chavas, 2009; Kassie *et al.*, 2015; Mukasa, 2018), the estimation strategy for the standard deviation of agriculture income consisted of computing moments of the income function. The moment-based approach has been widely used in the literature as an indicator of risk exposure. Furthermore, the central moment moments around the mean are widely considered as a proxy for downside risk or the probability of losses. According to Antle (1983), maximization of the expected utility of profit $\mathrm{E}[U(\pi)]$ is equal to the maximization of the relevant moments of the risk exposure (e) distribution conditional on inputs use. The estimation procedure involved first estimating each regime's net agriculture income function and then using the residuals to compute the simple moments for each farm household. The mean equation of agriculture income is estimated as follows:

$$R_{Vij} = \phi_{i1} H_{ij} + \gamma_{i1} \overline{H}_{ij} + \Psi_{ij} \tag{3.6}$$

where R_{Vij} is the mean agriculture income of farm household i in regime j, H_i is a vector of variables assumed to influence the mean agriculture income functions; $\overline{H}_i$ is a vector of inputs used that may shift the farm production, these include fertilizer, seed and labour use, land size, soil fertility, etc.; and Ψ denotes error terms distributed with mean zero $\mathrm{E}(\Psi_{ij}) = 0$. ϕ and γ are vectors of parameters to be estimated and associated with H and $\overline{H}$, respectively. If we assume that the independent variables in equation 3.6 are exogenous, then equation 3.6 can be consistently estimated by using OLS[4]. The first moment of agriculture income is then estimated as follows:

$$f(H_i, \phi_i, \gamma_i, \overline{H}_i) \equiv E\left[R_{Vij}(H_i, \overline{H}_i, e)\right] \tag{3.7}$$

The higher moments of agriculture income can be written as follows:

$$\begin{aligned} E\left[R_{Vij}(H_i, \overline{H}_i, e) - f(H_i, \phi_i, \gamma_i, \overline{H}_i)^k | H\right] &= \\ f_k(H_i, \phi_i, \gamma_i, \overline{H}_{ik}) \text{ where } k &= 1, 2, 3 \end{aligned} \tag{3.8}$$

where $k = 1$ is the mean agriculture income functions, $k = 2$ and $k = 3$ are the second (variance) and third (skewness) central moments of agriculture income functions under each risk management strategy, respectively. The standard deviation[5] of agriculture incomes is then estimated as the squared root of the second central moment (variance) of agriculture incomes. The estimated standard deviation of agriculture income functions was then used as dependent variables in equations 3.5 to estimate the impact of the adoption of each risk management portfolio on dispersions around agriculture income.

While the variables X_i in equation 3.1 and Z_i in equation 3.5 are allowed to overlap, proper model identification requires at least one variable (instrument) in X_i that does not appear in Z_i. However, finding true instruments in empirical work is sometimes challenging, or even impossible (Kassie *et al.*, 2015). Therefore, the selection equation 3.1 is estimated based on all explanatory variables specified in the outcome equations plus at least one or more instruments. Following Di Falco and Veronesi (2013), we establish the admissibility of the selected instruments by performing a simple falsification test: the selected or valid instrument (s) is required to significantly influence a farm household's choice of risk management strategy but have no significant effect on the outcome of interest (i.e. agriculture income and

[4]We employed two different specification: linear and log-linear for the mean agriculture income equation. By observing the AIC and BIC with each specification, we settled for the log-linear specification because it produced the smallest values for AIC and BIC.

[5]It must be noted that the standard deviation estimated here are nothing other than the residual standard deviation. Most of the literature have used variance, skewness and kurtosis extensively, however this does not meet the interest of this paper, hence the second central moment (variance) was transformed into standard deviations. This is more advantageous because standard deviation is expressed in the same units as agriculture income, hence making it more intuitive and informative.

standard deviation of agriculture incomes). We also followed Stock *et al.* (2002) and examined the strength of the instruments based on the F-statistic. In this study, we employ distance to a major city and insurance needs as identifying instruments. Distance to a major city is expected to significantly influence the adoption of risk management strategies but not agriculture income or dispersions around income. At the same time, the insurance need of a household is expected to significantly influence the choice of a risk management strategy but not agriculture income or dispersions around income. As shown by Antle (1983) the error terms in equations 3.5 are likely to exhibit heteroscedasticity, hence following Bourguignon *et al.* (2007), we bootstrapped the standard errors to deal with heteroscedasticity in the second stage.

3.3.4 Estimation of the treatment and counterfactual effects

The adoption of risk management strategies by farm households could result in positive welfare outcomes for households. However, estimating such outcomes in observational studies such as this one is important because of the difficulty of observing the counterfactual outcomes. In cases where experimental data are involved or available through randomized control trials, for instance, information on the counterfactual situation would normally be provided, and as such, the problem of causal inference can easily be resolved (Miguel and Kremer, 2004). The challenge of evaluating impacts using observational data is to estimate the counterfactual outcome, which is the outcome of interest when farm households that adopted a particular risk management strategy could have gained had they not adopted that strategy. Di Falco (2014), argues that in the absence of a self-selection problem, it would be appropriate to assign to farm households that adopted a counterfactual outcome of interest equal to the average outcome of interest of non-adopters with the same observable characteristics. However, unobserved heterogeneity in the propensity to choose a risk management strategy also affects the outcome of interest and creates a selection bias in the outcome of interest equation that cannot be ignored. The Multinomial Endogenous Switching Regression framework however can be used to examine average treatment effects (ATT) by comparing expected outcomes of adopters with and without adoption. Following Bourguignon *et al.* (2007), we first derive the conditional expected outcome of interest (agriculture income and standard deviation of agriculture income) of farm households that adopted, which in our study means $j = 2 \ldots M$ from equation 3.5, as

$$\begin{aligned} E\left(Q_{i2}|A_i=2\right) &= Z_{i2}\beta_2+\alpha_{i2}\overline{Z}_{i2}+\sigma_2\tau_{i2} \\ \vdots \qquad & \qquad \vdots \\ E\left(Q_{iM}|A_i=M\right) &= Z_{iM}\beta_M+\alpha_{iM}\overline{Z}_{iM}+\sigma_M\tau_{iM} \end{aligned} , \tag{3.9}$$

Then, we obtain the expected outcome of interest of farm households that adopted risk management strategy j in the counterfactual hypothetical case that they did not adopt ($j = 1$) as

$$\begin{aligned} E\left(Q_{i1}|A_i=2\right) &= Z_{i2}\beta_1+\alpha_1\overline{Z}_{i2}+\sigma_{i1}\tau_{i2} \\ \vdots \qquad & \qquad \vdots \\ E\left(Q_{i1}|A_i=M\right) &= Z_{iM}\beta_M+\alpha_{iM}\overline{Z}_{iM}+\sigma_{iM}\tau_{i1} \end{aligned} , \tag{3.10}$$

Equations 3.9 represent the actual expected outcomes of interest (agriculture income and standard deviation of agriculture income) observed in the sample for adopting farm households, while equations 3.10 are their respective counterfactual expected outcomes of interest. The use of these conditional expectations allows us to calculate the average treatment effects (ATT) – i.e., the treatment effect for treated farm households, which is the difference between equations 3.9 and 3.10.

3.3.5 Method for addressing potential endogeneity

An issue that needs to be addressed in estimating equation 3.1 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, hence the need to account for any potential reverse causality between the adoption decision of risk management strategies and the outcomes of interest. A potential source of endogeneity identified in the empirical literature comes from the risk attitude of a farmer. The risk profile or risk perception of a farmer may influence the choice of risk management strategy. Risk management strategies employed by a farmer can potentially correlate to his or her risk profile or risk perception. Studies by Pennings and Leuthold (2000), Miyata (2003), Sherrick *et al.* (2004), Wik *et al.* (2004), Pennings *et al.* (2008), Kouamé (2010), Dercon and Christiaensen (2011), Theuvsen (2013), Ullah and Shivakoti (2014), Ullah *et al.* (2015), Meraner and Finger (2017), and Asravor (2019) all show that farmers' risk attitudes are positively correlated with the choice of risk management strategy. Since some of the risk management strategies employed by farmers are technologies and management practices based, farm households having access to agricultural extension agents might be encouraged to adopt these strategies. Furthermore, being a member of a farmer-based organization might influence access to formal risk management instruments such as index-based insurance or informal risk management instruments such as self-help groups.

Thus, risk attitude, extension, and membership of farmer-based organizations variables may be jointly determined with the decision of farm households choosing to adopt risk management strategies. Hence, the study followed previous studies (see Abdulai and Huffman, 2014; Ma and Abdulai, 2016), and controlled for the potential endogeneity of these variables using the control function approach developed by Wooldridge (2015). Due to the dichotomous nature of the three variables, we employed a probit regression specification of the potential endogenous variable (i.e., risk attitude, extension, and membership of farmer-based organization) as a function of all other variables used in the selection equation (i.e., equation 3.1) in addition to instrumental variables in the first-stage estimation, such as:

$$S_i = X_{ij}\tau + G_{ij}\gamma + \epsilon_{ij} \tag{3.11}$$

where S_i is a vector of the observed potential endogenous variables, X is as described previously in equation 3.1, G_{ij} is a vector of instrumental variables. The vectors τ and γ are the parameters to be estimated and ϵ_{ij} is the random error term. To ensure identification in the estimation of the adoption specification, some of the variables included in the first-stage estimation in equation 3.11 are excluded from the adoption equation in 3.1. For this study, the three variables included as instruments in equation 3.11 are storage technology used by farm household which is expected to influence risk attitude, the need for support which is expected to influence extension access and lastly access to production contract which is expected to affect membership in farmer-based organizations. In addition, it is also worth noting here that the instrumental variable(s) used here is expected to not correlate with the other instrumental variables (distance to a major city and insurance needs) used for the multinomial endogenous switching regression model identification[6]. We incorporated both potential endogenous variables and the estimated residuals[7] pre-

[6]Results of the control function and the correlation of instruments and our outcomes of interest are presented in Table 3.8 and 3.9 in the appendix.

[7]Wooldridge (2015, Pp. 427 – 428) proposes estimating a "generalized residuals" which uses the inverse Mills ratio (the ratio of the standard normal density, ϕ, divided by the standard normal cumulative distribution function, Φ) to compute the "generalized residuals".

dicted from equation 3.11 in the selection equation 3.1 to account for endogeneity as follows:

$$Y_{ij}^{*} = X_{ij}\beta + S_i\vartheta + R_{ij}\alpha + \omega_{ij} \tag{3.12}$$

where X_{ij} is as defined previously, S_i is a vector of the observed potential endogenous variables, and R_{ij} is a vector of the "generalized residuals" terms from the first-stage regressions of the endogenous variables in equation 3.11. The vectors β, ϑ, and α are the parameters to be estimated and ω_{ij} is the random error term. The endogenous variables become appropriately exogenous in a second-stage estimation equation by adding appropriate "generalized residuals" since they serve as the control function. As suggested by Wooldridge (2015), the approach leads to a robust, regression-based Hausman test for the endogeneity of the suspected variables. If the coefficient of the residual term is statistically significant, it shows that endogeneity was indeed present and also well controlled for in the model (Gibson *et al.*, 2010; Ricker-Gilbert *et al.*, 2011; Amankwah *et al.*, 2016; Harris and Kessler, 2019; Katengeza *et al.*, 2019; Ogutu *et al.*, 2019). Furthermore, Wooldridge (2015) observed that if the coefficient on the estimated generalized residual is statistically significant, there is a need to adjust the standard errors for the two-step estimation by bootstrapping.

3.4 Data and variable measurement

3.4.1 Farm household survey

The data used in the study comes from a farm household survey as part of the larger Senegalese "Projet d'appui aux politiques agricoles (PAPA)" or the Agricultural Policy Support Project. The farm household survey was conducted between April and May 2017 across all the 14 administrative regions of Senegal and all the departments except for the departments of Dakar, Pikine, and Guédiawaye. A total of 42 agricultural departments were included in the survey. The survey was targeted towards cereals, horticultural crops, and fruit and vegetable producers. 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 is 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 is practised and localized crops were grown such as Senegal River Valley and Niayes Market Gardening Zone, stratification of the rural census districts was done before agricultural households were selected. Data collected include information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit, inputs use and cost, family and hired labour, sales volumes, and food processing activities. Others included household consumption, access to amenities, non-farm and livestock revenue, remittance, agricultural insurance, risks and adaptation strategies, perception on input subsidies, and membership of farmer-based organizations.

3.4.2 Risk management typologies

During the survey, farm households were asked to identify the most recurring risks they faced in the previous 5 years preceding the survey. Additionally, they were asked to list the various adaptation strategies used in dealing with these recurrent risks. Nine main strategies were outlined by households and this is provided in Table 3.6 in the appendix. In the presence of production shocks, diversification of agricultural activities was the largest (39%) strategy employed by farm households to deal with risk. This is subsequently followed by an orientation to non-agricultural activities, which is employed by about 30% of households. Reduction of land areas under cultivation as a risk management strategy is employed by about 20% of the surveyed households. After risks have occurred, measures related to the sale of livestock are employed by about 20% of the surveyed households. Both sales of grain stock and property are used by 9% of farm households. Based on the empirical literature (see World Bank, 2001, 2005; Lilleor *et al.*, 2005; Chetaille *et al.*, 2011), we aggregated these risk management strategies employed by farm households based 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 3.6.

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 mostly used in response to the variation of farm income.

Since evidence from the empirical literature (Harwood *et al.*, 1999; Makki *et al.*, 2001; Flaten *et al.*, 2005; Velandia *et al.*, 2009; Ullah and Shivakoti, 2014; Ullah *et al.*, 2015; World Bank, 2016) suggest 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 possible combinations or portfolio of strategies that farm households could choose from (see Table 3.1). Based on these risk management portfolios, about 61% 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 about 19% of farm households while about 14% of farm households employ both ex-ante and ex-post measures. About 5% of farm households employ no risk management strategy.

3.4.3 The empirical specification

The specification of our empirical model is based on economic theory, empirical studies on risk management strategies adoption (Goodwin *et al.*, 2004; McNamara and Weiss, 2005; Finocchio and Esposti, 2008; Tavernier and Onyango, 2008; Ashfaq *et al.*, 2008; Velandia *et al.*, 2009; Deressa *et al.*, 2010; Poon and Weersink, 2011; Dadzie and de Graft Acquah, 2012; Enjolras *et al.*, 2012a; Amanor-Boadu, 2013; Bowman and Zilberman, 2013; Bryan *et al.*, 2013; Nienaber and Slavič, 2013; Bartolini *et al.*, 2014; Ullah and Shivakoti, 2014; Huang *et al.*, 2015; Ullah *et al.*, 2015; Meraner and Finger, 2017; Asravor, 2019; Vigani and Kathage, 2019) and factors affecting the variability of farm incomes (Pope and Prescott, 1980; Dunn and Williams, 2000; Schurle and Tholstrup, 1987, 1989; Purdy *et al.*, 1997; Barry *et al.*, 2001; Poon and Weersink, 2011; Enjolras *et al.*, 2012b). Following this literature, we summarized variables that are hypothesized to affect risk management strategies adoption decisions, agriculture income, and standard deviation of agriculture income.

The first outcome variable, agriculture income is composed of income from both crops and livestock. Livestock income was directly provided by households during the survey; however, crop income was estimated as the value of all household crop production in CFA. In our data, farm households produced about 33 different crops but on average, households produce 2 crops. Using the reported farm gate price, we estimated the monetary value of each crop commodity produced by farm households. A sum of the monetary value across all crops grown by households and livestock incomes represented a household's total agriculture income. The second outcome, deviations of agriculture income was estimated as previously described in equation 3.6 to 3.8. Table 3.2 presents the definition of the variables used in the analysis. The summary statistics of variables across the various risk management strategies and the pooled data are presented in Table 3.7 in the appendix. Households employing both ex-ante and ex-post risk management strategies appear to have the highest agriculture incomes followed by those who use ex-post strategies only. Ex-ante risk management adopting households have the least agricultural incomes. Similarly, households adopting both ex-ante and ex-post risk management strategies have the lowest deviations of agriculture incomes followed by ex-post risk management strategies adopting households. Households, not managing risk have the highest deviations of agriculture incomes. Table 3.7 also shows that households adopting both ex-ante and ex-post risk management strategies experience the highest risk and loss counts while households not managing risks have the lowest risk and loss counts.

Table 3.2: Variables definition

Name	**Variable description**
Outcome variables	
Agriculture income	Log of agriculture income in CFA
Std. agriculture income	Standard deviation of agriculture income in CFA
Household characteristics	
Age	Age of household head in years
Gender	=1 if the household is male-headed
Education	=1 if the household head has formal education
HH size	Number of people residing in the household
Risk attitude	=1 if the household is risk-taking
Remittance	=1 if the household receives remittances
Lighting fuel[a]	=1 if the source of lighting fuel is electricity
Share	Agricultural income share (%) in total household income
Insurance knowledge	=1 if farmer has ever heard of agricultural insurance
Farm characteristics	
Land	Total land area cultivated by household (ha)
Diversification[b]	Crop diversification index
Cash crop	Share of land under cash crops (%)
Soil quality[c]	Soil quality index
AII[d]	Agriculture implement index
Irrigation	=1 if the household uses irrigation
Farming system	=1 if household practices rainfed subsistence agriculture
Fertilizer	Total fertilizer quantity used in kg
Seed	Total seed quantity used in kg
Labour	Total quantity of labour used
Risk indicators	
Std. Rainfall	Standard deviation of rainfall (2000 – 2015)
Rainfall	Log of mean annual rainfall in mm (2000 – 2015)
Risk count	Number of production risks faced by the household
Loss count	Number of risk-related losses experienced by household

[a] Source of lighting fuel is used as a proxy variable for household wealth.

[b] The diversification index estimated here is simply the Herfindahl-Hirschman Index (HHI) which is calculated by squaring the land area share of each crop grown by a household and then summing the resulting numbers. It can range from close to zero to 1. A value of 1 means that the household produces only one crop, while a value close to zero suggests a high crop diversification. This index is not meant to measure risk management by rather identify the crop portfolio of households.

[c] For soil quality, we computed a soil quality index using publicly available data from the International Soil Reference and Information Centre (ISRIC – World Soil Information). We describe the computation of this index in the appendix.

[d] The agricultural implement index was computed using a principal component analysis (PCA) based on the number of agricultural equipment owned by a household.

Table 3.2: Variables definition(*continued*)

Name	**Variable description**
Access to institutions	
Extension access	=1 if accessed extension service
Membership	=1 if a member of a farmer-based organization
Credit access	=1 if access to credit
Subsidy	=1 if access to subsidies
Mundlak Fixed Effects	
Mean land	Mean land (ha) allocation across all crops grown
Mean fertilizer	Mean fertilizer (kg) use across all crops grown
Mean seed	Mean seed (kg) use across all crops grown
Mean labour	Mean labour used across all crops grown
Instrumental variables	
Distance	Log of distance to a major city in km
Insurance needs	=1 if farmer has specific insurance needs
Contract	=1 if access to production contracts
Storage	=1 if household use metal silos
Support	=1 if farmer has support needs

3.5 Empirical Results

In this section, we first investigate factors driving the adoption of the various risk management strategies in isolation or combination. Secondly, we present the economic implications associated with each risk management portfolio on household agriculture incomes and the standard deviation of agriculture. We do not however discuss results of the econometric estimation of agriculture income, agriculture income function, and the standard deviation of agriculture income models. Related results are however provided in Table 3.11 to Table 3.13 in the appendix. The selectivity correction terms (m0 to m3) in Table 3.12 and 3.13 are significant in some of the risk management portfolio equations. This indicates the presence of sample selectivity effects and using OLS would have produced biased and inconsistent estimates. Thus, accounting for selectivity effects using the Multinomial Endogenous Switching Regression model was appropriate.

Table 3.3 shows the results of the multinomial logit model for the different risk management portfolios. We find that the multinomial logit model fits the data well, the Wald test is highly significant, hence rejecting the null hypothesis that all the regression coefficients are jointly equal to zero. The test for the joint significance of instruments across the different risk management portfolios is highly significant. The results from the control-function specification indicate that the correction for endogeneity in the model was necessary. We find the coefficient of the extension access and membership of farmer-based organization residual term to be statistically significant in two of the risk management strategies, implying the presence of endogeneity of extension access and membership of farmer-based organization. The results from the control-function approach are presented in Table 3.8. Our results also suggest that selected instruments used in the control function approached satisfied the necessary conditions. Not only do the instruments (storage technology, support needs, and contracts) have a significant effect on the potentially endogenous variables but they are also not correlated to the two instrumental variables (distance to a major city and insurance needs) used in the multinomial endogenous switching regression model identification. A correlation test between instrumental variables used (Table 3.9) in model identification and the control function also shows weak correlations, suggesting that the condition is met.

3.5.1 Drivers of Risk Management Strategies

From Table 3.3, the relative probability of adopting ex-ante risk management strategies (RMP1) is strongly negative and statistically significant for the education level of household head, membership of farmer-based organizations, remittance, the share of agriculture income in total household income, and distance to a major city. This suggests that household heads with formal education and households that are members of farmer-based organizations are less likely to adopt ex-ante risk management strategies. Receiving remittances, increasing share of agriculture income in total household income and an increasing distance of a household to a major city are associated with a less likelihood of ex-ante risk management strategies adoption. Conversely, we find that the number of risk and losses experienced, extension and credit access and insurance needs are strongly positive and statistically significant for the adoption of ex-ante risk mitigation strategies.

Concerning ex-post risk management strategies (RMP2), we find that the probability of adoption is positive and statistically significant for the gender of the household head, the number of risks and losses experienced, insurance knowledge, and needs. On the contrary, we find that the education level of household head, lighting fuel which is a proxy for household wealth, risk attitude, and distance to a major city is strongly negative and statistically significant for the adoption of ex-post strategies. We find that the age and education level of the household head, the proxy variable for household wealth – lighting fuel, membership of farmer-based organizations, and share of agriculture income in total household income are negatively associated with the adoption of both ex-ante and ex-post risk management strategies (RMP3). However, the number of risk and losses experienced, extension and credit access, subsidy access, and insurance needs and knowledge are positive and statistically significant for the adoption of both ex-ante and ex-post risk management strategies. The adoption of risk management strategies appears to be largely driven by the educational level of the household head, the number of risks and losses experienced, and insurance needs.

Table 3.3: Parameter estimates of risk management portfolios adoption, Multinomial Logit Selection Model

	RMP1		RMP2		RMP3	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	3.235***	0.754	1.285	0.812	-0.170	0.834
Age	-0.002	0.005	-0.009	0.006	-0.012*	0.006
Gender	0.023	0.238	0.602**	0.273	0.289	0.298
Education	-0.324**	0.158	-0.350**	0.171	-0.368**	0.181
HH size	0.021	0.022	0.031	0.023	0.036	0.024
Lighting fuel	0.013	0.141	-0.440***	0.155	-0.374**	0.175
Risk attitude	-2.250	1.775	-3.236*	1.892	-2.888	1.970
Risk count	0.238**	0.099	0.309***	0.104	0.564***	0.105
Loss count	0.432***	0.122	0.330**	0.129	0.772***	0.133
Std. Rainfall	0.000	0.003	0.001	0.003	0.001	0.003
Extension	1.941**	0.786	0.366	0.881	1.874*	0.961
Membership	-1.835*	1.004	-0.063	1.137	-3.914***	1.195
Credit	0.946**	0.440	0.732	0.499	1.280**	0.511
Land	0.017	0.024	0.033	0.026	0.016	0.025
Irrigation	0.258	0.236	0.001	0.276	0.265	0.305
Cash crop	0.001	0.004	0.001	0.004	0.005	0.004
Total labour	0.021	0.021	0.034	0.024	0.035	0.025
Subsidy	0.115	0.460	0.084	0.492	1.026**	0.506
Remittance	-0.413*	0.245	-0.284	0.271	-0.046	0.283
Share	-1.136*	0.610	-0.133	0.647	-1.126*	0.662
Insurance knowledge	0.090	0.200	0.410*	0.215	0.947***	0.229
Distance	-0.005**	0.002	-0.010***	0.002	-0.002	0.002
Insurance needs	0.731***	0.183	1.032***	0.199	0.865***	0.202
Resid risk	0.826	1.052	1.591	1.124	1.313	1.176
Resid extension	-1.072***	0.399	-0.459	0.449	-0.800	0.502
Resid membership	0.477	0.481	-0.536	0.557	1.615***	0.570
Joint sig. of instruments (χ^2)	27.020***		54.640***		21.280***	
Wald test, χ^2 (75)			1151.100***			
N			5,185			

Notes: The base category is farm households that did not adopt any of the risk management portfolios (i.e., RMP0). RMP1 – denotes ex-ante risk management, RMP2 – denotes ex-post risk management, and RMP3 – denotes both ex-ante and ex-post risk management. ***, **, * represent 1%, 5%, and 10% significance level, respectively. Reported standard errors are the bootstrapped standard errors.

3.5.2 Economic Implications of Risk Management Strategies

The objective of this paper is to identify which optimal risk management strategies allow households to maximize their objectives in terms of expected income and minimize variability of income. In this section, the study attempts to identify the "best" tools, in terms of maximizing and stabilizing farm households' agriculture incomes. The economic implications of adopting each risk management portfolio on farm households' agricultural incomes and the standard deviation of income measured in terms of the average treatment effects (ATT) for the treated farm households are presented in Tables 3.4 and 3.5, respectively. After controlling for the effects of several covariates and the selection bias stemming from both unobserved and observed factors on household agriculture incomes, the adoption of the ex-post risk management strategies either in isolation or in combination with ex-ante strategies is significantly associated with positive agriculture incomes. In the case of ex-ante risk management strategies, the observed effect was negative.

The adoption of ex-post risk management strategies provides higher agriculture incomes compared to a counterfactual case where farm households do not adopt it as a risk management measure. This is not surprising because ex-post risk management strategies rely largely on the sale of assets. By using ex-post risk management as a strategy, farm households obtain about 2.43% more agriculture income and this effect is statistically significant at 1%. Ex-post risk management might be an effective strategy to smooth household consumption in the short run. For wealthy or resource endowed households, this might be beneficial in terms of smoothing household incomes and consumption shortfalls. However, for poorer households, this might be a costly strategy, especially in the long run since they will be unable to recover the loss of productive assets ex-post the shock (Bhandari *et al.*, 2007; Barnett *et al.*, 2008; Amare *et al.*, 2018), which might partly be due to the cost in terms of production efficiency and reduced profits (World Bank, 2005).

Table 3.4: Impact on agriculture income by risk management strategy

Strategy	**Actual total agriculture income**	**Counterfactual total agriculture income - If households did not manage risk**	**ATT**	**Change (%)**
Ex-ante	5.362(0.007)	5.385(0.011)	-0.023*(0.013)	-0.43
Ex-post	5.567(0.011)	5.432(0.020)	0.135***(0.023)	2.43
Ex-ante and ex-post	5.591(0.010)	5.500(0.023)	0.091**(0.025)	1.63

Notes: Standard errors are in parentheses. ***, **, * represent 1%, 5%, and 10% significance level, respectively.

Table 3.5: Dispersions impact on agriculture income by risk management strategy

Strategy	**Actual std of agriculture income**	**Counterfactual std of agriculture income - If households did not manage**	**ATT**	**Change (%)**
Ex-ante	0.337(0.002)	0.368(0.003)	-0.030***(0.004)	-8.83
Ex-post	0.281(0.003)	0.343(0.007)	-0.062***(0.008)	-22.02
Ex-ante and ex-post	0.279(0.003)	0.301(0.007)	-0.021***(0.008)	-7.66

Notes: Standard errors are in parentheses. *** represent 1% significance level.

The adoption of both ex-ante and ex-post also leads to higher agriculture income compared to the counterfactual case of non-adoption. The adoption of this risk management strategy increases household agriculture incomes by about 1.63% compared to the counterfactual case of not adopting this strategy. By virtue of the treatment effects, adopting both ex-ante and ex-post risk management strategies does not appear to help households maximize their expected agriculture income incomes compare to adopting just adopting ex-post risk management strategies in isolation. Surprisingly managing risk ex-ante reduces household agriculture incomes by about 0.43%. The effect is also statistically significant at 10%. Table 3.6 sheds important insights as to why the use of ex-ante risk management strategies might have negative effects on household's agriculture incomes. We see from Table 3.6 that the ex-ante risk management strategies such as reduction of cultivated areas and orientation to non-agricultural activities account for about 20.4% and 30.2% of the ex-ante risk management strategies employed by households. Intuitively, there is an opportunity cost related effect to the use of these strategies. For example, Soullier (2017), estimates the opportunity cost of labour in Senegalese rice value chain to be about FCFA 500 (US$ 0.93) per day during the production season. Particularly for rice harvest, the opportunity cost for labour can be as high as FCFA 1,500 (about US$ 2.79) per day.

The use of these strategies causes losses in agricultural income. Furthermore, production or agricultural diversification, in particular, could lead to shifts or reallocation of resources (land) for high-value crops and staple crops and this can have a negative effect on agriculture income when a household 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). Evidently, we find that farm households using ex-ante risk management strategies allocate about 48.8% of their cultivated lands towards staple crop production and only about 25.9% towards cash crops. As argued by Skees *et al.* (2002) and Larochelle and Alwang (2013) diversification can also hinder important gains that can be obtained from specialization. Other results also suggest that diversification is beneficial up to a certain threshold only (Schoney *et al.*, 1994). Although a less important ex-ante risk management strategy used by households, renting out land is associated with an opportunity cost in the form of lost or foregone revenues or opportunities for profitable agriculture enterprises. For instance, Soullier (2017) observed the opportunity cost of land rental in Senegalese rice value chain to be about CFA 40,000 (about US$ 75) per hectare.

Perhaps the most effective ex-ante risk management strategy, insurance adoption, usually permits farm households to use more productive inputs such as organic fertilizer, improved or high yielding varieties of crops. However, the empirical literature suggests some adverse effects related to insurance use. Most of these are related to moral hazard problems. For instance, in the US, Smith and Goodwin (1996) found that fertilizer and chemical use among Kansas wheat producers tended to be negatively correlated with insurance purchases. They found that producers who purchased insurance use fewer inputs than those producers that did not buy insurance. Similarly, Giné and Yang (2009) and de Nicola (2015) finds insurance contracts to significantly reduce total input and investments in new agricultural opportunities. In Hungary, Spörri *et al.* (2012) also found a negative impact of insurance on farm profit, labour, and land productivity in arable farms. Similarly in France and Hungary, Vigani and Kathage (2019) also find that insurance negatively affects farm efficiency.

Furthermore, some risk transfer products have been found to reduce the use of complementary risk management strategies such as diversification (Schaffnit-Chatterjee, 2010; Nigus *et al.*, 2018; Matsuda *et al.*, 2019). This crowding-out effect could potentially have cascading effects which might be reflected in income shortfalls. At the same time, other behavioural biases related to less effort devoted towards farming activities by insurance policyholders might explain the findings. As shown in previous studies (see Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Goodwin, 2001; Goodwin *et al.*, 2004) insurance use leads to moral hazard problems and farmers with insurance are likely not going to take care in their production activities compared to a situation without insurance.

Results of the effect of risk management on dispersions around agriculture incomes are presented in Table 3.5. Managing production risks either through single strategies or in combination in effect helps to reduce dispersions around agriculture incomes. By using ex-ante risk management strategies, farm households reduce dispersions around agriculture incomes by about 9% and this effect is statistically significant at 1%. Not surprisingly, ex-post risk management strategies which are heavily skewed towards to sale of assets allow farm households to reduce dispersions around agriculture by about 22% compared to the counterfactual case of not employing ex-post risk management strategies. Employing a combination of ex-ante and ex-post risk management strategies significantly reduces dispersions around agriculture incomes by about 8% compared to the counterfactual case of not employing this combination. Additionally, the results suggest that adopting both ex-ante and ex-post risk management strategies does not provide the largest benefits in terms of reducing dispersions around agriculture income incomes compare to adopting just ex-ante or ex-post risk management strategies in isolation.

3.6 Conclusion

This study sought to investigate how effective the various risk management strategies employed by farm households to deal with risk are and to identify which optimal risk management strategies allow households to maximize their objectives in terms of expected income and reductions in the variability of income. We employed a multinomial endogenous switching regression that accounts for selectivity bias and a moment-based approach to determine the impacts of the various risk management strategies on agriculture incomes and their dispersions around agriculture incomes in a multinomial framework. Our results suggest that risk management strategies employed by households are largely driven by the educational level of the household head, the number of risks and losses experienced by the household, and insurance needs. We find a positive impact of ex-post risk management strategies adoption either in isolation or in combination with ex-ante risk management strategies on farm household agriculture incomes. Risk management through ex-ante risk management strategies appears to negatively affect agriculture incomes because these strategies are primarily related to opportunity costs and suboptimal allocation of productive resources. We find that adopting both ex-ante and ex-post risk management strategies do not lead to a significantly higher net impact in terms of agriculture incomes.

We find that the adoption of all risk management strategies by farm households are effective in reducing the dispersions around agriculture incomes. Ex-post risk management strategies have the highest observed effect on reducing dispersions around agriculture income. The use of these strategies reduces dispersions around agriculture incomes by about 22%. Although ex-ante risk management appears to have a negative impact on agriculture incomes, we find that it appears to have a larger dispersion reduction effect on agriculture incomes compared to using it in combination with ex-post risk management strategies. Overall, ex-post risk management strategies appear to be the most effective in terms of helping households to maximize their objectives in terms of expected income and reducing the variability of incomes. However, the use of ex-post strategies can have very severe implications in terms of deepening poverty through the reduction of assets and thus might not be an effective strategy for very poor households.

Our findings have some important policy implications. First, there is a need for a more targeted and systematic approach to agricultural risk management. Of particular relevance is the need for several kinds of implementation instruments such as agricultural investments and technical assistance that can amplify the benefits of some of the risk management strategies employed by households. For example, investments related to the provision of climate information, for example, can be beneficial for farmers adopting ex-ante risk management strategies through helping them to select the right crop commodities to produce for a particular season and at what time within the season to sow for instance. At the same time, empowering farmer's management of climate risks will require the adoption of context-suitable agricultural practices such as conservation agriculture, sustainable land management practices, etc., and technologies that are important low-cost risk mitigation strategies such as improved and drought-resistant varieties of crops. This will require the provision of information and technical assistance to farmers in the use and implementation of these practices. Although the study finds that ex-post risk management strategies appear to be more effective in terms of agriculture incomes and reducing dispersions around income, farm households' long-term management of risks should be encouraged and supplemented through the adoption of formal risk transfer products such as index-based insurance. For especially poor households, overcoming some socioeconomic and institutional barriers will be particularly important in improving access and use of these products.

In conclusion, there are some important caveats to be considered for this study. Due to the lack of panel or longitudinal datasets, the study relied solely on cross-sectional data. Hence the analysis used in this paper is a static one and also neglects the dynamic behaviour of production systems. Also, the effectiveness of the various risk management strategies might have both temporal and spatial dimensions which are not evaluated in this study. Some of the studied risk management strategies can be effective in the short run, while others might be effective in the long run. Hence, having access to data with a long-time dimension on various production systems, agriculture incomes, and risk management strategies employed by farm households would allow for the investigation of all these dimensions and provide a better comparison between the various risk management strategies. Such data would be needed to provide more robust evidence on the implication of risk management on important household welfare outcomes. Furthermore, since we clustered the various risk management strategies into three broad typologies, we failed to evaluate the impacts of their individual components. Because production conditions and the scope of risk management strategies are heterogeneous across farms, focusing on aggregate effects as we did in this study may obscure important individual strategy specific effects for instance.

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Appendix

Appendix A1

Table 3.6: Risk management strategies employed by farm households

Risk management strategies	**Frequency**	**Percent (%)**
Ex-ante strategies		
Diversify agricultural activities	2,040	39.34
Reduce the area under cultivation	1,055	20.35
Orientation to non-agricultural activities	1,565	30.18
Rent land to others	119	2.3
Subscribe to agricultural insurance	161	3.11
Ex-post strategies		
Sell grain stocks	483	9.32
Sell property	452	8.72
Sale of animals	1,055	20.35
Exchange/swap clothes or jewels for food	71	1.37
Total number of households	**5185**	**100**

Table 3.7: Means and standard deviation of variables by risk management strategy

	RMP0		RMP1		RMP2		RMP3		Pooled data	
Variable	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**	**Mean**	**Std. Dev**
Agriculture income	5.474	0.639	5.358	0.585	5.564	0.516	5.581	0.439	5.436	0.566
Std. agriculture income	0.356	0.351	0.339	0.313	0.280	0.260	0.277	0.227	0.320	0.296
Age	52.781	13.547	53.434	13.401	51.985	12.769	52.515	13.163	52.989	13.265
Gender	0.910	0.286	0.909	0.287	0.950	0.218	0.948	0.222	0.923	0.267
Education	0.470	0.500	0.381	0.486	0.372	0.483	0.356	0.479	0.380	0.485
HH size	9.355	4.694	9.556	5.305	10.030	5.177	10.484	5.274	9.768	5.255
Lighting fuel	0.366	0.482	0.377	0.485	0.259	0.438	0.307	0.462	0.344	0.475
Risk attitude	0.599	0.491	0.338	0.473	0.407	0.492	0.385	0.487	0.372	0.483
Risk count	1.043	1.311	1.725	1.395	1.839	1.593	3.066	1.635	1.899	1.549
Loss count	1.215	1.041	1.623	0.985	1.588	0.972	2.419	1.256	1.706	1.071
Std. Rainfall	107.629	24.557	109.318	24.038	110.556	23.976	111.176	25.984	109.728	24.346
Rainfall	6.358	0.469	6.396	0.454	6.407	0.436	6.439	0.431	6.402	0.448
Extension	0.229	0.421	0.154	0.361	0.102	0.302	0.170	0.376	0.150	0.358
Membership	0.315	0.466	0.135	0.341	0.082	0.274	0.105	0.307	0.130	0.336
Credit	0.039	0.195	0.046	0.210	0.043	0.203	0.041	0.199	0.045	0.206
Land	4.801	8.943	5.077	8.337	6.222	8.878	6.207	6.202	5.443	8.232
Fertilizer	365.627	1294.696	219.305	1190.949	186.673	578.637	251.247	2773.626	225.357	1451.056
Seed	148.807	178.095	141.178	171.168	157.245	178.077	177.093	188.539	149.756	175.835
Labour	3.918	2.446	3.966	3.151	4.170	3.415	4.185	2.930	4.034	3.141
Irrigation	0.280	0.450	0.219	0.414	0.127	0.334	0.123	0.329	0.191	0.393
Cash crop	23.004	28.176	25.917	27.679	29.319	23.932	33.695	26.980	27.514	27.075
Subsidy	0.591	0.492	0.493	0.500	0.444	0.497	0.662	0.473	0.513	0.500
Remittance	0.111	0.315	0.095	0.293	0.090	0.286	0.125	0.331	0.099	0.299
Share	0.953	0.153	0.884	0.252	0.927	0.173	0.863	0.231	0.893	0.232
Diversification	41.600	35.072	51.156	32.482	46.778	26.215	52.524	24.998	49.987	30.655
Mean land	2.538	5.400	2.402	4.365	2.439	2.667	2.689	3.389	2.457	4.026
Mean fertilizer	321.090	1312.552	141.816	1138.028	85.213	251.226	172.839	2768.860	144.658	1407.403
Mean seed	87.848	124.938	69.208	91.845	63.053	71.357	73.117	80.530	69.548	88.949
Mean labour	2.438	1.923	2.339	2.240	2.011	1.810	1.997	1.616	2.232	2.073
Insurance knowledge	0.258	0.438	0.254	0.435	0.274	0.446	0.363	0.481	0.273	0.446
Distance	68.808	52.852	54.368	40.609	45.769	38.331	49.849	32.138	52.843	40.176
Insurance needs	0.287	0.453	0.373	0.484	0.447	0.497	0.433	0.496	0.391	0.488
Storage	0.093	0.291	0.156	0.363	0.201	0.401	0.227	0.419	0.172	0.377
Support	0.699	0.460	0.759	0.428	0.718	0.450	0.804	0.397	0.754	0.431
Contract	0.018	0.133	0.026	0.160	0.021	0.143	0.018	0.132	0.024	0.152
AII	0.048	1.269	0.116	1.238	-0.272	1.305	-0.274	1.297	-0.018	1.274
Soil quality	0.349	0.118	0.384	0.100	0.402	0.086	0.380	0.088	0.385	0.098
Farming system	0.688	0.464	0.835	0.371	0.896	0.305	0.963	0.189	0.857	0.350
N	279		3,172		1,004		730		5,185	

Notes: RMP0 – denotes no risk management, RMP1 – denotes ex-ante risk management, RMP2 – denotes ex-post risk management, and RMP3 – denotes both ex-ante and ex-post risk management.

Table 3.8: Control function approach for potentially endogenous variables

	Risk attitude		**Extension**		**Membership**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	-1.996***	0.169	-3.087***	0.226	-1.686***	0.214
Age	0.000	0.001	0.003*	0.002	-0.004*	0.002
Gender	0.142*	0.076	0.066	0.092	-0.156*	0.093
Education	0.128***	0.040	0.081	0.051	0.193***	0.053
HH size	0.024***	0.004	-0.019***	0.006	0.021***	0.006
Lighting fuel	0.012	0.041	0.111**	0.051	-0.050	0.054
Risk attitude			0.015	0.054	0.393***	0.054
Risk count	-0.026	0.016	0.075***	0.019	-0.042**	0.020
Loss count	0.015	0.021	0.012	0.025	0.054**	0.027
Std. Rainfall	-0.001	0.001	0.001	0.001	-0.001	0.001
Extension	-0.011	0.057			0.652***	0.061
Membership	0.443***	0.060	0.701***	0.063		
Credit	0.310***	0.092	-0.064	0.103	0.556***	0.095
Land	0.019***	0.003	-0.006	0.004	-0.006	0.004
Irrigation	0.255***	0.057	0.508***	0.063	0.164**	0.067
Cash crop	0.003***	0.001	-0.003***	0.001	-0.005***	0.001
Total labour	0.006	0.007	0.012	0.009	0.003	0.009
Subsidy	0.710***	0.04	0.263***	0.053	0.264***	0.055
Remittance	-0.090	0.065	0.312***	0.073	-0.068	0.085
Share	0.670***	0.093	0.074	0.110	-0.142	0.115
Insurance knowledge	0.029	0.046	0.505***	0.054	0.142**	0.058
Distance	0.001	0.001	0.005***	0.001	0.005***	0.001
Insurance needs	0.143***	0.041	-0.182***	0.053	0.196***	0.053
Storage	**-0.191*** **	0.052				
Support			**0.981*** **	0.09		
Contract					**0.619*** **	0.125
Log-likelihood	-2958.131		-1696.226		-1557.932	
LR chi2(22)	949.75***				1041.04***	
N			5,185			

Notes: Standard errors are in parentheses. ***, **, * represent 1%, 5%, and 10% significance level, respectively.

Table 3.9: Correlation test of instrumental variables

Variables	**Distance**	**Insurance needs**	**Storage**	**Support**	**Contracts**
Distance	1.000				
Insurance needs	0.098	1.000			
Storage	-0.166	-0.055	1.000		
Support	0.081	0.219	0.021	1.000	
Contracts	0.076	0.066	0.017	0.065	1.000

Table 3.10: Test of the validity of the instrument (falsification test) on non-adopters

	Selection equation		**Agriculture income**		**Std of agriculture income**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	-3.235***	0.758	4.564***	0.316	0.518**	0.207
Age	0.002	0.005	-0.003	0.003	0.001	0.002
Gender	-0.023	0.235	0.371***	0.121	-0.073	0.080
Education	0.324*	0.168	0.073	0.074	0.009	0.049
HH size	-0.021	0.022	-0.008	0.009	0.005	0.006
Lighting fuel	-0.013	0.148	0.002	0.074	-0.024	0.049
Risk attitude	2.250	1.829	0.169**	0.076	-0.032	0.050
Risk count	-0.238**	0.109	-0.042	0.035	-0.008	0.023
Loss count	-0.432***	0.126	0.058	0.040	0.022	0.026
Std. Rainfall	0.000	0.003	-0.004***	0.001	0.000	0.001
Extension	-1.941**	0.765	-0.128	0.097	-0.007	0.064
Membership	1.835*	1.014	0.018	0.091	0.109*	0.060
Credit	-0.946**	0.446	-0.029	0.175	0.174	0.115
Land	-0.017	0.024	0.016***	0.004	0.001	0.003
Irrigation	-0.258	0.237	0.525***	0.101	0.040	0.066
Cash crop	-0.001	0.004	0.005***	0.001	-0.001	0.001
Labour	-0.021	0.023	0.040**	0.016	-0.018*	0.011
Subsidy	-0.115	0.495	0.194**	0.081	-0.134**	0.053
Remittance	0.413*	0.246	0.110	0.105	-0.015	0.069
Share	1.136*	0.637	0.435**	0.220	-0.049	0.144
Insurance knowledge	-0.090	0.194	0.023	0.089	-0.034	0.058
Distance	**0.005****	0.002	**0.000**	0.001	**0.000**	0.001
Insurance needs	**-0.731*****	0.174	**0.103**	0.088	**-0.022**	0.058
Resid risk	-0.826	1.101				
Resid extension	1.072***	0.373				
Resid membership	-0.477	0.498				

Note: In the reported selection equation, ex-ante risk management strategies (RMP1) was set as the base category. Selection equation results are for households, not managing risks (i.e. RMP0). ***, **, * represent 1%, 5%, and 10% significance level, respectively. Reported standard errors for the selection equation are the bootstrapped standard errors.

Table 3.11: Log-linear agriculture income function estimation

	RMP0		**RMP1**		**RMP2**		**RMP3**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Age	-0.002	0.002	0.000	0.001	0.000	0.001	0.000	0.001
Gender	0.346***	0.118	0.179***	0.030	0.302***	0.057	0.173***	0.062
Education	0.068	0.068	-0.032*	0.017	-0.006	0.026	0.000	0.029
HH size	-0.009	0.008	0.000	0.002	0.004	0.003	0.013***	0.004
Extension	-0.134	0.096	0.144***	0.025	0.164***	0.046	0.080**	0.038
Credit	-0.061	0.166	0.046	0.041	0.152**	0.064	0.086	0.073
Membership	0.033	0.089	0.071***	0.027	0.001	0.050	0.077*	0.046
Subsidy	0.177**	0.076	0.032*	0.018	0.094***	0.026	0.017	0.031
Remittance	-0.019	0.103	-0.031	0.029	0.026	0.044	-0.017	0.042
Contract	0.040	0.254	0.059	0.055	0.056	0.090	0.061	0.108
AII	-0.070**	0.033	-0.047***	0.008	-0.041***	0.011	-0.018	0.013
Rainfall	-0.000**	0.000	0.000	0.000	0.000**	0.000	0.000	0.000
Land	0.007*	0.004	0.005***	0.001	0.009***	0.002	0.013***	0.003
Fertilizer	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.000
Seed	0.001**	0.000	0.001***	0.000	0.001***	0.000	0.000***	0.000
Labour	0.018	0.016	0.010***	0.003	0.002	0.004	0.000	0.006
Soil quality	0.025	0.333	-0.439***	0.086	-0.500***	0.155	-0.025	0.161
Farming system	-0.580***	0.121	0.105***	0.036	0.261***	0.062	-0.150*	0.088
Cash crop	0.004***	0.001	0.001***	0.000	0.001*	0.001	-0.001	0.001
Diversification	0.000	0.001	-0.004***	0.000	-0.004***	0.001	-0.002***	0.001
Constant	5.419***	0.237	5.220***	0.059	5.016***	0.110	5.375***	0.136
Adj R^2	0.339		0.374		0.440		0.314	
Root MSE	0.520		0.463		0.386		0.363	
AIC	446.709		4137.159		958.711		614.242	
N	279		3,172		1,004		730	

Notes: RMP0 – denotes no risk management, RMP1 – denotes ex-ante risk management, RMP2 – denotes ex-post risk management, and RMP3 – denotes both ex-ante and ex-post risk management. $***$, $**$, $*$ represent 1%, 5%, and 10% significance level, respectively.

Table 3.12: Estimates of agriculture income equations

	RMP0		RMP1		RMP2		RMP3	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	6.674***	0.857	4.658***	0.205	4.061***	0.375	5.346***	0.409
Age	0.002	0.003	0.001	0.001	-0.001	0.001	0.001	0.001
Gender	0.309**	0.128	0.136***	0.041	0.274***	0.089	0.097	0.072
Education	-0.033	0.085	-0.037*	0.022	-0.011	0.027	-0.011	0.033
HH size	-0.020**	0.009	0.000	0.002	0.006*	0.003	0.010**	0.004
Lighting fuel	0.002	0.093	0.019	0.032	-0.039	0.042	0.077*	0.042
Risk attitude	0.019	0.144	-0.024	0.036	0.051	0.043	0.040	0.053
Risk count	-0.001	0.053	-0.014	0.016	0.050***	0.018	-0.016	0.021
Loss count	0.003	0.061	-0.023	0.017	-0.002	0.023	-0.006	0.024
Rainfall	-0.251***	0.074	0.014	0.019	0.056*	0.031	-0.021	0.034
Extension	-0.124	0.099	0.171***	0.031	0.107**	0.046	0.120**	0.049
Membership	0.124	0.132	0.009	0.038	-0.053	0.060	0.126**	0.057
Credit	-0.109	0.175	0.082*	0.045	0.171***	0.066	0.098	0.089
Land	0.011	0.024	0.013**	0.006	-0.009*	0.005	0.019**	0.009
Fertilizer	0.001***	0.000	0.000***	0.000	0.000	0.000	0.000	0.000
Seed	0.000	0.000	0.001***	0.000	0.001***	0.000	0.000	0.000
Labour	0.088***	0.027	0.059***	0.006	0.023***	0.008	0.005	0.012
Subsidy	0.187*	0.098	-0.004	0.032	0.065	0.043	0.016	0.056
Cash crop	0.005**	0.002	0.001*	0.000	0.003***	0.001	0.000	0.001
Irrigation	0.595***	0.126	0.087**	0.038	0.009	0.067	0.152***	0.057
Remittance	-0.026	0.105	-0.080**	0.035	0.008	0.051	-0.025	0.049
Diversification	0.000	0.001	-0.003***	0.000	-0.003***	0.001	-0.001	0.001
Mean land	-0.003	0.040	-0.017	0.012	0.070***	0.017	-0.015	0.019
Mean fertilizer	-0.001**	0.000	0.000	0.000	0.000***	0.000	0.000	0.000
Mean seed	0.001	0.001	0.000	0.000	-0.002***	0.001	0.000	0.001
Mean labour	-0.124***	0.039	-0.088***	0.009	-0.043**	0.017	-0.014	0.025
m0	-0.109	0.313	-1.115**	0.443	-1.322***	0.474	-0.269	0.562
m1	0.456	0.925	-0.469**	0.192	-1.062**	0.533	0.134	0.294
m2	-0.027	1.047	-0.920**	0.389	-0.256*	0.151	-0.848**	0.420
m3	-0.363	1.301	-1.249***	0.461	-0.441	0.506	-0.162	0.138
Joint significance of crop varying covariates χ^2 (4)	23.930***		143.570***		30.730***		2.840	
N	269		3150		992		726	

Notes: RMP0 – denotes no risk management, RMP1 – denotes ex-ante risk management, RMP2 – denotes ex-post risk management, and RMP3 – denotes both ex-ante and ex-post risk management. ∗∗∗, ∗∗, ∗ represent 1%, 5%, and 10% significance level, respectively. Reported standard errors are the bootstrapped standard errors.

Table 3.13: Estimates of the standard deviation of agriculture income equations

	RMP0		RMP1		RMP2		RMP3	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	0.139	0.571	0.185	0.112	0.482*	0.247	0.089	0.217
Age	0.002	0.002	0.002***	0.000	0.001	0.001	0.000	0.001
Gender	-0.089	0.078	0.019	0.023	-0.101*	0.058	0.001	0.037
Education	0.002	0.057	0.003	0.013	-0.046***	0.018	0.014	0.019
HH size	0.006	0.008	0.000	0.001	0.003	0.002	0.002	0.002
Lighting fuel	-0.027	0.068	0.092***	0.018	0.073**	0.029	0.049**	0.023
Risk attitude	-0.066	0.102	-0.056***	0.019	-0.015	0.029	0.014	0.027
Risk count	0.045	0.040	-0.018**	0.008	-0.004	0.011	-0.011	0.011
Loss count	0.047	0.039	-0.009	0.010	0.026*	0.013	0.013	0.012
Rainfall	-0.004	0.054	-0.023*	0.013	-0.014	0.019	0.014	0.021
Extension	-0.063	0.066	0.003	0.019	-0.037	0.029	-0.028	0.028
Membership	0.045	0.087	0.003	0.024	-0.042	0.034	0.021	0.032
Credit	0.147	0.148	0.015	0.027	0.046	0.041	0.032	0.056
Land	-0.009	0.014	0.003	0.002	0.000	0.003	-0.003	0.005
Fertilizer	0.000*	0.000	0.000**	0.000	0.000	0.000	0.000	0.000
Seed	0.000	0.000	-0.000***	0.000	0.000	0.000	-0.000*	0.000
Labour	-0.029	0.019	-0.006*	0.004	0.001	0.005	-0.009	0.007
Subsidy	-0.165**	0.065	-0.026	0.017	-0.030	0.026	0.007	0.030
Cash crop	-0.001	0.001	-0.001***	0.000	-0.002***	0.000	-0.001**	0.000
Irrigation	0.008	0.088	0.053**	0.022	0.097**	0.045	-0.030	0.030
Remittance	-0.014	0.072	-0.022	0.021	-0.055*	0.032	-0.013	0.026
Diversification	0.000	0.001	0.001***	0.000	0.003***	0.001	0.001	0.001
Mean land	0.021	0.027	-0.003	0.005	0.008	0.010	0.011	0.012
Mean fertilizer	-0.000*	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Mean seed	0.000	0.000	0.000***	0.000	0.000	0.000	0.001	0.000
Mean labour	0.012	0.033	0.009	0.006	0.002	0.009	0.007	0.014
m0	-0.216	0.221	-0.524***	0.192	-0.578**	0.283	0.150	0.309
m1	-0.778	0.608	-0.122	0.096	0.333	0.332	-0.234	0.168
m2	-0.398	0.772	-0.289*	0.167	-0.032	0.088	-0.110	0.210
m3	-0.242	0.852	-0.519***	0.195	-0.040	0.272	-0.079	0.073
Joint significance of crop varying covariates χ^2 (4)	6.22		19.550***		3.850		10.350**	
N	269		3150		992		726	

Notes: RMP0 – denotes no risk management, RMP1 – denotes ex-ante risk management, RMP2 – denotes ex-post risk management, and RMP3 – denotes both ex-ante and ex-post risk management. ***, **, * represent 1%, 5%, and 10% significance level, respectively. Reported standard errors are the bootstrapped standard errors.

Appendix A2

Soil Quality Index (SQI) Calculations Soil Quality Index (SQI) Calculations In computing the soil quality index for the study, we used the "Soil nutrient maps of Sub-Saharan Africa[8]" raster file at 250 m resolution provided by the International Soil Reference and Information Centre (ISRIC). Nutrients covered in this data include total nitrogen (N), total phosphorus (P), extractable phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), aluminium (Al), boron (B), copper (Cu), iron (Fe), manganese (Mn) and zinc (Zn) in (ppm). For the estimation approaches for the nutrients data, curious readers are referred to Hengl *et al.* (2017). Additionally, we used soil physical and biochemical properties data provided by ISRIC for the computation of the index. We also used free spatial data from DIVA-GIS[9] provided by ISRIC for the computation of the index. We also used free spatial data from DIVA-GIS[10] in the form of shapefiles for administrative regions of our study country. Using the free and open-source geographic information system, software called QGIS (previously known as Quantum GIS), and the geographic coordinate data of farm households, we calculate the soil parameters for each farm household. The Soil Quality Index (SQI) was calculated following the approaches described in Zheng *et al.* (2005), Mukherjee and Lal (2014), and Zhang *et al.* (2015). First, we used principal component analysis (PCA) to identify a minimum data set (MDS) to reduce the indicator load in the estimation of the index and avoid data redundancy. During the principal component analysis, only the 'highly weighted' variables were retained in the MDS. After the selection of parameters for the MDS, all selected observations were transformed using linear scoring functions (less is better, more is better, and optimum) based on the recommendations in the empirical literature (Amacher *et al.*, 2007; Mukherjee and Lal, 2014). Thereafter, the weighted additive SQI was computed using the formula below:

$\text{SQI} = \sum \text{Weight} \times \text{Individual soil parameter score}$

[8] https://data.isric.org/geonetwork/srv/eng/catalog.search#/search?resultType=details&sortBy=relevance&any=Soil%20nutrient%20maps%20of%20Sub-Saharan%20Africa%20at%20250%20m%20resolution&from=1&to=20

[9] https://github.com/ISRICWorldSoil/SoilGrids250m/blob/master/grids/models/META_GEOTIFF_1B.csv

[10] https://www.diva-gis.org/

Chapter 4

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

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Abstract

Climate change imposes risk to food production, and this is projected to increase in the coming decades, predominantly in low-income countries where adaptive capacity is weaker. In the absence of well-functioning markets to manage climatic related risks, farm households in low-income countries mostly rely on informal traditional risk hedging mechanisms to avoid, reduce exposure to risks and increase the resilience of production systems. The use of such risk management tools or strategies has consequences for input use, levels of investments, and allocation of scarce resources, and thus have implications for production efficiency. 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. The study employed a sample selection stochastic production frontier approach and a meta-frontier model. The findings of the study suggest that managing production risks has implications on farm household's technical efficiency. Furthermore, the result shows that the use of ex-post risk management strategies is associated with 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 compared to households not managing risks or employing ex-post risk management strategies either in isolation or in combination with ex-ante risk management strategies. The findings also suggest that managing production risks using multiple strategies does not necessarily result in the highest technical efficiency gain compared to the use of single or isolated strategies. The study, therefore, underscores the need to evaluate the trade-offs and likely consequences of risk management approaches used by farm households in order to provide context-specific policy recommendations.

Keywords: Risk management, sample selection, meta-frontier, efficiency, technology gap

JEL Codes: D13, G32, Q12.

4.1 Introduction

Agricultural production is particularly subjected to many risks, which cause distortions in farm output and profitability (Giné and Yang, 2009; Atozou *et al.*, 2017). 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 is impacting negatively on food production globally through rising temperatures, floods and droughts, pests, and plant diseases. Model projections by the IPCC (2014) show that climate change is expected to increase the inter-annual variability of crop yields in many regions of the world. Furthermore, risks are widely acknowledged as one of the factors that shape farmers' technology adoption decisions in the empirical literature (Feder, 1980; Feder *et al.*, 1981; Byerlee, 1993; Knight *et al.*, 2003; Gillespie *et al.*, 2004; Baerenklau and Knapp, 2005; Yang *et al.*, 2005; Liu, 2013).

Risk and uncertainty affect farm decision-making by significantly changing investment patterns. For instance, risk and uncertainty can lead to significant delays in investments (Sandmo, 1971; Dixit and Pindyck, 1994, 2004) and this can compound risk-averse farmers' disincentives to invest in profitable technologies and practices (McCarthy *et al.*, 2018). Risk presents an impediment to the adoption of more profitable agricultural production practices and technologies such as fertilizer, high-yielding seed, and livestock (Cai *et al.*, 2009; Clarke and Dercon, 2009; Mude *et al.*, 2012). Similarly, in anticipation of covariate shocks, such as droughts, for instance, poor farm households are especially prone to selecting less risky technology portfolios to evade lasting damage and these often also generate lower returns on average (Rosenzweig and Binswanger, 1993; Fufa and Hassan, 2006; Yesuf and Bluffstone, 2009; Alem *et al.*, 2010; Zerfu and Larson, 2010; Dercon and Christiaensen, 2011; Gebregziabher and Holden, 2011; Cavatassi *et al.*, 2011; Yu *et al.*, 2011; Berhane *et al.*, 2015).

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, reducing the effect of risks leads to partial and suboptimal investments due to the need to spread risk or uncertainty in order to generate less volatile returns. Furthermore, the management of risks can also withdraw resources from the production activity, resulting in a likely negative impact on the overall farm productivity and efficiency (Vigani and Kathage, 2019). Building on past work linking risk management, productivity, and efficiency, this study investigates the implication of risk management under climate change on farm household technical efficiency in Senegal. Previous studies have found considerable efficiency losses associated with 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; Anderson, 2001; Monchuk *et al.*, 2010; 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 (Schaffnit-Chatterjee, 2010; Nigus *et al.*, 2018; Matsuda *et al.*, 2019).

While the literature has extensively investigated the use and drivers of these risk management strategies (see Makus *et al.*, 1990; Sherrick *et al.*, 2004; Saqib *et al.*, 2016; Velandia *et al.*, 2009; Ullah and Shivakoti, 2014; Wang *et al.*, 2016) and their corresponding impacts on household welfare outcomes (Howard and D'Antonio, 1984; Li and Vukina, 1996; Dhuyvetter and Kastens, 1997; Kimura *et al.*, 2010; Di Falco and Veronesi, 2013; Kassie *et al.*, 2014; Birthal and Hazrana, 2019) and input use (Babcock and Hennessy, 1996; Smith and Goodwin, 1996; 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 productivity or technical efficiency. 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 is reflected by an increase in technical inefficiency. Other studies (Bojnec and Ferto, 2013; Roco *et al.*, 2017; Ahmed and Melesse, 2018; Khanal *et al.*, 2018; Imran *et al.*, 2019; Vigani and Kathage, 2019) have largely found a positive effect of risk management on technical efficiency. Since farm households use risk management strategies simultaneously, a major limitation of the literature exploring the link between risk management and technical efficiency 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.

The purpose of this paper is to investigate the impact of four different risk management strategies on Senegalese farm household's technical efficiency. 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. Although this paper is not the first to investigate the impact of risk management strategies on technical efficiency, it is the first to analyse the impact of multiple risk management strategies using the sample selection stochastic production and the meta-frontier approach. The methodological approach is relevant for a number of reasons. First farm households' decisions to adopt the various risk management strategies may not be random, implying that households endogenously self-select adoption or non-adoption. The implication is that the decision to adopt specific risk management strategies is likely influenced by both observed and unobservable characteristics that may be correlated with technical efficiency. The inability to capture these unobservable characteristics may lead to selection bias. Secondly, because each risk management strategy may be related to a specific production technology, farm households may operate under heterogeneous technologies.

This is also because the choice of a particular technology (risk management strategy) may be driven by several factors such as production environments and resources, relative input prices, etc. The presence of these factors inhibits farm households from choosing the best technology from the array of potential technology sets. Hence comparing farm households' technical efficiencies from their own frontier could bias results because they are measured against different production frontiers. Using the meta-frontier approach permits the estimation of the meta production frontier which envelopes the risk management strategy-specific frontiers, hence allowing for the estimation technology gap ratios 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 technical efficiency by providing a common technology of reference for both adopters and non-adopters of the various risk management strategies. Thirdly, our approach permits us not to only evaluate the technical efficiency of single or isolated risk management strategies but also their combinations.

The paper contributes to the literature in twofold: First, quantifying the technical efficiency implications of farm household risk management is critical for understanding the costs and benefits of climate change adaptation. Furthermore, quantifying the technical efficiency 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 identify more effective adaptation strategies, and to minimize or remedy any negative effects of adaptation. The rest of the paper is organized as follows. Section 4.2 and 4.4 formally present the analytical framework and empirical strategy, respectively. Section 4.5 describes the survey data used and the risk management strategies evaluated for the study. In Section 4.6, the empirical results and discussions are presented and finally, in Section 4.7 the conclusion is presented.

4.2 Analytical framework

The main motivation of this study is to investigate the impact of different risk management strategies (see Table 4.3) employed by Senegalese farm households on farm technical efficiency. 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, and resources, relative input prices, etc. 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 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 technical efficiency by providing a common technology of reference for both adopters and non-adopters of the various risk management strategies.

At the same time, farm households' decisions to adopt the various risk management strategies may not be random. As shown in previous studies (Bravo-Ureta *et al.*, 2012; Park, 2014; 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 technical efficiency. 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 nonlinear models such as the stochastic production frontier. Notably alternative attempts to address the issue of selectivity bias include the work of Kumbhakar *et al.* (2009) and Lai *et al.* (2009).

The former developed a model where the selection mechanism is assumed to operate through the one-sided error in the frontier whiles the latter formulated a model in which the selection mechanism is correlated through a copula function, with the composed error in the frontier instead of being correlated specifically with either the two-sided or the one-sided terms. However as suggested by Greene (2010), the log likelihood is substantially more computationally demanding in both cases. Furthermore, Greene (2010) suggests that the difference in the assumption of the impact of the selection effect is substantive. Hence 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 technical efficiency by adopting the framework developed by Greene (2010) that extends the 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:

$$\text{Sample selection[1]} : t_j = 1\left[\beta' X_j + \varepsilon_j > 0\right], \; \varepsilon_j \sim N(0,\ 1) \tag{4.1}$$

$$\text{Stochastic frontier model} : y_j = \gamma' W_j + \epsilon_j, \quad \epsilon_j \quad N\left(0,\ \sigma_\epsilon^2\right), \; \epsilon_j = \ v_j \ - \ u_j, \tag{4.2}$$

[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 4.1, each t_j is a binary variable and, thus, Equation 4.1 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.

where y_j and W_j are observed only when t_j =1, $v_j = \sigma_v v_j$ with $v_j \sim$ N(0, 1), u_j = $|\sigma_u u_j| = \sigma_u |u_j|$ with $u_j \sim$ N(0, 1), and $(\epsilon_j,\ v_j) \sim N_2[(0,\ 1),\ (1,\ \rho\sigma_v,\ \sigma^2\text{v})]$. Also, y_j denotes the logarithmic crop income 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 4.4) and 0 otherwise, 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 (v_j) and inefficiency term (u_j), and ϵ_j is the error term. The inefficiency term u_j is assumed to follow a half-normal distribution with the dispersion parameter σ_u, whereas ϵ_j and v_j follow a bivariate normal distribution with variances of 1 and σ^2v, respectively.

The correlation coefficient, $\rho\sigma_v$ 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 (BFGS) approach, and asymptotic standard errors are obtained by employing the Berndt-Hall-Hall-Hausman (BHHH) 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 technical efficiency estimates, $TE_{ji} = E[\,e^{-u_{ji}},\ i = 1,\ 2 \ldots .4]$.

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 in the paper, farm households have the potential access to an array of production technologies, however 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.

An issue that needs to be addressed in estimating equation 4.1 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, hence the need to account for any potential reverse causality between the adoption decision of risk management strategies. A potential source of endogeneity identified in the empirical literature comes from the risk attitude of a farmer, membership of farmer-based organizations, extension, and credit access. The risk attitude of a farmer may influence the choice of risk management strategy, therefore, risk management strategies employed by a farmer can potentially correlate to his or her risk attitude (see Ullah and Shivakoti, 2014; 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 household's membership of 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. Following previous studies (see Abdulai and Huffman, 2014; Ma and Abdulai, 2016), we control for the potential endogeneity of the variables using the control function approach[2] 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 of farmer-based organizations, extension, and credit access) as a function of all other variables used in the selection equation (i.e. equation 4.1). We incorporated both potential endogenous variables and the estimated residuals[3] predicted from the probit equation into the selection equation 4.1 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 4.1. 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 of farmer-based organizations. Similarly, support needs and location were employed as instruments to control for extension and credit access respectively. These in-

[2]This is also known as a two-stage residual inclusion model in the empirical literature (see Gibson *et al.*, 2010; Terza, 2017; Harris and Kessler, 2019)

[3]Wooldridge (2015, Pp. 427 – 428) proposes estimating a "generalized residuals" which uses the inverse Mills ratio (the ratio of the standard normal density, ϕ, divided by the standard normal cumulative distribution function, Φ) to compute the "generalized residuals".

struments are expected to influence their respective endogenous variables but not the choice of risk management strategy adoption. Furthermore, Wooldridge (2015) observed that if the coefficient on the estimated generalized residual is statistically significant, there is a need to adjust the standard errors for the two-step estimation by bootstrapping.

4.3 Meta-frontier Analysis

Following the approach outlined by O'Donnell *et al.* (2008), we estimate a meta-frontier[4] 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:

$$\begin{gathered} Y_i^* = f\left(X_j, \beta^*\right) = e^{X_j\beta^*}; \\ j = 1, 2 \ldots\ldots N,\ N = \sum_{k=1}^{2} N_k \end{gathered} \tag{4.3}$$

where β^* denotes the vector of parameters of the meta-frontier function such that $X_j\beta^* \geq X_i\beta_k$ for all j observations. We estimate the parameters of the meta-frontier function (β^*) in equation 4.3 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:

$$\begin{gathered} \min_{\beta^*} \sum_{j=1}^{N} |(\text{In } f(X_j, \beta^*) - \text{In } f(X_j, \hat{\beta}_k)| \\ s.t.\ \ \text{In } f\left(X_j, \beta^*\right) \geq \text{In } f\left(X_j, \hat{\beta}_k\right)\ \forall\ j \end{gathered} \tag{4.4}$$

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-technology gap ratio (TGR). As suggested by Issahaku and Abdulai (2019), a comparatively high average meta-technology gap ratio for a particular technology group indicates a lower technology gap between farm households in that group compared with all available set of production technologies represented

[4]The meta-frontier was estimated in R using the lpSolve package

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:

$$TGR = \frac{e^{X_j \hat{\beta}_k}}{e^{X_j \beta^*}} \tag{4.5}$$

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

$$MTE_j = TGR \times TE_{jk} \tag{4.6}$$

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 estimation of technical efficiency 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 λ = -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, L(H_0), L(H_1), L(H_2) and L(H_3) is the value of the sum for 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.

4.4 Empirical strategy

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 are the Cobb-Douglas and transcendental logarithmic, also known commonly as the translog (Bravo-Ureta *et al.*, 2007; Seymour, 2017). 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 provided 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 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). Hence for this study, the technology for crop production by farm households is represented by a Cobb–Douglas production frontier that can be specified as:

$$\ln(y_j) = \beta_0 + \sum_{j=1}^{4} \beta_j \ln W_j + \sum_{k=1}^{4} \delta_k D_{kj} + v_j - u_i \tag{4.7}$$

where ln is a natural logarithm, y_j denotes total crop income of farm household j, β_0 denotes farm household-specific fixed effects measuring heterogeneity, β_j and δ_k denote unknown parameters to be estimated, W_j is the quantity of the kth input of the jth household, D represents dummy variable for input subsidy access, improved seed use, irrigation, and fertilizer use. Following the approach of Battese (1997), the inclusion of the dummy variable for fertilizer use helps to account for zero values of fertilizer by including dummy 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. v_j denotes random error and u_j the inefficiency term. The inputs vectors include labour in man-days/ha, landholding in hectares, and fertilizer and seed quantities used in kg per hectare.

A summary of the variables and their definitions used in the analysis are presented in Table 4.1. The detailed summary statistics of variables across the various risk management portfolios are presented in Table 4.9 in the Appendix. The summary statistics show that households employing both ex-ante and ex-post risk management strategies appear to have the highest crop incomes followed by those who do not adopt any risk management strategy. Ex-ante risk management strategies adopting households have the least crop incomes. Similarly, households not adopting any risk management strategy have the highest total quantity of labour used followed by those adopting ex-ante risk management strategies. Households employing both ex-ante and ex-post risk management strategies have the lowest total quantity of labour used in production. Regarding land, the summary statistics show that households employing both ex-ante and ex-post risk management strategies have the largest landholdings, followed by households adopting ex-post risk management strategies. Households, not managing risk appear to have the smallest landholdings. The highest fertilizer use quantities are from households not employing any risk management strategies, followed by households employing ex-ante risk management strategies. Seed quantities are relatively higher for households employing both ex-ante and ex-post risk management strategies followed by those not employing any risk management. Table 4.9 also shows that households not adopting any risk management strategies use more improved seeds and irrigation. At the same time, households not managing risks experience the lowest risk and loss counts while households employing both ex-ante and ex-post risk management strategies experience the highest risk and loss counts.

4.5 Study area and data

4.5.1 Farm household survey

Senegal is a country within the Sahel region of West African. The country has six agro-ecological zones, based on biophysical and socioeconomic criteria and these are; Niayes, Senegal River Valley, Sylvo-pastoral Zone, Groundnut Basin, Eastern Senegal, and Casamance (D'Alessandro *et al.*, 2015). These agroecological zones have unimodal rainfall, hence they are characterized by varying levels of rainfall and

Table 4.1: Variables definition

Name	Variable description
Household characteristics	
Age	Age of household head in years
Gender	=1 if 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
Market	=1 if the household is integrated into markets
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 (%)
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/ha
Land	Total land holding of household in ha
Fertilizer	Fertilizer quantity used in kg
Seeds	Seed quantity used in kg
Output variables for stochastic frontier model	
Crop income	Crop production value in CFA
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 which is 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.

temperature with conditions that gradually become increasingly dry moving north from Senegal's high rainfall southern regions to its northern arid zones. The length of the rainy season differs from one year to the next and from one region to the other. With more than 95% of the total cropped area depending on rain-fed and less than 1% of agricultural land under irrigation, the growing season in Senegal strongly correlates to the rainy season. The strong dependence of crop production on rainfall results in highly variable production, as both rainfall amounts and the onset and cessation of the rains, are subject to marked space-time variability and temporal changes (D'Alessandro *et al.*, 2015). The main crops cultivated in Senegal by smallholders are groundnuts and millet, which together account for almost 75% of the planted area. Maize, rice sorghum, cowpeas, and cotton make up about 25% and less than 1% is sown to other crops, including vegetables (D'Alessandro *et al.*, 2015).

The data used in the study comes from a farm household survey as part of the larger Senegalese "Projet d'appui aux politiques agricoles (PAPA)" or the Agricultural Policy Support Project. The farm household survey was conducted between April and May across all the 14 administrative regions of Senegal and all the departments except for the departments of Dakar, Pikine, and Guédiawaye. A total of 42 agricultural departments were included in the survey. The survey was targeted towards cereals, horticultural crops, and fruit and vegetable producers. 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 is 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 practice and localized crops were grown such as the Senegal River Valley and Niayes Market Gardening Zone, stratification of the rural census districts was done before agricultural households were selected. Data collected include information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit, inputs use and cost, family and hired labour, sales volumes, and food processing activities. Others included household consumption, access to amenities, non-farm and livestock revenue, remittance, agricultural insurance, risks and adaptation strategies, perceptions about subsidized input, and membership of farmer-based organizations.

4.5.2 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 five years, risks faced during the past 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 five years. In the survey, 17 production risks were evaluated and this is presented in Table 4.2. In the context of this study, however, we only considered production risks related to the climatic shocks – drought, erratic rainfall, 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 4.3) 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 breakdown, and hydrology related issues appear to have been experienced in isolated cases (see Table 4.2).

Table 4.2: Risks often faced by farm households in the past 5 years

Risk	**Frequency**	**Percent (%)**
Insufficient rains[a]	2481	48.61
Early rains stop[b]	1579	30.94
Pause rainfall[c]	1298	25.43
Damage by animals (livestock)	1047	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	5104	

[a] Implies not enough rain for crops during the whole growing season.
[b] The rain stops before the plant completes its maturation process.
[c] The rain pauses one 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] The rain starts late, and this delays the sowing period.

Besides the shocks experienced by farm households, strategies employed to deal with the risks in Table 4.2 were solicited (Table 4.3). In the presence of production shocks, diversification of agricultural activities was the largest (39.7%) strategy employed by farm households to deal with risk. This is subsequently followed by orientation to non-agricultural activities, which is employed by 30.2% of the surveyed households. Reduction of land areas under cultivation as a risk management strategy is employed by 20.6% of the surveyed households. After risks have occurred, measures related to the sale of livestock are employed by 20.4% of the surveyed households. The sale of grain stocks and properties is used as a risk management strategy by 9.4 and 8.8% of farm households respectively. Based on the empirical literature (see World Bank, 2001, 2005; Lilleor *et al.*, 2005; Chetaille *et al.*, 2011), we aggregated the risk management strategies employed by farm households based 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 4.3.

Table 4.3: Risk management strategies employed by farm households

Risk management strategies	Frequency	Percent (%)
Ex-ante strategies		
Diversify agricultural activities	2026	39.7
Reduce the area under cultivation	1053	20.6
Orientation to non-agricultural activities	1539	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	1041	20.4
Exchange/swap clothes or jewels for food	78	1.5
Total	**5104**	**100**

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 of farm income. Since evidence from the empirical literature (Harwood *et al.*, 1999; Makki *et al.*, 2001; Flaten *et al.*, 2005; Velandia *et al.*, 2009; Ullah and Shivakoti, 2014; Ullah *et al.*, 2015; World Bank, 2016) suggest 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 possible combinations or portfolio of strategies that farm households could choose from (Table 4.4).

Table 4.4: Risk management portfolios available to farm households

Risk Management Portfolio	Portfolio ID	Frequency	Percent (%)
No risk management	RMP0	261	5
Ex-ante risk strategy only	RMP1	3119	62
Ex-post risk strategy only	RMP2	987	19
Ex-ante and Ex-post strategy	RMP3	737	14
Total		**5104**	**100**

Based on these risk management portfolios, about 62% 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 about 19% of farm households while about 14% of farm households employ both ex-ante and ex-post measures. About 5% of farm households employ no risk management strategy.

4.6 Empirical results

This section presents the findings from the empirical analysis by first presenting the first stage probit results. This is then followed by the results of the risk management-specific stochastic frontiers and the meta-frontier. Subsequently, we discuss estimates of the technical efficiency (TE) scores, technology gap ratios (TGR), and the group-specific technical efficiency with respect to the meta-frontier (MTE). The results of the control function approach for potentially endogenous variables are also presented in Table 4.10.

4.6.1 Drivers of use of risk management strategies

Table 4.5 shows the results of the probit model for the different risk management portfolios. We find that the individual probit models fit the data well, the Wald test is highly significant across all models, hence rejecting the null hypothesis that all the regression coefficients are jointly equal to zero. Furthermore, the results from the control-function specification indicate that the correction for endogeneity in the model was necessary. We find the coefficient of the membership in a farmer-based organization, extension access, and credit access residual terms to be statistically significant in three of the risk management portfolios, implying the presence of endogeneity of membership of farmer-based organization, extension access, and credit access.

The results show that household welfare status and membership of farmer-based organizations are positive and significantly related to the likelihood of not managing risks (RMP0). This suggests that households that are wealthier and are members of farmer-based organizations are more likely to adopt no-risk management strategies. On the contrary, the number of risks and losses experienced by the household, extension access, and credit access are negative and significantly related to the likelihood of not managing risks. This suggests that as the number of risks and related losses experienced by a household increases, they are less likely to adopt no risk management as a strategy.

Furthermore, as a household gains access to extension services and credit, they are less likely to adopt no risk management as a strategy. The use of ex-ante risk management strategies (RMP1) is strongly positive and statistically significant for the age of the household head. This suggests that older household heads are more likely to adopt ex-ante risk management strategies. Conversely, the gender of the household head, the number of risks experienced by the household, and remittance are negative and significantly related to the adoption of ex-ante risk management strategies. This implies that male-headed households, an increase in the number of risks experienced, and the receipt of remittances decrease the likelihood of ex-ante risk management strategies adoption.

Table 4.5: Probit model estimates for the various risk management strategies

	RMP0		RMP1		RMP2		RMP3	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	-1.528***	0.198	0.636***	0.110	-0.741***	0.134	-1.963***	0.149
Age	0.001	0.002	0.005***	0.001	-0.004**	0.002	-0.005**	0.002
Gender	0.019	0.144	-0.269***	0.083	0.327***	0.103	0.123	0.112
Education	0.114	0.098	0.063	0.044	-0.084	0.053	-0.048	0.063
HH size	-0.015	0.017	0.001	0.007	0.001	0.008	0.012	0.009
HWI	0.088***	0.021	0.005	0.012	-0.028**	0.014	-0.032**	0.016
Risk attitude	0.755	1.402	-0.425	0.564	0.142	0.662	-0.029	0.694
Risk count	-0.143***	0.043	-0.103***	0.018	0.004	0.023	0.184***	0.023
Loss count	-0.166***	0.052	-0.036	0.024	-0.088***	0.027	0.200***	0.028
Extension	-1.052***	0.361	0.343	0.272	-0.602**	0.292	0.731**	0.346
Membership	1.599***	0.587	-0.019	0.368	0.365	0.403	-1.605***	0.490
Credit	-2.544**	1.179	-0.449	0.706	0.838	0.857	1.167	0.988
Land size	-0.002	0.007	0.000	0.002	0.002	0.003	0.000	0.002
Cash crop	0.085	0.204	-0.122	0.099	-0.003	0.116	0.270**	0.118
Remittance	0.130	0.122	-0.133**	0.067	0.020	0.076	0.157**	0.078
Distance	0.002	0.001	0.001	0.001	-0.003***	0.001	0.001	0.001
Resid risk	-0.206	0.853	0.113	0.341	-0.043	0.402	0.107	0.422
Resid mem	-0.533**	0.222	0.040	0.164	-0.388**	0.177	0.812***	0.222
Resid ext	0.479**	0.185	-0.186	0.137	0.155	0.153	-0.166	0.177
Resid credit	0.958*	0.572	0.280	0.326	-0.458	0.403	-0.387	0.462
Log-likelihood	-912.528		-3302.805		-2433.509		-1828.75	
Wald chi2(19)	235.405***		215.971***		145.965***		557.026***	
N				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. Reported standard errors are bootstrapped errors.
***, **, * represent 1%, 5%, and 10% significance level, respectively.

For ex-post risk management strategies (RMP2), the findings suggest that the age of the household head, household welfare status, the number of risk-related losses experienced, extension access, and the distance to a major city are negative and significantly related to the likelihood of ex-post risk management strategies adoption. Hence, older household heads, wealthier households, an increase in the number of risk-related losses, access to extension services, and an increase in the distance to a major city decrease the likelihood of ex-post risk management strategies adoption. Additionally, male-headed households are more likely to adopt ex-post risk management strategies.

The adoption of both ex-ante and ex-post risk management strategies (RMP3) is negatively influenced by the age of the household head, household welfare status, and membership of farmer-based organizations. This implies that older household heads are less likely to adopt both ex-ante and ex-post risk management strategies. At the same time, wealthier households and membership in farmer-based organizations reduce the likelihood of adopting both ex-ante and ex-post risk management strategies. On the contrary, the number of risks and risk-related losses, extension access, the share of land area under cash crops, and remittance are positively related to the adoption of both ex-ante and ex-post risk management strategies. Thus an increase in the number of risks and risk-related losses experienced increases the likelihood of adopting both ex-ante and ex-post risk management strategies. Furthermore, access to extension services, an increase in the share of land area under cash crops, and receipt of remittances increase the likelihood of both ex-ante and ex-post risk management strategies adoption.

4.6.2 Production frontier estimates

We present the results of the risk management-specific stochastic frontiers and meta-frontier in Table 4.6. For all risk management-specific stochastic frontiers models, the results show that the inefficiency dispersion parameters Sigma (u) are significant, suggesting that inefficiency is an important contributor to total crop income 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 that 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 strategy and ex-ante risk management strategy frontier, the results suggest that labour has a negative effect. However, the effect is not 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 elasticity i.e. a measure of the percentage contribution of each input vector to a percentage change in total crop income. 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. This is followed by fertilizer, seeds, and labour in the case of no risk management strategy group frontier. For ex-ante, ex-post, and both ex-ante and ex-post risk management strategy group frontier, this is followed by seed, fertilizer, and labour respectively. The input subsidy access dummy variable was observed to have a negative effect across all the risk management specific frontiers. For the ex-ante risk management and both ex-ante and ex-post risk management strategy group frontier, the effect is statistically significant. This suggests that input subsidy access moves farm productivity away from the frontier. Improved seed use dummy variable has a positive across all risk management specific group frontiers. The effect is however significant for ex-ante and both ex-ante and ex-post risk management strategy. Irrigation use has a significant effect on the frontier of no risk management, suggesting it moves farm productivity towards the frontier. Results from the sample selection production frontiers models show that the estimated sample selectivity term, *Rho* is negative and statistically significant for ex-ante risk management strategies and both ex-ante and ex-post risk management strategies. 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, support the use of the sample selectivity framework.

Table 4.6: Parameter estimates for sample selection stochastic production function models and meta-frontier

	RMP0		RMP1		RMP2		RMP3		Meta-frontier	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std.Err.**
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		
RTS	1.18		0.92		1.08		0.94		1.22	
Log likelihood	-1033.05		-5670.984		-2701.221		-2099.903			
N	261		3119		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. ***, **, * represent 1%, 5%, and 10% significance level, respectively.

In the stochastic meta-frontier estimates (Table 4.6), we observe that all the input vectors except labour have a significant and positive effect in moving farm productivity to the meta-frontier. Just like the group level frontier estimates, the result suggests that land has the highest contribution to moving farm productivity to the meta-frontier, followed by fertilizer, seeds, and labour respectively. All three dummy variables, input subsidy access, improved seeds use and irrigation use is positive, suggesting that they move farm productivity towards the meta-frontier. The effect of improved seed use and irrigation use was found to be statistically significant. At the risk management-specific frontiers, returns to scale to was 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. This implies that farm households not managing production risks and those managing risks ex-post shocks are operating under increasing returns to scale. Meaning that holding all else constant, a 1% joint increase in all inputs will bring about more than a unit increase in crop income for non-risk managing households 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 increase all productive inputs by 1%, crop income would increase by less than 1%. As suggested by Chavas *et al.* (2005), the presence of such decreasing returns to scale implies that household resources are too large for the prevailing technology, thus households could benefit by expanding their scale of operation.

4.6.3 Technical efficiencies and technology gap ratios

Since the primary objective of this study was to investigate the nexus between risk management and production efficiency, the estimated technical efficiency (TE) scores, meta-technology gap ratios (TGR), and technical efficiency with respect to the meta-frontier (MTE) are presented in Table 4.7. At the risk management-specific frontiers, the average technical efficiency of farm households employing ex-post risk management strategies was the highest (60.3%) followed by both ex-ante and ex-post risk management strategies (58%) and ex-ante risk management strategies (51.8%). Farm households employing no risk management strategies were the least efficient (49.8%). 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. The result shows that farm households not adopting any risk management are slightly more efficient in adopting the best available technology. They can have a mean technology gap ratio of 0.934, followed by households adopting ex-ante risk management strategies (0.894). Households employing ex-post risk management strategies were observed to have the lowest mean technology gap ratio (0.857). 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 strategies are the production inputs – land, labour, fertilizer, and seeds. As reported earlier, households not managing risks use the largest quantities of labour and fertilizers, use more improved seeds and irrigation compared to households using the other risk management strategies. This likely explains the relatively high technology gap ratios 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 incomes 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%) followed by households employing both ex-ante and ex-post risk (51.6%). Furthermore, households employing no risk management strategy are 46.5% technically efficient, while those employing only ex-ante risk management strategies are the least technically efficient (46.3%). The use of multiple risk management strategies does not appear to necessarily result in the highest technical efficiency gain compared to the use of single or isolated strategies.

Table 4.7: 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

As discussed previously, risk management is related to changes or allocation in scarce production resources and these allocations have implications for the technical efficiency of farm households. To get a better understanding of the technical efficiency results, we refer back to Table 4.3 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 have a negative effect on crop income, when a household 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 suggests that farm households using ex-ante risk management strategies allocate about 50% of their cultivated lands towards staple crop production and only about 26% towards cash crops. As shown in previous studies, diversification hinders important gains that could be obtained from specialization. Renting out land, intuitively also has implied opportunity costs related to the loss of farm income and hence production efficiency.

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 technical efficiency. 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 technical efficiency. Recent findings of the impact of insurance on farm efficiency (see Vigani and Kathage, 2019) suggests that insurance negatively 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 (Horowitz and Lichtenberg, 1993; 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. Others (see Schaffnit-Chatterjee, 2010; 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 4.3) 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 technical efficiency. However, it is worth noting that the use of ex-post risk management strategies is costly especially to very poor households. In the long-run and persistent risk situations, poorer households might be unable to recover the loss of productive assets ex-post the shock (Bhandari *et al.*, 2007; Barnett *et al.*, 2008; Amare *et al.*, 2018). Furthermore, such strategies can reduce the value of human assets, hence presenting not only a barrier to poverty alleviation but also reinforcing poverty (Hoddinott and Kinsey, 2001; Dercon and Hoddinott, 2003; Thomas *et al.*, 2004; Hoddinott, 2006; Kouamé, 2010).

In the context of policy, it is useful to determine what influences efficiency or inefficiency to guide the design of performance-improvement programs that can help farmers better optimize the returns of input use or the various risk management strategies. Thus, the study explored the influence of some institutional variables on technical efficiency by regressing the technical efficiency scores with respect to the meta-frontier on these variables, using a Tobit model (Table 4.8). The estimates reveal that technical efficiency is significantly influenced by extension access, credit access, and membership in farmer-based organizations. The results show a positive and significant relationship between extension access and technical efficiency, suggesting that farmers with lower extension contacts tend to be less efficient compared to those with extension access. The result agrees with previous studies that have found extension access to have a positive and significant effect on technical efficiency. For example studies by Solís *et al.* (2007), Abdulai and Abdulai (2016), Yang *et al.* (2016), Yang *et al.* (2018), and Imran *et al.* (2019) found that extension access significantly reduces technical inefficiency. In addition, the results reveal a negative and significant relationship between membership in farmer-based organizations and credit access, suggesting that farmers that are members of farmer-based organizations and with access to credit tend to be less efficient. In a related study, Azumah *et al.* (2019) find that Ghanaian rice farmers belonging to farmer associations were less efficient compared to those not belonging to any farmer group. The effect of credit on technical efficiency in the literature is mixed. Some studies (Solís *et al.*, 2007; Abdulai and Abdulai, 2016; Yang *et al.*, 2018; Imran *et al.*, 2019) have found a positive impact on technical efficiency while others (Theriault and Serra, 2014; Azumah *et al.*, 2019) have found a negative effect.

Table 4.8: Determinants of technical efficiency

	Efficiency model	
Variable	**Coef.**	**Std. Err.**
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	
LR chi2(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. ***, * represent 1%, and 10% significance level, respectively.

The results also suggest that input subsidy access might have an adverse effect on technical efficiency although the effect is not statistically significant. The finding is consistent with previous studies such as Latruffe *et al.* (2017) who find a negative effect of subsidies on technical efficiency for some European Dairy Farms. Similarly, Alem *et al.* (2018) found subsidies to increase the level of inefficiency among Norwegian dairy farms. The study by Bojnec and Ferto (2013) also found government subsidies negatively influenced the technical efficiency of Slovenian family farms. The results also suggest that compared to households not adopting risk management strategies, the adoption of ex-ante risk management strategies reduces technical efficiency, although the effect is not statistically significant. Adopting ex-post risk management strategies or both ex-ante and ex-post risk management strategies significantly increases technical efficiency. The results here confirm the results discussed previously.

4.7 Conclusion

This study investigated the nexus between risk management and production efficiency, using empirical data from a nationally representative farm household survey in Senegal, a sample selection stochastic production frontier approach that corrects for selectivity biases, and a meta-frontier. The empirical results revealed significant variation in TE, MTE, and TGR values across the various risk management strategies employed by farm households. The findings suggest that managing production risks has implications on farm household's technical efficiency. The use of ex-post risk management strategies is associated with 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 risk to be relatively more efficient in adopting the best available technology. The findings from this study underscore the need for context-specific studies to guide policies that seeks to help farmers better manage production risks.

Most importantly it highlights some important trade-offs that have to be made. 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. Since 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 the two broad typologies, helped us to capture only aggregate effects. This approach obscures or fails to evaluate individual risk management specific effects on technical efficiency. Future research can therefore focus on more localized and isolated risk management strategies and their impacts on technical efficiency. Additionally, technical efficiency across the evaluated risk management strategies might have both temporal and spatial effects which our study fails to capture. Access to long term data such as a panel or longitudinal data can provide answers to these temporal and spatial technical efficiency effects of risk management strategies.

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Appendix

Table 4.9: Summary statistics across risk management portfolios

	RMP0		RMP1		RMP2		RMP3		Pooled data	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Crop income	12.501	1.433	12.252	1.343	12.482	1.230	12.583	1.137	12.357	1.305
Labour	3.232	1.313	3.049	1.246	2.835	1.122	2.775	0.973	2.977	1.197
Land	2.071	0.965	2.174	0.920	2.389	0.903	2.453	0.832	2.251	0.914
Fertilizer	3.469	2.790	2.386	2.790	2.230	2.770	2.256	2.782	2.392	2.796
Seed	4.451	1.210	4.253	1.369	4.437	1.299	4.588	1.240	4.347	1.335
Age	52.674	13.533	53.457	13.418	51.975	12.707	52.615	13.288	53.009	13.280
Gender	0.920	0.273	0.910	0.286	0.953	0.211	0.948	0.221	0.925	0.264
Education	0.464	0.500	0.378	0.485	0.368	0.482	0.360	0.480	0.378	0.485
HH size	9.421	4.679	9.578	5.312	10.059	5.192	10.463	5.279	9.791	5.263
HWI	0.471	1.660	-0.007	1.759	-0.155	1.620	-0.228	1.560	-0.043	1.706
Risk attitude	0.609	0.489	0.339	0.473	0.412	0.493	0.392	0.489	0.374	0.484
Risk count	1.034	1.245	1.743	1.394	1.856	1.596	3.099	1.634	1.924	1.551
Loss count	1.238	1.044	1.628	0.984	1.591	0.977	2.412	1.249	1.714	1.071
Extension	0.234	0.424	0.155	0.362	0.100	0.301	0.178	0.383	0.151	0.359
Membership	0.287	0.453	0.131	0.337	0.078	0.268	0.118	0.323	0.127	0.333
Market	0.586	0.493	0.556	0.497	0.554	0.497	0.562	0.497	0.558	0.497
Credit	0.038	0.192	0.046	0.208	0.042	0.200	0.039	0.195	0.043	0.204
Cash crop	0.246	0.285	0.263	0.277	0.296	0.237	0.334	0.269	0.279	0.270
Remittance	0.111	0.315	0.095	0.293	0.089	0.285	0.123	0.329	0.099	0.298
Distance	67.115	52.785	54.079	40.506	45.526	37.998	50.149	32.118	52.524	39.936
Storage	0.100	0.300	0.159	0.366	0.205	0.404	0.225	0.418	0.174	0.379
Contracts	0.019	0.137	0.026	0.159	0.021	0.144	0.019	0.137	0.024	0.152
Support needs	0.705	0.457	0.759	0.428	0.716	0.451	0.806	0.396	0.755	0.430
Location	0.149	0.357	0.162	0.368	0.128	0.334	0.138	0.346	0.151	0.358
Subsidy	0.264	0.442	0.214	0.411	0.195	0.396	0.360	0.480	0.234	0.423
Improved seeds	0.506	0.501	0.327	0.469	0.259	0.439	0.365	0.482	0.329	0.470
Irrigation	0.264	0.442	0.217	0.412	0.124	0.329	0.119	0.324	0.187	0.390
Fertilizer use	0.360	0.481	0.557	0.497	0.589	0.492	0.588	0.493	0.557	0.497
N	**261**		**3119**		**987**		**737**		**5104**	

Notes: RMP0 – denotes no risk management strategy, RMP1 – denotes ex-ante strategy, RMP2 – denotes ex-post strategy, RMP3 – denotes ex-ante and ex-post strategy.

Table 4.10: Control function approach for potentially endogenous variables

	Risk attitude		Membership		Extension access		Credit access	
Variable	**Coeff.**	**Std.Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	-1.253***	0.115	-1.721***	0.154	-2.599***	0.166	-1.772***	0.208
Age	0.001	0.001	-0.005***	0.002	0.002	0.002	-0.004	0.003
Gender	0.203***	0.075	-0.147	0.096	0.098	0.092	-0.034	0.134
Education	0.136***	0.039	0.197***	0.053	0.087*	0.050	0.078	0.070
HH size	0.029***	0.004	0.024***	0.005	-0.015***	0.005	0.010	0.006
HWI	0.000	0.011	-0.019	0.015	0.121***	0.014	0.026	0.021
Risk attitude			0.512***	0.053	0.129**	0.052	0.375***	0.070
Risk count	-0.043***	0.015	-0.063***	0.019	0.019	0.018	-0.031	0.025
Loss count	0.028	0.021	0.084***	0.027	0.074***	0.025	-0.010	0.037
Extension	0.176***	0.055	0.790***	0.061			0.101	0.088
Membership	0.615***	0.060			0.824***	0.063	0.642***	0.081
Credit	0.447***	0.091	0.682***	0.095	0.096	0.103		
Land size	0.011***	0.001	-0.002	0.002	-0.003	0.002	0.003**	0.001
Cash crop	0.315***	0.075	-0.544***	0.114	-0.557***	0.102	-0.327**	0.150
Remittance	-0.052	0.064	-0.040	0.086	0.291***	0.073	-0.096	0.119
Distance	0.001***	0.001	0.005***	0.001	0.006***	0.001	0.000	0.001
Storage	**-0.161*** **	0.051						
Contracts			**0.663*** **	0.125				
Support needs					**1.047*** **	0.088		
Location							**-0.890*** **	0.219
Log likelihood	-3112.033		-1506.57		-1721.2114		-802.971	
LR chi2(15)	526.099***		867.812***		898.180***		220.245***	
N				5104				

***, **, * represent 1%, 5%, and 10% significance level, respectively.

Chapter 5

Does Complementing the Adoption of Productivity Enhancing Technologies with Insurance Improve Technical Efficiency?

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Abstract

Using empirical data from Senegal, we investigated the nexus between insurance use and technical efficiency by comparing two distinct farm households; one adopting fertilizer and improved seeds with insurance and the other fertilizer and improved seeds only. We employed a sample selection stochastic production frontier, a meta-frontier model together with the propensity score matching, and an endogenous switching regression model to control for potential biases. The results show that households who adopted productivity-enhancing technologies with insurance tend to have higher levels of investment in production inputs, however, households that adopted productivity-enhancing technologies without insurance tend to be more technically efficient on average. Furthermore, households that adopted productivity-enhancing technologies with insurance seem to be slightly more efficient in adopting the best available technology set as measured by the technology gap ratio. At the meta-frontier, the results of the endogenous switching regression model show that adopting productivity-enhancing technologies with insurance decreases the technical efficiency of productivity-enhancing technologies with insurance adopters by about 50.17%. Conversely, for households adopting productivity-enhancing technologies without insurance, adopting with insurance could potentially increase the mean technical efficiency by about 37.44%. The results suggest that lower observed technical efficiencies for productivity-enhancing technologies with insurance adopters may be driven by unobserved effort or behavioural biases of farmers which can be an important source of heterogeneity in the observed treatment effects.

Keywords: Insurance, productivity, technology, technical efficiency, stochastic frontier

JEL Codes: Q12, Q16, G52

5.1 Introduction

In Senegal, agriculture is predominantly rain-fed, with more than 95% of the total cropped area depending on rain-fed systems, and most farmers practising subsistence agriculture (Khouma *et al.*, 2013). At the same time, agricultural productivity in Senegal has been observed to be lower due to a myriad of factors. Some of these include low levels of soil fertility, limited farmer use of improved seeds, fertilizers, and agro-chemicals, poor access to extension and financial services (World Bank, 2009; Affholder *et al.*, 2013; D'Alessandro *et al.*, 2015; USAID, 2017). These in essence have led to the stagnation of agricultural productivity, hampered agricultural growth, and caused a growing impoverishment of farmers in Senegal (World Bank, 2009).

In parallel, several studies (Heisey and Mwangi, 1996; Wopereis-Pura *et al.*, 2002; De Groote *et al.*, 2005; Duflo *et al.*, 2008; Marenya and Barrett, 2007; Asfaw, 2010; Cunguara and Darnhofer, 2011; Kassie *et al.*, 2014; Graf *et al.*, 2015; Khonje *et al.*, 2015; Koussoubé and Nauges, 2017; Mekonnen, 2017; Abdoulaye *et al.*, 2018) have observed that the returns on the adoption of productivity-enhancing technologies (PET) such as fertilizer, improved/high yielding varieties, improved livestock are very high and generally improves household welfare outcomes. However, few farmers invest in these technologies in Africa despite the high proven returns on investments. Empirical studies that have tried to investigate this adoption conundrum have identified many factors such as knowledge gaps (Matuschke and Qaim, 2008; Kabunga *et al.*, 2012; Ekbom *et al.*, 2013), risk and uncertainties (Knight *et al.*, 2003; Gillespie *et al.*, 2004; Yang *et al.*, 2005; Liu, 2013), liquidity and credit constraints (Foster and Rosenzweig, 2010; Andersson and D'Souza, 2014; Lambrecht *et al.*, 2014; Grabowski *et al.*, 2016), and behavioural biases (Choi *et al.*, 2011; Duflo *et al.*, 2011; Kremer *et al.*, 2013).

Particularly 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. Previous studies (see Lamb, 2003; Barnett *et al.*, 2008; Dercon and Christiaensen, 2011; Hill and Viceisza, 2012; Karlan *et al.*, 2014; You, 2014; Farrin and Miranda, 2015; Cole *et al.*, 2017) strongly suggests that uninsured risk or the lack of protection from downside risk accounts for deficiencies in technology uptake and inefficient production choices among low-income households. Recent innovations in formal insurance, such as index-based risk transfer products, offer an opportunity for smallholder farmers to manage production risks. Nevertheless, the impact of insurance on productivity and welfare in the empirical literature is contentious. Some studies find a positive impact on productivity mainly through reducing uncertainty, unlocking demand, and inducing higher investments in inputs (Horowitz and Lichtenberg, 1993; Goodwin *et al.*, 2004; Madajewicz *et al.*, 2013; Karlan *et al.*, 2014; Cai *et al.*, 2015; Cole *et al.*, 2017; Hill *et al.*, 2019; Sibiko and Qaim, 2020). Other studies on the other hand have found that insurance use lowers investments in inputs (Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Goodwin, 2001; Goodwin *et al.*, 2004; Giné and Yang, 2009; de Nicola, 2015). The use of insurance clearly has implications for input use, levels of investments, and allocation of scarce resources. Hence insurance use has repercussions for resource allocation and this can also affect technical efficiency. This paper examines the question of whether complementing the adoption of fertilizer and improved seeds with insurance improves technical efficiency.

While much attention has been devoted to investigating the impact of productivity-enhancing technologies and insurance on household welfare, studies addressing the link between composite technologies (such as productivity-enhancing technologies and insurance) and technical efficiency are still scarce. Few studies such as the recent one by Vigani and Kathage (2019) have attempted to evaluate the impacts of insurance and other risk management instruments under varying levels of risk on total factor productivity using a multinomial endogenous switching regression model and survey data from French and Hungarian farms. They found insurance to negatively affect farm efficiency. Similarly, an earlier study in Senegal by Atozou *et al.* (2017) employed a conventional stochastic frontier and propensity score matching to evaluate the technical efficiency impact of weather index insurance project piloted with groundnut farmers. They found groundnut farmers who had subscribed to insurance were less technically efficient compared to those who had not subscribed to insurance. Despite these previous studies providing important insights, they have some limitations. For instance, they fail to justify why insurance use has a negative effect on efficiency. The study of Atozou *et al.* (2017) in particular fails to account for unobservable variables that might be correlated with technical efficiency. Furthermore, it assumed a similar technology for adopters and non-adopters of weather index insurance. However, the two groups of farmers might be operating under two different frontiers making a direct comparison between their technical efficiency estimates inappropriate.

Our paper goes beyond these limitations and departs from the abovementioned literature in several ways. First, the study evaluated the impact of a composite technology (mineral fertilizer, improved seeds, and insurance) adoption on technical efficiency and levels of investment in production inputs. Secondly, the analysis is limited to two distinct farm households – farm household adopting two productivity-enhancing technologies (fertilizer and improved seeds) without insurance and the other adopting fertilizer, improved seeds with insurance. Thirdly, the study employs a sample selection stochastic production frontier to correct for biases from observed and unobserved variables and a meta-frontier framework. In this framework, the study assumes that households in the two distinct groups have the potential access to an array of production technologies, but each may choose a particular technology, depending on specific barriers, such as the production environments and resources, relative input prices, access to information and existing institutional environment. These barriers prevent farmers in one group from choosing the best technology from the array of potential technology sets. The resulting meta production frontier is assumed to be the most optimal, hence we estimate the technology gap ratios which is the difference between the optimal or "best" technology and the chosen sub-technology. Fourthly, the study also examined the impact of insurance on technical efficiency at the meta-frontier. This is particularly useful in helping to determine whether any behavioural biases might be related to insurance use.

The paper contributes to the literature in twofold: First, because risk management in agriculture is multifaceted, gaining a better understanding of the impact of agricultural insurance products or programs is important for developing effective strategies to counterbalance any negative unintended effects. Secondly, the findings of this study can also be used to design performance-improvement programs that can help farmers better optimize their returns on productivity-enhancing technologies and insurance. The rest of the paper is organized as follows. Section 5.2 formally presents the conceptual framework and econometric specification. In Section 5.3, the survey and data used are described. In Section 5.4, the empirical results and discussions are presented and finally, Section 5.6 offers conclusion and policy implications.

5.2 Conceptual and Econometric Framework

Agricultural production systems particularly in developing regions such as Africa have been observed to be generally inefficient due to a multitude of factors. Some of these factors include lack of infrastructure, lack of input, credit and insurance markets, low soil fertility and inefficient methods of cultivation, and insufficient use of fertilizer, insecticides, and improved seeds. Furthermore, the presence of risk in agricultural production systems imposes ex-ante barriers to the use of profitable technologies, which in turn affect agricultural productivity and economic growth (Binswanger and Sillers, 1983; Barnett *et al.*, 2008; Miller, 2008; Di Falco and Chavas, 2009; Kouamé, 2010; Dercon and Christiaensen, 2011; Demeke *et al.*, 2016; Poole, 2017; Amare *et al.*, 2018). Managing production risks is therefore seen as a potential to unlock demand for productivity-enhancing inputs (Liu, 2013; Mobarak and Rosenzweig, 2012; Elabed and Carter, 2014; Cai *et al.*, 2015). Concurrently, the provision of formal insurance in the form of index-based insurance is considered to be an effective risk management tool for smallholders to manage risk. However, as pointed out earlier, the use of insurance has implications for input use, levels of investments, and allocation of scarce resources, therefore, affecting smallholders' production and technical efficiency. At the same time, the use of insurance products leads to likely moral hazard problems and behavioural biases that do not only affect levels of investment in inputs but potentially, effort expended in production. These channels might correlate positively or negatively with household technical efficiency.

5.2.1 Sample selection stochastic frontiers approach

With the development of stochastic frontier analysis by Aigner *et al.* (1977), a large number of studies have analyzed the productivity and technical efficiencies among firms in several industries (e.g., Park, 2014; Vidoli *et al.*, 2016; Badunenko and Kumbhakar, 2017) and smallholders in developing countries (e.g., Ali and Chaudhry, 1990; Ali and Byerlee, 1991; Battese and Coelli, 1992; Wollni and Brümmer, 2012). At the same time, a substantial number of studies (Mal *et al.*, 2011; Abedullah *et al.*, 2015; Khanal *et al.*, 2018; Imran *et al.*, 2019; Torres *et al.*, 2019) have employed the stochastic frontier approach to examine the impact of technology adoption versus non-adoption on technical efficiency. The limitation of most of these studies is the failure to account for selectivity biases arising from both observable and unobservable factors. Studies such as those by Bravo-Ureta *et al.* (2012), Park (2014), Villano *et al.* (2015), Rahman *et al.* (2018) and Azumah *et al.* (2019), have shown the presence of selectivity effects hence failure to account for selectivity bias leads to inconsistent and biased estimates of technical efficiency.

In light of this, this study employed the sample selection approach proposed by Greene (2010) to estimate the impact of PET adoption with or without insurance on technical efficiency among farm households. The model which is an extension of the Heckman's approach considers sample selection in a stochastic frontier framework and assumes that unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier model. The sample selection stochastic frontier production frontier model by Greene (2010) is specified as follows:

$$\text{Sample selection} : t_j = 1\left[\beta' X_j + \varepsilon_j > 0\right],\ \varepsilon_j \sim N(0,\ 1) \tag{5.1}$$

$$\text{Stochastic frontier model} : y_j = \gamma' W_j + \epsilon_j,\ \ \epsilon_j \sim N\left(0,\ \sigma_\epsilon^2\right),\ \epsilon_j =\ v_j - u_j, \tag{5.2}$$

where y_j and W_j are observed only when t_j =1, $v_j = \sigma_v v_j$ with $v_j \sim$ N(0, 1), $u_j = |\sigma_u u_j| = \sigma_u |u_j|$ with $u_j \sim$ N(0, 1), and $(\epsilon_j,\ v_j) \sim N_2\left[(0,\ 1),\ (1,\ \rho\sigma\text{v},\ \sigma^2\text{v})\right]$. Also, y_j denotes the logarithmic crop income 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 PET with insurance, and 0 otherwise, 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 (v_j) and inefficiency term (u_j), and ε_j is the error term. The inefficiency term u_j is assumed to follow a half-normal distribution with the dispersion parameter σ_v, whereas ε_j and v_j follow a bivariate normal distribution with variances of 1 and σ^2v, respectively. The correlation coefficient, $\rho\sigma$v if statistically significant, indicates evidence of selectivity bias implying that estimates of the standard stochastic frontier model would be inconsistent (Greene, 2010). The specification described earlier permits the estimation of two separate selectivity corrected stochastic frontier models.

From the two estimated stochastic frontier models, the group-specific technical efficiency estimates, $TE_{ji} = \text{E}[\,e^{-u_{ji}},\ i\text{=}1,\ 0]$, for PET with insurance adopters and PET only adopters are derived. The estimated technical efficiency scores permit the comparison of the closeness of PET with insurance adopters and PET only adopters to their respective group production frontiers. However, as stated earlier in the paper, farm households in the two distinct groups have potential access to an array of production technologies, however 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 PET with insurance adopters and PET only adopters 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 for the preferred model.

5.2.2 Meta-frontier Analysis

Following the approach outlined by O'Donnell *et al.* (2008), the meta-frontier[1] that envelops the production frontiers of the PET with insurance and PET without insurance adopter group frontiers was estimated. The deterministic meta-frontier model for farm households adopting PET with and without insurance can be expressed as follows:

$$\begin{gathered} Y_i^* = f\left(X_j, \beta^*\right) = e^{X_j \beta^*}; \\ j = 1, 2 \ldots\ldots N,\ N = \sum_{k=1}^{2} N_k \end{gathered} \tag{5.3}$$

where β^* denotes the vector of parameters of the meta-frontier function such that $X_j\beta^* \geq X_i\beta_k$ for all j observations. The parameters of the meta-frontier function (β^*) in equation 5.3 are estimated 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:

$$\begin{gathered} \min_{\beta^*} \sum_{j=1}^{N} |(\text{In } f(X_j, \beta^*) - \text{In } f(X_j, \hat{\beta}_k)| \\ s.t. \;\; \text{In } f\left(X_j, \beta^*\right) \geq \text{In } f\left(X_j, \hat{\beta}_k\right) \;\; \forall\ j \end{gathered} \tag{5.4}$$

Based on the parameters of the meta-frontier function (β^*), the gaps between the meta-frontier and the individual group frontiers, termed the meta-technology gap

[1] The meta-frontier was estimated in R using the lpSolve package

ratio (TGR) are estimated. According to Issahaku and Abdulai (2019), a comparatively high average meta-technology gap ratio for a particular technology group suggests a lower technology gap between farm households in that group compared with all available set 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:

$$TGR = \frac{e^{X_j \hat{\beta}_k}}{e^{X_j \beta^*}} \tag{5.5}$$

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

$$MTE_j = TGR \times TE_{jk} \tag{5.6}$$

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 estimation of technical efficiency of farmers relative to the meta-frontier if all the data were generated from a single production frontier. Hence following the aforementioned authors, the likelihood-ratio test of the null hypothesis that there is no difference between two group-specific sample selection stochastic frontiers for all farm households was performed. By pooling data from PET with insurance and PET without insurance adopters 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 λ = -2[L(H_p) - (L(H_0) + L(H_1))] , where L(H_p) is the value of the log-likelihood function for stochastic frontiers estimated by pooling data for all farm households, L(H_0) and L(H_1) is the value of the sum for all the log-likelihood functions for the PET without insurance adopters and PET with insurance adopters respectively.

In estimating equation 5.1, some of the employed explanatory variables such as membership of farmer-based organizations, extension access, credit access, and non-farm work participation are potentially endogenous. As shown in several empirical studies, farmer-based organizations normally help their members to obtain inputs and credit, thus making membership of farmer-based organizations a potentially endogenous variable. Agricultural extension agents also normally disseminate new technologies to farmers, leading to the adoption of the technologies. Furthermore, farm households adopting these productivity-enhancing technologies may potentially attract more visits by extension staff than non-adopters and may also be encouraged to subscribe to agricultural insurance. Farm households that have access to credit can also afford to purchase fertilizer, improved seeds, and subscribe to agriculture insurance compared to households that are credit constrained, hence making credit access potentially endogenous. Furthermore, nonfarm work participation may also be potentially endogenous because income earned from nonfarm work can be invested in productivity-enhancing technologies and the purchase of insurance.

At the same time, engaging in off-farm work may reduce labour allocation to farming activities thus limiting the adoption of productivity-enhancing technologies. Therefore, addressing issues related to endogeneity 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. To address the potential endogeneity of membership of farmer-based organizations, extension access, credit access, and nonfarm work participation, the control function approach proposed by Wooldridge (2015) was employed. The approach involves the specification of the potential endogenous variable as a function of explanatory variables influencing adoption, together with a set of instruments in a first-stage probit regression. The employed instruments here should strongly influence the given potential endogenous variables (i.e. membership of farmer-based organizations, extension access, credit access, and nonfarm work participation) but not the choice of the two productivity-enhancing technologies with insurance. For the study, the use of coping strategies is used as instruments for membership farmer-based organization. Coping strategies are important informal risk-sharing arrangements within social networks such as microfinance, rotating savings, and credit. Hence farm households that use coping strategies are likely to be members of farmer-based organizations. In case of extension access, support needs of a farm household was considered as identifying instrument.

Farm households that require support needs, might actively seek to gain extension access. Location was used as an instrument for controlling credit access. Location in a populous region is normally associated with high urbanization rates and easy access to informal credit sources. Households located in populous regions are more likely going to have access to credit compared to households in a less populous location. Distance to a major city was considered as an instrument to control for nonfarm work participation. Shorter distances to a major city increase the likelihood of households obtaining nonfarm work compared to longer distances. Furthermore, these instruments are also excluded in the estimation of equation 5.1. Finally, both the observed factors and the "generalized residuals" predicted from a first-stage regression are included as covariates in the sample selection model. Including the residuals serves as a control function, enabling the consistent estimation of the four potential endogenous variables in the sample selection model.

5.2.3 Propensity score matching (PSM)

To mitigate biases coming from observables, the study followed previous studies (Bravo-Ureta *et al.*, 2012; Villano *et al.*, 2015) and use the PSM to create a suitable counterfactual dataset. As suggested by Monteiro (2010), the approach permits the generation of a control group with observed characteristics that are as similar as possible as those for the treated group, a condition that is necessary to get an accurate measure of impact. The use of PSM makes it possible to match farmers who adopt PET with insurance with those that did not adopt with insurance based on observed characteristics so that both groups are as similar as possible except for adoption. In the matching process, a binary choice model is used to generate a "score" which is equal to the probability of receiving treatment, considering both treated and non-treated groups based on a given set of predetermined covariates (Imbens and Wooldridge, 2009).

The generated scores are then used to match PET with insurance adopters with PET without insurance adopters for those farm households falling within a 'common support' area. In the process, observations from PET with insurance adopters with a score smaller than the minimum or larger than the maximum for the PET without insurance adopter group are removed from the sample (Caliendo and Kopeinig, 2008). To ensure that the samples within the common support area have the same distribution of observable characteristics, regardless of whether the farmer has adopted or not, it is necessary to test for the 'balancing property' (Becker and Ichino, 2002). This is achieved by conducting a t-test before and after matching to evaluate the null hypotheses that the means of observed characteristics of PET with insurance adopters and PET without insurance adopters are equal. If the mean of most of the observed characteristics is not statistically different, this suggests that the balancing property of the covariates is satisfied (Leuven and Sianesi, 2003). The study employed the kernel matching algorithm with six optimal number of blocks[2] identified.

[2] In the algorithm blocks for which the average propensity scores of treated and controls does

The matching procedure yielded a sample of 735 matched observations, made up of 145 PET with insurance adopters and 590 PET without insurance adopters.

5.2.4 Endogenous Switching Regression Model

For policy reasons, the study also evaluated the impact of productivity-enhancing technologies with insurance adoption on technical efficiency at the meta-frontier. Ideally, it would have been sufficient to use the estimated technical efficiency with respect to the meta-frontier production technology (MTE) in equation 5.6, however, doing this might introduce unknown biases in our results. This is because the endogenous switching regression model allows one to account for selectivity bias due to observed and unobserved factors. The estimation of the meta-technical efficiencies in equation 5.6 already accounted for likely selectivity bias due to observed and unobserved factors through equation 5.2. Using these meta-technical efficiency scores in the endogenous switching model will mean accounting for selectivity biases twice and this might result in estimation biases. Bearing this in mind, we employed the stochastic meta-frontier approach by Huang *et al.* (2014). This approach does not account for selectivity biases in the group level frontier estimation but permits the control for selectivity biases arising from observed and unobserved factors in the endogenous switching regression model.

Following the approach outlined by Huang *et al.* (2014), a stochastic meta-frontier production function of farm households adopting productivity-enhancing technologies with and without insurance was estimated as a two-step procedure. The first step involves estimating group-specific frontiers. In the second step, stochastic frontier techniques are used to determine the meta-frontier production function. At the same time, because farm households normally consider outcomes such as potential net utility when making decisions on the adoption of new technologies, they may self-select into adopting PET with and without insurance, depending on their inherent characteristics. The non-randomness of adoption decisions, therefore, raises issues of sample selection bias as previously mentioned. Hence to account for selectivity bias due to observed and unobserved factors, an endogenous switching regression approach was employed, where the adoption decision ($Y_j = 1$ or 0) is considered as a switch or adoption status indicator, with two outcome regimes. This approach

not differ is created. Subsequently, the covariates are balanced within each block between treated and controls groups. A detailed explanation of the approach can be found in paper of Becker and Ichino (2002). We estimated the PSM using the pscore package by Becker and Ichino (2002) in Stata.

employs the full information maximum likelihood (FIML) method to estimate one selection and two outcome equations simultaneously. The endogenous switching regression model was estimated using the full sample. A detailed description of the stochastic meta-frontier approach and the endogenous switching regression model is provided in the appendix.

5.3 Study area and data

Senegal is a country located within the Sahel region of West Africa. It has six main agro-ecological zones (Niayes, Senegal River Valley, Sylvo-pastoral Zone, Groundnut Basin, Eastern Senegal, and Casamance), based on biophysical and socioeconomic criteria (D'Alessandro *et al.*, 2015). Rainfall in these agroecological zones are unimodal and are characterized by varying levels of rainfall and temperature. With more than 95% of the total cropped area depending on rain-fed and less than 1% of agricultural land under irrigation, the growing season in Senegal is strongly correlated to the rainy season. The main crops cultivated in Senegal by smallholders are groundnuts and millet, which together account for almost 75% of the planted area. Maize, rice sorghum, cowpeas, and cotton make up about 25% and less than 1% is sown to other crops, including vegetables (D'Alessandro *et al.*, 2015).

The data used in the study comes from a farm household survey as part of the larger Senegalese "Projet d'appui aux politiques agricoles (PAPA)" or the Agricultural Policy Support Project funded by USAID under "Feed the Future". The implemented project focused on several value chains such as dry cereals, irrigated rice, horticulture, and inputs value chains such as seeds and fertilizers. The Senegalese National Agricultural Research Institute (ISRA) conducted the survey, with the support of the International Food Research Institute (IFPRI) between April and May 2017 across all the 14 administrative regions of Senegal and all the departments except for the departments of Dakar, Pikine, and Guédiawaye. A total of 42 agricultural departments were included in the survey. 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 is 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 rain-fed agriculture was practice and localized crops were grown such as Senegal River Valley and 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 2016/2017 and include information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit, inputs use and cost, family and hired labour, sales volumes, and food processing activities. Others included household consumption, access to amenities, non-farm and livestock revenue, remittance, agricultural insurance, risks and adaptation strategies, perception of subsidized inputs, and membership of farmer-based organizations.

As indicated earlier, our study considered two farm households, one adopting fertilizer and improved seeds without insurance and the other adopting fertilizer and improved seeds with insurance. After the data cleaning and preparation, a total of 1169 farm households (145 adopting fertilizer and improved seeds with insurance and 1024 adopting fertilizer and improved seeds without insurance) were retrieved from a total sample of 5,312 households.

5.3.1 The empirical 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, and consideration also for the type of data available and the context of the study. Hence for this study, the technology for crop production by farm households is represented by a Cobb–Douglas production frontier[3] that can be specified as:

$$\ln(y_j) = \beta_0 + \sum_{j=1}^{4} \beta_j \ln W_j + \sum_{k=1}^{2} \delta_k D_{kj} + v_j - u_i \tag{5.7}$$

where ln is the natural logarithm, y_j denotes the total value of crop output of farm household j, β_0 denotes farm household-specific fixed effects measuring heterogeneity, β_j and δ_k denote unknown parameters to be estimated, W_j is the quantity of the kth input of the jth household, D represents dummy variable for irrigation use and

[3]The sample selection stochastic frontier was estimated using Limdep version 11.

farming system. v_j denotes random error and u_i the inefficiency term. The inputs vectors include labour in man-days/ha, landholding in hectares, and fertilizer and seed quantities used in kg per hectare.

The specification of the empirical probit (selection) model is based on economic theory, empirical studies on technology adoption and production efficiency. From the empirical literature, we summarized variables that are hypothesized to affect productivity-enhancing technologies with or without insurance adoption decisions. These include farm household characteristics, farm characteristics, risk variables, and institutional variables. Table 5.1 presents the definition of the variables used in the analysis. The summary statistics of variables for farm households in each adoption group and across unmatched and matched samples is presented in Table 5.8 in the appendix. A significant difference exists between households adopting PET with insurance and PET without insurance. Households adopting PET with insurance appear to have relatively older male heads with formal education compared to households adopting PET without insurance. At the same time, PET with insurance adopting households are wealthier, have better access to extension and credit, have higher membership in farmer-based organizations, and are more market integrated than households adopting PET without insurance. Related to the risk variables, households adopting PET with insurance are less risk-averse, experience fewer risks but encounter the most losses related to risk.

Table 5.1: Variables definition

Name	**Variable description**
Dependent variable of the selection equation	
Adoption	=1 if household adopted PET with insurance
Outcome variable for ESR model	
MTE	Technical efficiency with respect to meta-frontier
Household characteristics	
Age	Age of household head in years
Gender	=1 if household head is male
Education	=1 if the household head has formal education
HH size	Total number of people in the household
Light	=1 if source of lighting fuel is electricity
HWI[1]	Household welfare index
Remittance	=1 if the household receives remittances
Nonfarm	=1 if household participates in nonfarm work
HH part	=1 if household head participates in farm work
Institutional variables	
Extension	=1 if accessed extension service
Membership	=1 if a member of a farmer-based organization
Credit	=1 if access to credit
Fert subsidy	=1 if access to subsidized fertilizer
Seed subsidy	=1 if access to subsidized seeds
Subsidy	=1 if access to both subsidized fertilizer and seeds
Market	=1 if the household is integrated into markets
Insurance	=1 if the household has insurance needs
Farm-related characteristics	
Cash crop	Share of land under cash crops (%)
Irrigation	=1 if a household uses irrigation
Diversification[2]	Crop diversification index
Farming system	=1 if household practices rainfed subsistence agriculture
Mixed farming	=1 if household rears livestock and grow crops
Soil degradation	=1 if the soil is perceived to be degraded
Soil quality[3]	Soil quality index
AII[4]	Agriculture implement index
Risk variables	
Rainfall	Log of mean annual rainfall in mm (2010 – 2017)
Std rainfall	Standard deviation of rainfall in mm (2010 – 2017)
Risk attitude	=1 if highly risk-averse
Risk count	Number of risks experienced by household
Loss count	Number of risk-related losses experienced by household

[1] This is an index computed 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.

[2] The diversification index estimated here is simply the Herfindahl-Hirschman Index (HHI) which is calculated by squaring the land area share of each crop grown by a household and then summing the resulting numbers. It can range from close to zero to 1. A value of 1 means that the household produces only one crop, while a value close to zero suggests a high crop diversification.

[3] For soil quality, we computed a soil quality index using publicly available data from International Soil Reference and Information Centre (ISRIC – World Soil Information). We describe the computation of this index in the appendix.

[4] We computed an agricultural implement index using a for the number of agricultural equipment owned by households.

Table 5.1: Variables definition(*continued*)

Name	**Variable description**
Instrumental variables	
Coping strategy	=1 if the household employs coping strategies
Support needs	=1 if farmer has support needs
Location	=1 if the household is located in a highly populous region
Distance	Log of distance to a major city in km
Sufficiency	=1 if subsidized seed is perceived sufficient
Stochastic production frontier	
Input variables	
Labour	Log of total quantity of labour used in man-days/ha
Land	Log of total land holding of household in hectares
Fertilizer	Log of fertilizer quantity used in kg/ha
Seeds	Log of seed quantity used in kg/ha
Output variable	
Crop income	Log of crop production value in CFA
Mundlak fixed effect variables	
Mean labour	Mean labour use across all crops grown
Mean land	Mean land (ha) allocation across all crops grown
Mean fertilizer	Mean fertilizer (kg) use across all crops grown
Mean seed	Mean seed (kg) use across all crops grown
Industry-level environmental variables	
AEZ BasinAra	=1 if agro-ecological zone is Bassin Arachide
AEZ RiverVall	=1 if agro-ecological zone is River Valley
AEZ Niayes	=1 if agro-ecological zone is Niayes
AEZ Casamance	=1 if agro-ecological zone is Casamance
AEZ CentEast	=1 if agro-ecological zone is Center East
AEZ VallAnambe	=1 if agro-ecological zone is Valley Anambe

5.4 Empirical results

In this section, the results from the empirical approaches used in the study are presented. Firstly, investments in fertilizer, seeds, and labour across farm households adopting PET with and without insurance were compared. Secondly, the first stage probit results and the sample selection stochastic frontiers for the unmatched and matched samples are presented. In each of these models, we provide estimates of the technical efficiency (TE) scores, technology gap ratios (TGR), and the group-specific technical efficiency with respect to the meta-frontier (MTE). Lastly, the results of the endogenous switching regression model and the technical efficiency implications of PET with insurance adoption are presented.

5.4.1 Input use and investment

With the empirical results providing mixed results related to the impact of insurance use on investments in production inputs, the quantities of production input use (labour, land, fertilizer, and seeds) per hectare and investments (CFA) across the various farm households adopting PET with and without insurance was compared. Referring to Table 5.8 in the appendix, significant differences in fertilizer and improved seeds use exists between PET with insurance and PET without insurance adopting households for the unmatched sample. In general, farm households adopting PET with insurance tend to use more production inputs than farm households adopting PET without insurance. Table 5.2 shows investments in fertilizer, seeds, and hired labour across the various farm households adopting PET with and without insurance. For the unmatched sample, we find statistically significant differences between PET with insurance and PET without insurance adopting households in terms of investment in fertilizer, general and improved seed. Generally, PET with insurance adopting households tends to have higher investments in fertilizer, seeds, and labour compared to PET without insurance adopting households. Households adopting PET with insurance make the highest investment, about 11.203 CFA/ha in fertilizers followed by labour (10.244 CFA/ha) and seeds (9.287 CFA/ha). The findings are congruent to previous studies (see Goodwin *et al.*, 2004; Mobarak and Rosenzweig, 2012; Berhane *et al.*, 2013; Karlan *et al.*, 2014; Cai *et al.*, 2015; Elabed and Carter, 2015; Delavallade *et al.*, 2015; Cole *et al.*, 2017; Hill *et al.*, 2019) that have found insurance to increase investments in inputs.

Table 5.2: PET investment levels and use

	PET only		PET with insurance	
Unmatched sample	**Mean[a]**	**SD**	**Mean[a]**	**SD**
Fertilizer expenditure (CFA/ha)	9.916	1.806	11.203∗∗∗	0.984
Seed expenditure (CFA/ha)[b]	8.995	1.469	9.287∗	1.559
Improved seeds expenditure (CFA/ha)	2.951	1.718	3.559∗∗∗	1.496
Labour expenditure (CFA/ha)	9.939	1.663	10.224	1.123
N	1024		145	
Matched sample				
Fertilizer expenditure (CFA/ha)	10.729	1.576	11.203∗∗∗	0.984
Seed expenditure (CFA/ha)	9.182	1.563	9.287	1.559
Improved seeds expenditure (CFA/ha)	3.328	1.705	3.559	1.496
Labour expenditure (CFA/ha)	10.106	1.645	10.224	1.123
N	590		145	

[a] Reported mean values are logged values.
[b] This is general seed use, hence it includes non-improved seeds as well. During the data collection period 1 US$= 615.81 CFA. ∗∗∗, ∗ represent 1% and 10% significance level, respectively.

5.5 Sample-Selection Stochastic Frontier Estimates

5.5.1 First-stage: Farm household adoption decision

Results of the first stage of the sample-selection stochastic frontier model, using both the original unmatched dataset and the matched dataset, are presented in Table 5.11 in the appendix. At the same time, the results of the control function approach to control for the effect of potentially endogenous variables in both unmatched and matched analysis are presented in Table 5.9 and 5.10 in the appendix. The results show that the instruments used to control for the potentially endogenous variables were appropriate. From Table 5.11, the chi-squared test statistic is significant, indicating a joint significance of the parameters for the adoption of PET with insurance for both matched and unmatched samples. For the unmatched sample, we find the estimate of the residual term for extension access to be significant suggesting the presence of simultaneity bias. The insignificance of the estimates of the residual for membership of farmer-based organizations, credit access, and nonfarm work participation indicates the absence of simultaneity bias, and hence a consistent estimation of these variables (Wooldridge, 2015). In both the unmatched and matched samples, we find that the education level of the household head, source of lighting fuel (a proxy for household wealth), access to extension, and insurance needs to be positively and significantly associated with farm household's decision to adopt PET with insurance. The share of land area devoted towards cash crops is however negative and significantly associated with PET with insurance adoption. Receipt of remittance was observed to be negative and significantly related to the adoption for PET with insurance for the unmatched sample. For the matched sample, the participation of household heads in farm work and risk attitude is negative and significantly associated with the adoption of PET with insurance. The number of losses related to production risks was however observed to be positive and significantly associated with the adoption of PET with insurance.

5.5.2 Second stage: Frontier estimates

The results of the group-specific stochastic frontiers and meta-frontier for both the unmatched sample and matched sample are presented in Table 5.3 and 5.4, respectively. A test of the null hypothesis that there is no difference between the pooled frontier model and the two group-specific stochastic frontiers was rejected[4] suggesting significant differences in technology between the frontiers for PET with and without insurance adopters. Thus, the estimation of separate frontiers for each group is justified. In both unmatched and matched samples, the input vectors for PET without insurance adopters are positive and significant for land, fertilizer, and seeds, implying that these inputs contribute to moving farm productivity to the frontier. For PET with insurance adopters, labour, land, and fertilizer are positive, with land and fertilizer being significant. Seed is however negative and insignificant, implying that it moves farm productivity away from the frontier.

[4] The generalized likelihood ratio test statistic $\chi^2(11) = 19.675$ ($p < 0.01$) for both unmatched and matched sample

Table 5.3: Estimates of sample-selection stochastic and meta-frontier model: Unmatched sample

Variable	PET without insurance Coeff.	Std. Err.	PET with insurance Coeff.	Std. Err.	Meta-Frontier Coeff.	Std. Err.
Constant	10.641***	0.275	10.599***	0.783	10.668***	0.595
Labour	0.048	0.042	0.123	0.163	0.130	0.120
Land	0.805***	0.046	0.978***	0.157	0.974***	0.149
Fertilizer	0.291***	0.025	0.501***	0.070	0.505***	0.095
Seed	0.111***	0.023	-0.044	0.071	0.018	0.032
Irrigate	0.189*	0.097	0.513*	0.308	0.591**	0.309
Farming system	-0.003	0.104	0.519	0.454	0.506*	0.369
Sigma(u)	0.697***	0.092	1.277***	0.193		
Sigma(v)	0.791***	0.027	0.537***	0.135		
Rho (w v)	0.062	0.155	-0.713**	0.278		
RTS	1.25		1.56		1.63	
Log likelihood	-1460.504		-389.448			
N	1024		145		1169	

***, **, * represent 1%, 5% and 10% significance level, respectively.

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 total crop income. In both unmatched and matched samples, land has the highest contribution to moving farm productivity to the frontier of PET without insurance adopters, followed by fertilizer, seeds, and labour. In the case of PET with insurance adopters, land has the highest contribution to moving farm productivity followed by fertilizer and labour. Seeds, however, reduces total crop income, perhaps because not all seeds used by farm households are improved seeds. In both unmatched and matched samples, the irrigation use dummy variable has a positive and significant effect in moving farm productivity to the frontier for both PET without insurance and PET with insurance adopters. Except for PET with insurance adopters in the unmatched sample, the farming system dummy variable has a positive effect in moving farm productivity to the frontier although the observed effect is not statistically significant. The estimated returns to scale (RTS) for the unmatched sample, shows a return to scale of 1.25 for PET without insurance adopters and 1.56 for PET with insurance adopters. This implies that both PET without insurance and PET with insurance adopting farm households are operating under increasing returns to scale. Implying that, holding all else constant, a 1% joint increase in all inputs will bring about more than a unit increase in crop income, however, the returns for PET with insurance adopters are higher. For the matched sample, we observe similar results. We observed returns to scale of 1.49 and 1.39 for PET without insurance and PET with insurance adopters, respectively. PET without insurance adopters, however, obtains slighter higher returns compared to PET with insurance adopters.

Table 5.4: Estimates of sample-selection stochastic and meta-frontier model: Matched sample

	PET without insurance		**PET with insurance**		**Meta-Frontier**	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	9.567∗∗∗	0.414	10.911∗∗∗	0.814	10.542∗∗∗	0.830
Labour	0.079	0.063	0.048	0.158	0.083	0.096
Land	0.879∗∗∗	0.067	0.899∗∗∗	0.153	0.939∗∗∗	0.140
Fertilizer	0.462∗∗∗	0.034	0.500∗∗∗	0.056	0.551∗∗∗	0.070
Seed	0.068∗	0.034	-0.055	0.076	0.017	0.031
Irrigate	0.323∗∗	0.138	0.530∗	0.311	0.594∗∗	0.298
Farming system	0.235	0.145	0.610	0.394	0.630∗∗	0.366
Sigma(u)	0.633∗∗∗	0.124	1.341∗∗∗	0.162		
Sigma(v)	0.844∗∗∗	0.035	0.485∗∗∗	0.110		
Rho (w v)	-0.083	0.201	-0.601∗	0.364		
RTS	1.49		1.39			
Log likelihood	-905.581		-379.541			
N	590		145			

∗∗∗, ∗∗, ∗ represent 1%, 5% and 10% significance level, respectively.

For both unmatched and matched samples, we find that the inefficiency dispersion parameters Sigma (u) are significant for both PET without insurance and PET with insurance adopters, suggesting that inefficiency is an important contributor to total crop income variability. However, Sigma (u) is much larger for farmers adopting PET with insurance, suggesting that PET with insurance adopting farm households are more affected by inefficiency than those adopting PET without insurance. Results from the sample selection production frontiers models show that the estimated sample selectivity term, *Rho* is negative and statistically significant in both unmatched and matched samples for PET with insurance adopters. This suggests the presence of selectivity bias, thus unobserved factors that affect the adoption of PET with insurance are correlated with the idiosyncratic error term of the stochastic frontier model. The results, therefore, support the use of the sample selectivity framework.

5.5.3 Technical efficiency scores and technology gap ratios

The main goal of this study is to investigate the nexus between insurance use and technical efficiency. Hence, the mean technical efficiencies scores and technology gap ratios of PET without insurance adopters and PET with insurance adopters were compared to draw inferences. Table 5.5, presents the estimated group-specific technical efficiency (TE) scores, technology gap ratios (TGR), and the group-specific technical efficiency with respect to the meta-frontier (MTE) for both unmatched and matched samples. Since farm households operate under heterogeneous technologies, the group-specific technical efficiency (TE) estimates cannot be directly compared across PET without insurance and PET with insurance adopters. This is because technical efficiency estimates are measured against different production frontiers, thus comparing farm households' technical efficiencies from their own frontier could bias results.

The results suggest that after controlling for biases arising from both observable and unobserved differences between PET without insurance adopters and PET with insurance adopters, the former performs better within their own frontier than the latter in both unmatched and matched sample. Nonetheless, technical efficiency is generally low for both PET without insurance and PET with insurance adopters. For the unmatched sample, PET without insurance adopters have a mean technical efficiency score of 58.6% while those of PET with insurance adopters is 43.9%. Similarly, for the matched sample, a mean technical efficiency score of 61.2% was observed for PET without insurance adopters while that of PET with insurance adopters is 43.1%. Therefore, it can be concluded that considering the group-specific frontiers, PET with insurance adoption is correlated to lower technical efficiencies.

The results from the meta-frontier estimates show that the technology gap ratios of farm households adopting PET without insurance and PET with insurance are both operating closer to the meta-frontier. However, the technology gap ratios of PET with insurance adopters are significantly higher than those of PET without insurance adopters, suggesting that PET with insurance adopters appear to be slightly more efficient in adopting the best available technology.

Table 5.5: Estimated technical efficiency and technology gap ratios

	Unmatched sample		Matched sample	
	Mean	**SD**	**Mean**	**SD**
PET without insurance				
TE	0.586	0.104	0.612	0.089
TGR	0.893	0.015	0.893	0.009
MTE	0.523	0.093	0.547	0.079
PET with insurance				
TE	0.439	0.217	0.431	0.218
TGR	0.977	0.011	0.973	0.008
MTE	0.428	0.211	0.419	0.213
Pooled				
TE	0.568	0.133	0.576	0.144
TGR	0.904	0.031	0.909	0.033
MTE	0.512	0.119	0.521	0.128
Test of means[1]				
TGR	0.083∗∗∗(0.001)		0.081∗∗∗(0.001)	
MTE	0.095∗∗∗(0.010)		0.127∗∗∗(0.011)	

[1] T-test of mean TGR and MTE difference between PET without insurance adopters and PET with insurance adopters. Values reported in brackets are standard errors. ∗∗∗ represent 1% significance level.

With the unmatched sample, the mean technical efficiency with respect to the meta-frontier for farm households adopting PET without insurance is about 52% and this is significantly higher than that of farm households adopting PET with insurance, who have a mean technical efficiency of about 43%. Similar results were also observed for the matched sample. On average PET without insurance adopting farm households are about 55% technically efficient compared to PET with insurance adopting farm households who have a mean technical efficiency of about 42%. This implies that the adoption of PET without insurance on average tends to increase technical efficiency by about 21% among adopters compared with PET with insurance adopters. Our results appear to be congruent to the study of Atozou *et al.* (2017) who found Senegalese groundnut farmers who had subscribed to insurance to be less technically efficient compared to those who had not subscribed to insurance. Furthermore, as suggested by Larochelle and Alwang (2013), the cost of risk management could simply be reflected by an increase in technical inefficiency due to resource reallocation effects. Previous studies (Horowitz and Lichtenberg, 1993; Smith and Goodwin, 1996; Goodwin, 2001; Goodwin *et al.*, 2004), also suggest that insurance use introduces some form of moral hazard problems. In the context of a developing country like Senegal, this might come from behavioural biases in the form of effort expended in production. This might likely be the case since no reduction in input use or investment in inputs is observed for PET with insurance adopters when compared with PET without insurance adopters. Hence farmers adopting PET with insurance might be devoting less effort to their farming activities. Earlier studies by Chassang *et al.* (2012) and Bulte *et al.* (2014) provide important insights into the effect of effort. Chassang *et al.* (2012) suggest that the unobserved effort of agents is a source of heterogeneity in treatment effects. They also suggest that effort expended by agents responds to beliefs, and beliefs respond to information. Congruent to the argument of Chassang *et al.* (2012), data from the investigation of behavioural responses of new agricultural technologies in Tanzania using a double-blind field experiment by Bulte *et al.* (2014) shows that if farmers do not have information about an intervention (improved technology), they do not expand greater effort in the use and management and hence resource allocations are inefficient compared to a situation where they are aware or have information about the intervention.

5.5.4 Endogenous Switching Regression Results

The results of the endogenous switching regression model are presented in Table 5.6. In the interest of brevity, we do not discuss the results of the stochastic meta-fronter model and first-stage regression results[5]. The results of the stochastic meta-frontier model are presented in Table 5.12 in the appendix. The generalized likelihood ratio test statistic $\chi^2(20) = 62.41$ ($p < 0.001$) of the null hypothesis that there is no difference between the pooled frontier model and the two group-specific stochastic frontiers was rejected suggesting significant technology differences between the frontiers for PET with and without insurance adopters. Thus, the estimation of separate frontiers for each group prior to estimating the stochastic meta-frontier is justified. The results of the test of the validity of instruments (insurance needs and perception of subsidized seed sufficient) used for model identification reported in Table 5.14 suggests that the instruments were appropriate. The parameter estimates of the residual term for extension access and nonfarm work participation are significant, suggesting the presence of simultaneity bias, and thus a consistent estimation of these variables (Wooldridge, 2015).

[5]The first-stage results of the endogenous switching regression model are also similar to that in the sample selection stochastic frontier reported in Table 5.11 in the appendix. Additionally, the results of the control function approach are reported in Table 5.13.

In the context of policy, it is useful to determine the drivers of technical efficiency or inefficiency to guide the design of performance-improvement programs that can help farmers better optimize the returns of productivity-enhancing technologies and insurance. Furthermore, understanding the impact of policy measures aimed at pushing farm households towards the meta-frontier is important in identifying likely inadvertent impacts. Thus, in Table 5.6 we identify some important socio-economic and institutional variables that drive technical efficiency. The estimates reveal that technical efficiency is significantly influenced by age, gender, education, household size, land size, extension access, membership of farmer-based organizations, credit access, the share of land area under cash crops, crop diversification, subsidy access, mixed farming, rainfall, and equipment ownership.

Table 5.6: ESR results for adoption and impact on technical efficiency

	Selection equation		MTE of PET adopters without insurance		MTE of PET adopters with insurance	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	-2.596**	1.319	0.671***	0.043	1.374***	0.266
Age	0.003	0.005	-0.000*	0.000	-0.001	0.001
Gender	0.155	0.230	0.022*	0.012	-0.020	0.091
Education	0.369***	0.132	0.019***	0.006	-0.081**	0.039
HH size	0.006	0.014	-0.001*	0.001	-0.003	0.004
Land	-0.008	0.008	-0.001	0.001	-0.018**	0.007
Extension	1.019**	0.508	0.028***	0.007	-0.025	0.048
Membership	1.334*	0.783	0.008	0.007	-0.160***	0.038
Credit	1.382	0.926	-0.001	0.011	-0.154***	0.051
Market	0.129	0.118	0.006	0.006	-0.022	0.039
Cash crop	-0.015**	0.007	-0.001***	0.000	0.002	0.002
Diversification	-0.003	0.003	0.002***	0.000	0.003***	0.001
Subsidy	0.509***	0.196	-0.040***	0.006	-0.113**	0.053
HWI	0.137***	0.043				
Nonfarm	-1.570**	0.731				
Risk	-0.146	0.188				
Risk count	-0.028	0.043				
Loss count	0.181**	0.074				
Soil degradation	0.306	0.227				
Remittance	-0.272*	0.154				
Soil quality			0.052	0.036	0.008	0.177
Std rainfall	-0.114	0.254				
Rainfall			-0.019***	0.006	-0.066**	0.032
Insurance	0.534***	0.111				
Sufficiency	-0.367*	0.205				
Mixed farming			0.048***	0.006	-0.081***	0.030
AII			0.001	0.003	0.045**	0.021
Mean labour			0.003	0.002	0.015	0.011
Mean land			-0.066**	0.027	0.378*	0.227
Mean fertilizer			0.000***	0.000	0.000***	0.000
Mean seed			0.000	0.000	0.006**	0.002
Resid mem	-0.688	0.461				
Resid ext	-0.633**	0.278				
Resid credit	-0.460	0.499				
Resid nonfarm	0.791*	0.435				
Sigma (σ)			0.087***	0.002	0.269***	0.031
Rho (ρ)			-0.167**	0.077	-0.927***	0.049
Wald chi2	523.360***					
Log-likelihood	792.007					
LR test of indep. eqns. Chi2	23.720***					
Joint sig. of crop varying covariates $\chi^2(4)$			19.230***		17.230***	

***, **, * represent 1%, 5% and 10% significance level, respectively.

For PET without insurance adopting households, the age of the household head, household size, the share of land area under cash crops, input subsidy access, and rainfall is negatively related to technical efficiency. On the contrary, the gender and education level of the household head, extension access, crop diversification, and mixed farming is positively related to technical efficiency. For PET with insurance adopting households, the education level of the household head, land size, membership in farmer-based organizations, credit access, subsidy access, mixed farming, and rainfall is negatively related to technical efficiency. We find that crop diversification and equipment ownership are positively related to the technical efficiency of PET with insurance adopting households.

The obtained results are largely congruent to previous studies that have investigated drivers of technical efficiency. For example studies by Solís *et al.* (2007), and Azumah *et al.* (2019) found gender to significantly influence technical efficiency. The effect of membership of farmer-based organizations on technical efficiency in the literature is mixed. Some studies (Khanal *et al.*, 2018; Yang *et al.*, 2018) have found a positive impact on technical efficiency while others (Wollni and Brümmer, 2012; Azumah *et al.*, 2019) have found a negative effect. The finding on the effect of subsidies is also consistent with that of Latruffe *et al.* (2017) who find that the effect of subsidies on technical efficiency was negative for some European Dairy Farms. Similarly, Alem *et al.* (2018) found subsidies to increase the level of inefficiency among Norwegian dairy farms. Bojnec and Ferto (2013) also found government subsidies negatively influenced the technical efficiency of Slovenian family farms.

5.5.5 Technical efficiency implications of PET with insurance adoption

An important part of this study is to understand the impact of insurance on technical efficiency at the meta-frontier if farmers decide to adopt PET with or without insurance. Table 5.7 presents the estimates of the treatment effects of adoption on technical efficiency under actual and counterfactual conditions. The results confirm the presence of likely behavioural biases or moral hazard problems with insurance use. The adoption of PET with insurance has a negative and statistically significant effect on the technical efficiency of households. The treatment effect indicates that the adoption of PET with insurance decreases technical efficiency by about 50%. On the contrary, for PET without insurance adopting households, the mean technical efficiency would be increased by about 37% had they adopted PET with insurance.

Table 5.7: Impact of PET with insurance adoption on technical efficiency

	Adoption decision stage			
	Adopt with insurance	**Adopt without insurance**	**Treatment effects**	**Change (%)**
Technical efficiency				
PET without insurance adopters	0.836(0.006)	0.608(0.002)	0.228∗∗∗(0.006)	37.44
PET with insurance adopters	0.424(0.015)	0.637(0.009)	0.213∗∗∗(0.018)	50.17
Heterogeneity effects	-0.412∗∗∗(0.016)	0.028∗∗∗(0.007)	-0.440∗∗∗(0.016)	

∗∗∗ represent 1% significance level.

Following Di Falco *et al.* (2011) we also adjusted for potential heterogeneity in outcomes by estimating the associated base heterogeneity effects and transitional heterogeneity related to the adoption of PET with insurance. The base heterogeneity effect is the difference in outcomes for farm households that adopted PET with insurance, and those that adopted PET without insurance across the two-adoption decision stage. Transitional heterogeneity on the other hand is the difference between the treatment effect for PET with insurance adopters and PET without insurance adopters. Results from Table 5.7 shows that PET without insurance adopters obtain better technical efficiency scores relative to PET with insurance adopters when they decide to adopt PET with insurance. The results also suggest that PET with insurance adopters have slightly higher technical efficiencies than PET without insurance adopters if the decision is not to adopt PET with insurance. Additionally, the transitional heterogeneity effect was observed to be negative, implying that overall, the adoption effect is larger for PET without insurance adopters relative to PET with insurance adopters. The results suggest that PET with insurance adoption per se do not lead to lower technical efficiencies, but lower observed technical efficiencies may be driven by unobserved effort or behavioural biases of farmers which can be an important source of heterogeneity in treatment effects.

5.6 Conclusion

This study examined the nexus between insurance use and technical efficiency by comparing two distinct groups of farm households in Senegal; PET with insurance adopters and PET without insurance adopters. We also evaluated the impact of complementing the adoption of PET with insurance on levels of investment in labour, fertilizer, and seeds. To address the nexus between insurance use and technical efficiency, the study employed a sample selection stochastic production frontier, meta-frontier together with propensity score matching, and an endogenous switching regression model to correct for potential selectivity biases. The results showed that complementing the adoption of PET with insurance increases investment in fertilizer, improved seeds, and labour.

Furthermore, PET with insurance adopting farm households appears to be less technically efficient compared to PET without insurance adopting farm households. Households that adopted PET with insurance decrease their technical efficiency by about 50%. At the same time, the mean technical efficiency of PET without insurance adopters would have been increased by about 37% had they adopted PET with insurance. The results suggest that lower observed technical efficiencies for PET with insurance adopters may be driven by unobserved effort or behavioural biases of farmers which can be an important source of heterogeneity in the observed treatment effects. The above findings have a number of policy implications. First, insurance products like index-based insurance will continue to play an important role in helping small-holders, particularly in developing countries better adapt to the effects and impacts of climate change. However, policymakers must recognize some unintended or pervasive effects and develop the necessary remedies. Since membership of farmer-based organizations, crop diversification, and mixed farming appears to reduce technical inefficiency, these should be promoted among farm households. Furthermore, the adoption of PET with insurance should be complemented 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, achieve higher yield thereby attaining environmental and economic sustainability.

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Appendix

Appendix A1: Supplementary empirical approach

Stochastic meta-frontier approach

Following the approach outlined by Huang *et al.* (2014), a stochastic meta-frontier production function of farm households adopting heterogeneous technologies is estimated as a two-step procedure. The first step involves estimating group-specific frontiers. In the second step, stochastic frontier techniques are used to determine the meta-frontier production function. The stochastic group-specific production frontier is formulated as

$$y_{ji} = f^i(W_{ji}, \gamma_i)\epsilon^{V_{ji}-U_{ji}}, \ j = \ 1, \ 2, \ ..., \ N_j; \ \ i = 1, 2, \ldots . \ M \tag{5.8}$$

where y_{ji} denotes the logarithmic crop income of farm household j in the ith group and W_{ji} refers to the vector of inputs of the jth farm household in the ith group, V_{ji} is the conventional error term that captures stochastic noise, U_{ji} represents technical inefficiency, and γ_i are parameters to be estimated. It is assumed that V_{ji} and U_{ji} are uncorrelated and V_{ji} is independently and identically distributed as N(0, $\sigma^2 V$) while U_{ji} follows a truncated-normal distribution (Huang *et al.*, 2014). Accordingly, technical efficiency derived from the model-specific to each farm household and adoption status (PET with or without insurance) can be stated as:

$$TE_j^i = \frac{y_{ji}}{f^i(W_{ji}, \gamma_i)\epsilon^{V_{ji}}} = \epsilon^{-U_{ji}} \tag{5.9}$$

The technical efficiency expressed in equation 5.8 is also assumed to be associated with a set of within-group firm-specific exogenous (environmental) variables Z_{ji} in addition to input vectors. For this study, the education level of household head, crop diversification, agriculture implement ownership, mixed farming, and market integration was employed as group-level environmental variables. Following Huang *et al.* (2014), the common underlying meta-frontier production function for all groups is defined as $f^M(W_{ji},\gamma_i)$ where the function is the same for all groups $i = 1 \ldots, M$. Their relationship is expressed as:

$$f^i(W_{ji}, \gamma_i) = \ f^M(W_{ji}, \gamma_i)\epsilon^{-U_{ji}^M}, \ \forall \ i, \ j, \tag{5.10}$$

where $U_{ji}^M \geq 0$. Thus, $f^M(W_{ji},\gamma_i) \geq f^i(W_{ji}, \gamma_i)$, and therefore, the ratio of the group frontier to the meta-frontier, referred to as the meta-technology gap ratio (TGR), can be expressed as:

$$TGR = \frac{f^i(W_{ji}, \gamma_i)}{f^M(W_{ji}, \gamma_i)} = \epsilon^{-U^M{}_{ji}} \leq 1 \tag{5.11}$$

According to Huang *et al.* (2014), the existence of the technology gap can be due to the choice of a particular technology that depends on the production environments and specific barriers. The meta-technology gap ratio is an index lying between zero and unity. A value equal to unity implies that farm households adopted the most advanced technology while a value of less than one means that farm households have failed to adopt the most advanced technology. The technology gap component U_{ji}^M in equation 5.11 is thus group and farm household-specific. Furthermore, at any given input level W_{ji}, a household's observed crop income y_{ji} relative to the meta-frontier $f^M(W_{ji},\gamma_i)$ can be decomposed into three components as:

$$\frac{y_{ji}}{f^M(W_{ji}, \gamma_i)} = TGR_j^i \times TE_j^i \times \epsilon_{ji}^V \tag{5.12}$$

The three components in equation 5.12 are the jth farmer's meta-technology gap ratio (TGR), technical efficiency (TE), and random noise (ϵ^V). Huang *et al.* (2014) emphasize that though both TGR and TE lie between 0 and 1, the meta-frontier does not necessarily envelope all farmers' observed outputs due to random noise. The unrestricted ratio in equation 5.12 distinguishes meta-frontier modelling by stochastic frontier analysis (SFA) from the data envelopment analysis (DEA). Hence, by accounting for the random noise, equation 5.12 can be reformulated as:

$$MTE_{ji} = \frac{y_{ji}}{f^M(W_{ji}, \gamma_i)\epsilon^{V_{ji}}} = TGR_{ji} \times TE_{ji} \tag{5.13}$$

where MTE_{ji} represents a farm household's technical efficiency with respect to the meta-frontier production technology, $f^M(W_{ji},\gamma_i)$. As proposed by Battese *et al.* (2004) and O'Donnell *et al.* (2008), the empirical measurement of the meta-frontier model comprises two steps: first, a maximum likelihood estimation is required to estimate each group-specific frontier regression in equation 5.8. Secondly, mathematical programming techniques are used to estimate the meta-frontier in equation 5.10 by minimizing the sum of squares of the deviations of the meta-frontier function from the estimated group-specific frontiers. However, as argued by Huang *et al.* (2014), the second step of this method presents potential difficulties because no statistical properties can be drawn of the meta-frontier estimators due to their deterministic nature. At the same time, Huang *et al.* (2014) and Chang *et al.* (2015) argue that the programming techniques do not isolate idiosyncratic shocks and thus results are susceptible to random shocks. In light of these shortcomings, Huang *et al.* (2014) proposed a stochastic meta-frontier model that uses stochastic frontier analysis to estimate meta-frontier parameters in the second stage rather than mathematical programming techniques. In the proposed approach by Huang *et al.* (2014), the conventional maximum likelihood estimation is used to estimate parameters of the meta-frontier model, hence allowing for the usual statistical inferences to be performed without depending on simulations or bootstrapping as in the case of mathematical programming techniques. The model of Huang *et al.* (2014) therefore builds on the equations 5.8 to 5.13. It considers the relation between the group-specific frontier and the meta-frontier functions in equation 5.10 to be reformulated as:

$$\mathrm{In} f^i(W_{ji}, \gamma_i) = \mathrm{In} f^M(W_{ji}, \gamma_i) - U_{ji}^M. \tag{5.14}$$

Because the group-specific frontier $f^i(W_{ji},\gamma_i)$ is unobservable but its estimate is available from the first step and for the reason that the fitted value $(\hat{f}^i W_{ji},\gamma_i)$ of f^i (W_{ji},γ_i) and the true frontier value $f^i(W_{ji},\gamma_i)$ are different, equation 5.14 can be reformulated as:

$$\mathrm{In} \hat{f}^i(W_{ji}, \gamma_i) = \mathrm{In} f^M(W_{ji}, \gamma_i) - U_{ji}^M + V_{ji}^M, \forall i, j = 1, 2. \ldots\ldots J \tag{5.15}$$

where U_{ji}^M is the statistical noise to represent the deviation between $\hat{f}^i(W_{ji},\gamma_i)$ and $f^i(W_{ji},\gamma_i)$ expressed as:

$$\mathrm{In} \hat{f}^i(W_{ji}, \gamma_i) = \mathrm{In} f^M(W_{ji}, \gamma_i) + V_{ji}^M \tag{5.16}$$

The specification in equation 5.15 is like the conventional stochastic frontier regression model and is therefore referred to as the stochastic meta-frontier (SMF) model. Because $\mathrm{In}\hat{f}^i(W_{ji},\gamma_i)$ is obtained by maximum likelihood-based methods, its parameter estimates are consistent and asymptotically normally distributed. The error V_{ji}^M is normally distributed as N(0, $\sigma^{M2}V$) while $U_{ji}^M \geq 0$ and $U_{ji} \sim N^+(\mu^M(Z_{ji}),$ $\sigma^{M2}(Z_{ji}))$, where Z_{ji} represents the industry-specific environmental variables which include deviations of rainfall, soil quality, and agro-ecological zones. The proposed two-step stochastic frontier approach of Huang *et al.* (2014) allows for the estimated group-specific frontier $(\hat{f}^i W_{ji},\gamma_i)$ to be greater than or equal to the meta-frontier $(f^M W_{ji},\gamma_i)$ due to the error of estimating $f^i(W_{ji},\gamma_i)$ in equation 5.15. According to Huang *et al.* (2014), the meta-frontier should be larger or equal to the true group-specific frontier, i.e., $f^M(W_{ji}, \gamma_i) \geq f^i(W_{ji}, \gamma_i)$. As previously stated, the estimated TGR must always be less than or equal to unity. The TGR is computed using the following formula:

$$\widehat{TGR}_{ji} = E(\epsilon^{-U_{ji}^M} | \hat{\varepsilon}_{ji}^M) \leq 1 \tag{5.17}$$

where $\hat{\varepsilon}_{ji}^M = \mathrm{In}\hat{f}^i(W_{ji},\gamma_i) - \mathrm{In}\hat{f}^M(W_{ji},\gamma_i)$ which represents the estimated composite residual of equation 5.15. At the same time, the estimated technology gap in equation 5.16 is a function of the production environments Z_{ji} via the mode μ^M (Z_{ji}) and the heteroscedastic variance $\sigma^{M2}(Z_{ji})$.

Endogenous Switching Regression Model

Following previous studies (see Di Falco *et al.*, 2011; Abdulai and Huffman, 2014; Ma and Abdulai, 2016) the empirical approach employed to evaluate the impact of PET with and without insurance adoption on technical efficiency was performed in two stages. In the first stage, the selection of a particular technology is specified using a binary model. The equations for the outcome of interest, in this case, the technical efficiency with respect to the meta-frontier are modelled for both PET with insurance adopters and PET without insurance adopters conditional on selection. Assuming risk neutrality, farmers will evaluate the net returns (utility) associated with the adoption of PET with and without insurance, let the latent net utility for adopters and non-adopters be denoted as Y^*, such that a utility-maximizing household j will choose to adopt PET with insurance if the utility gained from adopting is greater than the utility of not adopting with insurance ($Y^* = U^*_{iA} - U^*_{iN} > 0$). Given that a farm household utility level is a latent variable and cannot be observed, we observe only indicators of utility, namely choices. We specify the latent variable as:

$$Y^* = \beta X_j + \varepsilon_j,\ Y_j = 1\ \left[Y_j^* > 0\right], \tag{5.18}$$

where Y_j is a binary variable that equals 1 for farm households who adopt PET with insurance and zero otherwise (i.e. PET without insurance), with β denoting a vector of parameters to be estimated. Thus, the farm household adopts PET with insurance only if the perceived net benefits are positive. The error term ε is assumed to be normally distributed with zero mean. X is a vector of explanatory variables that influence the adoption decision such as risk attitude, knowledge, household, and farm-level characteristics, etc. The probability that a farm household adopts PET with insurance can be expressed as follows:

$$\Pr\left(Y_j = 1\right) = \Pr\left(Y_j^* > 0\right) = \Pr\left(\varepsilon_j > -\beta X_j\right) = 1 - F(-\beta X_j) \tag{5.19}$$

where F is the cumulative distribution function of the error term.

In the second stage, separate outcome equations[6] are specified for PET with insurance adopters and PET without insurance adopters.

$$MTE_{j_1} = \alpha_1 Z_{j_1} + \mu_1 \qquad \text{if}\ \ Y_j = 1 \tag{5.20a}$$
$$MTE_{j_0} = \alpha_0 Z_{j_0} + \mu_0 \qquad \text{if}\ \ Y_j = 0 \tag{5.20b}$$

where MTE_{j1} and MTE_{j0} are the technical efficiencies with respect to the meta-frontier for PET with insurance adopters and PET without insurance adopters,

[6] The Endogenous Switching Regression Model was estimated using the Movestay package in Stata.

respectively. Z_j is a vector of explanatory variables that include farm and household-level characteristics, such as the age, gender, education level of household head, household size, access to extension services, farm size, crop portfolio, land share under cash crops, etc. The vectors α_1 and α_0 are the parameters to be estimated and μ is the error term.

To overcome the possible correlation of farm-invariant unobserved heterogeneity with observed covariates, the approach of Mundlak (1978) and Wooldridge (2018) which has also been used by Di Falco (2014), Kassie *et al.* (2015), Teklewold *et al.* (2013) and Vigani and Kathage (2019)[7] was employed. This was achieved by exploiting crop-level information and including the mean of crop varying explanatory variables, which include labour, landholding, fertilizer, and seed quantity to deal with the issue of unobserved heterogeneity in the outcome equations 5.20a and 5.20b. Controlling for unobserved heterogeneity is particularly important to help address farm or plot-specific unobservables as they may contain useful missing information regarding land quality (Kassie *et al.*, 2015) for instance. Concurrently, if farm households obtain private information about unobservable effects such as how good the soil is on the plot or some shocks, they will adjust their factor input decisions accordingly (Fafchamps, 1993; Levinsohn and Petrin, 2003; Assunção and Braido, 2007). Hence, this approach permits the exploitation of crop-level information to deal with the issue of farm household's unobservable characteristics and farm-specific effects. As suggested by Teklewold *et al.* (2013), a Wald test of the null hypothesis that the vectors of the crop varying explanatory variables are jointly equal to zero is required to indicate the relevance of crop-specific heterogeneity.

Model identification requires at least one variable in the selection equation 5.18 that does not appear in the outcome equations 5.20a and 5.20b. The valid instrument (s) is required to influence a farm household's adoption decision but do not affect technical efficiency. The variables representing insurance needs and perception about the sufficiency of subsidized seeds are used as the instrument variables. While these variables are expected to affect adoption decisions, it is assumed that these do not affect technical efficiency directly. We conducted a validity check of these instruments, by estimating a simple probit model for the selection equation and an OLS model for the outcome equation separately to checked that both variables are in effect, significant when included in the selection equation but not significant when included in the outcome equation. The three error terms ε_j in equation 5.18, and μ_1 and μ_0 in equation 5.20a and 5.20b are assumed to have a trivariate normal distribution, with zero mean and the following covariance matrix:

$$\operatorname{Cov}(\varepsilon_j, \mu_1, \mu_0) = \Sigma = \begin{bmatrix} \sigma_\varepsilon^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 0} \\ \sigma_{1\varepsilon} & \sigma_{\mu_1}^2 & . \\ \sigma_{0\varepsilon} & . & \sigma_{\mu_0}^2 \end{bmatrix} \tag{5.21}$$

[7]In most of these studies, plot-variant variables were used to control for unobserved heterogeneity but due to the lack of plot-level data we use an alternative approach by using crop-variant variables since household produce multiple crops and we have crop-level data.

where $\text{Var}(\varepsilon) = \sigma^2\varepsilon$, $\text{Var}(\mu_1) = \sigma^2\mu_1$, $\text{Var}(\mu_0) = \sigma^2\mu_0$, $\text{Cov}(\varepsilon, \mu_1) = \sigma_{\varepsilon 1}$, and $\text{Cov}(\varepsilon, \mu_0) = \sigma_{\varepsilon 0}$. Since we do not observe MTE_{j1} and MTE_{j0} simultaneously, the covariance between μ_1 and μ_0 is not defined. The error term, ε_j of the sample selection equation 5.18 is correlated with the error terms of the outcome equation 5.20a and 5.20b. For this reason, the error terms in equation 5.20a and 5.20b, conditional on the sample selection criterion, have nonzero expected values, and hence using an ordinary least squares regression to estimate the coefficients α_1 and α_0 will result in sample selection bias (Lee, 1982). The expected values of the truncated error terms (μ_1 | Y =1) and (μ_0 | Y = 0) are then given as:

$$E(\mu_1|Y=1) = \sigma_{1_\varepsilon}\frac{\varphi(\beta X_j)}{\phi(\beta X_j)} = \sigma_{1_\varepsilon}\lambda_1 \quad (5.22)$$

and

$$E(\mu_0|Y=0) = \sigma_{0_\varepsilon}\frac{\varphi(\beta X_j)}{1-\phi(\beta X_j)} = \sigma_{0_\varepsilon}\lambda_0 \quad (5.23)$$

where $\Phi(.)$ and $\phi(.)$ are the probability density and the cumulative distribution function of the standard normal distribution, respectively. The terms λ_1 and λ_0 refer to the inverse Mills ratio evaluated at βX_j and are incorporated into outcome equations to account for sample selection bias. A drawback of the two-step approach for the endogenous switching regression model is that it generates residuals that are heteroskedastic and as a result cannot be used to obtain consistent standard errors without cumbersome adjustments (Lokshin and Sajaia, 2004). The full information maximum likelihood method suggested by Lokshin and Sajaia (2004) overcomes the problem through a simultaneous estimation of the two equations, that is, equation 5.18 and equations 5.20a and 5.20b.

The signs and significance levels of the correlation coefficients (ρ) from the estimates which are the correlation coefficients between the error term ε_j of the selection equation and error terms μ_1 and μ_0 of the outcome equations 5.20a and 5.20b are of particular interest. Specifically, there is endogenous switching, if either ρ_1 or ρ_0 is significantly different from zero, which would result in selection bias.

Estimating treatment effects

In this study, our main interest is to estimate the treatment effect (switching impacts) of PET with and without insurance adoption on technical efficiency. The endogenous switching regression method can be used to compare expected technical efficiency with the counterfactual hypothetical technical efficiency that farm households did not adopt PET with insurance and vice versa. This can be represented as follows:

Farm households that adopted PET with insurance (observed):

$$E[\,MTE_{j1}|Y_j = 1] \,= \alpha_1 Z_{j1} + \sigma_{\varepsilon_1}\lambda_1 \tag{5.24a}$$

Counterfactual case if PET with insurance adopting farm households did not adopt:

$$E[\,MTE_{j1}|Y_j = 0] \,= \alpha_1 Z_{j0} + \sigma_{\varepsilon_1}\lambda_0 \tag{5.24b}$$

Farm households that adopted PET without insurance (observed):

$$E[\,MTE_{j0}|Y_j = 0] \,= \alpha_0 Z_{j0} + \sigma_{\varepsilon_0}\lambda_0 \tag{5.24c}$$

Counterfactual case if PET without insurance adopting farm households adopted PET with insurance:

$$E[\,MTE_{j0}|Y_j = 1] \,= \alpha_0 Z_{j1} + \sigma_{\varepsilon_0}\lambda_1 \tag{5.24d}$$

The change in outcome due to adoption can then be specified as the difference between adoption and non-adoption. The use of these conditional expectations from equations 5.24a to 5.24d permits the calculation of average treatment effects (ATT) – i.e., the treatment effect for treated farm households (i.e., PET with insurance adopters), which is the difference between equations 5.24a and 5.24b. Furthermore, the average treatment effect on the untreated (ATU) households (i.e., PET without insurance adopters) is of interest and this is simply the difference between equations 5.24c and 5.24d. Just as previously mentioned in the paper, the control function approach was employed to account for the potential reverse causality and endogeneity problems that may arise with some explanatory variables in equation 5.18 such as membership of farmer-based organizations, extension access, credit access, and nonfarm work participation.

Appendix A2: Supplementary results

Table 5.8: Summary statistics for the matched and unmatched sample

	Unmatched sample						**Matched sample**[a]					
	PET without insurance		**PET with insurance**		**Total**		**PET without insurance**		**PET with insurance**		**Total**	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Crop income	12.867	1.189	13.474∗∗∗	1.341	12.943	1.225	12.773	1.272	13.474∗∗∗	1.341	12.911	1.315
Labour	4.017	1.403	4.082	1.071	4.025	1.366	4.426	1.389	4.082∗∗	1.071	4.358	1.339
Land	1.011	1.324	0.806	1.155	0.986	1.306	0.563	1.373	0.806∗	1.155	0.611	1.335
Fertilizer	4.440	1.469	5.449∗∗∗	0.919	4.565	1.451	5.094	1.265	5.449∗∗∗	0.919	5.164	1.212
Seed	3.606	1.154	3.736	1.447	3.622	1.195	3.727	1.291	3.736	1.447	3.728	1.322
Improved seeds	2.951	1.718	3.559∗∗∗	1.496	3.027	1.704	3.328	1.705	3.559	1.496	3.374	1.668
Age	53.324	12.893	53.545	12.996	53.352	12.901	52.919	12.368	53.545	12.996	53.042	12.488
Gender	0.934	0.249	0.945	0.229	0.935	0.247	0.936	0.246	0.945	0.229	0.937	0.242
Education	0.430	0.495	0.510	0.502	0.440	0.497	0.464	0.499	0.510	0.502	0.473	0.500
HH size	10.473	5.653	9.586∗	4.614	10.363	5.540	9.851	5.283	9.586	4.614	9.799	5.156
Light	0.348	0.476	0.579∗∗∗	0.495	0.376	0.485	0.392	0.489	0.579∗∗∗	0.495	0.429	0.495
Extension	0.322	0.468	0.621∗∗∗	0.487	0.359	0.480	0.459	0.499	0.621∗∗∗	0.487	0.491	0.500
Membership	0.311	0.463	0.593∗∗∗	0.493	0.346	0.476	0.471	0.500	0.593∗∗	0.493	0.495	0.500
Credit	0.095	0.293	0.283∗∗∗	0.452	0.118	0.323	0.137	0.344	0.283∗∗∗	0.452	0.166	0.372
Market	0.576	0.494	0.676∗	0.470	0.589	0.492	0.620	0.486	0.676	0.470	0.631	0.483
HH part	0.732	0.443	0.745	0.437	0.734	0.442	0.761	0.427	0.745	0.437	0.758	0.429
Nonfarm	0.263	0.440	0.152∗∗∗	0.360	0.249	0.433	0.198	0.399	0.152	0.360	0.189	0.392
Risk attitude	0.439	0.497	0.283∗∗∗	0.452	0.420	0.494	0.353	0.478	0.283	0.452	0.339	0.474
Risk count	1.448	1.669	0.869∗∗∗	1.560	1.376	1.666	0.939	1.489	0.869	1.560	0.925	1.502
Loss count	1.697	1.056	1.800	1.084	1.710	1.059	1.741	1.128	1.800	1.084	1.752	1.119
Cash crop	0.207	0.254	0.030∗∗∗	0.115	0.185	0.248	0.075	0.165	0.030∗∗∗	0.115	0.066	0.158
Diversification	33.681	32.875	23.701∗∗	40.298	32.443	34.024	27.040	37.151	23.701	40.298	26.381	37.787
Soil degradation	0.060	0.237	0.117∗	0.323	0.067	0.250	0.088	0.284	0.117	0.323	0.094	0.292

Notes: A t-test is used to determine if PET with insurance adopting farm household's means are statistically different from that of PET only adopting farm households. ∗∗∗, ∗∗, ∗ represent 1%, 5%, and 10% significance level, respectively.
[a] As previously noted, the balancing property is carried out on covariates of treated and control observations within each block of which the average propensity scores of treated and control observations do not differ. In this table, however, the average of all blocks treated and controlled observations are used.

Table 5.8: Summary statistics for the matched and unmatched sample (*continued*)

	Unmatched sample						**Matched sampled**[a]					
	PET without insurance		**PET with insurance**		**Total**		**PET without insurance**		**PET with insurance**		**Total**	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Rainfall	6.325	0.488	6.149∗∗∗	0.513	6.303	0.495	6.239	0.503	6.149	0.513	6.221	0.506
Insurance	0.487	0.500	0.752∗∗∗	0.434	0.520	0.500	0.603	0.490	0.752∗∗∗	0.434	0.633	0.482
Fert subsidy	0.683	0.466	0.814∗∗∗	0.391	0.699	0.459	0.720	0.449	0.814∗	0.391	0.739	0.440
Seed Subsidy	0.551	0.498	0.359∗∗∗	0.481	0.527	0.499	0.410	0.492	0.359	0.481	0.400	0.490
Remittance	0.104	0.305	0.097	0.296	0.103	0.304	0.110	0.313	0.097	0.296	0.107	0.310
Coping	0.287	0.453	0.262	0.441	0.284	0.451	0.253	0.435	0.262	0.441	0.254	0.436
Support	0.835	0.371	0.966∗∗∗	0.183	0.851	0.356	0.888	0.315	0.966∗∗∗	0.183	0.903	0.296
Location	0.147	0.355	0.014∗∗∗	0.117	0.131	0.337	0.085	0.279	0.014∗∗∗	0.117	0.071	0.257
Distance	71.870	48.918	93.040∗∗∗	40.068	74.495	48.400	89.408	50.129	93.040	40.068	90.124	48.307
Irrigation	0.398	0.490	0.731∗∗∗	0.445	0.440	0.497	0.586	0.493	0.731∗∗∗	0.445	0.615	0.487
Farming system	0.594	0.491	0.214∗∗∗	0.411	0.547	0.498	0.368	0.483	0.214∗∗∗	0.411	0.337	0.473
Subsidy	0.464	0.499	0.324∗∗	0.470	0.447	0.497	0.371	0.484	0.324	0.470	0.362	0.481
HWI	0.165	1.742	0.835∗∗∗	1.797	0.249	1.762	0.354	1.826	0.835∗∗	1.797	0.449	1.829
Mixed farming	0.341	0.474	0.297	0.458	0.335	0.472	0.336	0.473	0.297	0.458	0.328	0.470
Std rainfall	4.653	0.222	4.577∗∗∗	0.218	4.644	0.222	4.623	0.213	4.577∗	0.218	4.614	0.215
Sufficiency	0.241	0.428	0.193	0.396	0.235	0.424	0.242	0.429	0.193	0.396	0.233	0.423
AEZ BasinAra	0.299	0.458	0.028∗∗∗	0.164	0.265	0.442	0.112	0.315	0.028∗∗∗	0.164	0.095	0.294
AEZ RiverVall	0.293	0.455	0.628∗∗∗	0.485	0.334	0.472	0.469	0.499	0.628∗∗∗	0.485	0.501	0.500
AEZ Niayes	0.017	0.128	0.000∗∗∗	0.000	0.015	0.120	0.019	0.135	0.000∗∗∗	0.000	0.015	0.121
AEZ Casamance	0.122	0.328	0.028∗∗∗	0.164	0.110	0.313	0.075	0.263	0.028∗∗	0.164	0.065	0.247
AEZ CentEast	0.075	0.264	0.021∗∗∗	0.143	0.068	0.253	0.053	0.223	0.021∗	0.143	0.046	0.210
AEZ VallAnambe	0.161	0.368	0.290∗∗	0.455	0.177	0.382	0.241	0.428	0.290	0.455	0.250	0.434
Soil quality	0.355	0.095	0.351	0.097	0.355	0.095	0.344	0.103	0.351	0.097	0.346	0.102
AII	0.104	1.290	0.957∗∗∗	0.833	0.209	1.274	0.603	1.042	0.957∗∗∗	0.833	0.673	1.013
Mean labour	2.241	1.659	1.983	1.554	2.209	1.648	2.118	1.551	1.983	1.554	2.091	1.552
Mean land	0.111	0.163	0.028∗∗∗	0.078	0.100	0.158	0.056	0.133	0.028∗∗∗	0.078	0.051	0.124
Mean fertilizer	18.046	35.697	61.392∗	243.540	23.423	92.913	22.567	44.216	61.392	243.540	30.226	115.948
Mean seed	6.646	7.394	6.951	7.836	6.684	7.447	5.587	7.326	6.951	7.836	5.856	7.444
N	**1024**		**145**		**1169**		**590**		**145**		**735**	

Notes: A t-test is used to determine if PET with insurance adopting farm household's means are statistically different from that of PET only adopting farm households. ∗∗∗, ∗∗, ∗ represent 1%, 5%, and 10% significance level, respectively. [a] As previously noted, the balancing property is carried out on covariates of treated and control observations within each block of which the average propensity scores of treated and control observations do not differ. In this table, however, the average of all blocks treated and controlled observations are used.

Table 5.9: Control function approach estimates: Unmatched sample

	Membership		Extension		Credit		Nonfarm work	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	-1.372**	0.602	-1.869***	0.640	-0.333	0.755	-0.365	0.631
Age	-0.006*	0.003	0.001	0.004	0.005	0.004	-0.004	0.004
Gender	-0.018	0.163	0.125	0.168	-0.147	0.196	-0.145	0.174
Education	0.058	0.087	0.052	0.090	0.207*	0.108	0.251***	0.090
HH size	0.023***	0.008	-0.023***	0.009	0.009	0.010	0.013	0.008
Land	0.007	0.006	-0.002	0.007	0.006	0.007	-0.006	0.007
Light	-0.185**	0.088	0.189**	0.090	-0.280**	0.114	-0.013	0.092
Extension	0.587***	0.090			0.018	0.115	-0.069	0.099
Membership			0.648***	0.093	0.365***	0.109	-0.047	0.101
Credit	0.467***	0.122	-0.010	0.130			-0.092	0.139
Market	0.120	0.084	-0.002	0.087	0.083	0.105	-0.026	0.088
Nonfarm	-0.067	0.102	-0.097	0.104	-0.119	0.130		
HH part	-0.069	0.106	-0.068	0.112	0.343**	0.139	0.157	0.110
Risk attitude	-0.127	0.090	0.193**	0.090	0.112	0.107	0.558***	0.088
Risk count	-0.071**	0.034	0.071**	0.035	-0.044	0.044	0.004	0.033
Loss count	0.199***	0.044	-0.116**	0.045	-0.041	0.058	0.173***	0.045
Cash crop	-0.013***	0.002	-0.010***	0.003	0.003	0.003	-0.006***	0.002
Diversification	0.010***	0.001	-0.002	0.001	-0.004*	0.002	0.007***	0.001
Soil degradation	0.175	0.169	0.132	0.166	-0.481**	0.221	0.845***	0.169
Rainfall	0.081	0.086	0.061	0.088	-0.224**	0.110	-0.120	0.091
Insurance needs	0.126	0.084	-0.135	0.087	0.217**	0.104	0.110	0.088
Fert subsidy	0.017	0.099	0.404***	0.102	0.068	0.123	-0.325***	0.105
Seed Subsidy	-0.029	0.101	-0.693***	0.102	-0.156	0.126	0.316***	0.107
Remittance	0.035	0.135	0.333**	0.134	0.007	0.167	-0.096	0.143
Coping	-0.370***	0.102						
Support needs			1.401***	0.176				
Location					-0.702***	0.237		
Distance							-0.003***	0.001
Wald Chi2(23)	229.934***		338.434***		74.451***		169.750***	
Log Likelihood	-638.66		-594.144		-387.146		-571.118	
N				1169				

***, **, * represent 1%, 5% and 10% significance level, respectively.

Table 5.10: Control function approach estimates: Matched sample

	Membership		**Extension**		**Credit**		**Nonfarm work**	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	-1.139	0.739	-2.127∗∗∗	0.777	0.135	0.875	-0.487	0.875
Age	-0.008∗	0.004	0.005	0.004	0.005	0.005	-0.005	0.005
Gender	-0.219	0.201	0.076	0.211	-0.068	0.235	-0.302	0.238
Education	-0.172	0.111	0.137	0.112	0.083	0.129	0.393∗∗∗	0.129
HH size	0.013	0.011	-0.022∗	0.011	0.018	0.012	0.021∗	0.013
Land	0.005	0.007	0.004	0.007	-0.002	0.011	-0.008	0.011
Light	-0.317∗∗∗	0.105	0.186∗	0.107	-0.394∗∗∗	0.129	-0.033	0.128
Extension	0.363∗∗∗	0.108			0.018	0.129	0.119	0.129
Membership			0.410∗∗∗	0.111	0.186	0.127	0.216∗	0.130
Credit	0.285∗∗	0.138	0.013	0.139			0.048	0.162
Market	-0.025	0.104	-0.128	0.106	0.147	0.126	0.124	0.127
Nonfarm	0.230∗	0.139	0.105	0.140	0.140	0.161		
HH part	-0.112	0.141	-0.285∗∗	0.143	0.211	0.174	0.323∗	0.178
Risk attitude	0.064	0.115	0.309∗∗∗	0.110	0.207	0.127	0.388∗∗∗	0.125
Risk count	-0.026	0.047	0.110∗∗	0.047	-0.054	0.060	-0.039	0.054
Loss count	0.145∗∗∗	0.054	-0.201∗∗∗	0.053	-0.098	0.066	0.261∗∗∗	0.059
Cash crop	-0.001	0.004	-0.011∗∗∗	0.004	0.014∗∗∗	0.005	-0.013∗∗	0.005
Diversification	0.012∗∗∗	0.002	-0.001	0.002	-0.005∗∗	0.002	0.006∗∗∗	0.002
Soil degradation	0.140	0.184	0.154	0.180	-0.522∗∗	0.231	0.772∗∗∗	0.188
Rainfall	0.212∗∗	0.104	0.135	0.104	-0.254∗∗	0.125	-0.198	0.122
Insurance needs	-0.241∗∗	0.108	-0.236∗∗	0.110	0.134	0.127	0.236∗	0.130
Fert subsidy	-0.151	0.125	0.488∗∗∗	0.124	-0.076	0.142	-0.102	0.150
Seed Subsidy	0.236∗	0.124	-0.628∗∗∗	0.123	-0.039	0.146	0.086	0.146
Remittance	0.134	0.163	0.300∗	0.165	0.079	0.188	-0.005	0.187
Coping	-0.419∗∗∗	0.128						
Support needs			1.442∗∗∗	0.211				
Location					-0.965∗∗∗	0.368		
Distance							-0.005∗∗∗	0.001
Wald Chi2(23)	147.253∗∗∗		186.557∗∗∗		62.762∗∗∗		140.633∗∗∗	
Log Likelihood	-435.803		-416.07		-298.976		-286.113	
N				735				

∗∗∗, ∗∗, ∗ represent 1%, 5% and 10% significance level, respectively.

Table 5.11: Estimates of the sample-selection equation: unmatched and matched sample

	Unmatched sample		**Matched sample**	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	-2.056*	1.095	-2.540**	1.171
Age	0.002	0.006	0.001	0.006
Gender	0.161	0.278	0.203	0.284
Education	0.327**	0.154	0.331**	0.159
HH size	0.011	0.018	0.008	0.017
Land	-0.005	0.010	-0.004	0.011
Light	0.504**	0.182	0.653***	0.232
Extension	1.184*	0.617	1.006*	0.517
Membership	0.909	1.134	1.021	1.064
Credit	0.993	1.403	2.084	1.461
Market	0.187	0.126	0.212	0.148
Nonfarm	0.137	0.217	0.167	0.229
Participation	-1.471	1.114	-1.409*	0.839
Risk attitude	-0.286	0.228	-0.457**	0.207
Risk count	-0.006	0.065	-0.024	0.064
Loss count	0.178	0.110	0.225**	0.108
Cash crop	-0.015*	0.008	-0.019**	0.008
Diversification	-0.002	0.005	-0.002	0.005
Soil degradation	0.270	0.381	0.338	0.340
Rainfall	-0.212	0.161	-0.185	0.178
Insurance	0.589***	0.149	0.624***	0.176
Fert subsidy	0.120	0.226	0.242	0.202
Seed Subsidy	0.171	0.246	0.015	0.214
Remittance	-0.453*	0.236	-0.367	0.246
Resid mem	-0.362	0.682	-0.391	0.642
Resid ext	-0.620*	0.347	-0.480	0.309
Resid cred	-0.185	0.782	-0.785	0.839
Resid nonfarm	0.627	0.640	0.522	0.457
Log likelihood	-308.4513		-304.014	
LR chi2(27)	259.598***		121.984***	
N	1169		735	

***, **, * represent 1%, 5% and 10% significance level, respectively. Standard errors reported are the bootstrapped errors. In the probit model 1 = adoption of PET with insurance and 0=adoption of PET only

Table 5.12: Estimates of group-level and meta-frontier

	PET without insurance		PET with insurance		Meta-frontier	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Labour	0.039	0.040	0.019	0.101	-0.006	0.015
Land	0.780***	0.044	0.935***	0.097	0.861***	0.017
Fertilizer	0.285***	0.029	0.509***	0.070	0.362***	0.011
Seed	0.117***	0.027	-0.022	0.040	0.078***	0.010
Irrigate	0.187*	0.101	0.481*	0.282	0.264***	0.037
Farm system	-0.335	0.290	0.382	0.296	-0.057	0.060
Constant	10.512***	0.354	10.526***	0.638	10.669***	0.102
Group-specific environmental variables						
Education	-0.521	0.694	0.626	0.685		
Diversification	-0.219*	0.130	-0.024	0.016		
AII	0.065	0.469	-0.327	0.338		
Mixed farming	-1.036	2.564	0.755	0.630		
Market	-0.148	0.663	0.448	0.597		
Constant	0.116	1.235	-0.692	1.833		
Industry-specific environmental variables						
Std rainfall					0.028	0.042
Soil quality					-0.456***	0.145
AEZ BasinAra					0.085	0.066
AEZ RiverVall					-0.493***	0.077
AEZ Niayes					0.087	0.113
AEZ Casamance					-0.027	0.069
AEZ CentEast					0.012	0.073
AEZ VallAnambe					-0.311***	0.083
Subsidy					-0.012	0.030
Constant					0.543**	0.213
Sigma u	0.628*	0.334	1.467***	0.441	0.002	0.007
Sigma v	0.868***	0.024	0.397***	0.077	0.353***	0.007
Lambda	0.723**	0.330	3.697***	0.425	0.007	0.010
Technical efficiency and technology gap ratios						
TE	0.857^{m}	0.153^{s}	0.457^{m}	0.238^{s}		
TGR	0.731^{m}	0.171^{s}	0.898^{m}	0.115^{s}		
MTE	0.608^{m}	0.116^{s}	0.424^{m}	0.244^{s}		
Log likelihood	-1333.023		-177.69		-440.916	
N	1024		145		1169	

^{m} denotes mean values

^{s} denotes standard deviations.

***, **, * represent 1%, 5% and 10% significance level, respectively.

Table 5.13: Control function approach for endogenous switching regression model

	Membership		Extension		Credit		Nonfarm	
Variable	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**	**Coeff.**	**Std. Err.**
Constant	0.400	0.913	-2.223**	0.985	1.339	1.153	0.043	0.963
Age	-0.005	0.003	0.000	0.003	0.002	0.004	-0.003	0.004
Gender	-0.011	0.162	0.175	0.169	-0.131	0.194	-0.149	0.174
Education	0.058	0.087	-0.028	0.091	0.175	0.107	0.311***	0.090
HH size	0.021***	0.008	-0.023**	0.009	0.010	0.010	0.015*	0.008
Land	0.006	0.006	-0.002	0.007	0.003	0.007	-0.001	0.007
HWI	-0.068***	0.025	0.155***	0.026	-0.050	0.032	-0.110***	0.027
Extension	0.622***	0.090			0.028	0.115	-0.080	0.100
Membership			0.683***	0.094	0.343***	0.109	-0.073	0.102
Credit	0.440***	0.122	0.031	0.130			-0.129	0.139
Market	0.120	0.084	0.034	0.087	0.078	0.105	-0.030	0.088
Nonfarm	-0.108	0.102	-0.131	0.104	-0.111	0.128		
Risk	-0.118	0.090	0.213**	0.090	0.135	0.106	0.554***	0.088
Risk count	-0.066*	0.034	0.089**	0.035	-0.053	0.043	0.004	0.033
Loss count	0.175***	0.045	-0.083*	0.045	-0.038	0.057	0.150***	0.045
Cash crop	-0.013***	0.002	-0.012***	0.002	0.002	0.003	-0.004*	0.002
Diversification	0.010***	0.001	0.000	0.001	-0.005***	0.002	0.005***	0.001
Soil degradation	0.165	0.168	0.146	0.167	-0.476**	0.222	0.860***	0.170
Std rainfall	-0.294	0.189	0.138	0.199	-0.576**	0.239	-0.231	0.197
Subsidy	-0.008	0.107	-0.647***	0.112	-0.063	0.134	-0.151	0.108
Remittance	0.024	0.135	0.321**	0.135	-0.047	0.168	-0.073	0.145
Insurance	0.108	0.084	-0.140	0.088	0.190*	0.103	0.089	0.088
Sufficiency	-0.067	0.117	0.465***	0.122	-0.083	0.146	0.288**	0.114
Coping	-0.353***	0.102						
Support			1.495***	0.179				
Location					-0.686***	0.240		
Distance							-0.004***	0.001
Log-likelihood	-636.619		-586.084		-391.945		-565.331	
LR chi2(22)	234.02***		354.56***		64.85***		181.32***	
N				1,169				

***, **, * represent 1%, 5% and 10% significance level, respectively.

Table 5.14: Test of validity of instruments used in the first stage ESR model

	Selection equation		**MTE of PET without insurance adopters**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	-2.596**	1.319	0.797***	0.064
Age	0.003	0.005	-0.000*	0.000
Gender	0.155	0.230	0.026**	0.012
Education	0.369***	0.132	0.017***	0.006
HH size	0.006	0.014	0.000	0.001
Land	-0.008	0.008	-0.001**	0.000
HWI	0.137***	0.043	0.002	0.002
Extension	1.019**	0.508	0.027***	0.007
Membership	1.334*	0.783	0.008	0.007
Credit	1.382	0.926	0.011	0.010
Market	0.129	0.118	0.008	0.006
Nonfarm	-1.570**	0.731	0.004	0.007
Risk	-0.146	0.188	-0.006	0.006
Risk count	-0.028	0.043	-0.008***	0.002
Loss count	0.181**	0.074	0.004	0.003
Cash crop	-0.015**	0.007	-0.002***	0.000
Diversification	-0.003	0.003	0.002***	0.000
Soil degradation	0.306	0.227	0.033***	0.013
Std rainfall	-0.114	0.254	-0.047***	0.013
Subsidy	0.509***	0.196	-0.030***	0.007
Remittance	-0.272*	0.154	0.011	0.010
Insurance	**0.534*** **	0.111	**0.008**	0.006
Sufficiency	**-0.367***	0.205	**-0.002**	0.008
Resid mem	-0.688	0.461		
Resid ext	-0.633**	0.278		
Resid credit	-0.460	0.499		
Resid nonfarm	0.791*	0.435		

***, **, * represent 1%, 5% and 10% significance level, respectively.

Appendix A3: Computation of Soil Quality Index (SQI)

In computing the soil quality index for the study, the "Soil nutrient maps of Sub-Saharan Africa[8]" raster file at 250 m resolution provided by the International Soil Reference and Information Centre (ISRIC) was used. Nutrients covered in this data include; total nitrogen (N), total phosphorus (P), extractable phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), sodium (Na), aluminium (Al), boron (B), copper (Cu), iron (Fe), manganese (Mn) and zinc (Zn) in (ppm). The estimation approaches for these nutrients data have been well discussed in Hengl *et al.* (2017). Additionally, soil physical and biochemical properties data[9] provided by ISRIC were used for the computation of the index. Free spatial data in the form of shapefiles for the administrative regions of Senegal were obtained from DIVA-GIS[10] provided by ISRIC were used for the computation of the index. Free spatial data in the form of shapefiles for the administrative regions of Senegal were obtained from DIVA-GIS . Using the free and open-source geographic information system software and the geographic coordinate data of farm households, the soil parameters for each farm household were calculated. The Soil Quality Index (SQI) was calculated following the approaches described in Zheng *et al.* (2005), Mukherjee and Lal (2014), and Zhang *et al.* (2015). First, the principal component analysis (PCA) was used to identify a minimum data set (MDS) to reduce the indicator load in the estimation of the index and to avoid data redundancy. During the principal component analysis, only the 'highly weighted' variables were retained in the MDS. After the selection of parameters for the MDS, all selected observations were transformed using linear scoring functions (less is better, more is better, and optimum) based on the recommendations in the empirical literature (Amacher *et al.*, 2007; Mukherjee and Lal, 2014). Thereafter, the weighted additive SQI was computed using the formula below: $\text{SQI} = \sum \text{Weight} \times \text{Individual soil parameter score}$

[8] https://data.isric.org/geonetwork/srv/eng/catalog.search#/search?resultType=details&sortBy=relevance&any=Soil%20nutrient%20maps%20of%20Sub-Saharan%20Africa%20at%20250%20m%20resolution&from=1&to=20

[9] https://github.com/ISRICWorldSoil/SoilGrids250m/blob/master/grids/models/META_GEOTIFF_1B.csv

[10] https://www.diva-gis.org/

Chapter 6

Welfare impacts of managing climate risk through the adoption of risk-reducing technologies and insurance

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Abstract

In this paper, we used a nationally representative survey data from Senegal to investigated the joint welfare impact of risk-reducing technologies and insurance by comparing three distinct farm households: non-adopters of mineral fertilizer, improved seeds and insurance, mineral fertilizer, and improved seeds adopters without insurance, and mineral fertilizer and improved seeds adopters with insurance. Using a multinomial endogenous switching regression model to control for selection bias stemming from both unobserved and observed factors, we find that adopting mineral fertilizer and improved seeds generally lead to increases in food calorie availability and crop income per capita. However, complementing the adoption of mineral fertilizer and improved seeds with insurance leads to higher household welfare outcomes compared to adopting mineral fertilizer and improved seeds in isolation. These findings underscore the need to scale up and encourage the adoption of productivity-enhancing technologies and insurance products to help smallholders not only improve their welfare but also better adapt to climate change impacts.

Keywords: Technology, Mineral fertilizer, Improved seeds, insurance, Food calorie, Crop income.

JEL Codes: Q16, Q18, G52, Q12

6.1 Introduction

Climate variability is a major source of risk to smallholder farmers in Sub-Saharan Africa. Increasing erratic weather and climate shifts will further erode smallholder farmers' long-term livelihood potential through the loss of productive assets, stifling investments, and imposing ex-ante barriers to the use of technologies (D'Alessandro *et al.*, 2015; Dercon and Christiaensen, 2011; Demeke *et al.*, 2016; Amare *et al.*, 2018). In the coming decades, climate variability is projected to increase in terms of frequency and severity and this will pose elevating threats to food production and access, especially for vulnerable and resource-poor communities (Bates *et al.*, 2010; Thornton and Gerber, 2010). Concurrently, a growing body of evidence has linked climate-related risk to the extent and the persistence of rural poverty in developing regions of the world (World Bank, 2016; Hansen *et al.*, 2019). At the same time, growth in agricultural productivity which requires the use of modern inputs and technologies remains a key instrument for poverty reduction and food security.

Facing climate and production risks, the empirical literature documents a range of alternative strategies employed by farm households to avoid or minimize losses related to climatic risk. Some of these include adopting agronomic practices such as conservation farming practices, mulching, sustainable land management (Di Falco and Veronesi, 2013; World Bank, 2016; Obiri and Driver, 2017), diversification which could be crop or income-based (Ullah and Shivakoti, 2014; Obiri and Driver, 2017; Birthal and Hazrana, 2019). Another strand of literature also suggests the adoption of the so-called "risk-reducing inputs or technologies" such as improved and high yielding seeds, inorganic fertilizer, pesticides, and irrigation (Holzmann and Jørgensen, 2001; World Bank, 2005; Barnett *et al.*, 2008; Kahan, 2008; Schaffnit-Chatterjee, 2010; Chetaille *et al.*, 2011; Breen *et al.*, 2013; Obiri and Driver, 2017; Hansen *et al.*, 2019). Beyond risk-reducing effects, "risk-reducing inputs or technologies" which are also referred to as productivity-enhancing technologies play an important role in increasing agricultural productivity and closing yield gaps in Sub-Saharan Africa. Simultaneously, several studies (see Lamb, 2003; Barnett *et al.*, 2008; Dercon and Christiaensen, 2011; Hill and Viceisza, 2012; Karlan *et al.*, 2014; You, 2014; Farrin and Miranda, 2015; Cole *et al.*, 2017) suggests that uninsured risk or lack of protection from downside risk accounts for deficiencies in technology uptake and inefficient production choices among low-income households.

Skees and Collier (2008) argued that risk-driven averseness to invest in inputs such as mineral fertilizer and improved seeds may be partially responsible for the reason why Africa has not undergone a green revolution. With an increasing call for a Green Revolution in Sub-Saharan Africa, Hansen *et al.* (2019) argue that a central challenge to achieving this is to go beyond increased agricultural production and mitigate risks posed by increasing variable climate and marginal production conditions. Complementing risk-reducing production technologies with insurance has therefore been suggested as the way forward (Skees and Collier, 2008; Lybbert and Carter, 2015; Carter *et al.*, 2017). However, the extent to which the joint adoption of risk-reducing technologies and insurance affects household welfare is still not fully understood. In this paper, we investigate whether managing climate risks through the joint adoption of mineral fertilizers, improved seeds, and insurance improves household welfare compared to adopting only mineral fertilizers and improved seeds. Studies addressing this issue are still scarce.

So far, the literature has focused separately on the impact of "risk-reducing inputs or technologies" (Wopereis-Pura *et al.*, 2002; Duflo *et al.*, 2008; Marenya and Barrett, 2009a,b; Asfaw, 2010; Birthal *et al.*, 2012; Kassie *et al.*, 2014; Emerick *et al.*, 2016; Savini *et al.*, 2016; Koussoubé and Nauges, 2017; Abdoulaye *et al.*, 2018) and insurance (Goodwin *et al.*, 2004; Madajewicz *et al.*, 2013; Ragoubi *et al.*, 2013; Karlan *et al.*, 2014; de Nicola, 2015; Elabed and Carter, 2015; Fuchs and Wolff, 2016; Isaboke *et al.*, 2016; Cole *et al.*, 2017; Mebada, 2018; Hill *et al.*, 2019; Janzen and Carter, 2019; Vigani and Kathage, 2019; Sibiko and Qaim, 2020) on several household welfare outcomes. At the same time, the results from these studies have been contentious. For example, studies by Duflo *et al.* (2008), Suri (2011), Foltz *et al.* (2012), Matsumoto (2014), Magnan *et al.* (2015) and Wossen *et al.* (2019) find returns or profitability heterogeneities in the use of these "risk-reducing inputs or technologies" which might be an important precipitant for non-adoption. Similarly, some studies have found that insurance lowers investments in productivity-enhancing technologies (Babcock and Hennessy, 1996; Smith and Goodwin, 1996; Giné and Yang, 2009; de Nicola, 2015), decrease farm profit and productivity (Spörri *et al.*, 2012; Vigani and Kathage, 2019), and reduces the use of complementary risk management strategies (Schaffnit-Chatterjee, 2010; Nigus *et al.*, 2018; Matsuda *et al.*, 2019).

There are important reasons for studying the joint welfare impact of "risk-reducing technologies" and insurance as opposed to evaluating their separate impacts. Although "risk-reducing technologies" are known to reduce production or income losses when weather-related stresses occur, they can also potentially increase risk when used in isolation (Just and Pope, 1979; Horowitz and Lichtenberg, 1993; Gardebroek *et al.*, 2010; Moser and Mußhoff, 2017). Under moderate climate fluctuations, "risk-reducing technologies" can stabilize production, but may not be able to buffer the impacts of extreme events (Lybbert and Bell, 2010). However, complementing adoption with insurance provides a "risk cushioning" attribute that incentivizes not only higher investments in inputs as already shown in the literature but also improve access to credit (Boucher *et al.*, 2008; Farrin and Miranda, 2015), and reduce opportunity costs associated with risk-averse farmers' precautionary ex-ante strategies (Hansen *et al.*, 2019). At the same time, insurance use can also increase farm household resilience by indemnifying farm households in bad years, hence helping them to protect assets and improve production in better years (Hellmuth *et al.*, 2009; Greatrex *et al.*, 2015). Such changes in investments and input use have far-reaching effects on household welfare which is still not fully understood.

We build on past work that have separately evaluated the impact of "risk-reducing technologies" and insurance to quantify both the individual and composite[1] impact of two "risk-reducing inputs" – mineral fertilizer and improved seeds adoption with or without insurance on farm households' food calorie availability and crops income per capita using a nationally representative farm household survey data from Senegal. Three distinct farm households are compared in the study; 1) those who do not adopt mineral fertilizers and improved seeds, and insurance, 2) those who adopt mineral fertilizers and improved seeds without insurance and 3) those who adopt mineral fertilizers and improved seeds with insurance. We address our objective by employing a multinomial endogenous switching regression which accounts for selectivity biases and unobserved heterogeneity.

Evaluating the impact of productivity-enhancing technologies and insurance on household welfare in Senegal important for several reasons. First, with agriculture being predominantly rain-fed, Senegal's agricultural sector faces highly variable rainfall and is highly vulnerable to the effects of climate change. These climatic shocks have been observed to be a major limiting factor to the adoption of productivity-enhancing technologies (D'Alessandro *et al.*, 2015). Between the period, 2002 – 2016, for instance, consumption of fertilizer in Senegal was lower than the Sub-Saharan African average. The low adoption of productivity-enhancing technologies has resulted in low agricultural productivity which is reflected by large yield gaps observed for principal crop commodities. Complementing the adoption of productivity-enhancing technologies with insurance, therefore, presents an oppor-

[1]What is meant by individual and composite impact here is that mineral fertilizer and improved seed adoption are considered together as one technology. With this, farm household can either decide to adopt this technology in isolation or with insurance. When adopted in combination with insurance, this becomes a composite technology, otherwise it is considered as a single technology.

tunity for smallholders to increase productivity while at the same time effectively improving the adaptive capacity of Senegalese farm households in the midst of climate change. At the same time, evaluating the impact of the joint adoption of mineral fertilizers, improved seeds, and insurance can help guide policymakers to better design, target and scale-up intervention programs.

The study is organized as follows; 6.2 introduces the conceptual framework and econometric approach. Section 6.3 presents the data and variables measurement and the empirical specification. The findings of the study are presented in Section 6.4, and finally, Section 6.5 concludes.

6.2 Conceptual framework and econometric specification

Farm household adoption decisions could result in positive outcomes, however, estimation of such outcomes in observational studies such as this one is difficult because one does not directly observe the counterfactual outcomes of interest. This difficulty is easily addressed in cases where experimental data is available through randomized control trials, for instance, information on the counterfactual situation would normally be provided, and as such, the problem of causal inference can easily be resolved (Miguel and Kremer, 2004). Furthermore, farm households' decisions to adopt the two "risk-reducing inputs" – mineral fertilizer and improved seeds with or without insurance may not also be random and they may endogenously self-select into adoption or non-adoption. Therefore, decisions are likely to be influenced systematically by both observed and unobservable characteristics that may be correlated with the two outcomes of interest (food calorie availability and crop income per capita). Such unobservable characteristics may include for example the innate managerial and technical abilities of the farmers or the types of social networks formed by farmers that are not captured, such as the kind of neighbours the farmer communicates with and whether such neighbours have adopted mineral fertilizer, improved seeds, or insurance. The inability to capture these unobservable characteristics may lead to selection bias.

Hence, to disentangle the pure effects of adoption, farm households' choice of adoption and its impacts were modelled in a multinomial endogenous switching regression framework. This approach is a selection-bias correction methodology based on the multinomial logit selection model developed by Bourguignon *et al.* (2007). This approach allows consistent and efficient estimates of the selection process and a reasonable correction for the outcome equations to be obtained, even with violations of the axiom of the independence of irrelevant alternatives (IIA). Estimation of the multinomial endogenous switching regression occurs simultaneously in two steps. In the first stage, farm households' choices of adoption packages are modelled using a multinomial logit selection model. In the second stage, the individual and composite impact of the two "risk-reducing inputs" with or without insurance on food calorie availability and crop income per capita are evaluated using OLS with selectivity correction terms from the first stage. Following the studies of Di Falco and Veronesi (2013), Kassie *et al.* (2015), Teklewold *et al.* (2017) and Vigani and Kathage (2019) we describe the empirical econometric approach used in the study below.

6.2.1 Stage I: Multinomial Adoption Selection Model

Farm households are assumed to maximize their expected utility by adopting mineral fertilizer and improved seeds with insurance. The ith farm household's expected utility, U^*_{ij}, from adopting a package j, where j (j = 1,..., M; in our case $M = 3$), is a latent variable determined by observed household, land, and climatic characteristics, X_i and unobserved characteristics ε_{ij}, such that:

$$U^*_{ij} = X_i\varpi + \varepsilon_{ij} \tag{6.1}$$

Let I be an index that denotes the farmers' choice of package, such that:

$$I = j \text{ iff } U^*_{ij} > \underset{k\neq j}{\text{Max}}(U^*_{ik}) \text{ or } \eta_{ij} < 0 \quad \forall\ k \neq j, \tag{6.2}$$

Where $\eta_{ij} = \underset{k\neq j}{\text{Max}}\ (U^*_{ik} - U^*_{ij}) < 0$ (Bourguignon *et al.*, 2007). The formulation in equation 6.2 implies that the ith farm household will adopt a package j to maximize their expected benefit if it provides greater expected utility than any other package $k \neq j$, i.e. if $\eta_{ij} = \underset{k\neq j}{\text{Max}}\ (U^*_{ik} - U^*_{ij}) < 0$. The probability that farm household i with characteristics X will choose a package j can be specified by a multinomial logit model (McFadden, 1974) as:

$$P_{ij} = P\left(\eta_{ij} < 0 | X_i\right) = \frac{\exp\left(X_i \varpi_j\right)}{\sum_{k=1}^{J} \exp\left(X_i \varpi_k\right)}. \tag{6.3}$$

The parameter estimates of the latent variable model can be estimated by maximum likelihood estimation. In our specification, the base category, non-adoption of mineral fertilizer, improved seeds, and insurance, is denoted as $j = 1$. In the remaining portfolios ($j = 2, 3$), at least one package is used by a farm household.

6.2.2 Stage II: Multinomial Endogenous Switching Regression Model

In the second stage, a multinomial endogenous switching regression model is estimated to investigate the impact of each package on food calorie availability and crop income per capita by applying the Bourguignon *et al.* (2007) selection bias correction model. The model implies that farm households face a total of 3 regimes (one regime per package, where $j = 1$ is the reference category or non-adopting category). It is assumed that the vector of outcome variables is a linear function of explanatory variables. Hence, the stochastic function to evaluate food calorie availability and crop income per capita implications of each package j is given as:

$$\text{Outcome } j: \quad Q_{ij} = Z_{ij}\beta_{ij} + \overline{Z}_{ij}\alpha_{ij} + \mu_{ij} \text{ if } \; I = j; \; j = 1, \; 2, \; 3 \tag{6.4}$$

where Q_{ij} is the outcome variable of farm household i in regime j, and Z_i represents a vector of inputs, and farm household head and household's characteristics, asset ownership, soil fertility, and climatic characteristics included in X_i. β and α represent the corresponding vector of coefficients to be estimated. μ_{ij} represents the unobserved stochastic component distributed with $\mathrm{E}(\mu_{ij} \mid Z_i, X_i) = 0$ and $\mathrm{V}(\mu_{ij} \mid Z_i, X_i) = \sigma_j^2$. To overcome the possible correlation of farm-invariant unobserved heterogeneity with observed covariates, the study employed the approach of Mundlak (1978) and Wooldridge (2018) which has also been used by Di Falco (2014), Kassie *et al.* (2015), Teklewold *et al.* (2017) and Vigani and Kathage (2019)[2]. We exploit crop-level information and include the mean of crop varying $\overline{Z}$ explanatory variables, which include landholding, labour, fertilizer, and seed quantity to deal

[2]In most of these studies, plot-variant variables were used to control for unobserved heterogeneity but due to the lack of plot-level data on inputs, we use an alternative approach by using crop-variant variables since household produce multiple crops and we have crop-level data on inputs.

with the issue of unobserved heterogeneity. According to Teklewold *et al.* (2013), a Wald test of the null hypothesis that the vectors α_j are jointly equal to zero is required to indicate the relevance of crop-specific heterogeneity.

For each sample observation, Q_{ij} is observed if and only if one among the M dependent regimes is observed. When estimating an ordinary least squares (OLS) model, the outcomes of interest, food calorie availability, and crop income per capita equations 6.4 are estimated separately. However, if the error terms of equation 6.1, ε_{ij} are correlated with the error terms μ_{ij} of the outcome model in equation 6.4, then the expected values of μ_{ij} conditional on the sample selection are nonzero i.e., corr(ε_{ij}, μ_{ij}) $\neq 0$, and the OLS estimates will be biased and inconsistent. To correct for the potential inconsistency, we employ the multinomial endogenous switching regression model by Bourguignon *et al.* (2007), which takes into account the correlation between the error terms ε_{ij} from the multinomial logit model estimated in the first stage and the error terms from each outcome equation μ_{ij}. Bourguignon *et al.* (2007) show that consistent estimates of β and α in the outcome equation 6.4 can be obtained by estimating the following selection bias-corrected food calorie availability and crop income per capita equations:

$$\text{Outcome } j: \quad Q_{ij} = Z_{ij}\beta_{ij} + \overline{Z}_{ij}\alpha_{ij} + \sigma_{j\varepsilon}\lambda_{ij} + \omega_{ij} \ if \quad I = j; \quad j = 1,\ 2,\ 3 \qquad (6.5)$$

where $\sigma_{j\varepsilon}$ is the covariance between ε_{ij} in equation 6.1 and μ_{ij} from equation 6.4, λ_j is the inverse Mills ratio computed from the estimated probabilities in equation 6.3 as follows:

$$\lambda_{ij} = \sum_{k \neq j}^{j} \rho_j \left[\frac{\hat{P}_{ik}\text{In}\left(\hat{P}_{ik}\right)}{1 - \hat{P}_{ik}} + \text{In}\left(\hat{P}_{ij}\right) \right] \qquad (6.6)$$

where $\hat{P}$ represents the probability that farm household i chooses package j as defined in equation 6.3, ρ_j is the correlation between ε_{ij} and μ_{ij}. The specification in equation 6.5 implies that the number of selection correction (bias) terms in each equation are equal to the number of multinomial logit choices M.

While the variables X_i in equation 6.1 and Z_i in equation 6.4 are allowed to overlap, proper identification requires at least one variable in X_i that does not appear in Z_i. Therefore, the selection equation 6.1 is estimated based on all explanatory variables specified in the outcome equation 6.4 plus at least one or more instruments. Following Di Falco and Veronesi (2013), we establish the admissibility of the selected instruments by performing a simple falsification test: the selected or valid instrument (s) is required to significantly influence a farm household's choice of mineral fertilizer and improved seeds adoption with or without insurance but have no significant effect on outcomes (i.e. food calorie availability and crop income per capita). In this study, the perceptions about subsidized fertilizer sufficiency and perception about subsidized seed quality were employed as identifying instrument. These are expected to influence the adoption of mineral fertilizer and improved seeds with or without insurance but not food calorie availability and crop income per capita.

Estimation of the treatment and counterfactual effects

The Multinomial Endogenous Switching Regression framework by allowing us to control for potential selectivity biases can be used to examine average treatment effects (ATT) by comparing expected outcomes of adopters with and without adoption. Following Bourguignon *et al.* (2007), the following conditional expectations for each outcome variable of interest (food calorie availability and crop income per capita) from equation 6.5 can be computed as:
Adopters with adoption (actual):

$$E\left(Q_{ij}\middle|I=j,\ Z_{ij},\overline{Z}_{ij},\lambda_{ij}\right)=Z_{ij}\beta_j+\overline{Z}_{ij}\alpha_j+\sigma_j\lambda_{ij} \tag{6.7}$$

Non-adopters without adoption (actual):

$$E\left(Q_{i1}\middle|I=1,\ Z_{i1},\overline{Z}_{ij},\lambda_{i1}\right)=Z_{i1}\beta_1+\overline{Z}_{i1}\alpha_1+\sigma_1\lambda_{i1} \tag{6.8}$$

Adopters had they decided not to adopt (counterfactual):

$$E\left(Q_{i1}\middle|I=j,\ Z_{ij},\overline{Z}_{ij},\lambda_{ij}\right)=Z_{ij}\beta_1+\overline{Z}_{ij}\alpha_1+\sigma_1\lambda_{ij} \tag{6.9}$$

Non-adopters had they decided to adopt (counterfactual):

$$E\left(Q_{ij}\middle|I=1,\ Z_{i1},\overline{Z}_{i1},\lambda_{i1}\right)=Z_{i1}\beta_j+\overline{Z}_{i1}\alpha_j+\sigma_j\lambda_{i1} \tag{6.10}$$

Equations 6.7 and 6.8 represent the actual expected outcomes of interest observed in the sample for adopting and non-adopting farm households respectively, while equations 6.9 and 6.10 are their respective counterfactual expected outcomes of interest. The use of these conditional expectations allows us to calculate the average treatment effects (ATT) – i.e. the treatment effect for treated farm households, which is the difference between equations 6.7 and 6.9:

$$\begin{aligned} ATT &= E\left[Q_{ij}|I=j\right] - E\left[Q_{i1}|I=j\right] \\ &= Z_{ij}\left(\beta_j - \beta_1\right) + \overline{Z}_{ij}\left(\alpha_j - \alpha_1\right) + \lambda_{ij}(\sigma_j - \sigma_1) \end{aligned} \tag{6.11}$$

Additionally, the average adoption effect for non-adopters, also known as the average treatment effect on the untreated (ATU) can be computed as the difference between equations 6.8 and 6.10.

$$\begin{aligned} ATU &= E\left[Q_{i1}|I=1\right] - E\left[Q_{ij}|I=1\right] \\ &= Z_{i1}\left(\beta_1 - \beta_j\right) + \overline{Z}_{i1}\left(\alpha_1 - \alpha_j\right) + \lambda_{i1}(\sigma_1 - \sigma_j) \end{aligned} \tag{6.12}$$

Method for addressing potential endogeneity

To study the impact of mineral fertilizer and improved seed adoption with or without insurance on the welfare outcomes of interest, it is important to account for the potential reverse causality and endogeneity problems that may arise with some variables. This is important because the presence of reverse causality and endogeneity in models can make the identification of causal effects difficult due to biased estimates. In estimating equation 6.1, some of the employed explanatory variables such as membership of farmer-based organizations, extension access, credit access, and nonfarm work participation are potentially endogenous (see Abdulai and Huffman, 2014; Ma and Abdulai, 2016). As shown in several empirical studies, farmer-based organizations normally help their members to obtain inputs and credit, thus making membership of farmer-based organizations a potentially endogenous variable. Furthermore, agricultural extension agents also normally disseminate new technologies to farmers, leading to the adoption of the technologies. Farm households adopting mineral fertilizer and improved seeds may potentially attract more visits by extension staff than non-adopters and may also be encouraged to subscribe to agricultural insurance. Farm households that have access to credit can also afford to purchase mineral fertilizer, improved seeds, and subscribed to agriculture insurance compared to households that are credit constrained, hence making credit access potentially endogenous. Furthermore, nonfarm work participation may also be potentially endogenous because income earned from nonfarm work can be invested in productivity-enhancing technologies and the purchase of insurance. At the same time, nonfarm work participation may impose labour constraints on households, limiting their ability to adopt mineral fertilizer and improved seeds.

To address the potential endogeneity of membership of farmer-based organizations, extension access, credit access, and nonfarm work participation we used the control function approach proposed by Wooldridge (2015). The approach involves the specification of the potential endogenous variable as a function of all explanatory variables influencing adoption decision in equation 6.1, together with a set of instruments in a first stage probit regression. The employed instruments here should strongly influence the given potential endogenous variables (i.e., membership of farmer-based organizations, extension access, credit access, and nonfarm work participation) but not the choice of mineral fertilizer and improved seeds adoption with or without insurance. For our study, the use of coping strategies is used as identifying instruments for membership of farmer-based organizations. Coping strategies are important informal risk-sharing arrangements within social networks such as microfinance, rotating savings, and credit associations. Hence farm households that use coping strategies are likely to be members of farmer-based organizations. The use of coping strategies is expected to significantly influence membership in farmer organizations but not the adoption of mineral fertilizer and improved seeds adoption with or without insurance.

In the case of extension access, support need was considered as identifying instruments. Farm households that require support needs, might actively seek to gain extension access. Support needs of a household are expected to significantly influence extension access but not the adoption of mineral fertilizer and improved seeds adoption with or without insurance. The number of regional microfinance subscribers was used as an instrument for controlling credit access. Farm households residing in regions with high microfinance subscribers are likely going to have much easier access to credit. Location in a populous region was considered as an instrument to control for nonfarm work participation. Populous regions are associated with high urbanization rates and easy access to nonfarm occupations. An important consideration in selecting instruments is that the instrumental variables used here (coping strategy, support needs, microfinance subscribers, and location in a populous region) are required not to be correlated with the instruments (i.e., perceptions about subsidized fertilizer sufficiency and perception about subsidized seed quality) used for the multinomial endogenous switching regression model identification. Furthermore, these instruments are also excluded in the estimation of equation 6.1. Finally, both the observed factors and the "generalized residuals" predicted from a first-stage probit regression are included as covariates in the multinomial adoption selection model. As suggested by Wooldridge (2015), the approach leads to a robust, regression-based Hausman test for the endogeneity of the suspected variables. If the coefficient of the residual term is statistically significant, it shows that endogeneity was indeed present and also well controlled for in the model (Gibson *et al.*, 2010; Ricker-Gilbert *et al.*, 2011; Amankwah *et al.*, 2016; Harris and Kessler, 2019; Katengeza *et al.*, 2019; Ogutu *et al.*, 2019). Furthermore, Wooldridge (2015) observed that if the coefficient on the estimated generalized residual is statistically significant, there is a need to adjust the standard errors for the two-step estimation by bootstrapping.

6.3 Data and variable measurement

6.3.1 Farm household survey

The data used in the study comes from a farm household survey as part of the larger Senegalese "Projet d'appui aux politiques agricoles (PAPA)" or the Agricultural Policy Support Project conducted between April and May 2017 across 14 administrative regions of Senegal. The survey which was targeted towards cereals, horticultural crops, and fruit and vegetable producers was a two-stage, nationally based random survey design that included rural census districts as the primary units and farm households as the secondary units. 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. Data collected include information on household demographic characteristics, plot and land holdings, agricultural equipment ownership, crop production for the 2016/2017 growing season, credit, inputs use and cost, family and hired labour, sales volumes and prices, and food processing activities. Others included household consumption, access to amenities, extension, non-farm and livestock incomes, remittance, agricultural insurance, risks and adaptation strategies, perception on subsidized inputs (fertilizer, seeds, and agricultural equipment), and membership of farmer-based organizations.

6.3.2 Measuring food calorie availability and crop income per capita

In measuring household food calorie availability, the study focused only on the supply of foodstuffs in a household from own production. We used the daily per adult-equivalent food availability because it helps determine the capacity of each household to provide proper food energy to its members during a whole calendar year. The total quantity of food calories produced per equivalent adult per day or a household daily food calories availability was estimated using staple food crops grown by households. A total of 9 staple crops were used in estimating household food calorie availability. This includes 5 cereal staples (maize, rice, millet, sorghum, and fonio), 2 legumes (groundnut[3] and cowpeas), 1 oilseed crop (sesame), and 1 root tuber crop (cassava). According to Hathie (2019), Senegal has food traditions, both in urban and rural, based on the consumption of cereals (rice, millet, maize, and sorghum) as staple foods, and these constitute about 40% of households' food budget. Furthermore, rice, millet/sorghum, wheat, and maize are the foundations of the Senegalese diet with Senegalese deriving about 60% of their calories from grain consumption. Household food calorie availability was computed using the gross household production of these 9 crops. We first, estimated the available food crop by multiplying the farm-gate production of each crop by the appropriate post-harvest losses ratios[4].

Subsequently, the derived available food crops were converted into calories (kcal) available using the crop-specific energy ratios and edible portions conversion factors from the West African Food Composition[5] table by Stadlmayr *et al.* (2012). For each household, we estimated the total adult equivalent following Claro *et al.* (2010)[6] by considering the gender and age composition of family members. Household adult equivalents (AE) for each household member are obtained by dividing the Recommended Dietary Allowance (RDA) for the energy of each household member, according to the specific age and gender, by the average energy RDA reference value of 2,550 kcal (Claro *et al.*, 2010). The sum of all of the individual adult equivalents within a household was further computed to obtain the household adult equivalent

[3] As reported in D'Alessandro *et al.* (2015) despite considered as an important cash crop, groundnut is also grown for household consumption

[4] The postharvest losses ratios used were obtained from the African Postharvest Losses Information System (APHLIS), Affognon *et al.* (2015) and Tomlins *et al.* (2016) are provided in Table 6.15 of the Appendix.

[5] Conversion ratios for edible fractions and energy equivalence (kilo calories) are presented in Table 6.16 in the Appendix.

[6] The Adult-equivalent conversion factors for estimated calorie requirements according to age and gender are presented in Table 6.17.

(AE) value. This approach is particularly important because some family members such as children might have distinct energy needs which differ from adults. We subsequently divided the calories available at the household level by the households' total adult equivalents (AE) to make the values comparable. Finally, the obtained values were divided by 365 to obtain the daily food available per adult equivalent.

Our second outcome variable crop income per capita was measured as the value of all household crop production in CFA. In our data, farm households produced about 33 different crops but on average, households produce 2 crops. Using the reported farm gate price, we estimated the monetary value of each crop commodity produced by farm households. A sum of all the monetary value of all crops grown by households represented a household crop income. This was then divided by the total number of household members to obtain crop income per capita.

6.3.3 Empirical specification

A wide range of factors has been found in the empirical literature to affect household food availability (security or insecurity) and incomes. These variables fall largely into sociodemographic factors, farm characteristics, agro-climatic variables, access to market and credit, access to government intervention programs, etc. Variables considered for our analysis is based on the review of the empirical literature on technology adoption and impact evaluation studies (see Feder, 1980; Feder *et al.*, 1981; Adesina and Zinnah, 1993; Baidu-Forson, 1999; Doss, 2003; Duflo *et al.*, 2008, 2011; Adhikari *et al.*, 2009; Admassie and Ayele, 2010; Asfaw and Shiferaw, 2010; Simtowe *et al.*, 2010, 2011, 2012; Sharma *et al.*, 2011; Suri, 2011; Dandedjrohoun *et al.*, 2012; Awotide *et al.*, 2013; Bonou *et al.*, 2013; Arslan *et al.*, 2014; Donkor *et al.*, 2016). Table 6.1 describes all the variables used in the analysis. A comparison of variables across the three household types is also provided in Table 6.2. Households adopting mineral fertilizer and improved seeds with insurance appear to have the largest food calorie availability and crop income per capita. This is followed by households adopting mineral fertilizer and improved seeds without insurance. Non-adopting households have the least food calorie availability and crop income per capita. Apart from landholding, households adopting mineral fertilizer and improved seeds with insurance use large volumes of improved seeds, fertilizers, and hired labour. They also appear to be relatively wealthier as measured by the proxy variable lighting fuel. On average, households are headed by males with an average age of 53 years. Formal education is also low among household heads. Households have an average of 9 members and have low land areas under cash crops, low access to credit, extension, and a lower membership in farmer-based organizations.

Table 6.1: Variables and their description

Name	**Variable description**
Outcome variables	
Food calorie availability	Log of food calorie availability per adult equivalent per day
Crop income per capita	Log of total crop income in CFA/capita
Farm household characteristics	
Age	Age of household head in years
Gender	=1 if the household is male-headed
Education	=1 if the household head has formal education
HH size	Number of people residing in the household
Hired labour	Total hired labour used by the household
Roof material[a]	=1 if the roof material of household is concrete or slate
Risk attitude	=1 if highly risk-averse
Nonfarm work	=1 if household participates in nonfarm work
Plough	=1 if the household owns a plough
Access to services and institutions	
Extension	=1 if access to extension service
Credit	=1 if access to credit
Membership	=1 if a member of a farmer-based organization
Market integration	=1 if integrated into markets
Subsidy	=1 if access to input subsidies
Insurance needs	=1 if farmer has specific insurance needs
Farm and biophysical characteristics	
Land	Total land area owned by household (ha)
Improved seeds	Total quantity of improved seeds used in kg
Cash crop	Share of land under cash crops (%)
Soil degradation	=1 if the soil is perceived to be degraded
Rainfall	Mean annual rainfall in mm (2010 – 2017)
Std. Rainfall	Standard deviation of rainfall in mm (2010 – 2017)
AEZ BasinAra	=1 if agro-ecological zone is Bassin Arachide
AEZ RiverVall	=1 if agro-ecological zone is River Valley
AEZ Casamance	=1 if agro-ecological zone is Casamance
AEZ CentEast	=1 if agro-ecological zone is Center East
AEZ VallAnambe	=1 if agro-ecological zone is Center East
Location variables	=1 if agro-ecological zone is Valley Anambe
Road	Log of distance to the nearest road (km)
Market	Log of distance to the nearest market (km)
Mundlak fixed effects variables	
Mean labour[b]	Mean labour allocation across all crops grown
Mean land	Mean land (ha) allocation across all crops grown
Mean fertilizer	Mean fertilizer (kg) use across all crops grown
Mean seed	Mean seed (kg) use across all crops grown
Instrumental variables	
Fertilizer sufficiency	=1 if subsidized fertilizer is perceived to be sufficient
Seed quality	=1 if subsidized seed is perceived to be of a good quality
Coping strategy	=1 if the household employs coping strategies
Support needs	=1 if farmer has farming support needs
Subscribers	Log of regional distribution of microfinance subscribers
Location	=1 if the household is located in a populous region

[a] The type of household roof material is used as a proxy variable for household wealth.
[b] This is the mean of total labour used by farm household (i.e., household labour and hired labour)

6.4 Empirical results

In this section, we first examine factors driving the adoption of mineral fertilizer and improved seeds with and without insurance. Secondly, we present the economic implications associated with each adoption decision on household food calorie availability and crop income per capita. We present the results of the econometric estimation of the two outcomes of interest in Table 6.11 and 6.12 in the appendix, but for the sake of brevity, we do not discuss the results. The selectivity correction terms (m0 to m2) in Table 6.11 and 6.12 are significant in some of the technology package equations. This indicates the presence of sample selectivity effects and using OLS would have produced biased and inconsistent estimates. Thus, accounting for selectivity effects using the multinomial endogenous switching regression model as we did in this study was appropriate. At the same time, the Wald test of the joint significance of mean of crop-variant variables in our model (see Table 6.11 and 6.12) was significant, hence giving a justification for their inclusion in our model.

6.4.1 Determinants of adoption

Table 6.3 shows the results of the multinomial logit model for the different adoption decisions. We find that the multinomial logit model fits the data well, the Wald test is highly significant, hence rejecting the null hypothesis that all the regression coefficients are jointly equal to zero. Furthermore, the test for the joint significance of instruments across the different technology packages is highly significant. The results from the control-function specification indicate that the correction for endogeneity in the model was necessary. We find the coefficient of the membership of a farmer-based organization residual terms to be statistically significant, implying the presence of endogeneity of membership in farmer-based organizations. The control function approach was therefore appropriate in controlling for the endogeneity of membership of a farmer-based organization. The results from the control-function approach are presented in Table 6.10. Our results also suggest that selected instruments used in the control function approach satisfied the necessary conditions. Not only do the instruments (use of coping strategies, support needs, regional distribution of microfinance subscribers, and location in a populous region) have a significant effect on the potentially endogenous variables but they are also not correlated to the two instrumental variables (perception of subsidized fertilizer sufficiency and perception of subsidized seed quality) used in the multinomial endogenous switching regression model identification as shown in Table 6.14.

The results of the multinomial logit model in Table 6.3 suggest that the adoption of mineral fertilizer and improved seeds without insurance is mostly influenced by farm household characteristics, access to services and institutions, and farm and biophysical characteristics. Male-headed households, education level of household head, household size, and land holdings are positively associated with the likelihood of mineral fertilizer and improved seeds adoption without insurance. At the same time, market integration, the land area devoted to cash crops, location in the River Valley and Valley Anambe agro-ecological zones, insurance needs, input subsidy access, and perception about fertilizer sufficiency are positively associated with the adoption of mineral fertilizer and improved seeds without insurance. On the contrary, plough ownership, membership of farmer-based organizations, distance to a major market, risk attitude, and perception about subsidized seed quality is associated with a low relative probability of adopting mineral fertilizer and improved seeds without insurance.

Table 6.2: Summary statistics across packages

	Non-adopters		**Fertilizer and improved seeds only adopters**		**Fertilizer and improved seeds with insurance adopters**		**Pooled data**	
Variable	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**	**Mean**	**Std.**
Crop income per capita	3.996	1.122	4.609	0.585	4.933	0.613	4.209	1.029
Food availability per capita	1.969	0.532	2.441	0.505	2.837	0.598	2.146	0.587
Age	53.113	13.345	53.273	12.877	53.592	12.926	53.178	13.193
Gender	0.907	0.290	0.929	0.257	0.946	0.228	0.915	0.279
Education	0.347	0.476	0.430	0.495	0.517	0.501	0.378	0.485
HH size	9.118	4.812	10.367	5.619	9.599	4.646	9.496	5.081
Land	4.341	4.641	5.544	7.924	4.204	6.310	4.681	5.863
Improved seeds	0.000	0.000	129.317	176.400	186.361	221.331	44.541	122.743
Hired labour	0.122	1.012	0.255	0.996	0.510	1.201	0.176	1.019
Roof material	0.140	0.348	0.230	0.421	0.245	0.431	0.170	0.376
Plough	0.310	0.463	0.179	0.384	0.068	0.253	0.263	0.440
Extension	0.075	0.264	0.316	0.465	0.619	0.487	0.166	0.372
Credit	0.010	0.102	0.095	0.293	0.293	0.456	0.046	0.209
Membership	0.042	0.200	0.316	0.465	0.592	0.493	0.142	0.349
Market integration	0.557	0.497	0.577	0.494	0.680	0.468	0.568	0.495
Nonfarm work	0.272	0.445	0.262	0.440	0.150	0.358	0.265	0.441
Road	3.556	0.884	3.711	0.880	4.012	0.698	3.619	0.882
Market	3.977	0.466	3.930	0.429	4.043	0.630	3.967	0.464
Risk attitude	0.484	0.500	0.435	0.496	0.279	0.450	0.462	0.499
Cash crop	0.270	0.282	0.204	0.255	0.030	0.114	0.241	0.275
Soil degradation	0.004	0.063	0.062	0.240	0.122	0.329	0.025	0.157
Std. Rainfall	110.739	24.480	107.408	24.612	100.413	23.678	109.371	24.594
Rainfall	679.828	299.976	625.573	314.916	548.416	315.916	659.016	306.694
AEZ BasinAra	0.453	0.498	0.290	0.454	0.027	0.163	0.389	0.488
AEZ RiverVall	0.072	0.258	0.307	0.461	0.633	0.484	0.162	0.368
AEZ Casamance	0.232	0.422	0.118	0.323	0.027	0.163	0.192	0.394
AEZ CentEast	0.101	0.301	0.073	0.260	0.020	0.142	0.090	0.286
AEZ VallAnambe	0.004	0.060	0.160	0.367	0.286	0.453	0.060	0.237
Insurance needs	0.308	0.462	0.484	0.500	0.748	0.435	0.376	0.484
Mean labour	1.780	1.331	2.224	1.646	1.976	1.544	1.915	1.450
Mean land	0.096	0.107	0.108	0.162	0.028	0.078	0.097	0.125
Mean fertilizer	0.000	0.000	17.880	35.311	60.786	241.926	7.557	53.495
Mean seed	2.973	3.601	6.514	7.353	6.908	7.803	4.146	5.430
Subsidy	0.284	0.451	0.765	0.424	0.857	0.351	0.445	0.497
Fertilizer sufficiency	0.036	0.185	0.375	0.484	0.537	0.500	0.153	0.360
Seed quality	0.162	0.368	0.223	0.417	0.054	0.228	0.175	0.380
Coping strategy	0.341	0.474	0.280	0.449	0.265	0.443	0.320	0.467
Support needs	0.703	0.457	0.832	0.374	0.959	0.199	0.751	0.433
Subscribers	11.319	0.937	11.205	0.802	11.363	0.392	11.288	0.886
Location	0.201	0.401	0.061	0.239	0.007	0.082	0.153	0.360
N	**2,478**		**1,056**		**147**		**3,681**	

Just like the adoption of mineral fertilizers and improved seeds without insurance, we find that the adoption of mineral fertilizers and improved seeds with insurance is mostly influenced by farm household characteristics. We find that the education level of the household head, household size, land holdings, extension access, market integration, insurance needs, and access to input subsidies are positively associated with the adoption of mineral fertilizers and improved seeds with insurance. Conversely, risk attitude and perception of subsidized seed quality are negatively associated with the adoption of mineral fertilizer and improved seeds with insurance. The results suggest that the adoption of mineral fertilizer and improved seeds with and without insurance is largely driven by the education level of household head, household size, landholding, market integration, risk attitude, insurance needs, access to input subsidies, and perception about subsidized seed quality.

Table 6.3: Parameter estimates of adoption decision, multinomial logit selection model

	Fertilizer and improved seeds only		**Fertilizer and improved seeds with insurance**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	-3.708***	0.711	-11.214	7.093
Age	0.002	0.004	0.004	0.011
Gender	0.429*	0.250	0.524	0.877
Education	0.254**	0.127	1.079***	0.302
HH size	0.047***	0.013	0.090**	0.035
Land	0.075***	0.014	0.099***	0.024
Roof material	0.189	0.162	-0.493	0.339
Plough	-0.547***	0.164	-0.257	0.534
Extension	0.957	0.590	2.644*	1.427
Credit	1.674	2.027	-1.084	2.995
Membership	-2.323*	1.216	-2.001	2.254
Market integration	0.212*	0.111	0.558**	0.260
Nonfarm work	2.128	1.326	-1.374	2.930
Road	0.085	0.078	-0.074	0.171
Market	-0.416***	0.132	0.028	0.392
Risk attitude	-0.717***	0.216	-1.026**	0.458
Cash crop	0.617**	0.242	-0.665	0.982
Soil degradation	0.355	0.596	0.768	0.899
Std. Rainfall	0.002	0.002	-0.006	0.006
AEZ BasinAra	0.033	0.245	-0.025	6.848
AEZ RiverVall	3.047***	0.347	6.323	6.794
AEZ Casamance	-0.144	0.355	1.359	6.966
AEZ CentEast	-0.093	0.354	1.749	7.303
AEZ VallAnambe	4.838***	0.554	8.876	6.816
Insurance needs	0.578***	0.135	1.637***	0.294
Subsidy	2.197***	0.156	3.627***	0.494
Fertilizer sufficiency	1.265***	0.216	0.463	0.466
Seed quality	-0.451***	0.145	-1.027*	0.548
Resid mem	2.019***	0.613	2.396*	1.241
Resid ext	0.265	0.286	-0.179	0.778
Resid credit	0.074	0.897	2.271	1.434
Resid nonfarm	-1.258	0.781	0.311	1.698
Joint sig of instruments (χ^2)	42.910***		4.780*	
Wald test, χ^2 (62)	1009.910***			
Log-likelihood	-1555.512			
N		3681		

Notes: The base category is farm households that did not adopt either fertilizer and improved seeds adopters with or without insurance. ***, **, * represent 1%, 5%, and 10% significance level, respectively. Reported standard errors are the bootstrapped standard errors.

6.4.2 Impacts of adoption on food calorie availability and crop income per capita

The impact of mineral fertilizer and improved seed adoption with or without insurance on household food calorie availability and crop income per capita is shown in Table 6.4 and 6.5, respectively. We compare expected food calorie availability and crop income per capita under the actual case that the farm household adopted a particular package and the counterfactual case that they did not. Controlling for the effects of several covariates and the selection bias stemming from both unobserved and observed factors on household food calorie availability and crop income per capita, the adoption of mineral fertilizer and improved seeds with or without insurance is associated with significant increases in household food calorie availability and crop income per capita compared with the counterfactual case of non-adoption. By adopting mineral fertilizer and improved seeds without insurance, households increase their food calorie availability per adult equivalent per day by about 16% compared to the counterfactual case of not adopting (Table 6.4). The observed effect is highly significant at 1%. On the other hand, households that adopt mineral fertilizer and improved seeds with insurance increase their food calorie availability per adult equivalent per day by about 33% compared to the counterfactual case of not adopting and the effect is significant at 1%.

Table 6.4: Adoption impact on food calorie availability per AE/day

Package	**Actual food calorie availability per AE/day**	**Counterfactual outcome - If households did not adopt**	**ATT**	**Change (%)**
Fertilizer and improved seeds only adopters	7.364(0.027)	6.211(0.029)	1.153∗∗∗(0.039)	15.66
Fertilizer and improved seeds with insurance adopters	8.606(0.095)	5.791(0.068)	2.815∗∗∗(0.116)	32.71

Notes: Standard errors are in parentheses. ∗∗∗ represent 1% significance level.

Table 6.5: Adoption impact on crop income per capita

Package	**Actual crop income per capita**	**Counterfactual outcome - If households did not adopt**	**ATT**	**Change (%)**
Fertilizer and improved seeds only adopters	4.627(0.010)	4.253(0.016)	0.374∗∗∗(0.018)	8.08
Fertilizer and improved seeds with insurance adopters	4.933(0.041)	3.998(0.029)	0.935∗∗∗(0.050)	18.95

Notes: Standard errors are in parentheses. ∗∗∗ represent 1% significance level.

Similar to the observed results for food calorie availability per adult equivalent per day, we find that the adoption of mineral fertilizer and improved seeds without insurance significantly increases crop income per capita by about 8% compared to the counterfactual case of not adopting (Table 6.5). At the same time, by adopting mineral fertilizer and improved seeds with insurance, households significantly increase their crop income per capita by about 19% compared to the counterfactual case. The results obtained are congruent to similar studies in the empirical literature that have evaluated the impact of single productivity-enhancing technologies on household outcomes.

For example, the study by Kassie *et al.* (2014) finds 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. In rural Ethiopia, Zeng *et al.* (2017) find positive and significant impacts of improved maize varieties adoption on child nutrition outcomes. In Uganda, Kassie *et al.* (2011) found that the adoption of improved groundnut varieties significantly increases crop income of farm households and reduces poverty. Similarly, in Zambia, Khonje *et al.* (2015) find that the adoption of improved maize had significant poverty-reducing impacts through significant gains in crop incomes, consumption expenditure, and food security. Studies on the combined impact of these risk-reducing inputs or productivity-enhancing technologies are scanty. However, a limited number of studies such as those by Ariga *et al.* (2008) and Nyangena and Juma (2014) show that adoption of productivity-enhancing technologies as a package significantly increases yields, rather than as individual elements.

We also examined whether the adoption of mineral fertilizer and improved seeds with insurance actually improves farm household welfare, by evaluating welfare impacts if farm households switch to or from using insurance in addition to mineral fertilizer and improved seeds. We find that farm household by switching from the adoption of mineral fertilizer and improved seeds without insurance to adopting with insurance increase their food calorie availability per adult equivalent per day by about 5% and crop income per capita by 6% with the observed effects being significant at 1% (Table 6.6). In the same fashion, we evaluated the resulting welfare impact in a situation where farm households that adopted mineral fertilizer and improved seeds with insurance decide to adopt without insurance. We find that farm households by switching from adopting mineral fertilizer and improved seeds with insurance to adopting without insurance reduce their food calorie availability and crop income per capita by about 2.13% and 1.88% respectively, however, the observed effect is not significant (Table 6.7). As pointed out earlier, several empirical studies show that insurance use has positive welfare impacts on adopting farm households mainly through unlocking additional demand or increase investments in inputs, assets, and higher-return farm enterprises, stabilizing farm production and incomes, and improving household food security.

Table 6.6: Switching impact for adopters without insurance

	Actual outcome	**Counterfactual outcome - If households adopted with insurance**	**ATT**	**Change (%)**
Food calorie availability per AE/day	7.364(0.027)	7.760(0.044)	0.396***(0.051)	5.38
Crop income per capita	4.627(0.010)	4.915(0.018)	0.288***(0.020)	6.23

Notes: Standard errors are in parentheses. *** represent 1% significance level.

Table 6.7: Switching impact for adopters with insurance

	Actual outcome	**Counterfactual outcome - If households adopted without insurance**	**ATT**	**Change (%)**
Food calorie availability per AE/day	8.606(0.095)	8.423(0.228)	-0.183(0.247)	-2.13
Crop income per capita	4.933(0.041)	4.840(0.095)	-0.093(0.104)	-1.88

Note: Standard errors are in parentheses.

Additionally, we evaluated the counterfactual adoption impacts of non-adopting households by estimating the average treatment effects on the untreated (ATU) for food calorie availability per adult equivalent per day and crop income per capita. Controlling for the effects of several covariates and the selection bias stemming from both unobserved and observed factors on household food calorie availability and crop income per capita, the adoption of mineral fertilizer and improved seeds with or without insurance by non-adopting households is associated with significant increases in household food calorie availability and crop income per capita. Had non-adopting farm households adopted mineral fertilizer and improved seeds without insurance, they would have increased their food calorie availability per adult equivalent per day by about 7% (Table 6.8). At the same time, the counterfactual case of mineral fertilizer and improved seed adoption with insurance would have increased their food calorie availability by about 6%. The observed effects in both cases are significant at 1%.

Regarding crop income per capita, we find that in the counterfactual case of non-adopting households adopting mineral fertilizer and improved seeds without insurance, crop income per capita would have increased by about 7% and the observed effect is significant at 1% (Table 6.9). On the contrary, adopting mineral fertilizer and improved seeds with insurance would have increased crop income per capita by about 10% compared to the actual case of non-adoption and the observed effect is significant at 1%.

Table 6.8: Adoption impact on food availability per capita for non-treated households

Package	**Actual food availability per capita**	**Counterfactual food availability per capita - If households adopted**	**ATU**	**Change (%)**
Fertilizer and improved seeds without insurance	6.232(0.013)	6.651(0.012)	0.419***(0.018)	6.72
Fertilizer and improved seeds with insurance	6.232(0.013)	6.606(0.024)	0.374***(0.027)	6.00

Notes: Standard errors are in parentheses. *** represent 1% significance level.

Table 6.9: Adoption impact on crop income per capita for non-treated households

Package	**Actual crop income per capita**	**Counterfactual crop income per capita - If households adopted**	**ATU**	**Change (%)**
Fertilizer and improved seeds without insurance	4.241(0.007)	4.523(0.005)	0.282***(0.009)	6.65
Fertilizer and improved seeds with insurance	4.241(0.007)	4.682(0.010)	0.440***(0.012)	10.39

Notes: Standard errors are in parentheses. *** represent 1% significance level.

6.5 Conclusion

In this study we examined both individual and composite impact of two "risk-reducing inputs" – mineral fertilizer and improved seeds adoption with or without insurance on farm households' food calorie availability and crop income per capita using a nationally representative farm household survey data from Senegal. We find that adoption of mineral fertilizer and improved seeds with or without insurance to be largely driven by the education level of household head, household size, landholding, market integration, risk attitude, insurance needs, access to input subsidies, and perception about subsidized seed quality. We find that adopting mineral fertilizer and improved seeds generally lead to an increase in welfare outcomes for farm households. However, complementing the adoption of mineral fertilizer and improved seeds with insurance leads to higher household welfare outcomes compared to adopting mineral fertilizer and improved seeds in isolation.

We find that by switching from mineral fertilizer and improved seeds adoption without insurance to adopting with insurance, farm households can significantly increase their food calorie availability and crop income per capita by about 5% and 6% respectively. On the contrary, if farm households that adopted mineral fertilizer and improved seeds with insurance were to adopt without insurance, their food calorie availability and crop income per capita reduce by about 2.13% and 1.88% respectively. For non-adopting or untreated households, the adoption of mineral fertilizer and improved seeds without insurance can increase both their food calorie availability and crop income per capita by about 7%. However, adopting mineral fertilizer and improved seeds with insurance would have increased their food calorie availability and crop income per capita by about 6% and 10% respectively. The above findings have several policy implications. First, since extension access, market integration and input subsidies access are important drivers for adoption, development interventions around these institutions are important channels to encourage the adoption of productivity-enhancing technologies such as fertilizers, improved seeds, and insurance uptake. Lastly, mineral fertilizer and improved seed adoption with insurance appear to be an important instrument in increasing the adaptive capacity and resilience of smallholders, and hence policy directives should focus on scaling it up.

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Appendix

Table 6.10: Control function results for potentially endogenous variables

	Membership		Extension		Credit		Nonfarm work	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	-1.645***	0.394	-3.171***	0.406	-1.351	0.942	-0.904***	0.306
Age	-0.004	0.002	0.004*	0.002	-0.002	0.003	-0.002	0.002
Gender	-0.080	0.108	0.094	0.108	-0.158	0.144	-0.195**	0.085
Education	0.102	0.063	0.149**	0.062	0.124	0.085	0.174***	0.050
HH size	0.027***	0.006	-0.008	0.006	0.012	0.008	0.013***	0.005
Land	0.015***	0.005	0.011**	0.005	0.016***	0.006	-0.008	0.005
Roof material	-0.081	0.082	0.136*	0.080	0.141	0.108	-0.155**	0.073
Plough	-0.100	0.086	-0.003	0.082	-0.111	0.121	0.256***	0.061
Extension	0.773***	0.073			0.034	0.103	0.046	0.073
Credit	0.486***	0.109	-0.014	0.117			-0.015	0.118
Membership			0.809***	0.077	0.453***	0.096	0.001	0.078
Market integration	0.112*	0.061	0.009	0.060	-0.020	0.083	-0.015	0.048
Nonfarm work	0.053	0.072	0.049	0.070	-0.061	0.101		
Road	-0.002	0.038	-0.096***	0.036	-0.023	0.052	-0.105***	0.029
Market	0.014	0.072	0.053	0.071	0.194*	0.105	0.140**	0.054
Risk attitude	-0.134**	0.065	0.181***	0.061	0.082	0.086	0.463***	0.048
Cash crop	-0.216	0.144	-0.158	0.135	0.226	0.206	-0.228**	0.099
Soil degradation	0.008	0.151	0.094	0.152	-0.467**	0.211	0.727***	0.151
Std. Rainfall	-0.001	0.001	0.001	0.001	-0.001	0.002	-0.001	0.001
AEZ BasinAra	-0.322**	0.131	0.163	0.145	0.556*	0.297	-0.377***	0.093
AEZ RiverVall	0.450***	0.133	1.177***	0.148	1.225***	0.296	-0.434***	0.113
AEZ Casamance	0.126	0.130	0.230	0.150	0.681**	0.301	0.566***	0.093
AEZ CentEast	-0.027	0.154	0.538***	0.162	0.616*	0.319	0.405***	0.109
AEZ VallAnambe	0.987***	0.153	0.021	0.176	1.535***	0.308	0.279**	0.135
Insurance needs	0.147**	0.063	-0.117*	0.062	0.190**	0.084	-0.135***	0.051
Subsidy	0.254***	0.088	0.349***	0.082	0.228**	0.116	0.198***	0.070
Fertilizer sufficiency	0.266***	0.093	0.514***	0.091	0.081	0.121	-0.089	0.087
Seed quality	0.035	0.100	-0.240**	0.095	-0.124	0.135	0.069	0.078
Coping strategy	**-0.247*****	0.073						
Support needs			**1.194*****	0.114				
Subscribers					**-0.189*****	0.062		
Location							**0.191****	0.082
Log-likelihood	-1101.443		-1155.876		-563.764		-1867.881	
LR chi2(27)	809.730***		997.220***		243.980***		518.120***	
N					3681			

***, **, * represent 1%, 5%, and 10% significance level, respectively.

Table 6.11: Estimates of food calorie availability per AE/day equations

	Non-adopters		**Fertilizer and improved seeds without insurance adopters**		**Fertilizer and improved seeds with insurance adopters**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	5.543***	0.276	6.537***	0.466	10.259***	3.563
Age	0.000	0.002	-0.004*	0.003	-0.009	0.009
Gender	0.243***	0.083	0.444***	0.150	-0.210	0.531
Education	-0.052	0.052	0.104	0.066	-0.168	0.330
HH size	-0.088***	0.007	-0.076***	0.007	-0.082***	0.031
Land	-0.001	0.009	0.000	0.006	0.123**	0.057
Improved seeds			0.001***	0.000	0.001	0.001
Hired Labour	0.028	0.051	0.076**	0.039	0.052	0.171
Roof material	-0.074	0.091	-0.068	0.095	0.475	0.368
Plough	0.068	0.052	0.063	0.080	-0.613	0.618
Extension	0.365***	0.121	-0.124	0.083	-0.159	0.357
Credit	-0.078	0.262	-0.018	0.124	-0.818	0.500
Membership	0.183	0.151	-0.220**	0.093	-0.562*	0.34
Market integration	-0.001	0.046	-0.033	0.063	-0.190	0.286
Nonfarm work	-0.010	0.063	0.113	0.081	0.291	0.522
Road	-0.034	0.029	-0.069*	0.039	0.288	0.320
Market	0.133**	0.055	0.443***	0.080	0.265	0.362
Risk attitude	-0.112**	0.054	0.161**	0.073	0.130	0.335
Cash crop	-0.714***	0.131	-0.897***	0.269	-2.138	9.272
Soil degradation	-0.027	0.295	0.161	0.121	0.175	0.383
Rainfall	0.000*	0.000	0.000	0.000	0.000	0.000
AEZ BasinAra	0.314*	0.177	-0.543**	0.228	0.929	3.740
AEZ RiverVall	0.259	0.246	-0.022	0.276	-0.872	1.763
AEZ Casamance	0.497***	0.130	-0.865***	0.228	0.041	4.959
AEZ CentEast	0.900***	0.169	-0.380	0.257	-1.237	4.101
AEZ VallAnambe	1.929***	0.462	-0.096	0.294	-1.341	1.793
Insurance needs	0.038	0.057	0.094	0.074	-0.226	0.402
Subsidy	-0.035	0.149	-0.153	0.118	-0.050	0.701
Mean labour	0.028	0.022	-0.011	0.023	-0.044	0.081
Mean land	4.524***	0.673	1.389***	0.405	0.644	2.675
Mean fertilizer			0.011***	0.001	-0.001	0.003
Mean seed	0.033**	0.014	0.011	0.009	-0.001	0.043
m0	-0.941***	0.355	-0.018	0.304	-0.092	2.739
m1	-0.953	0.729	-0.285**	0.138	0.024	1.914
m2	-1.182	2.217	-0.963*	0.539	-1.222	0.779
Joint significance of crop varying covariates	131.690***		83.930***		0.490	
N	2478		1056		147	

$***$, $**$, $*$ represent 1%, 5%, and 10% significance level, respectively. Reported standard errors are the bootstrapped standard errors.

Table 6.12: Estimates of crop income per capita equations

Variable	Non-adopters Coef.	Std. Err.	Fertilizer and improved seeds without insurance adopters Coef.	Std. Err.	Fertilizer and improved seeds with insurance adopters Coef.	Std. Err.
Constant	3.668***	0.118	4.152***	0.204	5.510***	1.557
Age	0.001	0.001	-0.003**	0.001	-0.004	0.004
Gender	0.128***	0.035	0.216***	0.053	-0.038	0.209
Education	0.003	0.024	0.079***	0.030	-0.039	0.137
HH size	-0.040***	0.003	-0.032***	0.003	-0.021	0.013
Land	-0.002	0.004	0.003	0.003	0.053**	0.026
Improved seeds			0.000	0.000	0.000	0.001
Hired Labour	0.005	0.025	0.039**	0.016	0.105	0.071
Roof material	-0.107***	0.040	-0.092**	0.042	0.183	0.156
Plough	0.035	0.022	0.046	0.038	-0.119	0.238
Extension	0.143***	0.046	-0.059	0.038	-0.088	0.151
Credit	-0.004	0.104	-0.001	0.067	-0.316	0.209
Membership	0.053	0.066	-0.012	0.043	-0.253*	0.148
Market integration	-0.001	0.019	-0.014	0.028	-0.027	0.118
Nonfarm work	-0.016	0.028	0.014	0.035	0.317	0.232
Road	-0.019*	0.011	-0.048***	0.018	0.110	0.145
Market	0.058***	0.022	0.178***	0.037	0.131	0.155
Risk attitude	-0.059***	0.022	0.055*	0.031	0.094	0.150
Cash crop	0.285***	0.042	0.033	0.113	-0.019	3.536
Soil degradation	-0.050	0.136	0.036	0.054	0.004	0.163
Rainfall	0.000*	0.000	0.000	0.000	0.000	0.000
AEZ BasinAra	0.177**	0.084	-0.049	0.121	-0.029	1.361
AEZ RiverVall	0.278***	0.105	0.029	0.120	-0.347	0.810
AEZ Casamance	0.237***	0.056	-0.185*	0.097	-0.268	1.840
AEZ CentEast	0.455***	0.073	-0.067	0.112	-0.631	0.966
AEZ VallAnambe	0.741***	0.207	-0.058	0.135	-0.695	0.799
Insurance needs	0.017	0.022	0.032	0.032	-0.216	0.178
Subsidy	0.016	0.060	-0.075	0.053	0.060	0.253
Mean labour	0.013	0.009	0.003	0.011	-0.039	0.035
Mean land	2.190***	0.297	0.658***	0.161	0.470	1.098
Mean fertilizer			0.004***	0.001	-0.001	0.001
Mean seed	0.021***	0.006	0.017***	0.004	0.014	0.020
m0	-0.242**	0.111	-0.020	0.137	-0.417	1.094
m1	-0.297	0.244	-0.034	0.063	0.413	0.693
m2	-0.170	0.874	-0.141	0.253	-0.443	0.310
Joint significance of crop varying covariates	182.820***		109.220***		2.340	
N	2335		1052		147	

***, **, * represent 1%, 5%, and 10% significance level, respectively. Reported standard errors are the bootstrapped standard errors.

Table 6.13: Correlation test of instruments

Variable	Fertilizer sufficiency	Seed quality	Coping strategy	Support needs	Subscribers	Location
Fertilizer sufficiency	1.000					
Seed quality	-0.011	1.000				
Coping strategy	-0.047	0.021	1.000			
Support needs	0.090	0.008	0.003	1.000		
Subscribers	-0.002	-0.022	-0.147	0.035	1.000	
Location	-0.116	0.124	-0.014	-0.031	0.551	1.000

Table 6.14: Test of the validity of the instrument (falsification test) on non-adopters

	Selection model		**Food calorie availability per AE/day**		**Crop income per capita**	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Constant	3.708***	0.684	5.791***	0.289	3.742***	0.121
Age	-0.002	0.004	0.000	0.002	0.001	0.001
Gender	-0.429*	0.247	0.291***	0.083	0.159***	0.034
Education	-0.254**	0.127	-0.060	0.049	-0.002	0.021
HH size	-0.047***	0.013	-0.078***	0.005	-0.034***	0.002
Land	-0.075***	0.013	0.082***	0.005	0.042***	0.002
Roof material	-0.189	0.169	-0.097	0.076	-0.141***	0.030
Plough	0.547***	0.172	0.038	0.054	0.025	0.022
Extension	-0.957	0.596	0.377***	0.091	0.158***	0.038
Credit	-1.674	1.928	-0.405*	0.239	-0.154	0.100
Membership	2.323**	1.126	0.117	0.128	0.045	0.055
Market integration	-0.212*	0.112	-0.018	0.045	-0.014	0.019
Nonfarm work	-2.128*	1.287	-0.075	0.054	-0.042*	0.023
Road	-0.085	0.074	-0.020	0.027	-0.010	0.011
Market	0.416***	0.129	0.118**	0.050	0.049**	0.021
Risk attitude	0.717***	0.214	-0.171***	0.047	-0.088***	0.020
Cash crop	-0.617***	0.230	-0.183*	0.100	0.469***	0.036
Soil degradation	-0.355	0.753	-0.130	0.640	-0.093	0.237
Std. Rainfall	-0.002	0.002	0.000	0.001	0.000	0.000
AEZ BasinAra	-0.033	0.254	0.319***	0.079	0.203***	0.032
AEZ RiverVall	-3.047***	0.346	0.142	0.130	0.236***	0.053
AEZ Casamance	0.144	0.341	0.392***	0.087	0.197***	0.036
AEZ CentEast	0.093	0.351	0.745***	0.102	0.397***	0.042
AEZ VallAnambe	-4.838***	0.539	1.540***	0.559	0.565**	0.238
Insurance needs	-0.578***	0.130	0.032	0.050	0.014	0.021
Subsidy	-2.197***	0.170	-0.119	0.075	0.026	0.032
Fertilizer sufficiency	**-1.265*** **	0.212	**0.030**	0.137	**0.008**	0.058
Seed quality	**0.451*** **	0.155	**0.077**	0.086	**-0.019**	0.036
Resid mem	-2.019***	0.563				
Resid ext	-0.265	0.290				
Resid credit	-0.074	0.875				
Resid nonfarm	1.258*	0.758				
N				3681		

***, **, * represent 1%, 5%, and 10% significance level, respectively. Reported standard errors for the selection model are the bootstrapped standard errors.

Table 6.15: Post-harvest loss ratios per crop and region (%)

Region	**Maize**[a]	**Rice**[a]	**Sorghum**[a]	**Millet**[a]	**Fonio**[a]	**Groundnut**[b]	**Sesame**[c]	**Cowpea**[b]	**Cassava**[b]
Dakar	17.19	0.00	11.09	8.02	0.00	10.10	25.00	23.50	42.3
Diourbel	20.52	0.00	12.29	20.80	0.00	10.10	25.00	23.50	42.3
Fatick	20.45	11.09	12.29	8.69	0.00	10.10	25.00	23.50	42.3
Kaffrine	28.85	10.85	22.19	20.67	18.76	10.10	25.00	23.50	42.3
Kaolack	20.34	10.85	11.31	8.54	11.48	10.10	25.00	23.50	42.3
Kédougou	26.57	11.79	11.40	10.63	23.70	10.10	25.00	23.50	42.3
Kolda	26.57	22.69	12.49	22.60	23.55	10.10	25.00	23.50	42.3
Louga	17.19	10.85	11.31	8.34	0.00	10.10	25.00	23.50	42.3
Matam	17.19	11.25	11.20	8.12	18.76	10.10	25.00	23.50	42.3
Saint-Louis	17.19	11.37	11.31	8.46	0.00	10.10	25.00	23.50	42.3
Sédhiou	26.54	22.76	22.39	10.76	23.58	10.10	25.00	23.50	42.3
Tambacounda	17.19	11.05	22.23	8.34	11.48	10.10	25.00	23.50	42.3
Thiès	25.94	10.85	22.13	20.67	0.00	10.10	25.00	23.50	42.3
Ziguinchor	17.91	23.07	11.40	10.63	0.00	10.10	25.00	23.50	42.3

[a] Source: African Postharvest Losses Information System (APHLIS). `https://www.aphlis.net/en`
[b] Source: Affognon *et al.* (2015)
[c] Source: Tomlins *et al.* (2016)

Table 6.16: Conversion ratios for edible fractions and food energy equivalence

Crop	**Edible conversion factor**	**Kcal/100g**
Maize	1.00	349
Rice	1.00	353
Sorghum	1.00	344
Millet	1.00	348
Fonio	1.00	347
Cowpea	1.00	316
Groundnut	1.00	578
Cassava	0.84	153
Sesame	1.00	577

Source: Stadlmayr *et al.* (2012)

Table 6.17: Adult-equivalent conversion factors according to age and gender

Age (years)	**Calories (kcal)**	**Adult-equivalent conversion factor**
New-borns		
0-1	750	0.29
Children		
1-3	1,300	0.51
4-6	1,800	0.71
7-10	2,000	0.78
Men		
11-14	2,500	0.98
15-18	3,000	1.18
19-24	2,900	1.14
25-50	2,900	1.14
51+	2,300	0.90
Women		
11-14	2,200	0.86
15-18	2,200	0.86
19-24	2,200	0.86
25-50	2,200	0.86
51+	1,900	0.75

Source: Claro *et al.* (2010)

Chapter 7
General conclusion

7.1 Conclusion

In the context of climate change, farm households are increasingly exposed to weather changes such as prolonged drought, late start of rains, shifting rainfall patterns, etc. These changes present an enormous risk to food production particularly in developing countries that are disproportionally affected by climate change. With limited access to credit or insurance markets and resources, farm households most often have challenges managing the myriad of risks they face. Hence farm households heavily rely on a range of traditional risk management strategies to avoid or minimize losses, but these are mostly incomplete, suboptimal, and mitigate only a small part of overall risk. Furthermore, risk management by farm households is multifarious with each having a different cost and resource use or allocation implications. These risk management strategies usually include agronomic adaptation practices, diversifying income sources, coping strategies, share tenancy contracts, traditional moneylending, and risk-sharing within the extended family and other community networks.

Furthermore, formal risk management instruments such as index-based insurance, production, and market or sales contracts are increasingly playing an important role in farm households risk management. The use of any of these strategies can potentially shift scarce production resources and this can affect production efficiency and household welfare. For example, insurance can unlock additional demand for fertilizer, seeds, and labour thus having implications for input use, levels of investments and allocation of scarce resources which can have long-term implications on production efficiency. The use of coping strategies such as the sale of product assets might plunge households into poverty due to their inability to recover the loss of assets ex-post the shock for instance. This PhD research, therefore, sought to explore the impact of climate change and various risk management strategies employed by Senegalese farm households across multiple outcomes including, agriculture incomes and dispersions around income, technical efficiency and food security. To achieve this, the study employed different econometric analyses using nationally representative farm household survey data collected in 2017. This chapter summarizes the main findings, offers relevant policy implications of the study, discusses some caveats related to the study, and offers recommendations for future research.

7.2 Main findings

The first introductory paper to the PhD research in chapter 2 examined the impact of climate change in the form of rainfall variability on inter-household income inequality, daily food calorie availability, and agricultural labour productivity in Senegal, and the role of adaptation (risk management) strategies. To address model uncertainty, the study employed the recently developed model-averaging techniques and the Gini decomposition approach. The findings of the study suggest that rainfall variability negatively affects income equality by increasing the Gini elasticity of income. Particularly for agriculture incomes, the study found that the Gini elasticity of agriculture income increases for every deviation in rainfall. In the case of non-farm income, the Gini elasticity decreases for every deviation in rainfall. Because agriculture income sources constitute the largest share and contributor to household income inequality, any shocks to the sector will largely be responsible for any observed increases in income inequality.

The study also finds that rainfall variability decreases household daily food calorie availability and agricultural labour productivity. Especially for agricultural labour productivity, the study provides empirical proof of how rainfall variability will impact labour productivity beyond heat stress which has been widely studied in the literature. The study finds that rainfall variability will affect agricultural labour productivity through a reduction in household food calorie availability. The study also finds varying impacts of adaptation strategies on household outcomes. Insurance (risk transfer) use despite being positively correlated to income equality, increases both household food security and agricultural labour productivity. Risk mitigation strategies were also observed to be positively correlated with income inequality and appear to decrease household food security and agricultural labour productivity. Risk coping measures correlates negatively with income inequality, decrease household food security and increase agricultural labour productivity. The use of insurance, irrigation, subsidies access, and the adoption of productivity-enhancing technologies (fertilizer and improved seeds) are the most important instruments to help households deal with rainfall variability related shocks.

The paper presented in Chapter 3, evaluated the adoption effect of different risk management strategies employed by farm households on agriculture income and dispersions around incomes. Because the adoption of these risk management strategies is non-random, failure to account for this might introduce biases in the estimates. The study thus employed a Multinomial Endogenous Switching Regression model to control for potential selectivity bias problems. To evaluate dispersions around incomes, the study also employed a Moment-Based Approach. Findings in this chapter first showed that the use of ex-ante risk management strategies significantly reduces agriculture incomes. Intuitively, there is an opportunity cost effect, mostly in the form of income losses related to the use of ex-ante risk management strategies. The use of ex-post strategies either in isolation or in combination with ex-ante risk management strategies significantly increases agriculture incomes. Risk coping strategies rely largely on the sale of assets and thus appears an effective strategy to smoothen household income shortfalls in the short run. All the risk management strategies employed by households significantly reduce dispersions around agriculture incomes, however, ex-post strategies produce the largest dispersion reduction effect.

The study reported in Chapter 4 analysed the technical efficiency implications of the risk management strategies employed by farm households. To achieve this the study employed a sample selection stochastic production frontier to control for potential self-selectivity biases in adoption together with a meta-frontier model to evaluate the impact of risk management strategies on technical efficiency. The empirical results showed that risk management has implications on farm household's technical efficiency. Farm households adopting ex-post risk management strategies appear to have a relatively higher technical efficiency with respect to the meta-frontier compared to the other risk management strategies. Households employing ex-ante risk management strategies were observed to be the least technically efficient compared to households not managing risks or those employing ex-post risk management strategies in isolation or in combination with ex-ante risk management strategies. Households not managing risks appear to slightly have a higher meta technology gap, suggesting that they are adopting the best production technology. The results also suggest that managing production risks using multiple strategies does not necessarily result in the highest technical efficiency gain compared to the use of single or isolated strategies.

In Chapter 5, the study assessed the complementary impact of productivity-enhancing technologies (mineral fertilizer and improved seeds) adoption with insurance on technical efficiency. The analysis compared two distinct farm households – one adopting fertilizer and improved seeds without insurance and the other fertilizer and improved seeds with insurance. The study employed a sample selection stochastic production frontier with a meta-frontier model, propensity score matching (PSM) approach, and an endogenous switching regression model to control for potential biases. The empirical results show that households that adopted productivity-enhancing technologies with insurance tend to have higher levels of investment in production inputs. However, households that adopted productivity-enhancing technologies without insurance tend to be more technically efficient on average. Households that adopted productivity-enhancing technologies with insurance seem to be slightly more efficient in adopting the best available technology set as measured by the technology gap ratio. At the meta-frontier, the results of the endogenous switching regression model suggest that adopting productivity-enhancing technologies with insurance decreases the technical efficiency of productivity-enhancing technologies with insurance adopters by about 50%. Conversely, for households adopting productivity-enhancing technologies without insurance, adopting with insurance could potentially increase the mean technical efficiency by about 37%. The results suggest that lower observed technical efficiencies for productivity-enhancing technologies with insurance adopters may be driven by unobserved effort or behavioural biases of farmers which can be an important source of heterogeneity in the observed treatment effects.

The study in Chapter 6, assessed the joint welfare impacts of managing climate risks through the adoption of risk-reducing technologies and insurance by comparing three distinct farm households: 1) non-adopters of mineral fertilizer, improved seeds and insurance, 2) mineral fertilizer and improved seeds adopters without insurance and 3) mineral fertilizer and improved seeds adopters with insurance. Because the adoption of these technology packages or portfolios is non-random, failure to account for this might introduce biases in the estimates. The study thus employed a Multinomial Endogenous Switching Regression model to control for potential selectivity bias problems. The empirical results show that the adoption of mineral fertilizer and improved seeds with or without insurance is associated with significant increases in household food calorie availability and crop income per capita. However, complementing the adoption of mineral fertilizer and improved seeds with insurance leads to higher household welfare outcomes compared to adopting mineral fertilizer and improved seeds without insurance. Furthermore, the empirical result suggests that farm households by switching from the adoption of mineral fertilizer and improved seeds without insurance to adopting with insurance significantly increase their food calorie availability and crop income per capita. At the time, the study finds that farm households by switching from adopting mineral fertilizer and improved seeds with insurance to adopting without insurance reduce their food calorie availability and crop income per capita although the observed effect is not significant.

7.3 Policy implications

Important policy implications can be drawn from the findings of this study. First, the findings underscore the need for context-specific studies to guide policies that seeks to help farmers better manage production-related risks. Most importantly it highlights that some trade-offs have to be made in managing risks, thus policymakers must recognize the presence of some unintended effects and develop the necessary remedies. For instance, insurance increases food security and labour productivity but at the same time increases income inequality and potentially reduces technical efficiency because of moral hazard problems. At the same time, ex-post risk management strategies appear to be effective in terms of increasing household agriculture incomes and reducing dispersions around incomes and providing better technical efficiencies compared to other strategies. Ex-post risk management strategies may be effective in managing risk in the short term, however, in the long term, it might not be an effective strategy. Particularly for very poor households, the use of ex-post strategies will not be a feasible risk management option since the sale of productive assets may plunge them deeper into poverty. There is therefore a need for a more targeted and systematic approach to agricultural risk management. Most importantly, investments in services such as the provision of timely relevant weather information can help farm households better harness the use of risk management strategies. For instance, it will help farmers to select the right crop commodities to produce for a particular season and at what time within the season to sow for instance.

Index-based insurance products should be widely promoted to farm households since they appear to help households better manage production-related risks. However, achieving this requires overcoming some socioeconomic and institutional hurdles. Improving better access to credit is particularly important for index-based insurance access as well as the provision of hands-on practical information on how insurance works. Beyond credit, there is a need to provide and expand functioning markets for inputs such as fertilizers, improved seeds, irrigation, and post-harvest facilities. There is also the need to not only scale up index-based insurance products to more farm households but also offer subsidies to encourage widespread uptake. Promoting index-based insurance products should be done through farmer-based organizations for instance since they are important drivers of the adoption of risk management strategies and at the same time can potentially lower related administrative costs of running index-based insurance schemes.

Empowering farmer's management of climate risks will also require the adoption of context-suitable agricultural practices such as conservation agriculture, sustainable land management practices, etc., and technologies that are important low-cost risk mitigation strategies such as improved and drought-resistant varieties of crops, and irrigation facilities. This will also require the provision of information and technical assistance to farmers in the use and implementation of these practices. Providing such technical assistance programs can help in amplifying the benefits of some of the risk management strategies employed by households. Furthermore, provision of technical assistance should go beyond information but also soil testing services and recommendations on fertilizer application rates to help farmers to use appropriate amounts of fertilizer, which can go a long way to minimize input costs, achieve higher yield thereby attaining environmental and economic sustainability.

7.4 Caveats and future research

There are some important caveats to be considered for this PhD study. Climate change and for that matter adaptation or risk management usually occurs over long periods. Due to the data used in this PhD research being limited to cross-sectional data, the analysis is rather static. For instance, some of the risk management strategies evaluated in this research can be effective in the short run, while others might deliver payoffs in the long run. Similarly, technical efficiency evaluated across the various risk management strategies might also have both temporal and spatial effects which the study fails to capture. The analysis used in this study therefore obscures or fails to capture important spatial and temporal shifts in outcomes, that can provide critical thresholds to identify the impact of risk management. Furthermore, since we clustered the various risk management strategies into three broad typologies, the study only evaluated or captured aggregate impacts of risk management strategies as supposed to individual impacts. At the same time, because production conditions and the scope of risk management strategies are heterogeneous across various farm enterprises, focusing on aggregate effects as done in this study may obscure enterprise-specific effects for instance. Future research can therefore focus on using long term data such as panel or longitudinal data on various production systems, agriculture incomes, and risk management strategies employed by farm households to investigate all these dimensions and provide a better comparison between the various risk management strategies. Such data would be needed to provide more robust evidence on the implication of risk management on important household welfare outcomes.

Additionally, the nexus between risk management and allocative and economic efficiency will be an interesting research theme to pursue for future research. This will provide important insights into how households allocate resources pre and post-climate shocks. This is particularly interesting for government intervention programs like cash transfers and input subsidies that are sometimes provided to farm households post major climate shocks. Such a study will provide important cues as to how best households can build new assets post-climate shocks. In an experimental setting, future studies can also explore the role of farmers' "effort" in the use of insurance products to better understand how behavioural biases might offset the benefits of such products.

Appendix A

Empirical methods

A.1 Weighted Average Least Squares

Chapter 2 of the PhD study employed a model averaging technique to investigate the impact of climate change in the form of rainfall variability on inter-household inequality, food security and labour productivity. A major problem in empirical models' estimation is the so-called "problems of model uncertainty". In most cases, economic theory provides some information about empirical model specifications but offers little guidance about how to specify the exact data-generating process for the outcome of interest (De Luca and Magnus, 2011). At the same time, the lack of a one-to-one link between theory and empirical model specification generates uncertainty regarding, for example, which explanatory variables must be included in the model, which functional forms are appropriate, or which lag length captures dynamic responses. A key feature behind model uncertainty is therefore the existence of a wide range of functional forms and explanatory variables without much consensus concerning which canonical model is appropriate. The implication of this is that empirical researchers need to choose among a set of possible model specifications. In such cases, empirical results will typically be influenced by the inclusion or omission of specific variables. Depending on the model selection procedure, different researchers may arrive at different conclusions even when using the same data (De Luca and Magnus, 2011). Hence addressing model uncertainty is clearly important. Model averaging techniques alleviate such inconsistencies by comparing the robustness of regression coefficients over the entire model space. Two main model averaging techniques exist in the empirical literature: Bayesian model averaging (BMA) and Weighted-average least squares (WALS). For this study, the latter technique which was developed by Magnus *et al.* (2010) was employed because of two main following reasons:

1. Weighted-average least squares (WALS) is theoretically and practically superior to the standard Bayesian model averaging (BMA) because the prior is 'neutral' and the risk properties of the estimator are close to those of the minimax regret estimator (Magnus *et al.*, 2010).

2. It is also practically superior because of the space over which model selection is performed increases linearly rather than exponentially with size. WALS unlike BMA relies on preliminary orthogonal transformations of the auxiliary regressors and the parameters. Thus the computational burden required to obtain an exact WALS estimate is lower compared to BMA (De Luca and Magnus, 2011). Also, the choice of the prior distribution on parameters is independent of prior information availability as in the case of BMA.

Considering the linear regression model of the form:

$$y = X_1\beta_1 + X_2\beta_2 + \mu \tag{A.1}$$

where y is an $n \times 1$ vector of observations on the outcome of interest; the X_j, $j = 1$, 2, are $n \times k_j$ matrices of observations on two subsets of deterministic regressors; the β_j are $k_j \times 1$ vectors of unknown regression parameters; and u $\sim$ N(0, σ^2), an $n \times 1$ random vector of unobservable disturbances whose elements are independent and identically matrix $X = (X_1, X_2)$ has full column-rank k. The reason for partitioning the design distributed. We assume that $k_1 \geq 1$, $k_2 \geq 0$, $k = k_1 + k_2 \leq n$ - 1, and the design matrix X in two subsets of regressors is that X_1 contains explanatory variables that we want in the model because of theoretical reasons or other considerations about the phenomenon under investigation, whereas X_2 contains additional explanatory variables of which we are less certain. Using the terminology of Danilov and Magnus (2004), the k_1 columns of X_1 are called focus regressors and the k_2 columns of X_2 are called auxiliary regressors.
where y is an $n \times 1$ vector of observations on the outcome of interest, X_j, $j = 1$, 2, are $n \times k_j$ matrices of observations on two subsets of deterministic regressors, μ is a random vector of unobservable disturbances, and β_1 and β_2 are unknown parameter vectors. We assume that $k_1 \geq 1$, $k_2 \geq 0$, $k = k_1 + k_2 \leq n$ - 1, that $X = (X_1, X_2)$ has full column-rank, and that the disturbances (μ_1, ..., μ_n) are independent and identically distributed N(0, σ^2). The design matrix X is assumed to be in two subsets of regressors; X_1 contains explanatory variables that are called focus regressors (i.e., variables wanted in the model because of theoretical reasons or other

considerations about the phenomenon under investigation), X_2 contains additional explanatory variables of which we are less certain which are referred to as auxiliary regressors. The primary interest is the estimation of the vector of focus parameters β_1 in equation A.1, whereas β_2 is treated as a vector of nuisance parameters. By the properties of partitioned inverses, the unrestricted ordinary least-squares (OLS) estimators of β_1 and β_2 are given by:

$$\hat{\beta}_{1_\mu} = \hat{\beta}_{r_\mu} - Q\hat{\beta}_{2_\mu} \tag{A.2}$$

$$\hat{\beta}_{2_\mu} = (X_2^\top M_1 X_2)^{-1} X_2^\top M_{1y} \tag{A.3}$$

where $\hat{\beta}_{r\mu} = (X_1^\top X_1)^{-1} X_1^\top y$ is the restricted OLS estimator from a regression of y on X_1 (with β_2 restricted to zero), Q $= (X_1^\top X_1)^{-1} X_1^\top X_2$ is the multivariate OLS estimator from a regression of X_2 on X_1, and $M_1 = I_n$ - $X_1(X_1^\top X_1)^{-1} X_1^\top$ is a symmetric and idempotent matrix. Within this framework, model uncertainty arises because different subsets of auxiliary regressors could be excluded from X_2 to improve, in the mean squared error (MSE) sense, the unrestricted OLS estimator $\hat{\beta}_{1_\mu}$ of β_1. It is a basic result from the least-squares theory that by restricting some elements of β_2 to zero we can indeed obtain an estimator of β_1 which is subject to omitted variable bias but is also more precise than the unrestricted OLS estimator $\hat{\beta}_{1_\mu}$. The choice of excluding different subsets of auxiliary regressors is therefore motivated by a trade-off between bias and precision in the estimators of the focus regression parameters. Because model uncertainty is confined to the k_2 variables of X_2, the number of possible models to be considered is $I = 2^{k_2}$. Subsequently, assume M_i is the ith model in the model space which is obtained by including only a subset of k_{2i} (with $0 \leq k_{2i} \leq k_2$) auxiliary regressors. Model M_i is represented as follows:

$$y = X_1\beta_1 + X_{2_i}\beta_{2_1} + \varepsilon_{i,} \quad \text{i} = 1 = \ \ldots, \ I \tag{A.4}$$

where X_{2i} is an $n \times k_{2i}$ matrix of observations on the included subset of k_{2i} auxiliary regressors, β_{2i} is the corresponding subvector of auxiliary parameters, and ϵ_i is the new vector of disturbances after excluding k_2 - k_{2i} auxiliary regressors. Estimation of model averaging proceeds in two steps. In the first step one first estimates the parameters of interest conditional on each model in the model space. In the second step, the unconditional estimate as a weighted average of these conditional estimates is computed. A model averaging estimate of β_1 is given by:

$$\hat{\beta}_1 = \sum_{\mathrm{i}=1}^{I} \lambda_{\mathrm{i}} \hat{\beta}_{1_i} \tag{A.5}$$

where the λ_i are non-negative random weights that add up to one, and $\hat{\beta}_{1i}$ is the estimate of β_1 obtained by conditioning on model M_i. Weighted-average least-squares (WALS) estimation starts with the orthogonal transformations of the auxiliary regressors and their parameters, which greatly reduce the computational burden of the model-averaging estimator and allow for exploiting prior distributions corresponding to a more transparent concept of ignorance about the role of the auxiliary regressors. The first step of WALS consists of computing an orthogonal $k_2 \times k_2$ matrix P and a diagonal $k_2 \times k_2$ matrix $\wedge$ such that $P^\top X_2^\top M_1 X_2 = \wedge$. These matrices are then used to define $Z_2 = X_2 \mathrm{P} \wedge^{-1/2}$ and $\gamma_2 = \wedge^{1/2} P^\top \beta_2$ such that $Z_2^\top M_1 Z_2 = I_{k2}$ and $Z_2 \gamma_2 = X_2 \beta_2$. The original vector of auxiliary parameters β_2 can always be recovered from $\beta_2 = \mathrm{P} \wedge^{-1/2} \gamma_2$. After applying these orthogonal transformations to equation A.1, the unrestricted OLS estimators of β_1 and γ_2 from a regression of y on X_1 and Z_2 are given by:

$$\hat{\beta}_{1_\mu} = \hat{\beta}_{1_r} \; - \; R \hat{\gamma}_{2_\mu} \tag{A.6}$$

$$\hat{\gamma}_{2_i} = \; W_i \hat{\gamma}_{2_\mu} \tag{A.7}$$

where $R = (X_1^\top X_1)^{-1} X_1^\top Z_2$ is the multivariate OLS estimator from a regression of Z_2 on X_1. If we also define the $k_2 \times (k_2 \text{ - } k_{2i})$ selection matrix S_i by $S_i^\top = (I_{k2-k2i}, 0)$, or a column permutation thereof, such that S_i captures the restrictions placed on γ_2 under model M_i, then the restricted OLS estimators of β_1 and γ_{2i} are given by:

$$\hat{\beta}_{1_i} = \hat{\beta}_{1_r} - R W_i \hat{\gamma}_{2_\mu} \tag{A.8}$$

$$\hat{\gamma}_{2_i} = W_i \hat{\gamma}_{2_\mu} \tag{A.9}$$

where $W_i = I_{k2}$ - S_i $S_i^\top$ is a $k_2 \times k_2$ matrix whose jth diagonal element is zero if γ_{2j}

is restricted to zero; otherwise, the jth diagonal element is one. A key advantage of these transformations lies in the fact that $\hat{\gamma}_{2\mu} \sim N_{k2}(\gamma_2,\sigma^2 I_{k2})$. This result has several implications on the computational aspects and the statistical properties of the WALS estimator. First, under some minimal regularity conditions on the model weights λ_i, the WALS estimator of β_1 is of the form:

$$\widetilde{\beta}_1 = \sum_{i=1}^{I} \lambda_i \hat{\beta}_{1_i} = \hat{\beta}_{1_r} - RW\hat{\gamma}_2 \tag{A.10}$$

where W$=\sum_{i=1}^{I} \lambda_i W_i$ is a $k_2 \times k_2$ diagonal random matrix (because the λ_i are random). Therefore, even if the model space contains 2^{k2} models, the computational burden of the WALS estimator $\widetilde{\beta}_1$ is of the order k_2 due to the need to only consider the diagonal elements of W, that is k2 linear combinations of the model weights λ_i. Also, the equivalence theorem proved in Danilov and Magnus (2004) implies that the MSE of the WALS estimator $\widetilde{\beta}_1$ of β_1 is crucially related to the MSE of the less complicated shrinkage estimator $W\hat{\gamma}_2$ of γ_2,

$$MSE(\widetilde{\beta}_1) \;=\; \sigma^2(X_1^\top X_1)^{-1} + RMSE(W\hat{\gamma}_2)R^\top \tag{A.11}$$

Thus, if we can find the diagonal elements of W such that the shrinkage estimator $W\hat{\gamma}_2$ is an optimal estimator of γ_2, then the same estimator will also provide the optimal WALS estimator $\widetilde{\beta}_1$ of β_1. Additionally, because the k_2 components of γ_2 are independent, they can be estimated separately by exploiting the information that $\hat{\gamma}_{2j} \sim$ N$(\gamma_{2j},\ \sigma^2)$. According to Magnus *et al.* (2010), this problem is addressed using a Laplace estimator $\hat{\eta}_j$ for the theoretical t-ratio $\eta_j = \gamma_{2j}/\sigma$.

A.2 Decomposing the Gini index by sources of income

Assume that farm households obtain income y_k from different income components or source k. Total farm household income is then given by the sum of income from all income sources k. This can be formalized as $y_0 = \sum_{k=1}^{k} y_k$. Following Stark *et al.* (1986), the Gini index for total farm household income y_0 is then given by:

$$G_0 \;=\; \frac{2Cov[\,y_0, F(y_0)]}{\mu_0} \tag{A.12}$$

where G_0 is the Gini index of all household incomes, μ_0 is the mean of farm household incomes, F_{y_0} is the cumulative distribution function of overall household income y_0. Given the property that $y_0 = \sum_{k=1}^{k} y_k$, we can rewrite equation A.12 as:

$$G_0 \;=\; \frac{2\sum_{k=1}^{k} Cov[\,y_0, F(y_0)]}{\mu_0} \tag{A.13}$$

where $Cov[\,y_k, F(y_0)]$ is the covariance between income source k and the cumulative distribution of income,$F(y_0)$. Utilising the properties of the covariance, the overall Gini G_0 can then be decomposed. Multiplying equation A.13 with $\frac{Cov(y_k,F_k)}{Cov(y_k,F_k)}$ and $\frac{y_k}{y_k}$ yields:

$$G_0 \;=\; \frac{2\sum_{k=1}^{k} Cov[\,y_0, F(y_0)]}{\mu_0 \cdot y_0} \cdot \frac{Cov(y_k, F_k)}{Cov(y_k, F_k)} \cdot \frac{y_k}{y_k} \tag{A.14}$$

Assume that $S_k = \frac{y_k}{y_0}$ denote the share of income from source k in total household income y_0 and G_k is the corresponding Gini index measuring the level of inequality within income component k. Using S_k and G_k, equation A.14 can be rewritten as follow:

$$\begin{aligned} G_0 &= \sum_{k=1}^{K} R_k * G_k * S_k \\ &= \sum_{k=1}^{K} \frac{Cov[\,y_k, F(y_0)]}{Cov[y_k, F(y_k)]} \cdot \frac{2Cov[\,yk, F(yk)]}{\mu_k} \cdot \frac{y_k}{y_0} \end{aligned} \tag{A.15}$$

R_k which is equal to the term $\frac{Cov[\,y_k,F(y_0)]}{Cov[\,y_k,F(y_k)]}$ in equation A.15 represents the so-called Gini correlation of component k with total household income. According to Stark *et al.* (1986), the properties of the Gini correlation are a mixture of the properties of Pearson's and Spearman's correlation coefficients. Similarly, R_k is bounded by -1 $\leq R_k \leq 1$ and will be equal to zero when y_k and y_0 are uncorrelated, equal to 1(-1) if y_k is an increasing (decreasing) function of total income.

Taking the derivative for a small percentage change in income from a particular income source, permits the analysis of the effect of a marginal change in an income source on the overall Gini index at that point in time, holding all other income sources constant. Following Stark *et al.* (1986), let G_0 be the Gini index before multiplying each household's income from source j by (I + e), and let $G_{(e)}$ be the Gini after the multiplication. As already shown in equation A.15, the Gini index ($G_{(0)}$) is given by:

$$G_0 = \sum_{k=1}^{K} R_k * G_k * S_k$$

The multiplication of income source j by (I + e) does not affect G_k (k = I, ..., K). However, R_k is a function of the ranks of total income. The rank function is not well defined for incomes that are equal. To avoid the problem created in this case, we assume that incomes vary slightly across households (aside from households whose income from source j is zero). Then, R_k does not change for k = I, ..., K. Hence

$$G(e) = \sum_{k=1}^{K} R_k * G_k * S_k(e) \tag{A.16}$$

By definition,

$$S_k(e) = \frac{\mu_k}{\sum_{k \neq j} \mu_k + (1+e)\mu_j} = \frac{\mu_k}{\sum_{k=1}^{K} \mu_k + e\mu_j} \text{ for } k \neq j \tag{A.17}$$

while for source j,

$$S_k(e) = \frac{(1 + e)\mu_j}{\sum_{k=1}^{K} \mu_k + e\mu_j} . \tag{A.18}$$

Let us now evaluate:

$$\begin{aligned} G &= G(e) - G_0 = \sum_{k=1}^{K} R_k * G_k * S_k(e) - G_0 = \sum_{k=1}^{K} R_k * G_k * S_k \\ & \sum_{k=1}^{K} = [S_k(e) - S_k] R_k * G_k \end{aligned} \tag{A.19}$$

This simplifies to:

$$S_k(e) - S_k = \frac{-eS_kS_j}{1 + eS_j} \tag{A.20}$$

Now for $k = j$

$$S_j(e) - S_j = \frac{eS_j - eS_j^2}{1 + eS_j} \tag{A.21}$$

Substituting equations A.20 and A.21 into A.19, we have:

$$\begin{aligned} G(e) - G_0 &= \sum_{k=1}^{K} [S_k(e) - S_k] R_k * G_k \\ &= \sum_{k \neq j} \frac{-eS_k S_j}{1 + eS_j} R_k * G_k + \frac{eS_j - eS_j^2}{1 + eS_j} R_j * G_j \\ &= \sum_{k=1} \frac{-eS_k S_j}{1 + eS_j} R_k * G_k + \frac{eS_j}{1 + eS_j} R_j * G_j \end{aligned} \tag{A.22}$$

Using equation A.22, we can examine the derivative:

$$\begin{aligned} \lim_{e \to 0} \frac{G(e) - G_0}{e} &= -S_j \lim_{e \to 0} \sum_{k=1}^{K} \frac{S_k}{1 + eS_j} R_k * G_k + \lim_{e \to 0} \frac{eS_j}{1 + eS_j} R_j * G_j \\ &= -S_j \sum_{k=1}^{K} R_k * G_k * S_k + R_j * G_j * S_j \\ \frac{\partial G_0}{\partial e_j} &= S_j (R_j * G_j - G_0) \end{aligned} \tag{A.23}$$

A.3 Multinomial Endogenous Switching Regression

Chapter 3 and 6 of the PhD study employed a multinomial endogenous switching regression model to address issues of selection bias arising from self-selection and unobservable characteristics. To disentangle the pure effects of risk management strategies adoption, and its impacts were modelled in a multinomial endogenous switching regression framework. This approach is a selection-bias correction methodology based on the multinomial logit selection model developed by Bourguignon *et al.* (2007). This approach allows consistent and efficient estimates of the selection process and a reasonable correction for the outcome equations to be obtained, even with violations of the axiom of the independence of irrelevant alternatives (IIA). Estimation of the multinomial endogenous switching regression occurs simultaneously in two steps. In the first stage, farm households' choices of risk management strategies (here in strategy) are modelled using a multinomial logit selection model. In the second stage, the outcomes associated with each risk management strategy choices are evaluated using OLS with selectivity correction terms from the first stage. The empirical econometric approach used is described below.

Stage I: Multinomial Adoption Selection Model

Farm households are assumed to maximize their expected utility by adopting a particular risk management strategy. The ith farm household's expected utility, U*ij, from adopting a strategy j, where j (j = 1,..., M), is a latent variable determined by observed household, land, and climatic characteristics, X_i and unobserved characteristics ε_{ij}, such that:

$$U^*_{ij} = X_i\varpi + \varepsilon_{ij} \tag{A.24}$$

Let I be an index that denotes the farmers' choice of strategy, such that:

$$I = j \text{ iff } U^*_{ij} > \underset{k \neq j}{\text{Max}}(U^*_{ik}) \text{ or } \eta_{ij} < 0 \quad \forall\ k \neq j, \tag{A.25}$$

Where $\eta_{ij} = \underset{k \neq j}{\text{Max}}\ (U^*_{ik} - U^*_{ij}) < 0$ (Bourguignon *et al.*, 2007). The formulation in equation A.25 implies that the ith farm household will adopt a strategy j to maximize their expected benefit if it provides greater expected utility than any other strategy $k \neq j$, i.e. if $\eta_{ij} = \underset{k \neq j}{\text{Max}}\ (U^*_{ik} - U^*_{ij}) < 0$. The probability that farm household i with characteristics X will choose a strategy j can be specified by a multinomial logit model McFadden (1974) as:

$$P_{ij} = P\left(\eta_{ij} < 0|X_i\right) = \frac{\exp\left(X_i\varpi_j\right)}{\sum_{k=1}^{J}\exp\left(X_i\varpi_k\right)}. \tag{A.26}$$

The parameter estimates of the latent variable model can be estimated by maximum likelihood estimation. In our specification, the base category, no strategy, is denoted as $j = 1$. In the remaining portfolios (j = 2, 3.... M), at least one strategy is used by a farm household.

Stage II: Multinomial Endogenous Switching Regression Model

In the second stage, a multinomial endogenous switching regression model is estimated to investigate the impact of each strategy on the outcomes of interest by applying the Bourguignon *et al.* (2007) selection bias correction model. The model implies that farm households face a total of M regimes (one regime per strategy, where $j = 1$ is the reference strategy). It is assumed that the vector of outcome variables is a linear function of explanatory variables. Hence, the stochastic function to evaluate the outcomes of interest of each strategy j is given as:

$$\text{Outcome } j: \quad Q_{ij} = Z_{ij}\beta_{ij} + \overline{Z}_{ij}\alpha_{ij} + \mu_{ij} \; if \quad I = j; \; j = 1, \; 2, \; 3 \tag{A.27}$$

where Q_{ij} is the outcome variable of farm household i in regime j, and Z_i represents a vector of inputs, and farm household head and household's characteristics, asset ownership, soil fertility and climatic characteristics included in X_i. β and α represent the corresponding vector of coefficients to be estimated. μ_{ij} represents the unobserved stochastic component distributed with $\mathrm{E}(\mu_{ij} \mid Z_i, X_i) = 0$ and $\mathrm{V}(\mu_{ij} \mid Z_i, X_i) = \sigma_j^2$. To overcome the possible correlation of farm-invariant unobserved heterogeneity with observed covariates, the study employed the approach of Mundlak (1978) and Wooldridge (2018). We exploit crop-level information and include the mean of crop varying $\overline{Z}$ explanatory variables, which include landholding, labour, fertilizer and seed quantity to deal with the issue of unobserved heterogeneity. According to Teklewold *et al.* (2013), a Wald test of the null hypothesis that the vectors α_j are jointly equal to zero is required to indicate the relevance of crop-specific heterogeneity. For each sample observation, Q_{ij} is observed if and only if one among the M dependent regimes is observed. When estimating an ordinary least squares (OLS) model, the outcomes of interest, in equations A.27 are estimated separately. However, if the error terms of equation A.24, ε_{ij} are correlated with the error terms μ_{ij} of the outcome model in equation A.27, then the expected values of μ_{ij} conditional on the sample selection are nonzero i.e., $\mathrm{corr}(\varepsilon_{ij}, \mu_{ij}) \neq 0$, and the OLS estimates will be biased and inconsistent. To correct for the potential inconsistency, the multinomial endogenous switching regression model by Bourguignon *et al.* (2007), is employed. It takes into account the correlation between the error terms ε_{ij} from the multinomial logit model estimated in the first stage and the error terms from each outcome equation μ_{ij}. Bourguignon *et al.* (2007) show that consistent estimates of β and α in the outcome equation A.27 can be obtained by estimating the following selection bias-corrected outcomes of interest equations:

$$\text{Outcome } j: \quad Q_{ij} = Z_{ij}\beta_{ij} + \overline{Z}_{ij}\alpha_{ij} + \sigma_{j\varepsilon}\lambda_{ij} + \omega_{ij} \; if \quad I = j; \quad j = 1,\ 2,\ 3 \tag{A.28}$$

where $\sigma_{j\varepsilon}$ is the covariance between ε_{ij} in equation A.24 and μ_{ij} from equation A.27, λ_j is the inverse Mills ratio computed from the estimated probabilities in equation A.26 as follows:

$$\lambda_{ij} = \sum_{k \neq j}^{j} \rho_j \left[\frac{\hat{P}_{ik}\text{In}\left(\hat{P}_{ik}\right)}{1 - \hat{P}_{ik}} + \text{In}\left(\hat{P}_{ij}\right) \right] \tag{A.29}$$

where $\hat{P}$ represents the probability that farm household i chooses strategy j as defined in equation A.26, ρ_j is the correlation between ε_{ij} and μ_{ij}. The specification in equation A.28 implies that the number of selection correction (bias) terms in each equation are equal to the number of multinomial logit choices M. While the variables X_i in equation A.24 and Z_i in equation A.27 are allowed to overlap, proper identification requires at least one variable in X_i that does not appear in Z_i. Therefore, the selection equation A.24 is estimated based on all explanatory variables specified in the outcome equation A.27 plus at least one or more instruments. Following Di Falco and Veronesi (2013), we establish the admissibility of the selected instruments by performing a simple falsification test: the selected or valid instrument (s) is required to significantly influence a farm household's choice of strategy adoption but have no significant effect on the outcomes of interest.

Estimation of the treatment and counterfactual effects

The Multinomial Endogenous Switching Regression framework by allowing us to control for potential selectivity biases can be used to examine average treatment effects (ATT) by comparing expected outcomes of adopters with and without adoption. Following Bourguignon *et al.* (2007), the following conditional expectations for each outcome variable of interest from equation A.28 can be computed as:

Adopters with adoption (actual):

$$E\left(Q_{ij} \middle| I = j,\ Z_{ij}, \overline{Z}_{ij}, \lambda_{ij}\right) = Z_{ij}\beta_j + \overline{Z}_{ij}\alpha_j + \sigma_j\lambda_{ij} \tag{A.30}$$

Non-adopters without adoption (actual):

$$E\left(Q_{i1}\middle|I=1,\ Z_{i1},\overline{Z}_{ij},\lambda_{i1}\right)=Z_{i1}\beta_1+\overline{Z}_{i1}\alpha_1+\sigma_1\lambda_{i1} \tag{A.31}$$

Adopters had they decided not to adopt (counterfactual):

$$E\left(Q_{i1}\middle|I=j,\ Z_{ij},\overline{Z}_{ij},\lambda_{ij}\right)=Z_{ij}\beta_1+\overline{Z}_{ij}\alpha_1+\sigma_1\lambda_{ij} \tag{A.32}$$

Non-adopters had they decided to adopt (counterfactual):

$$E\left(Q_{ij}\middle|I=1,\ Z_{i1},\overline{Z}_{i1},\lambda_{i1}\right)=Z_{i1}\beta_j+\overline{Z}_{i1}\alpha_j+\sigma_j\lambda_{i1} \tag{A.33}$$

Equations A.30 and A.31 represent the actual expected outcomes of interest observed in the sample for adopting and non-adopting farm households respectively, while equations A.32 and A.33 are their respective counterfactual expected outcomes of interest. The use of these conditional expectations allows us to calculate the average treatment effects (ATT) – i.e., the treatment effect for treated farm households, which is the difference between equations A.30 and A.32:

$$\begin{aligned} ATT &= E\left[Q_{ij}|I=j\right]-E\left[Q_{i1}|I=j\right] \\ &= Z_{ij}\left(\beta_j-\beta_1\right)+\overline{Z}_{ij}\left(\alpha_j-\alpha_1\right)+\lambda_{ij}(\sigma_j-\sigma_1) \end{aligned} \tag{A.34}$$

Additionally, the average adoption effect for non-adopters, also known as the average treatment effect on the untreated (ATU) can be computed as the difference between equations A.31 and A.33.

$$\begin{aligned} ATU &= E\left[Q_{i1}|I=1\right]-E\left[Q_{ij}|I=1\right] \\ &= Z_{i1}\left(\beta_1-\beta_j\right)+\overline{Z}_{i1}\left(\alpha_1-\alpha_j\right)+\lambda_{i1}(\sigma_1-\sigma_j) \end{aligned} \tag{A.35}$$

A.4 Sample Selection Stochastic Frontier and Metafrontier Approach

Chapter 4 and 5 of the PhD study evaluated the technical efficiency outcomes associated with various risk management strategies. As already established in chapter 3 of the thesis, farm households' decisions to adopt risk management strategies is not random, hence giving rise to selectivity effects in 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 technical efficiency. The inability to capture these unobservable characteristics may lead to selection bias. In acknowledging the presence of selectivity biases, earlier studies attempted to address this issue by relying on the Heckman approach (see Bradford *et al.*, 2001; Sipiläinen and Lansink, 2005; Solís *et al.*, 2007), copula function (Lai *et al.*, 2009) and a system approach (Kumbhakar *et al.*, 2009). However, as argued by Greene (2010) the Heckman approach is unsuitable for nonlinear models such as the stochastic production frontier. Furthermore, the log-likelihood is substantially more computationally demanding in the copula function and a system approach. 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 technical efficiency 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:

$$\begin{aligned} \text{Sample selection}: t_j = 1\left[\beta' X_j + \varepsilon_j > 0\right],\ \varepsilon_j \sim N(0,\ 1) \\ \text{Stochastic frontier model}: y_j = \gamma' W_j + \epsilon_j,\ \ \epsilon_j \sim N\left(0,\ \sigma_\epsilon^2\right),\ \epsilon_j =\ v_j - u_j, \end{aligned} \tag{A.36}$$

where y_j and W_j are observed only when t_j =1, $v_j = \sigma_v v_j$ with $v_j \sim$ N(0, 1), u_j = $|\sigma_u u_j| = \sigma_u |u_j|$ with $u_j \sim$ N(0, 1), and $(\epsilon_j,\ v_j) \sim N_2$ $[0,1,$ (1, $\rho\sigma$v, σ^2v)]. Also, y_j denotes the logarithmic crop income 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 particular risk management strategy and 0 otherwise, 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 (v_j) and inefficiency term (u_j), and ϵ_j is the error term. The inefficiency term u_j is assumed to follow a half-normal distribution with the dispersion parameter σu, whereas ϵ_j and v_j follow a bivariate normal distribution with variances of 1 and $\sigma^2 v$, respectively. The correlation coefficient, $\rho\sigma v$ if statistically significant, indicates evidence of selectivity bias implying that estimates of the standard stochastic frontier model would be inconsistent Greene (2010). The log-likelihood for the model in A.36 is formed by integrating out the unobserved $|u_j|$ and then maximizing with respect to the unknown parameters. Thus,

$$LogL(\gamma,\sigma_u,\sigma_v,\beta,\ \rho) \ = \sum_{i\ =1}^{N} log \int_{|U_j|} f(y_j|W_j,X_j,t_j,|U_j|)\ p(|U_j|)t|U_j|. \qquad \text{(A.37)}$$

Because the integral in equation A.37 is not known it is approximated. To simplify the estimation, Greene (2010) uses a two-step approach. The single equation MLE of β in the Probit equation in equation A.36 is consistent but inefficient. However, for the estimation of the parameters of the sample selection stochastic frontier model, it is not necessary to re-estimate β and the estimates of β are taken as given in the simulated log-likelihood. The standard errors of the parameters are adjusted using the approach by Murphy and Topel (2002) and estimated using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) approach, and asymptotic standard errors are obtained by employing the Berndt-Hall-Hall-Hausman (BHHH) algorithm estimator. Furthermore, Greene (2010) argues that the non-selected observations (i.e., when t_j =0) do not contribute information about the parameters to the simulated log-likelihood and thus the function to be maximized becomes:

$$LogL_{S,C}(\gamma,\sigma_u,\sigma_v,\ \rho) \ = \sum_{t_j=1} log\frac{1}{R}\sum_{r=1}^{R}\left[\frac{\frac{exp\left(-\frac{1}{2}(y_j\ -\ \gamma'W_j+\sigma_u|U_{jr}|)^2/\sigma_v^2\right)}{\sigma_v\sqrt{2\pi}}\times}{\Phi\left(\frac{\rho(y_j\ -\ \gamma'W_j+\sigma_u|U_{jr}|)/\sigma_\epsilon+a_i}{\sqrt{1\ -\ \rho^2}}\right)}\right] \qquad \text{(A.38)}$$

Where $a_i = \widehat{\beta}'X_j$. The parameters of the model are estimated using a conventional gradient-based approach, the BFGS method, and use the BHHH estimator to obtain the asymptotic standard errors. The maximand reduces to that of the maximum simulated likelihood estimator of the basic frontier model when ρ equals zero. This provides a method of testing the specification of the selectivity model against the simpler model using a (simulated) likelihood ratio (LR) test. The specification described earlier in equation A.36 allow 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 technical efficiency estimates,

$$TE_{ji} = E[\,e^{-u_{ji}},\ i = 1,\ 2 \ldots .4]$$

.

Meta-frontier Analysis

A direct comparison of technical efficiencies between adopters of the various risk management strategies outlined above is not possible because these scores are relative to each group's own frontier. To address this issue, a meta-frontier that envelopes the risk management specific frontiers is estimated to allow for the comparison among the risk management strategies. 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 and resources, relative input prices etc. The presence of these factors inhibits producers in some groups from choosing the best technology from the array of the potential technology set. 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 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 technical efficiency by providing a common technology of reference for both adopters and non-adopters of the various risk management strategies. Following the approach outlined by O'Donnell *et al.* (2008), we estimate a meta-frontier 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:

$$Y_i^* = f\left(X_j, \beta^*\right) = e^{X_j \beta^*}; j = 1, 2 \ldots\ldots N,\ N = \sum_{k=1}^{2} N_k \tag{A.39}$$

where β^* denotes the vector of parameters of the meta-frontier function such that $X_j\beta^* \geq X_i\beta_k$ for all j observations. We estimate the parameters of the meta-frontier function (β^*) in equation A.39 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:

$$\begin{aligned} &\min_{\beta^*} \sum_{j=1}^{N} |(\text{In } f(X_j, \beta^*) - \text{In } f(X_j, \hat{\beta}_k)| \\ &s.t.\ \ \text{In } f\left(X_j, \beta^*\right) \geq \text{In } f\left(X_j, \hat{\beta}_k\right)\ \ \forall\ j \end{aligned} \tag{A.40}$$

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-technology gap ratio (TGR). A comparatively high average meta-technology gap ratio for a particular technology group indicates a lower technology gap between farm households in that group compared with all available set of production technologies represented in the all-encompassing production frontier. For given levels 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:

$$TGR = \frac{e^{X_j \hat{\beta}_k}}{e^{X_j \beta^*}} \tag{A.41}$$

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

$$MTE_j = TGR \times TE_{jk} \tag{A.42}$$

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 estimation of technical efficiency 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 various 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 λ = -2[L(H_p) - L($H_{0\,...,k}$)] where L(H_p) is the value of the log-likelihood function for stochastic frontiers estimated by pooling data for all farm households, L($H_{0\,...,k}$) is the value of the sum for all the log-likelihood functions for the various risk management strategy adopters.

A.5 Endogenous Switching Regression (ESR)

A variant of the multinomial endogenous switching regression model used in chapter 3 and 6 of the PhD study was also employed in chapter 5. The endogenous switching regression model is suitable when two treatments or regimes are involved. Similar to the multinomial endogenous switching regression model, the ESR model is estimated in two stages. In the first stage, the selection of a particular technology is specified using a binary model. The equations for the outcome of interest, in this case, the technical efficiency with respect to the meta-frontier are modelled for both PET with insurance adopters and PET without insurance adopter's conditional on selection. Assuming risk neutrality, farmers will evaluate the net returns (utility) associated with the adoption of PET with and without insurance, let the latent net utility for adopters and non-adopters be denoted as Y^*, such that a utility-maximizing household j will choose to adopt PET with insurance if the utility gained from adopting is greater than the utility of not adopting with insurance ($Y^* = U^*_{iA} - U^*_{iN} > 0$). Given that a farm household utility level is a latent variable and cannot be observed, we observe only indicators of utility, namely choices. We specify the latent variable as:

$$Y^* = \beta X_j + \varepsilon_j,\; Y_j = 1 \;\left[Y_j^* > 0\right], \tag{A.43}$$

where Y_j is a binary variable that equals 1 for farm household who adopt PET with insurance and zero otherwise (i.e., PET without insurance), with β denoting a vector of parameters to be estimated. Thus, the farm household adopts PET with insurance only if the perceived net benefits are positive. The error term ε is assumed to be normally distributed with zero mean. X is a vector of explanatory variables that influence the adoption decision such as risk attitude, knowledge, household, and farm-level characteristics etc. The probability that a farm household adopts PET with insurance can be expressed as follows:

$$\Pr\left(Y_j = 1\right) = \Pr\left(Y_j^* > 0\right) = \Pr\left(\varepsilon_j > -\beta X_j\right) = 1 - F(-\beta X_j) \tag{A.44}$$

where F is the cumulative distribution function of the error term. In the second stage, separate outcome equations are specified for PET with insurance adopters and PET without insurance adopters.

$$MTE_{j1} = \alpha_1 Z_{j1} + \mu_1 \qquad \text{if } \ Y_j = 1 \tag{A.45}$$

$$MTE_{j0} = \alpha_0 Z_{j0} + \mu_0 \qquad \text{if } \ Y_j = 0 \tag{A.46}$$

where MTE_{j1} and MTE_{j0} are the technical efficiencies with respect to the meta-frontier for PET with insurance adopters and PET without insurance adopters, respectively. Z_j is a vector of explanatory variables that include farm and household-level characteristics, such as the age, gender, education level of household head, household size, access to extension services, farm size, crop portfolio, land share under cash crops etc. The vectors α_1 and α_0 are the parameters to be estimated and μ is the error term.

To overcome the possible correlation of farm-invariant unobserved heterogeneity with observed covariates, the approach of Mundlak (1978) and Wooldridge (2018) was employed. This was achieved by exploiting crop-level information and including the mean of crop varying explanatory variables, which include labour, landholding, fertilizer and seed quantity to deal with the issue of unobserved heterogeneity in the outcome equations A.45 and A.46. Controlling for unobserved heterogeneity is particularly important to help address farm or plot-specific unobservables as they may contain useful missing information regarding land quality (Kassie *et al.*, 2015) for instance. Concurrently, if farm households obtain private information about unobservable effects such as how good the soil is on the plot or some shocks, they will adjust their factor input decisions accordingly (Fafchamps, 1993; Levinsohn and Petrin, 2003; Assunção and Braido, 2007). Hence, this approach permits the exploitation of crop-level information to deal with the issue of farm household's unobservable characteristics and farm-specific effects. As suggested by Teklewold *et al.* (2013), a Wald test of the null hypothesis that the vectors of the crop varying explanatory variables are jointly equal to zero is required to indicate the relevance of crop-specific heterogeneity.

Model identification requires at least one variable in the selection equation A.43 that does not appear in the outcome equations A.45 and A.46. The valid instrument (s) is required to influence a farm household's adoption decision but do not affect technical efficiency. The variables representing insurance needs and perception about the sufficiency of subsidized seeds are used as the instrument variables. While these variables are expected to affect adoption decisions, it is assumed that these do not affect technical efficiency directly. We conducted a validity check of these instruments, by estimating a simple probit model for the selection equation and an OLS model for the outcome equation separately to checked that both variables are in effect, significant when included in the selection equation but not significant when included in the outcome equation. The three error terms ε_j in equation A.43, and μ_1 and μ_0 in equation A.45 and A.46 are assumed to have a trivariate normal distribution, with zero mean and the following covariance matrix:

$$\mathrm{Cov}\left(\varepsilon_j, \mu_1, \mu_0\right) = \Sigma = \begin{bmatrix} \sigma_{\varepsilon}^2 & \sigma_{\varepsilon 1} & \sigma_{\varepsilon 0} \\ \sigma_{1\varepsilon} & \sigma_{\mu_1}^2 & . \\ \sigma_{0\varepsilon} & . & \sigma_{\mu_0}^2 \end{bmatrix} \tag{A.47}$$

where Var (ε) = $\sigma^2\varepsilon$, Var (μ_1) = $\sigma^2\mu_1$, Var (μ_0) = $\sigma^2\mu_0$, Cov(ε, μ_1) = $\sigma_{\varepsilon 1}$, and Cov(ε, μ_0) = $\sigma_{\varepsilon 0}$. Since we do not observe MTE_{j1} and MTE_{j0} simultaneously, the covariance between μ_1 and μ_0 is not defined. The error term, ε_j of the sample selection equation A.43 is correlated with the error terms of the outcome equation A.45 and A.46. For this reason, the error terms in equation A.45 and A.46, conditional on the sample selection criterion, have nonzero expected values, and hence using an ordinary least squares regression to estimate the coefficients α_1 and α_0 will result in sample selection bias (Lee, 1982). The expected values of the truncated error terms (μ_1 | Y =1) and (μ_0 | Y = 0) are then given as:

$$E\left(\mu_1 | Y = 1\right) = \sigma_{1_\varepsilon} \frac{\varphi(\beta X_j)}{\phi(\beta X_j)} = \sigma_{1_\varepsilon} \lambda_1 \tag{A.48}$$

and

$$E\left(\mu_0|Y=0\right) = \sigma_{0_\varepsilon}\frac{\varphi(\beta X_j)}{1-\phi(\beta X_j)} = \sigma_{0_\varepsilon}\lambda_0 \tag{A.49}$$

where $\Phi(.)$ and $\phi(.)$ are the probability density and the cumulative distribution function of the standard normal distribution, respectively. The terms λ_1 and λ_0 refer to the inverse Mills ratio evaluated at βX_j and are incorporated into outcome equations to account for sample selection bias. A drawback of the two-step approach for the endogenous switching regression model is that it generates residuals that are heteroskedastic and as a result cannot be used to obtain consistent standard errors without cumbersome adjustments (Lokshin and Sajaia, 2004). The full information maximum likelihood method suggested by Lokshin and Sajaia (2004) overcomes the problem through a simultaneous estimation of the two equations, that is, equation A.43 and, equations A.45 and A.46.

The signs and significance levels of the correlation coefficients (ρ) from the estimates which are the correlation coefficients between the error term ε_j of the selection equation and error terms μ_1 and μ_0 of the outcome equations A.45 and A.46 are of particular interest. Specifically, there is endogenous switching, if either ρ_1 or ρ_0 is significantly different from zero, which would result in selection bias.

Estimating treatment effects

In this study, our main interest is to estimate the treatment effect (switching impacts) of PET with and without insurance adoption on technical efficiency. The endogenous switching regression method can be used to compare expected technical efficiency with the counterfactual hypothetical technical efficiency that farm households did not adopt PET with insurance and vice versa. This can be represented as follows:

Farm households that adopted PET with insurance (observed):

$$E[\,MTE_{j1}|Y_j=1] = \alpha_1 Z_{j1} + \sigma_{\varepsilon 1}\lambda_1 \tag{A.50a}$$

Counterfactual case if PET with insurance adopting farm households did not adopt:

$$E[\,MTE_{j1}|Y_j=0] = \alpha_1 Z_{j0} + \sigma_{\varepsilon 1}\lambda_0 \tag{A.50b}$$

Farm households that adopted PET without insurance (observed):

$$E[MTE_{j0}|Y_j = 0] = \alpha_0 Z_{j0} + \sigma_{\varepsilon 0}\lambda_0 \tag{A.50c}$$

Counterfactual case if PET without insurance adopting farm households adopted PET with insurance:

$$E[MTE_{j0}|Y_j = 1] = \alpha_0 Z_{j1} + \sigma_{\varepsilon 0}\lambda_1 \tag{A.50d}$$

The change in outcome due to adoption can then be specified as the difference between adoption and non-adoption. The use of these conditional expectations from equations A.50a to A.50d permits the calculation of average treatment effects (ATT) – i.e., the treatment effect for treated farm households (i.e., PET with insurance adopters), which is the difference between equations A.50a and A.50b. Furthermore, the average treatment effect on the untreated (ATU) households (i.e., PET without insurance adopters) is of interest and this is simply the difference between equations A.50c and A.50d.

A.6 Control Function Approach

Throughout chapter 2 to 6, we employ the control function approach to deal with potential reverse causality and endogeneity problems that may arise with some variables used in the models. 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. To address the potential endogeneity of these variables (e.g. membership of farmer-based organizations, extension access, credit access and nonfarm work participation) we used the control function approach proposed by Wooldridge (2015). The approach involves the specification of the potential endogenous variable as a function of all explanatory variables used in the main/selection equation, together with a set of instruments in a first stage probit regression for dichotomous variables or linear regression for continuous variables. Employed instruments should strongly influence the given potential endogenous variable (s) but not the selection into the treatment of interest for instance or the dependent variable in the main equation. For dichotomous variables (e.g., membership of farmer-based organizations or extension access) we employed a probit regression specification of the potential endogenous variable in addition to instrumental variables in the first-stage estimation, such as:

$$S_i = X_{ij}\tau + G_{ij}\gamma + \epsilon_{ij} \tag{A.51}$$

where S_i is a vector of the observed potential endogenous variables, X are the variables used in the main/selection equation, G_{ij} is a vector of instrumental variables. The vectors τ and γ are the parameters to be estimated and ϵ_{ij} is the random error term. To ensure identification, the instrumental variable, G_{ij} included in equation A.51 are excluded from the estimation of the main/selection equation. In the case of the multinomial endogenous switching regression model and the standard endogenous switching regression (ESR) model, it is also worth noting that the instrumental variable(s) used for the control function approach is expected to not correlate with the other instrumental variables used for model identification. Wooldridge (2015) then proposes estimating a "generalized residuals" which uses the inverse Mills ratio (the ratio of the standard normal density, ϕ, divided by the standard normal cumulative distribution function, Φ) to compute the "generalized residuals" as follows.

$$R_{ij} = S_i\lambda(X_{ij}\hat{\tau}) - \ (1 \ - S_i)\lambda(-X_{ij}\hat{\tau}),\ i = 1, ...,\ N \tag{A.52}$$

where $\lambda(.) \ = \phi(.)/\Phi(.)$ is the well- known inverse Mills ratio. Both potential endogenous variable (s) and the estimated residuals predicted from equation A.52 are then incorporated into the main/selection equation to account for endogeneity as follows:

$$U^*_{ij} = X_{ij}\beta + S_i\vartheta + R_{ij}\alpha + \omega_{ij} \tag{A.53}$$

where X_{ij} is as defined previously, S_i is a vector of the observed potential endogenous variable(s), and R_{ij} is a vector of the "generalized residuals" terms from the first-stage regressions of the endogenous variables in equation A.52. The vectors β, ϑ and α are the parameters to be estimated and ω_{ij} is the random error term. The endogenous variables become appropriately exogenous in a second-stage estimation equation by adding appropriate "generalized residuals" since they serve as the control function. As suggested by Wooldridge (2015), the approach leads to a robust, regression-based Hausman test for endogeneity of the suspected variables. If the coefficient of the residual term is statistically significant, it shows that endogeneity was indeed present and also well controlled for in the model. Furthermore, Wooldridge (2015) observed that if the coefficient on the estimated generalized residual is statistically significant, there is a need to adjust the standard errors for the two-step estimation by bootstrapping.

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Concept: Formulation of the basic scientific problem based on theoretical questions which require clarification, including a summary of the general questions which, it is assumed, will be answerable via analyses or concrete experiments/investigations	C
Planning: Planning of experiments/analyses and formulation of investigative methodology, including choice of method and independent methodological development, in such a way that the scientific questions asked can be expected to be answered	C
Execution: Involvement in the analysis or the concrete experiments/investigation	C
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3. Declaration on the individual phases of the scientific work (A, B, C)	**Extent**
Concept: Formulation of the basic scientific problem based on theoretical questions which require clarification, including a summary of the general questions which, it is assumed, will be answerable via analyses or concrete experiments/investigations	C
Planning: Planning of experiments/analyses and formulation of investigative methodology, including choice of method and independent methodological development, in such a way that the scientific questions asked can be expected to be answered	C
Execution: Involvement in the analysis or the concrete experiments/investigation	C
Manuscript preparation: Presentation, interpretation and discussion of the results obtained in article form	C

4. Signature of all co-authors		
Date	**Name**	**Signature**
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25/01/2021	Kougblenou Christophe Adjin	
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5. Signature of the doctoral candidate		
Date	**Name**	**Signature**
27.01.2021	Peron Agbeti Collins-Sowah	

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