

The Institute for Food Economics and Consumption Studies
of the Christian-Albrechts-Universität Kiel

Contribution of Conservation Agriculture to Household Welfare in Ghana

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutrition Sciences

of the

Christian-Albrechts-Universität zu Kiel

Submitted

Baba Adam, M.Sc.

Born in Ghana

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Dedication

I dedicate this dissertation to my mother, Hajia Nafisatu Adam, my late father Sheikh Sani Abdulai, my wife Zakiyatu Alhassan, my children (Abdul Waduud Adam, Saabir Adam) for their unflinching support, patience prayers through my PhD journey.

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I will begin with a verse in the Holy Quran 14:7, where Almighty Allah states as follows:

And [remember] when your Lord proclaimed, 'If you are grateful, I will certainly give you more. But if you are ungrateful, surely My punishment is severe.'"

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Baba Adam

Abstract

Climate variability and soil degradation pose numerous risks to agricultural production and impede economic growth and sustainable development. Achieving food security and improved nutrition while promoting sustainable agriculture has become a major challenge for policymakers, especially in SSA. Current food production systems have become more dependent on the use of external inputs and intensive approaches in addressing the growing food demand. These practices tend to degrade the environment and threaten the proper functioning of the ecosystem services with possible negative consequences on soil fertility, global food and nutrition security, and poverty. Several pieces of evidence suggest that conservation agriculture has the potential to increase resilience and sustainability of the food systems, stimulate inclusive growth whilst reducing the emission of greenhouse gases emanating from agricultural systems. To promote sustainable adoption of these technologies, a comprehensive study of the drivers, opportunities, and constraints associated with its adoption is required. Thus, this study contributes to the growing empirical literature by examining the contribution of conservation agriculture on household welfare among smallholder farmers in Ghana. In particular, the study investigates the heterogeneous treatment effects of conservation agriculture on farm performance and inorganic fertilizer use, employing a marginal treatment effect (MTE) framework to account for the treatment effect heterogeneity in both observed and unobserved characteristics and to analyze policy-relevant treatment effect (PRTE). Second, using geo-referenced historical weather data, the study provides microeconomic evidence of the impact of minimum tillage on maize yields, food and nutrition security, and farm labor demand, employing an ordered probit selection model to account for potential selection bias and omitted variable problems. Further, climate change has reignited interest in crop diversification as a climate-smart agricultural practice. Thus, the study sheds light on the heterogeneous impact of crop diversification on farm net returns and risk exposure, employing a dose response function and instrumental variable techniques to address potential endogeneity

concerns. Finally, improving the efficiency of agricultural production while promoting resilient agricultural technologies and sustainable food systems contributes to the SDG by reducing hunger and food insecurity. Various interventions such as conservation agriculture and field demonstrations have been rolled out within this objective. While some of these interventions aim to increase the production frontier, others are meant to reduce the level of production inefficiency. Further, it is important to understand the role of a mediator in effectively achieving the desired outcome. This study contributes to the literature by employing a stochastic frontier model with an endogenous treatment status and mediator, using two instrumental variable methods to address potential endogeneity concerns. Decomposing the treatment effects into production frontier and inefficiency components, the study further examines the direct effects of conservation agriculture and the indirect effects via a mediator (i.e. field demonstrations).

The empirical results show that smallholder farmers with high propensity to adopt conservation agriculture reduce nitrogen usage from inorganic sources and experience significant increases in maize yields and farm net returns when compared to those with low propensity to adopt. Further, our PRTEs reveal that increasing training sessions, and providing incentives to reduce the cost of implementation are crucial for the promotion of conservation agriculture. The findings also reveal that transitioning into medium to long-term adoption of minimum tillage significantly increases households' food and nutrient security and contributes to a net saving in labor demand. Furthermore, the results show that crop diversification is a welfare-enhancing strategy that significantly increases farm net returns, lowers the probability of crop failure, and thus decreases downside risk exposure. However, the dose response function estimates reveal that crop diversification generates positive benefits at relatively lower intensities up to a threshold and tends to decline as diversification level increases. Lastly, the study observes that the adoption of conservation agriculture technologies increases yield, shifts the technology frontier upward, and reduces the level of inefficiency. More importantly, a larger share of the

total treatment effects is driven by the indirect effects via participation in field demonstrations. These findings call for sustainable policy measures to improve access to climate information, strengthen field demonstration activities, and provide tailored extension messages for a diverse landscape of farmers to accelerate adoption and expand food production in the face of increasing climate variability and a growing population.

Zusammenfassung

Klimaschwankungen und Bodendegradation stellen zahlreiche Risiken für die landwirtschaftliche Produktion dar und behindern Wirtschaftswachstum und nachhaltige Entwicklung. Das Erreichen von Ernährungssicherheit und verbesserter Ernährung bei gleichzeitiger Förderung einer nachhaltigen Landwirtschaft ist zu einer großen Herausforderung für politische Entscheidungsträger geworden, insbesondere in afrikanischen Staaten südlich der Sahara. Die derzeitigen Lebensmittelproduktionssysteme sind stärker von externen Inputs und intensiven Methoden abhängig geworden, um den wachsenden Nahrungsmittelbedarf zu decken. Diese Praktiken führen zu einer Belastung der Umwelt und bedrohen Ökosysteme mit möglichen negativen Folgen für die Bodenfruchtbarkeit, globale Nahrungsmittel- und Ernährungssicherheit und Armut. Mehrere Belege deuten darauf hin, dass die konservierende Landwirtschaft das Potenzial hat, die Widerstandsfähigkeit und Nachhaltigkeit von Ernährungssystemen zu erhöhen, ein integratives Wachstum zu fördern und gleichzeitig den Ausstoß von Treibhausgasen aus landwirtschaftlichen Systemen zu verringern. Um eine nachhaltige Anwendung dieser Technologien zu fördern, ist eine umfassende Studie bezüglich der Treiber, Möglichkeiten und Beschränkungen im Zusammenhang mit ihrer Einführung erforderlich. Daher trägt diese Studie zur wachsenden empirischen Literatur bei, indem sie den Beitrag der konservierenden Landwirtschaft zum Wohlstand von Kleinbauern in Ghana untersucht. Die Studie untersucht insbesondere die heterogenen Behandlungseffekte der konservierenden Landwirtschaft auf die Leistung des Betriebs und den Einsatz anorganischer Düngemittel, unter Anwendung des *marginal treatment effect frameworks (MTE)*, um die Heterogenität der Behandlungseffekte bei beobachteten und unbeobachteten Merkmalen zu berücksichtigen und *policy-relevant treatment effects (PRTE)* zu analysieren. Zweitens liefert die Studie unter Verwendung georeferenzierter historischer Wetterdaten mikroökonomische Belege für die Auswirkungen der Minimalbodenbearbeitung auf die Maiserträge, die Nahrungsmittel- und Ernährungssicherheit und die Nachfrage nach landwirtschaftlichen

Arbeitskräften, wobei ein *ordered probit selection model* verwendet wird, um potenzielle Selektionsverzerrungen und Probleme mit ausgelassenen Variablen zu berücksichtigen. Darüber hinaus hat der Klimawandel das Interesse an der Diversifizierung von Anbauprodukten als klimafreundliche landwirtschaftliche Praxis neu entfacht. Daher beleuchtet die Studie die heterogenen Auswirkungen der Anbaudiversifizierung auf die Nettoerlöse und die Risikoexposition der landwirtschaftlichen Betriebe, wobei eine *dose-response function* und *instrumental variable techniques* eingesetzt werden, um mögliche Endogenitätsprobleme zu berücksichtigen. Schließlich trägt eine Verbesserung der Effizienz der landwirtschaftlichen Produktion bei gleichzeitiger Förderung widerstandsfähiger landwirtschaftlicher Technologien und nachhaltiger Nahrungsmittelsysteme durch eine Reduktion von Hunger und Ernährungsunsicherheit zu den SDGs bei. Im Rahmen dieses Ziels wurden verschiedene Interventionen wie konservierende Landwirtschaft und Felddemonstrationen durchgeführt. Während einige dieser Maßnahmen darauf abzielen, die Produktionsgrenze zu erhöhen, zielen andere darauf ab, das Niveau der Produktionsineffizienz zu senken. Darüber hinaus ist es wichtig zu verstehen, welche Rolle ein Vermittler bei der effektiven Erreichung des gewünschten Ergebnisses spielt. Die vorliegende Studie leistet einen Beitrag zur Literatur, indem sie ein *stochastic frontier model* mit einem *endogenous treatment status and mediator* anwendet und zwei Instrumentalvariablenmethoden einsetzt, um potenzielle Endogenitätsprobleme zu lösen. Die Studie zerlegt die Behandlungseffekte in Komponenten der Produktionsgrenze und der Ineffizienz und untersucht darüber hinaus die direkten Effekte der konservierenden Landwirtschaft und die indirekten Effekte über einen Mediator (d.h. Felddemonstrationen).

Die empirischen Ergebnisse zeigen, dass Kleinbauern mit einer hohen Bereitschaft, konservierende Landwirtschaft anzuwenden, den Stickstoffverbrauch aus anorganischen Quellen reduzieren und im Vergleich zu denjenigen mit einer geringen Bereitschaft,

konservierende Landwirtschaft anzuwenden, signifikante Steigerungen der Maiserträge und der landwirtschaftlichen Nettoerträge erfahren. Darüber hinaus zeigen unsere PRTEs, dass mehr Schulungen und Anreize zur Senkung der Umsetzungskosten entscheidend für die Förderung der konservierenden Landwirtschaft sind. Die Ergebnisse zeigen auch, dass der Übergang zu einer langfristigen Anwendung von minimaler Bodenbearbeitung die Nahrungsmittel- und Nährstoffsicherheit der Haushalte deutlich erhöht und zu einer Nettoeinsparung beim Arbeitsbedarf beiträgt. Darüber hinaus zeigen die Ergebnisse, dass die Diversifizierung der Kulturen eine wohlfahrtssteigernde Strategie ist, die die Nettoerträge der Betriebe deutlich erhöht, die Wahrscheinlichkeit von Ernteaussfällen senkt und somit das Ausfallrisiko verringert. Die Schätzungen der *dose response function* zeigen, dass die Anbaudiversifizierung bei einer relativ geringen Intensität bis zu einem bestimmten Schwellenwert einen positiven Nutzen bringt, jedoch mit zunehmendem Diversifizierungsgrad tendenziell abnimmt. Schließlich konnte die Studie zeigen, dass die Einführung von Konservierungstechnologien in der Landwirtschaft die Erträge erhöht, die Technologieschwelle nach oben verschiebt und den Grad der Ineffizienz verringert. Noch wichtiger ist, dass ein großer Anteil der gesamten Behandlungseffekte auf die indirekten Effekte durch die Teilnahme an Felddemonstrationen zurückzuführen ist.

Diese Ergebnisse erfordern nachhaltige politische Maßnahmen zur Verbesserung des Zugangs zu Klimainformationen, zur Intensivierung von Felddemonstrationen und zur Bereitstellung von maßgeschneiderten Beratungsangeboten für diverse Landwirte, um angesichts zunehmender Klimaschwankungen und einer wachsenden Bevölkerung die Einführung neuer Technologien zu beschleunigen und die Nahrungsmittelproduktion zu steigern.

Chapter 1

General Introduction

1.1 Background

The adoption of the 2030 Agenda on Sustainable Development provides a blueprint for reducing poverty and meeting the food and nutrition demands of the growing global population without compromising the ability of future generations to meet their own needs (FAO, 2016; UN, 2021). That notwithstanding, agricultural activities compared to other economic sectors are extremely exposed and vulnerable to weather-related shocks, and several studies have highlighted that agricultural productivity is facing numerous risks imposed by climate change (Huffman et al., 2018; Tol, 2018; IPCC, 2019a). Particularly in sub-Saharan Africa (SSA), where agricultural production is predominantly rain-fed, climate variability has contributed to a reduction in economic growth and increasing income inequality between countries and thus affects the long-term growth prospects (Castells-Quintana et al., 2018).

Climate change has a wide range of effects on the agricultural sector: through rising temperatures, rainfall variability, unpredictability of seasonal weather patterns, as well as increases in the frequency and intensity of extreme weather events such as droughts, dry spells, flood, El Niño-Southern Oscillation (see Figure 1.1) (FAO, 2016; IPCC, 2019a). The 2015 Paris Climate Agreement set a long-term ambitious target to keep the global temperature increases below 2 °C relative to the pre-industrial levels while acknowledging that this would substantially reduce the risks and adverse impacts of climate variability. In the recent assessment report (AR6) of the Intergovernmental Panel on Climate Change (IPCC), risks from extreme weather events such as droughts and rainfall deficits are projected to be higher at 2°C compared to 1.5°C of global warming in some regions. The consequences of climate change on agricultural production and livelihoods of low-income households are expected to even worsen

over time, and become more heterogeneous and pronounced across countries and regions (FAO, 2016; IPCC, 2021).

The impact of climate variability on agricultural productivity is a global concern with worldwide implications on all dimensions of food security, from the ability to access food to the availability of food supplies, as well as the production chains that ensure the distribution of food (see Figure 1.1). It is estimated that close to 10 percent (770 million people) of the global population suffered from hunger in 2020, compared with 8.4 percent in 2019. The situation is worrying, particularly in SSA, where the prevalence of undernourishment and the number of hungry people increased by 3 percentage points and 20 percent (46 million), respectively, in 2020 (FAO, 2021b). Whereas the impact of the COVID-19 pandemic cannot be underestimated, climate variability has contributed immensely to this state of affairs. Thus, there is a danger of regressing and failing to meet the SDG on Zero Hunger by 2030 if these trends continue (FAO et al., 2020; UN, 2021).

At the same time, attempts to bolster food production have also resulted in changes in food production systems and have contributed to the degradation of ecosystems and the loss of biodiversity (Tilman et.al., 2002; FAO, 2011). Contemporary farming systems have become more dependent on the use of external inputs and intensive approaches in addressing productivity constraints. However, these practices cause environmental externalities (Lee, 2005; Pretty, 2008). For instance, agricultural land expansion specifically through deforestation, and bush burning have led to the loss of habitats as well as increase in greenhouse gases (GHGs).

Of particular concern is also the trends of depleted soils characterized by low soil organic matter (SOM) and soil carbon, highly weathered soils, and high rates of nutrient depletion with low capacity to hold nutrients and moisture (Marenja and Barrett, 2009; Jones et al., 2013), thereby limiting crop responsiveness to inorganic fertilizer (Liverpool-Tasie et al., 2017;

Abdulai and Abdulai, 2017). For instance, due to the poor soil conditions, only 18% to 49% of nitrogen applied is used by cereal crops (Cassman et al., 2002). The remainder leaches to pollute water bodies, escape into the air, causing air pollution, including GHG nitrous oxide, as well as increasing the prevalence of pests and diseases (Zhang et al., 2015). Hence, simply increasing inorganic fertilizer use is not the panacea for resolving farm productivity constraints (Marenya and Barrett, 2009; Abdulai and Abdulai, 2017).

Although the agriculture sector has a huge capacity to absorb carbon dioxide (CO₂), it contributes directly and indirectly to substantial emission of greenhouse gases. More precisely, Agriculture, Forestry, and Other Land Use (AFOLU) are responsible for about 21 percent of total greenhouse gas emissions, mainly attributable to land-use changes (FAO, 2016; Searchinger et al., 2019). Furthermore, the United Nations Convention to Combat Desertification (UNCCD) reports that approximately two-thirds of arable lands in sub-Saharan Africa are estimated to be subjected to soil degradation (UNCCD, 2013). Thus, agriculture, and farming systems as a whole, have to contribute in stabilizing the global climate, through sustainable practices, in a manner that reduces emission and increases carbon sequestration in biomass and soils (Ross et al., 2019).

Against this backdrop, the growing global population, rising income levels and rapid urbanization have increased global food demand (Jayne et al., 2014). The Food and Agriculture Organization (FAO) has projected that global food demand will rise by 60% as the world population approaches 10 billion by 2050. Interestingly, population growth will be concentrated largely in areas with higher levels of malnutrition and low adaptive capacity to climate change. Rising rural population densities have further contributed to the shrinking of arable lands. For instance, the global average cropland area per capita declined in all regions in the last decade by 17 percent, to 0.20 ha per capita while sub-Saharan Africa recorded the largest decline (-26 percent, to 0.21 ha per capita) (FAO, 2021b). This state of affairs has led to reduced fallow

periods, leading to unsustainable forms of agricultural intensification, such as continuous cropping systems (Jayne et al., 2014). The challenge facing policymakers and international organizations is threefold: (i) to increase agricultural production to meet the growing food demand of an increasing population and changing dietary preferences; (ii) restore soil health and fertility through the promotion of sustainable soil management practices; (iii) significantly reduce emissions and build the resilience of low-income farm households and the agrifood systems.

In light of the aforementioned challenges, farming systems particularly in SSA require a paradigm shift to become more climate-smart and responsive to the growing food demand. Thus, the promotion of conservation agriculture (CA) can lead to a significant improvement in food production, household income, poverty, and climate resilience. Conservation agriculture has the potential to increase productivity and reduce downside risk caused by changing realities such as global warming and land degradation, as well as contribute to the objectives of climate-smart agriculture (CSA): (i) sustainably raising agricultural productivity and household income; (ii) enhancing the adaptive capacity and resilience to shocks; and (iii) reducing greenhouse gas emissions and increasing carbon sequestration (Thierfelder et al., 2017; FAO et al., 2020).

Conservation agriculture, as defined by FAO is a farming system that promotes minimum soil disturbance (i.e. minimum tillage), maintenance of a permanent soil organic cover (e.g. crop residue retention, mulch, cover cropping), and species diversification (e.g. crop rotation, intercropping). The IPCC special report “Climate Change and Land” (2019) mentions conservation agriculture among the adaptation options to address climate variability (IPCC, 2019b). The adoption of CA could help protect the environment, reduce both the impacts of climate change on food production systems (adaptation) and the contribution of unsustainable farming practices to greenhouse gas emissions (mitigation) through sustainable land management (FAO, 2017).

To motivate the promotion and adoption of CA in SSA requires a comprehensive study on the opportunities and constraints associated with conservation agriculture. This study thus attempts to provide an insight into the key drivers influencing the adoption of conservation agriculture, as well as its economic and environmental potential, using the northern Savanna zone of Ghana as a case study. Such empirical evidence improves our understanding of the extent of its adoption and provides useful policy insight and implications for its widespread promotion.

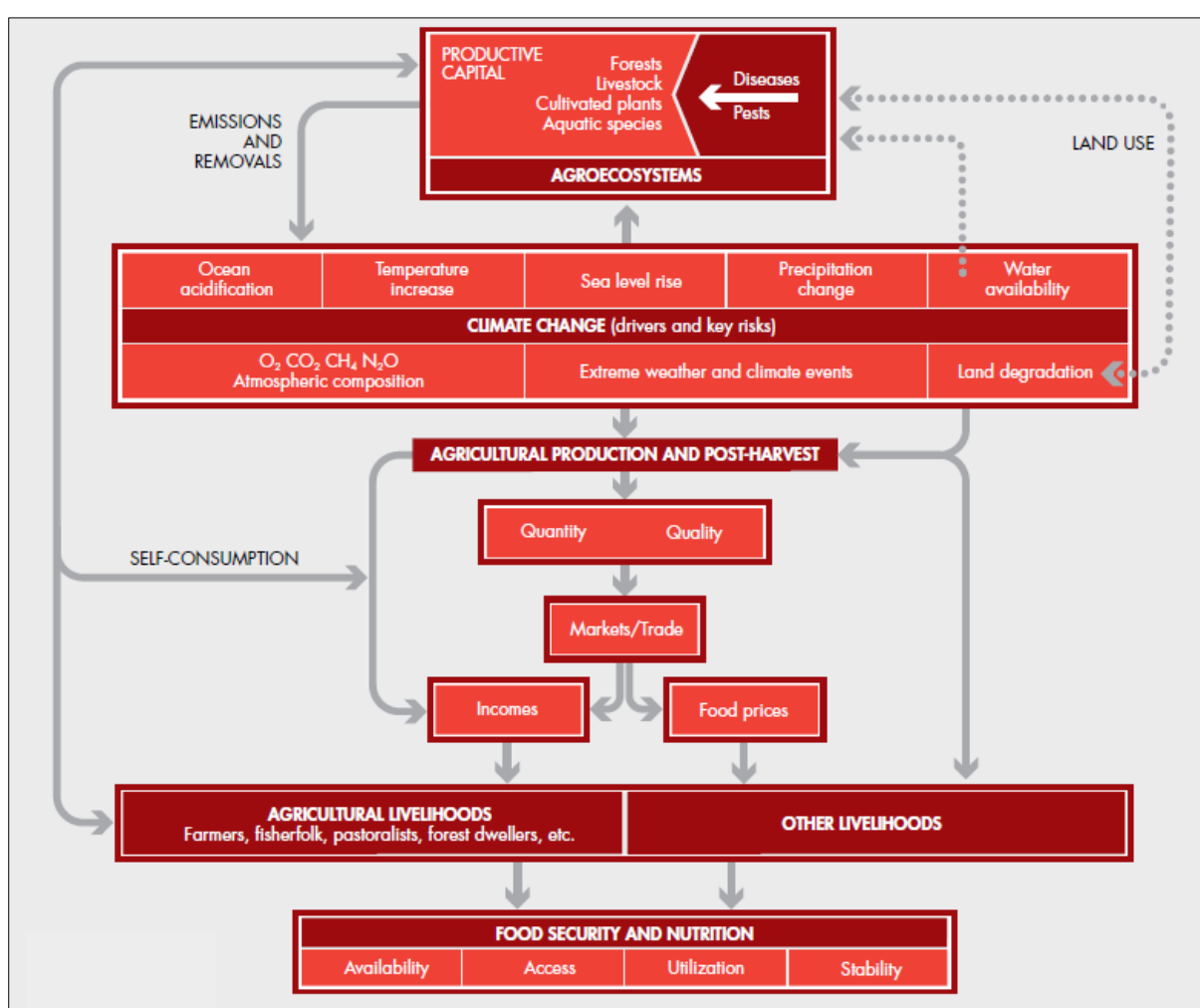


Figure 1.1: Schematic diagram showing the impact pathways of climate change on agriculture, livelihood, and food security and nutrition
Source: FAO, 2016

1.2 Problem setting and motivation

In line with the 2015 Paris Agreement on Climate Change, the Government of Ghana submitted its Nationally Determined Contributions (NDCs), which contains thirty-one adaptation and mitigation actions covering seven priority areas including energy, transport, water, agriculture, climate services, early warning system, and forestry. Although the promotion of conservation agriculture technologies has received significant focus under the agricultural priority area (Republic of Ghana, 2020; MESTI, 2021), adoption by smallholder farmers is still low. It is estimated that a meager 0.04 percent of arable lands are under conservation agriculture practices (African Union Commission, 2018). Even though CA has been shown to have economic and environmental benefits, there are still questions regarding its ability to increase food production, raise household incomes, and reduce the incidence of poverty. Further, the extent to which CA is adapted to, and hence suitable for the heterogeneous farming systems has been a source of contention (Giller et al., 2009).

In general, evidence on the impacts of CA on yield, household income, and poverty is still scanty. This is partly due to the difficulty in conducting a rigorous impact assessment, which necessitates creating a counterfactual while controlling for confounding observables and unobservables (Ngoma et al., 2021). Indeed, recent empirical evidence show a positive impact of CA on household welfare (e.g. crop yields, income, and poverty) (e.g. Abdulai and Huffman, 2014; Boimah et al., 2018; Issahaku and Abdulai, 2020). However, there is insufficient evidence on its impact on inorganic fertilizer use. Conservation agriculture has been reported to positively affect soil organic matter, mineralizable nitrogen, and extractable phosphorus, and hence lower the amount of inorganic nitrogen fertilizer use over time (Lee, 2005; Pretty et al., 2011). Therefore, understanding the nexus between its adoption and the implication on inorganic fertilizer use is important to promote and boost its adoption.

Another major concern that hampers the adoption of CA is the fact that productivity benefits remain uncertain and controversial (Giller et al., 2009; Brouder and Gomez–Macpherson, 2014). While some studies have found immediate positive benefit of CA (e.g. minimum tillage) on crop yields (Ngwira et al., 2013; Tessema et al., 2019), others observed a lag period of 2–5 cropping seasons or even longer before any positive benefit is observed (Thierfelder and Wall, 2010; Michler et al., 2019). Smallholder farmers have short-term planning horizons due to high discount rates and may see immediate tangible welfare benefits of minimum tillage as a key driver behind adoption (Pannell et al., 2014). Therefore, understanding the inter-temporal adoption decisions of farmers and their impacts is important in formulating targeted policies that can address the adoption constraints (Maggio et al., 2021).

Furthermore, in the absence of well-functioning formal risk coping mechanisms such as agricultural insurance, credit markets (Addey et al., 2021; Jensen and Barrett, 2017), crop diversification has become integral in recent agricultural policies and programs in SSA to enhance the resilience of smallholder farm households and provide them with more options in managing current and future risks (Kassie et al., 2015; Arslan et al., 2017; Asfaw et al., 2018). However, in the short term, there may be potential trade-offs between managing weather-related risks through diversification on one hand and efficiency on the other (FAO, 2021a). Baumgärtner and Quaas (2010) suggest that low-income farm households may resort to greater diversification intensity because it may provide them with greater natural insurance. Although the economic gains (e.g. income, downside risk exposure) from crop diversification are quite evident in the literature, emerging work on this topic fail to disaggregate its effect with respect to the different levels of diversification intensities. The gains from crop diversification may diminish once a certain threshold is attained, owing to competition for the same resources (e.g. nutrients and water) (Kray et al., 2019).

The present dissertation, therefore, attempts to fill these gaps and address some of the salient issues raised above. Specifically, the study contributes to the growing literature by examining the heterogeneous impact of CA on farm performance and inorganic fertilizer use, food and nutrition security, labor demands, risk exposure, production frontier, and technical efficiency, using data from a recent survey of smallholder maize farmers from the northern Savanna zone of Ghana. The specific research questions are presented in the next section.

1.3 Research questions

The overarching objective of this dissertation is to examine the contribution of conservation agriculture on household welfare among smallholder farmers in the northern Savanna zone of Ghana. In assessing this objective, this dissertation comprises four main chapters, each addressing the following research questions:

1. What are the impacts of CA on farm performance and inorganic fertilizer use? (Chapter 2)
2. What are the impacts of minimum tillage on food and nutrition security and labor demands? (Chapter 3)
3. How does crop diversification as a risk management strategy impact farm performance and risk exposure? Does the level of crop diversification generate heterogeneous benefits? (Chapter 4)
4. What are the joint impacts of CA adoption and participation in field demonstrations on productivity and efficiency? (Chapter 5)

1.4 Overview of Ghana's agriculture sector

The agriculture sector continues to provide important contribution to Ghana's economy although the share of its contribution to the Gross Domestic Product (GDP) has declined from 35.3% in 2000 to 19.3% in 2020 (see Figure 1.2) (World Bank, 2022). Moreover, the sector's growth declined in 2019 to 4.6 percent compared to a growth rate of 4.8 percent in 2018. Crops

are Ghana's third major economic activity, accounting for 13.8 percent of GDP. It accounted for 0.7 percentage points of annual GDP growth in 2019. The forestry and logging sub-sector grew by (-1.7%) in 2019 compared to 2.4 percent the previous year (Ghana Statistical Service, 2020). The sector comprises peasant farmers with approximately 90% of farm households cultivating less than 2 hectares and contributing about 80% of food crops (MoFA, 2017). The use of irrigation to hedge against rainfall volatility is particularly low across the country. For instance, it is estimated that irrigated farmland is 0.3% of the total arable land (FAO, 2021b).

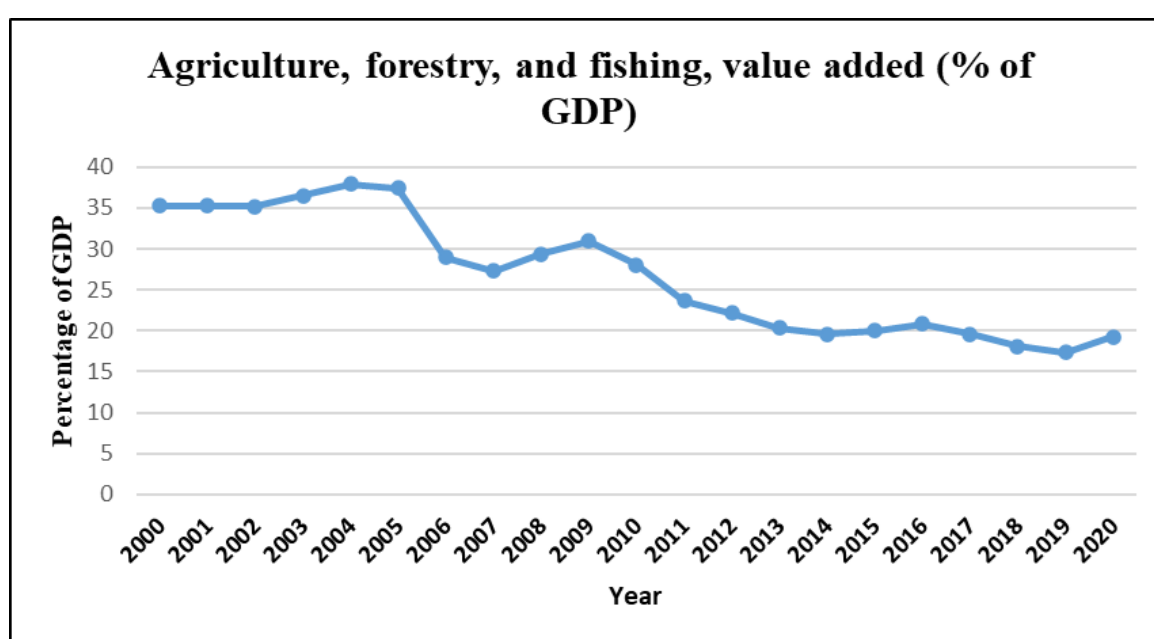


Figure 1.2: Share of agriculture sector to GDP from 2010 to 2020

Source: World Development Indicators¹

In Ghana, the sector consists of crops, livestock, forestry and logging, and fishing. The main agricultural commodities include: Cocoa, yam, cassava, plantain, maize, groundnuts, cocoyam, rice, oil palm, tomatoes, pepper, oranges, onions, sorghum, and pineapples. Although the contribution of the crops sub-sector to agricultural GDP, excluding cocoa, increased from 2011 (61.1%) to 2016 (67.7%), the sector is characterized by low productivity due to several factors including poor extension services, aging farming population, low investment, limited access to improved seed and fertilizer, limited access to credit, inadequate access to domestic

¹ <https://databank.worldbank.org/reports.aspx?source=2&country=GHA> [Accessed 27 March 2022].

and international markets, as well as storage and irrigation facilities (MoFA, 2018). The extension officer to farmer ratio stands at 1:706 as compared to the FAO standard of 1:500. It is important to note that, climate variability, poor soil conditions, diseases and pests, and unsustainable farming practices including soil degradation, overgrazing, small-scale mining, bush burning have contributed to low productivity in the agriculture sector (MoFA, 2018).

Given the aforementioned challenges, various policies and programs that set out the national priorities on agriculture and climate change have been initiated. The agricultural sector's policy objectives are detailed in the Food and Agriculture Sector Development Policy (FASDEP I and II). The Medium-Term Agriculture Sector Investment Plan (METASIP I and II) for implementation of FASDEP I and II provides a blueprint for the implementation of the Comprehensive Africa Agriculture Development Program (CAADP), which focuses on investments for addressing constraints on productivity, access to market, and sustainable production (FAO, 2020).

More recently, a plan for transforming Ghana's Agriculture (2018-2021)² has been developed to operationalize the Medium-Term National Development Policy Framework (MTNDPF), which is titled "*Agenda for Jobs: Creating Prosperity and Equal Opportunity for All (2018-2021)*". It incorporates various international development frameworks such as the SDGs, CAADP-Malabo declaration, and Economic Community of West Africa Agricultural Policy (ECOWAP). This medium-term plan aims to transform the agricultural sector by allocating at least 10% of the national budget to agriculture and achieving a corresponding annual sector growth rate of at least 6% within its implementation period, as stipulated in the Malabo declaration. More importantly, the plan acknowledges the adverse impact of climate

² <http://mofa.gov.gh/site/publications/policies-plans/316-national-agriculture-investment-plan-ifj>

change on agricultural value chains, particularly in the northern Savannah zone where farming is predominantly rain-fed, despite the intensity of extreme weather events (MoFA, 2018).

In line with the objectives of the *Agenda for Jobs* framework, the Government has initiated the Planting for Food and Jobs (PFJ) Program, which aims to modernize agriculture and encourage food production to achieve food self-sufficiency and surplus for export. The program, which began in 2017 is built around five program pillars, namely: (i) seed access and development; (ii) fertilizers; (iii) extension services; (iv) marketing; and (v) e-agriculture (MoFA 2017). Further, it supports smallholder farmers with seed and input subsidies, facilitates export and job creation along agricultural value chains. In addition, smallholder farmers receive other complementary services such as extension advice and marketing support (MoFA, 2017). Other flagship programs including Planting for Export and Rural Development, Rearing for Food and Jobs, One-District-One Factory, One-District One-Warehouse are being implemented.

In 2016, the sector accounted for 24 percent of total national greenhouse gas emissions. Crop management practices accounted for 16 percent, while livestock accounted for the remaining 8 percent. As a result, it is expected that policies and programs like the National Climate Smart Agriculture and Food Security Action Plan, the National Climate Change Policy (NCCP), and the Nationally Determined Contribution will be able to effectively address the sector's adaptation and mitigation challenges (MESTI, 2021).

1.5 Conservation agriculture promotion in Ghana

A number of programs and policies have supported the promotion of conservation agriculture, particularly in the northern Savanna zone over the past two decades. First among such initiatives was the Sasakawa Global 2000 program that promoted the adoption of improved seed varieties, zero tillage, and no burning. Subsequently, the DANIDA sponsored Savannah Resources Management project also promoted sustainable management of farm systems including

maintenance of permanent soil cover. In the last decade, the Howard G. Buffett Foundation (HGBF) has supported the Centre for No-Till Agriculture (CNTA) to promote and demonstrate measurable impacts of CA practices including no-till, crop residue retention, cover cropping, crop rotation. Furthermore, the USAID Feed the Future Agricultural Technology Transfer Program integrated CA as part of its interventions, promoted practices such as intercropping with cover cropping and retention of crop residues. Other projects such as the International Fund for Agricultural Development (IFAD) funded Ghana Agriculture Sector Investment Program (GASIP), GIZ funded Adaptation of Agro-Ecosystems to Climate Change in Ghana project (AAESCC), as well as the World Bank funded Sustainable Land and Water Management Practice Project (SLWMP) have all mainstreamed CA into their interventions (Ambler et al., 2020).

Not only do the effects of weather-related shocks on food production vary across agro-ecological zones and biophysical environments, but also the adaptive capacities of farm households are heterogeneous. Thus, conservation agriculture may have broad application operating differently in different agri-environment based on soil and crop types, as well as farming systems while still conforming to its core principles. Some of the CA practices adopted in the northern Savanna zone include crop rotation (i.e. maize-legumes rotation), minimum tillage, cover cropping, mulching, and organic amendments (i.e. animal manure and compost) (Dalton et al., 2014; Ambler et al., 2020).

Crop diversification including crop rotation is a key part of the CA system, and various approaches emphasize the use of cereal (e.g. maize)-legumes rotations (Giller et al., 2009). Legumes commonly cultivated include soybean (*Glycine max* (L.) Merrill), groundnut (*Arachis hypogaea* L.), beans (*Phaseolus vulgaris* L.), and cowpea (*Vigna unguiculata* (L.) Walp.). Combining legumes with maize in a rotation facilitates the buildup of soil organic matter pool and nitrogen that contribute to maize productivity. In addition, permanent cover using crop

residues and plant biomass, and reduced soil disturbance through minimum tillage practices such as the Zai and ripping. The Zai technique is a minimum tillage practice where seeds are sown in small planting pits and filled with organic material such as crop residues, compost, and manure. This practice reduces soil erosion, improves microbial activities, and concentrates soil water around the base of the plant, thereby supporting plant growth during seasonal dry spells. It is mainly practiced in the dry savannah zones, particularly in the Upper East region. Thus, it increases soil organic carbon content and soil moisture content and enhances water use efficiency (FAO, 2017; Ehiakpor et al., 2019).

1.6 Overview of the maize sector in Ghana

Maize (*Zea mays* L.) is an important cereal crop accounting for 12 percent (1.1 billion tons) (see Figure 1.3) of the total global production of primary crops (FAO, 2021b). In Ghana, maize is widely consumed and cultivated in all agro-ecological zones and accounts for more than one-quarter of calories consumed and about twice that of cassava (Ghana Statistical Service, 2018). It represents more than half of Ghana's total cereal production, with annual yields increasing at a rate of 1.1 percent (IFPRI, 2014). Moreover, maize output represents 3.37 percent and 0.24 percent of the total maize production in Africa and worldwide, respectively (FAO, 2021b).

Maize contributes substantially to the economy, both upstream (i.e. input segment) and downstream (i.e. processing segment) (IFPRI, 2020). Maize productivity appears to have been responsive to the expansion of fertilizer supply under the Planting for Food and Jobs Program. Since the introduction of the program, maize production has improved significantly. For example, compared to the period between 2013 and 2016, the average maize yield increased by 40% from 2017 to 2019 (MoFA 2020). That notwithstanding, yields are well below their potential. Average maize yields range between 1.2 and 1.9 metric tons (Mt) per hectare (ha), while on-station and on-farm trials indicate achievable average yields between 4 and 6 Mt/ha. Poor soil fertility, low water holding capacity, and climate variability are three major

biophysical constraints that contribute to the production gap (Obour et al., 2022). Most climate scenarios have projected that maize yields will decline and gradually worsen under more extreme scenarios (Lobell, 2008; Deutsch et al., 2018; Obour et al., 2022). Furthermore, the northern Savanna zone, which is part of the major maize producing areas, is characterized by low organic matter and nutrient supplies, as well as agro-climate regimes that are likely to be most affected by climate change (Warren, 2005; Jayne and Rashid, 2013).

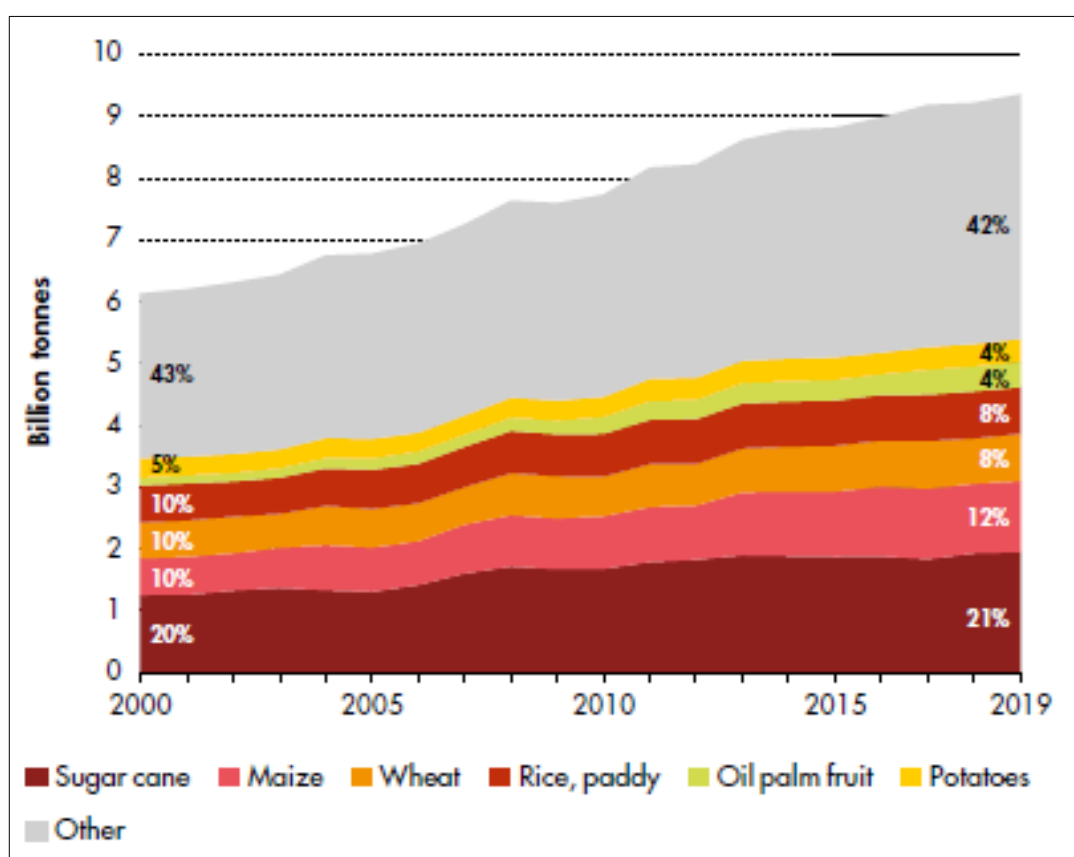


Figure 1.3: World production of main crop commodities

Source: FAO, 2021b³

1.7 Study Area and Agro-ecological zones

Ghana has six main agro-ecological zones namely: Sudan Savannah, Guinea Savannah, Forest Savannah Transition, Semi-Deciduous Rainforest, High Rainforest, and Coastal

³ <https://doi.org/10.4060/cb4477en-fig21>

Savannah, which is defined based on climate change, is mirrored by natural vegetation, soil types. The present study sampled maize farm households from the Sudan and Guinea Savannah agro-ecological zones (see Figure 1.4). In terms of administrative regions, these zones cover the Northern, North East, Savanna, Upper East, and Upper West, which together is referred to as the northern Savanna zone. Agriculture is the main source of livelihood for households in these areas. They experience a uni-modal rainfall season, which begins in May until September. The mean annual rainfall total is around 1000mm and 90 percent of rain occurs within May and September. Furthermore, several climate models have confirmed that temperature has increased over the years by 1°C between 1960 and 2003, at an average rate of 0.21°C per decade (MESTI, 2021). There is also inter-annual and inter-decadal variability in the intensity, timing, and duration of yearly rainfall, because of the effect of the inter-tropical convergence zone, specifically El Niño Southern Oscillation (ENSO) events, which lead to drier than average conditions.

The Guinea Savanna vegetation comprises ground cover of grasses of varying heights interspersed with largely fire resistant, deciduous broad-leaved trees at the forest margins in the south. During the dry season, the dry grasses are highly inflammable. In the less eroded areas, *Andropogon gayanus*, the commonest grass, may be replaced by *Hyparrhenia* and *Heteropogon spp*, whilst *Aristida* and *Cymbopogon gigantus* dominate the badly eroded sites. *Vetiveria nigriflora*, *Seteria anceps* and sedges occur in alluvial sites. The vegetation of the Sudan Savanna is made of short drought and fire-resistant deciduous trees, interspersed with open Savanna grassland. Grass cover is very sparse in most areas and tree density is low. Most of the land is bare and severely eroded. Some of the important economic trees include *Andansonia digitata*, *Ceiba pentandra*, *Vitellaria paradoxa*, *Tamarindus indica*, and *Faidherbia albida* (Barry et al., 2005).

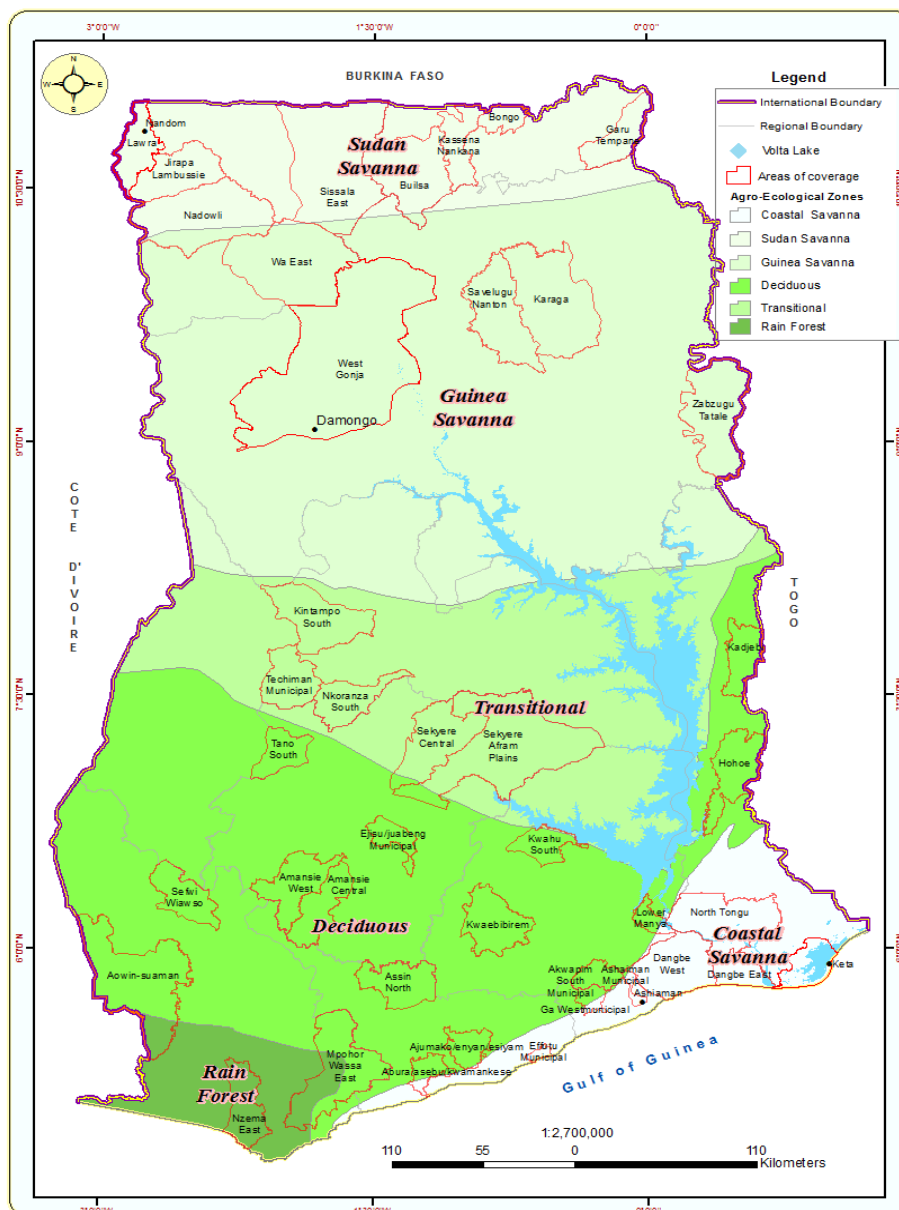


Figure 1.4. Map showing six agro-ecological zones in Ghana⁴

The three major land preparation methods employed in these regions are tractor, animal traction, and manual. Farmers produce a wide range of crops including sorghum, millet, maize, rice, cowpea, soybean, groundnuts, yam, cassava, vegetables, dawadawa, and mango. The majority of farmers practice various forms of farming methods including mixed cropping, intercropping, sole cropping, and mixed farming. Livestock production is a very important

⁴https://agmip-ie.wenr.wur.nl/waf_nav_crops_livestock

activity and almost every household in these areas keep various types of livestock for different reasons such as a form of security in times of hardship. (MoFA, 2016).

1.8 Structure of the dissertation

The present dissertation is organized into six chapters. The first and the last chapters provide a general introduction and conclusion, respectively. The remaining chapters (i.e. two to five) are collections of journal articles. Specifically, chapter one investigates the heterogeneity in the impact of conservation agriculture on farm performance and inorganic fertilizer use, employing the marginal treatment effect (MTE) framework. Chapter three examines the role of minimum tillage (MT) as climate-smart agriculture practice and its impact on maize yields, food and nutrition security, and labor demand using an ordered probit selection model to estimate two transition-specific treatment effects: from conventional tillage systems to short-term MT adoption and from short-term to medium to long-term MT adoption. In chapter four, the study empirically examines the heterogeneous impact of crop diversification on farm performance and risk exposure using the dose response function and instrumental variable techniques to account for potential endogeneity issues. Chapter five contributes to the literature by bringing together methodological elements from the mediation analysis in treatment effect setting and the stochastic production frontier framework. More precisely, the study employs the stochastic frontier model with an endogenous treatment status and mediator to explore the direct and indirect impacts of conservation agriculture. Chapter six presents the summary, conclusions and policy implications of the study.

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Chapter 2

Heterogeneity in the Impact of Conservation Agriculture Practices on Farm Performance and Inorganic Fertilizer Use in Ghana

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Abstract

We employ farm household data to investigate the heterogeneous treatment effects of conservation agriculture (CA) practices on farm performance and inorganic fertilizer use in Ghana. We use the marginal treatment effect (MTE) framework to account for the treatment effect heterogeneity in both observed and unobserved characteristics and to analyze policy-relevant treatment effect (PRTE). Results show that farmers with high propensity to adopt CA reduce Nitrogen usage from inorganic sources to a greater extent and experience significant increases in maize yields and farm net returns when compared to those with low propensity to adopt. Further, our PRTEs reveal that increasing training sessions, and providing incentives to reduce the cost of implementation are crucial for CA promotion.

Keywords: Impact assessment, Marginal treatment effects, Conservation Agriculture

JEL CLASSIFICATION: Q12, Q56, C31

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2.1 Introduction

There are growing concerns about whether agriculture can sustainably meet the rising food demand, given the threats of increasing world population and deteriorating natural resources, exacerbated by climate change, especially in most of sub-Saharan Africa (SSA). The challenge facing most governments and policymakers in SSA, including in Ghana, is not only to increase agricultural production and reduce poverty given limited resources but also to increase productivity in a sustainable manner that protects the natural resource base and prevents further environmental degradation (Beddington et al., 2012; Bationo et al., 2018).

Recent approaches to agricultural production pose a huge threat to many ecosystem services such as nitrogen fixation, soil regeneration, and biological control of pests (Lee, 2005; Pretty, et al., 2011). For example, agricultural land expansion, deforestation, and mono-cropping have led to habitats loss and an increase in greenhouse gases (GHGs) (Tilman et al., 2002; Beddington et al., 2012). Farming practices such as bush burning, removing crop residues, and continuous cropping have depleted soil fertility through erosion and nutrient removal (FAO, 2015). According to the Food and Agricultural Organization (FAO), an estimated 33 percent of global soils are degraded due to unsustainable farming practices (FAO, 2015).

These practices have contributed to spiraling declines in productivity and, farm revenues, and increased food insecurity, and poverty (Nkonya et al., 2015; MoFA, 2017). Estimates show that in SSA, nutrient depletion from 105 hectares of cropland by unsustainable practices constitutes an annual loss of about 280 million tons of cereals (ELD Initiative and UNEP, 2015). This productivity loss has contributed to a 3.3 percent and 5 percent decline in agricultural gross domestic product (AGDP) in Africa and Ghana, respectively over the years (Diao and Sarpong, 2007; Global HarvestChoice, 2011). Further, maize productivity and output in Ghana remain among the lowest in SSA and the world (Ragasa et al., 2014), with an average yield of 1.2-1.8

tons/ha, compared with yields of around 2 tons/ha, the average in Africa, and less than half the world average of approximately 5.5 tons/ha. Potential yields of 4–6 tons/ha could be realized under a comprehensive soil fertility management approach (Cairns et al., 2013; FAO, 2016).

To address the agricultural productivity and output challenges, input subsidy programs, particularly those focusing on boosting inorganic fertilizer use, have become popular policy instruments among SSA governments (World Bank, 2007). However, while inorganic fertilizers could help increase short-run agricultural productivity (Marenja and Barrett, 2009), their increased use may not be sufficient to increase productivity in a sustainable manner and could even pose potential environmental challenges over time (Lee, 2005; Pretty, et al., 2011).

Of greater concern in Ghana and other parts of SSA are the trends of degraded farmlands characterized by low soil organic matter (SOM) (Marenja and Barrett, 2009; Jones et al., 2013). Low SOM means that the nutrients from inorganic fertilizers are inefficient and less productive, contributing to low fertilizer yield response, and subsequent low rates of inorganic fertilizer application (Liverpool-Tasie et al., 2017; Abdulai and Abdulai, 2017). It is estimated that cereal crops utilize only 18% - 49% of nitrogen (N) applied as fertilizers, partly due to poor soil conditions; the remainder leaches to pollute water bodies and the atmosphere, as well as increase the prevalence of pests and diseases (Cassman et al., 2002). Merely increasing inorganic fertilizer use alone is not a panacea for resolving farm productivity challenges (Marenja and Barrett, 2009; Abdulai and Abdulai, 2017).

Several studies (e.g. Lee, 2005; Pretty et al., 2011, Jayne et al., 2019) have made compelling arguments for a more sustainable and equitable food system in SSA. The sustainable development goals (SDGs) also acknowledge the need for a well-functioning and sustainable food system that protects the environment. In particular, the second goal of the SDGs advocates for increased investments in infrastructure and technology to ensure widespread adoption of alternative and complementary agriculture intensification practices capable of addressing

current and future threats to food security and ecosystem services (UN, 2015); this goal has become a major research and policy issue (Jayne et al., 2019).

The 2014 Malabo Declaration⁶ by African heads of states further underscores the need for sustainable use of natural resources, including land and water, to realize their enormous potential (African Union Commission, 2014). In the case of Ghana, the government's flagship program on "Planting for Food and Jobs" (PFJ) describes soil degradation as high-risk factor that could impede its smooth implementation. As a result, it recognizes the importance of promoting sustainable soil conservation practices as an effective way to boost food production through improved soil health (MoFA, 2017).

Conservation agriculture (CA) has emerged as a response to sustainable soil management, climate change adaptation and mitigation, and environmental conservation. According to the Food and Agriculture Organization of the United Nations (2017), CA is a cropping system based on three agronomic management principles: (i) minimum mechanical soil disturbance (e.g. zero tillage); (ii) permanent soil organic cover (e.g. crop residue retention, mulch, cover cropping); and (iii) species diversification (e.g. crop rotation, intercropping). These practices promote good soil structure and contribute to building up the pool of soil organic matter over time, which is essential for improving soil properties and processes fostering plant growth including, nutrient recycling, moisture retention, erosion prevention, and enhanced biological activity. Soil organic matter (SOM), a good indicator of fertile soil releases available N that may better correspond with crop N demand than inorganic N fertilizer. Thus, soils with enhanced SOM may require less inorganic N fertilizer over time. CA practices further build up soil organic carbon capital, contributing immensely to climate change mitigation (Giller et.al., 2009; FAO, 2017).

⁶ Declaration on "Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods", AU Summit in Malabo, June 2014 (see declaration III - Commitment to Ending Hunger in Africa by 2025).

Given the well-documented advantages of CA practices in contributing to sustainable food production systems (see Lee, 2005; Issahaku and Abdulai, 2020), a long-standing puzzle is why adoption rates remain low in parts of SSA (Jayne et al., 2019). This is true for Ghana where, despite domestic and donor-sponsored initiatives, there are limited on-farm investments in sustainable soil conservation practices. According to a recent report by the African Union Commission (2018), only around 0.04 percent of farmlands are managed under soil conservation practices (African Union Commission, 2018). Although it has been argued that CA practices can provide economic and environmental benefits, there are still concerns about its potential to increase food production and farm incomes (Giller et al., 2009). For instance, Di Falco et al., (2011) also found positive and significant impacts on crop yields in Ethiopia. Similarly, Manda et al., (2016) found that CA practices had a positive impact on yield and income in Zambia. Abdulai and Huffman (2014) and Issahaku and Abdulai (2020) found significant increases in crop yields and reduction in poverty among farmers who adopted CA in Ghana, while Boimah et al. (2018) found no significant impact of CA on maize yield, and rather negative impact on profits.

While these studies have contributed to understanding the factors that hinder or facilitate the adoption of CA practices, as well as their impact on crop production and other welfare indicators, not enough empirical evidence exists on its impact on inorganic fertilizer use. Often-cited impact pathways of CA indicate among others its ability to increase soil organic matter, build up N capital, reduce leaching of applied nutrients, and thus lower the amount of inorganic N fertilizer use over time (Lee, 2005; Pretty et al., 2011). Understanding the nexus between the adoption of CA practices and their implication for inorganic fertilizer use is crucial for its widespread promotion and adoption in SSA. Using recent survey data of 512 farm households

from the northern Savanna regions of Ghana⁷, this study examines the factors that affect farmers' decision to adopt CA practices, as well as the impact of adoption on inorganic fertilizer use, maize yields, and farm net returns.

Our study contributes to the empirical literature on CA adoption, first, by examining how adoption contributes to economic and environmental sustainability. Much of the concerns over calls to adopt CA practices stems from its potential impact on food production (Giller, 2009). This study, seeks to address these concerns by examining whether adopting CA practices could ensure productivity gains and at the same time manage the use of inorganic N fertilizer. An earlier study by Boimah et al. (2018), using an endogenous switching regression approach found no significant impact of CA practices on yields and inorganic fertilizer use in Ghana. However, CA practices are location-specific and will need localized farm-level empirical evidence to boost their adoption in SSA (Jayne et al., 2019). Thus, the heterogeneity of agro-climatic conditions as well as socio-economic and biophysical factors is non-trivial.

Second, much of the previous empirical work on impact of agricultural technology adoption has assumed homogeneous treatment effects using approaches such as endogenous switching regression (ESR) or propensity score matching (PSM) (e.g. Di Falco et al., 2011; Boimah et al., 2018; Singha et al., 2019). However, agents differ in their benefits from adoption of technologies (Heckman et al., 2018). Failure to account for this heterogeneity can lead to confusion in interpreting the estimated effects of adoption. In this paper, we employ the marginal treatment effect (MTE) approach to account for treatment effect heterogeneity in both observed and unobserved characteristics (Cornelissen et al., 2018). The MTE approach estimates a continuum of treatment effects along the whole distribution of farmer's unobserved resistance to adoption (Frölich and Sperlich, 2019). In addition, it allows us to estimate several

⁷ As rightly noted by an anonymous reviewer, another way of analyzing the impact of CA would be to look at the various practices and their impacts. However, to the extent that the focus of the present paper is on the heterogeneity in the impact of conservation, we define CA in line with Di Falco et al. (2011) and Michler et al. (2019).

economically useful treatment effect parameters, including average treatment effect (ATE), treatment effect on the treated (TT), and treatment effect on the untreated (TUT), and policy-relevant treatment effect (PRTE).

2.2 Data and Descriptive Statistics

2.2.1 Data

The data used for this study come from a survey conducted for the 2018/2019 cropping season in 15 communities across six districts and three regions in the savanna zone of Ghana. We selected and interviewed 512 maize farming households in the Sustainable Land and Water Management Project (SLWMP)⁸ intervention areas. First, based on the operational areas of the project and the prevalence of CA practices, we purposively selected six districts from the three regions: Bawku and Talensi from the Upper East region; Sissala West and Wa East from the Upper West region; and West Mamprusi and West Gonja from the Northern region.

Second, we randomly selected three to six communities from each district, taking into account the concentration of the project interventions. The intervention primarily focused on agriculture technologies such as contour bonds, zero tillage, adoption of intercropping/mixed cropping, crop rotation, vegetative barrier, and integrated nutrient management (e.g. animal manure and compost, maize-legumes rotation, cover cropping, and mulching). Beneficiaries received one-time support in the form of materials (e.g. seedlings), and training to adopt CA technologies of their choice. The maize farm households were randomly sampled in proportion to the farmer population in the community. The survey data were collected using a structured questionnaire by trained and qualified researchers and enumerators with good working knowledge of the farming system in the study areas.

⁸ The project is funded through a grant facility from the Global Environment Facility (GEF) and is implemented through the Ministries of Environment, Science, Technology and Innovation (MESTI), and Agriculture (MoFA). The objective of the project is to support sustainable land and water management practices with the aim of reducing land degradation and enhancing the protection of ecosystem services in the Northern Savannah region of Ghana (Verheijen, 2016).

Based on a review of theoretical works and existing empirical literature on adoption and impact of agricultural technology (see Asafu-Adjaye, 2008; Di Falco et al., 2011; Manda et al., 2016), we collected self-reported plot-level characteristics such as soil erosion (moderate or severe erosion), slope of the land, and soil fertility level (fertile or moderately fertile). The survey also included detailed information on production costs, prices, household demographic, access to market information, extension contacts, and CA practices being implemented. In line with existing literature on the impact pathways of CA practices (e.g. Lee, 2005; Pretty et al., 2011), the data also contain detailed information on the three main outcome variables used in the context of this study; inorganic N fertilizer use, maize yield, and farm net returns. We also controlled for location, differentiating among the three regions, to account for heterogeneity of agricultural practices across areas.

Concerning the outcome variable on inorganic fertilizer use, our primary focus is on N content⁹ (hereafter referred to as inorganic N fertilizer) of the applied inorganic fertilizer. Therefore, following Liverpool-Tasie et al. (2017), and Ragasa and Chapoto (2017), we obtain the N content from the chemical composition of the applied inorganic fertilizer. The most widely used fertilizers in Ghana for maize cultivation include nitrogen, phosphorus, and potassium (NPK) (15:15:15)¹⁰ as basal fertilizer, together with either urea or sulfate of ammonia as top dressing, each containing of 15%, 46%, and 21% N, respectively (MoFA, 2017). We then computed the sum of the total amount of N by multiplying those percentages by the amount of inorganic fertilizer used per plot.

2.2.2 Conservation Agriculture Use Patterns in the Study

A key limitation of empirical studies on CA adoption is the lack of clarity on the contextual definition of CA practices (Michler et al., 2019). Although the three main pillars of CA are in

⁹ N is often the most deficient nutrients particularly for maize production largely because of the very low organic matter content in the soils. Efforts to increase N content using inorganic fertilizers has resulted in environmental problems such as leaching and loss of N into the atmosphere (Cassman et al., 2002).

¹⁰ MoFA recommends using two bags each of NPK and either urea or sulphate of ammonia per acre.

principle common to global CA systems, their application varies considerably because of the heterogeneity of farming systems and agri-environments (Corbeels et al., 2014). Following Michler et al. (2019), our study adopts a more practical definition of CA given the context of the study area. Notable CA practices implemented by farm households in our sample include crop rotation (i.e. maize-legumes rotation), zero tillage, cover cropping, mulching, and organic amendments (i.e. animal manure and compost). Other studies such as Dalton et al. (2014) and Ambler et al. (2020) have observed similar practices among farmers in the study area. A focus of our study is on practices that help build up the N content of soils, hence, the inclusion of crop rotation, cover cropping, and organic soil amendments as CA options. Crop rotation is an essential part of the CA system, and numerous approaches underscore the use of rotating cereal and legumes plantings (Giller et al., 2009), which contributes to building up soil organic matter pool and N, boosting maize yields (FAO, 2017). Commonly cultivated legumes in our study area include; soybean (*Glycine max* (L.) Merrill), groundnut (*Arachis hypogaea* L.), beans (*Phaseolus vulgaris* L.), and cowpea (*Vigna unguiculata* (L.) Walp.).

With an adoption rate of approximately 59 percent, representing 300 farm households (see Table 1), we define CA adoption as the use of one of the above-mentioned practices (henceforth referred to as ‘adopters’). Table 2.A3 (in the supplementary appendix) summarizes the pattern of adoption of CA practices. By disaggregating these practices based on the number of adopters and farm size, we observed that maize-legume rotations and cover cropping are the most common CA practices adopted. The adoption of zero tillage and mulching were comparatively lower and the adoption of organic soil amendments remained the lowest. The average farmer adopted an average of three of the above-mentioned CA practices. Table A3 also shows a lower average farm size for farmers who adopted organic amendments (e.g. compost and manure). Anecdotal evidence suggests that these inputs are usually not available

in large quantities, and the bulkiness of compost and manure, indicating increased costs of transportation and labor, usually deters those with larger farms.

2.2.3 Descriptive Statistics

Tables 2.1 reports descriptive statistics for the variables employed in our econometric analysis and the mean differences between adopters and nonadopters in the sample. As shown in Table 2.1, the average household size is six persons. The majority of households in the sample are smallholder farmers, with an average farm size of two hectares. These results corroborate a recent UNDP report that showed an average household size of six persons in the Northern Savanna Ecological Zone (NSEZ) with the majority of the households classified as small-scale farmers, with farm size of less than 5ha (UNDP, Ghana 2018). Education and age represent the human capital characteristics in our study. The mean educational level is approximately 3.6 years of schooling, suggesting lower years of education across the study areas, compared to the national average of 7.3 years (UNDP, 2020).

The table also provides *t*-test values showing differences between CA adopters and nonadopters. The coefficients suggest statistically significant differences between adopters and nonadopters with respect to some household and plot-level characteristics. For example, there are significant differences between adopters and nonadopters concerning extension contacts, credit constraints, farm size, membership in farmer-based organizations (FBO) membership, and other household characteristics.

Table 2.1: Definition of variables, and descriptive statistics for adopters and nonadopters

Variable	Description	Full sample (mean)	Std. Dev	Adopter	Non adopters	Diff (t-stats)
Maize yields	Quantity of Maize output per acre (kg)	780.95	508.20	915.33	590.79	324.54***
Farm net returns	Maize gross revenue less variable cost (GHS) per acre	427.46	428.97	564.14	234.04	330.09***
Inorganic N Fertilizer	Total amount of Nitrogen from inorganic fertilizers used (kg/acre)	29.75	21.02	25.74	35.43	- 9.69***
CA training	Average number (village level) of CA training (days) received	4.11	2.11	4.84	3.08	1.76***
Cost of CA	Cost of CA implementation per HH (GHS)	178.20	248.74	304.14	0.000	304.14***
Average CA cost	Average cost (village level) of CA implementation (GHS)	245.38	52.63	236.69	257.67	20.98***
Farm Distance	Farm distance from homestead to plot (km)	2.93	1.26	2.53	3.488	-0.97***
Distance to Agric. office	Distance to Agricultural Extension office (km)	24.26	10.35	22.31	27.01	-4.69***
Age	Age of household head in years	42.44	12.66	43.42	41.07	2.35**
Male	Male =1, Female =0	0.63	0.48	0.77	0.44	0.33
Household size	Size of Household	5.96	2.95	5.96	5.95	0.01
Education	Years of schooling of household head	3.63	4.74	4.33	2.64	1.69***
FBO	1 if a member of Farmer Based Organization (FBO), 0 otherwise	0.31	0.46	0.37	0.24	0.13***
Farm Revenue	Monetary value of maize produce (GHS) per acre	980.11	610.01	1092.99	820.37	272.62***
Price	Maize price per bag (100 kg) in GHS	199.44	45.84	196.05	204.24	-8.19**
Hired labor	Total hired labor per acre	15.01	7.71	15.66	14.20	1.45**
Farm size	Total farm size of HH in acres	5.41	4.37	4.80	6.27	-1.47***
Extension contact	Number of extension contacts per annum	10.38	7.00	11.56	8.72	2.85***
Credit constraint	1 if HH is credit constrained, 0 otherwise	0.37	0.48	0.31	0.45	0.14***
Livestock	Number of Livestock in Tropical Livestock (TLU) Units	1.85	4.07	2.26	1.27	0.99***
Market distance	Distance to the nearest market (km)	8.657	4.629	7.395	10.442	-3.048
Slope	Perception that plot is moderately to steeply sloped (1=yes; 0=no)	0.660	0.470	0.646	0.680	-0.034
Moderate erosion	Perception that plot is moderately eroded (1=yes; 0=no)	0.480	0.500	0.583	0.335	0.25***
Severe erosion	Perception that plot is severely eroded (1=yes; 0=no)	0.086	0.280	0.127	0.028	0.098***
No erosion	Perception that plot has no erosion (1=yes; 0=no)	0.434	0.496	0.290	0.637	-0.348***
Fertile plot	Perception that plot is fertile (1=yes; 0=no)	0.375	0.485	0.373	0.377	-0.004
Moderately fertile	Perception that plot is moderately fertile (1=yes; 0=no)	0.510	0.500	0.550	0.453	0.097**
Infertile plot	Perception that plot is infertile (1=yes; 0=no)	0.115	0.320	0.077	0.170	-0.093***
Northern region	Northern region=1, 0 otherwise	0.371	0.484	0.287	0.491	-0.203***
Upper East	Upper East region=1, 0 otherwise	0.330	0.471	0.360	0.288	0.072*
Upper West	Upper West region=1, 0 otherwise	0.299	0.458	0.353	0.222	0.132***
<i>Number of observations</i>		512		300	212	

The exchange rate at the time of the survey: 1 USD = 5.14 Ghana Cedis (GHS)

Adopters and nonadopters also have notable differences in the outcome variables. For example, adopters obtained an average maize yield of 915.33 kg/acre (2.26 ton/ha), higher than both the 590.79 kg/acre (1.46 ton/ha) for nonadopters, and the 1.2-1.8 ton/ha average yields in Ghana. Adopters also earned significantly higher farm net returns, 330.09 GHS/ acre more than nonadopters. Nonadopters use 9.69 kg/acre more N from inorganic sources than adopters. The significant differences between the outcome variables (i.e. maize yields, farm net returns and inorganic N fertilizer use) may not indicate impacts of adoption, as this comparison does not consider confounding factors that affect adoption of CA practices. It is important to note that, these outcome variables are essential ingredients towards achieving, in particular, the second of the sustainable development goals (SGD), which among others, aims to end hunger and achieve food security in a sustainable manner that does not lead to environmental degradation. Thus, according to the United Nations *2030 Agenda for Sustainable Development*, achieving this goal would require increasing smallholder farmers crop productivity and income through widespread promotion of CA practices (UN, 2015).

2.3 Conceptual Framework and Estimation Procedures

This section presents the conceptual and empirical framework. In particular, we begin with a description of farmers' adoption decisions of sustainable agricultural practices. The section also presents the marginal treatment effect (MTE)¹¹ framework and illustrates the details of the estimation procedure.

2.3.1 Model Set-Up¹²

We assume that adoption is binary denoted by C_i , with Y_{1i} and Y_{0i} denoting the potential outcome for farmer i in the adoption ($C_i = 1$) and nonadoption ($C_i = 0$) states, respectively.

We model the potential outcomes as:

¹¹ The MTE approach was first introduced by Björklund and Moffitt, (1987) and generalized by Heckman and Vytlačil (2001, and 2005, 2007).

¹² We follow the approach of Cornelissen et.al. (2018)

$$(1) \quad Y_{1i} = \mu_1(X_i) + \varepsilon_{1i}$$

$$(2) \quad Y_{0i} = \mu_0(X_i) + \varepsilon_{0i}$$

where $\mu(X_i)$ is the conditional mean of Y_i given X_i (which is the vector of observed exogenous characteristics), and ε_{1i} and ε_{0i} are the error terms. Equations (1) and (2) indicate that the treatment effect of farmer i , which is the difference between the potential outcomes in the adoption and nonadoption states, is given as:

$$(3) \quad Y_{1i} - Y_{0i} = \mu_1(X_i) - \mu_0(X_i) + \varepsilon_{1i} - \varepsilon_{0i}$$

where equation (3) shows that the benefits from adoption are allowed to vary across farmers with different observed (X 's) and unobserved characteristics ($\varepsilon_1, \varepsilon_0$), and that is an important aspect of our study, which emphasizes heterogeneity in the impact of CA adoption.

We model CA adoption decision under the assumption that farmers are risk-neutral and take into consideration the net benefit (C_i^*) derived from adoption or nonadoption of CA practices. Thus, farmer i will adopt ($C_i = 1$), if $C_i^* \geq 0$. Since C_i^* is the latent propensity to adopt and cannot be observed, we specify it as a function of observed variables (Z) and an unobserved component (V) in the following latent variable discrete model:

$$(4) \quad C_i^* = \mu_C(Z_i) - V_i, \quad C_i = 1 \text{ if } C_i^* \geq 0, \text{ and } C_i = 0 \text{ otherwise}$$

where Z includes the same covariates X_i as in the outcome equations (1) and (2), as well as an instrument used for model identification. That is, Z includes a variable that enters the selection equation (4) but is excluded from outcome equations (1) and (2). In this study, we use distance from the homestead to the farm as the identifying instrument. The error term V_i goes into selection equation (4) with a negative sign, and represents unobserved characteristics that make farmers less likely to adopt CA practices. Thus, V_i is often described in the literature as unobserved “resistance” or “distaste” to treatment (Cornelissen et.al., 2018), indicating that

farmers with high values of V (low propensity scores) are less likely to adopt CA practices compared to those with low values of V (high propensity scores).

It is a convention in the MTE literature to capture the treatment effect against the quantiles of V instead of its absolute values, in accordance with the following transformation of the selection rule in equation (3) (Cornelissen et al., 2018) :

$$\mu_D(Z_i) - V_i \geq 0 \Leftrightarrow \mu_D(Z_i) \geq V_i \Leftrightarrow F(\mu_D(Z_i)) \geq F(V_i)$$

where $F()$ denotes the cumulative distribution function of V . The term $F(\mu_D(Z_i))$, also represented by $P(Z_i)$, is the propensity scores (farmer's probability of adopting CA), and $F(V_i)$ represented by $F(V_i) \equiv U_{Di}$, is the quantiles of the distribution of V .

To identify the parameters of the models, we assume that the identifying instrument denoted as \tilde{Z} , is statistically independent of the unobserved components of the outcome and selection equations $(\varepsilon_0, \varepsilon_1, V)$, given the observable characteristics; i.e. $(\varepsilon_0, \varepsilon_1, V) \perp \tilde{Z} | X$. This assumption further requires that conditional on X , \tilde{Z} can only affect the outcome variables through its influence on adoption (referred to as exclusion restriction).

The use of distance from homestead to farm in this study as an excluded instrument is assumed to influence the adoption behavior of farmers. Recent changes in settlement and land use patterns coupled with increased population pressure have contributed to reduced access to farmlands closer to homesteads. This is assumed to have contributed to a reduction or abandonment of fallowing periods in favor of continuous cropping. Continuous cultivation of farmland leads to depletion of soil nutrients as well as increased soil erosion. On the other hand, more distant farmlands are often virgin lands with inherent soil nutrients capable of sustaining crop growth over time. Thus, the declining soil fertility and limited access to farmlands tend to increase the adoption of CA practices (e.g. leguminous cover cropping, maize-legume rotations, mulching) for those farming at closer distances to homestead, to rejuvenate and improve the

fertility of the soil (McCall, 1985). Thus, the instrument plays an important role in the adoption of CA, but should not directly affect the outcome variables¹³.

In line with Cornelissen et.al. (2018), we also assume that the MTE is additively separable into observed and unobserved components:

$$(5) \quad \begin{aligned} \text{MTE}(x, u_D) &= E(Y_{1i} - Y_{0i} | X_i = x, U_{Di} = u_D) \\ &= \underbrace{x(\delta_1 - \delta_0)}_{\text{Observed component}} + \underbrace{E(\varepsilon_{1i} - \varepsilon_{0i} | X_i = x, U_{Di} = u_D)}_{\text{Unobserved component}} \end{aligned}$$

where $(\delta_1 - \delta_0)$ represent the difference in the treatment effect between the adoption and the nonadoption states. This assumption enables the MTE to be identified over the unconditional support of the propensity score, which is generated by both the instrument and the observed covariates, X_i , instead of the support of the propensity score conditional on $X_i = x$ (Brinch et al., 2017).

2.3.2 Estimation Procedures

We employ the method of local IV to estimate the MTEs (Cornelissen et.al., 2018). The outcomes in equations (1) and (2) yield the following outcome equation, conditioned on the observed covariates X and propensity score $P(Z)$:

$$(6) \quad E(Y|X, P) = X_i\delta_0 + X_i(\delta_1 - \delta_0)P + K(P)$$

where $K(P)$ is a nonlinear function of the propensity scores (P). Thus, the MTE equals the derivative of Eq. (6) with respect to the propensity scores (Carneiro et al., 2017):

$$(7) \quad \text{MTE}(X_i = x, U_{Di} = P) = \frac{\partial E(Y|X, P)}{\partial P} = X(\delta_1 - \delta_0) + \frac{\partial K(P)}{\partial P}$$

¹³ To check the validity of our instrument, we follow Di Falco et al. (2011) and run separately a probit model of the selection equation and OLS regression for the outcome equations of nonadopters. The estimates show that the instrument negatively affects adoption of soil conservation practices and is statistically significant at 1% level (see the first column of Table 2.2) but did not show any statistically significant impact on the outcome variables among farmers who did not adopt (see Table 2.A1). In addition, a chi-square test of the effect of the instrument on CA practices shows a *p-value* of 0.000, suggesting that the distance to the farm variable is significantly different from zero. A further test of correlation reveals the instrument employed is not correlated with any of the outcome variables (see Table 2.A2).

There are two stages to our estimation procedure. We first obtain propensity score estimates from a first-stage probit estimation from the selection equation (4) and then proceed to model $K(P)$ as a polynomial in P of degree k . Thus, we estimate the impact of adoption of CA practices in the second stage, using the following outcome equation¹⁴:

$$(8) \quad Y_i = X_i\delta_0 + X_i(\delta_1 - \delta_0)P + \sum_{k=1}^K \alpha_k P^k + \epsilon_i$$

The derivative of equation (8) with respect to P delivers the MTE curve. We estimate our baseline model using a second-order polynomial ($K = 2$) in the propensity scores. We also conduct robustness check analysis with $K = 3, K = 4$, and semiparametric specifications, but observed a similar pattern of results.

2.4 Empirical Results and Discussion

In this section, we discuss the results from the empirical analysis. The estimates of the determinants of CA adoption decisions are presented in Table 2.2. Based on equation (8), we present estimates of the effects of the covariates on the outcome variables in column 1 and the treatment effects across covariates in column 2 of Tables 2.3, 2.4, and 2.5. Next, we present the results of the marginal treatment effects and the treatment effects parameters in Figure 2.1, and Table 2.6 respectively. Finally, we report the robustness checks results, as well as the estimates of the policy simulation analysis. The distributions of the predicted probabilities for both adopters and nonadopters are shown in Figure 2.A3 (in the supplementary appendix). The identification of the MTE depends on the common support of propensity scores, which requires sufficient overlap in the characteristics of the adopters and the nonadopters. As depicted in Figure A3, there is considerable overlap between these two groups, suggesting that there are adopters and nonadopters with comparable characteristics.

¹⁴ We estimate our model using the `mtfe` stata command (see Andresen, 2018)

2.4.1 Determinants of Adoption of Conservation Agriculture Practices

In the interest of easing interpretation, Table 2.2 reports the marginal effects of the determinants of CA adoption. The results indicate that the key factors that significantly influence adoption decisions include household characteristics (age, gender, education), resource constraints (livestock, farm size), institution and social capital (extension contacts, member of FBO), and plot-level characteristics (soil erosion). The coefficient of farm size is negative and statistically significant (at the 1% level). That is, a 1-acre increase in farm size decreases adoption by about 6%, suggesting that maize farmers cultivating smaller farm sizes are more likely to adopt CA practices such as compost and manure application (see Table 2.A3). A possible explanation for this finding is that farmers with larger farms may not have a higher incentive to implement these practices due to the cumbersome nature as well as the unavailability of these organic materials in larger quantities. The coefficient of age is positive and significantly different from zero, suggesting that older farmers with more farming experience are more likely to adopt, a result consistent with earlier work on technology adoption (e.g. Shahzad and Abdulai, 2020).

Consistent with previous findings (e.g. Abdulai and Huffman, 2014), our estimates reveal that more educated farmers have a higher probability of adopting CA practices. The estimates show that soil conditions are strong predictors of adoption of CA practices. Specifically, farms characterized by moderate and severe erosion are more likely to undertake conservation agriculture techniques. The results also show that livestock ownership increases farmer's propensity to adopt, underscoring the important role livestock plays as a source of organic fertilizer (see Abdulai and Goetz, 2014). Also, the estimate of the moderately fertile variable is positive and statistically significant (at the 5% level), suggesting that CA practices are more likely to be implemented on moderately fertile farms. The coefficient of the variable representing extension service is positive and statistically significant, indicating that more contacts with extension agents increase the likelihood of adoption. Similarly, FBO membership

is positive and highly significant (at the 1% level), suggesting that farmers belonging to these associations are more likely to adopt, a finding which further underscores the crucial role of farmer groups in disseminating information on agricultural technologies.

Table 2.2: Marginal Effects of the determinants of CA adoption

Variables	Marginal effects	Standard Error
Age	0.005***	0.001
Male	0.172***	0.034
Household size	-0.011*	0.006
Education	0.009**	0.004
FBO	0.103***	0.038
lnFarm size	-0.066***	0.025
Extension contact	0.007**	0.003
Credit constraints	-0.048	0.037
lnMarket distance	-0.093***	0.022
Livestock	0.004	0.007
Hired labor	0.003	0.002
Slope	-0.022	0.035
Moderate erosion	0.244***	0.029
Severe erosion	0.295***	0.075
Fertile plot	0.080	0.052
Moderately fertile plot	0.098*	0.051
Upper East	-0.016	0.048
Upper West	0.122***	0.042
Farm Distance	-0.093***	0.014
χ^2 test of instrument	32.32	
p value of instrument	0.000	
Number of observations = 512		

Note: Table 2.2 reports the marginal effects estimates of the adoption decision from the probit selection model. The p – value for the excluded instrument (farm distance) is reported. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Both extension contact and FBO membership results are consistent with previous findings from the literature (e.g. Ma et al., 2018). The results also reveal that male-headed households are more likely to invest in these practices to improve their soils compared to female-headed households.

2.4.2 Heterogeneity in Treatment Effect in Observed Characteristics (Maize Yields and Farm Net Returns)

Tables 2.3 and 2.44 report the treatment effect of adoption based on equation (8), for maize yields and farm net returns, respectively. The estimates indicate the extent to which treatment

effects differ depending on the farmers' observed characteristics. Columns 1 and 2 in the Tables report the estimates of the outcome equations in the untreated (nonadoption) state (δ_0)¹⁵ and the treatment effect ($\delta_1 - \delta_0$)¹⁶ respectively.

Table 2.3: Maize Yields (log) Equation

Variable	Outcome δ_0		Outcome ($\delta_1 - \delta_0$)	
	(1)		(2)	
	Coefficient	SE	Coefficient	SE
Age	-0.005	0.004	0.005	0.005
Male	-0.08	0.11	0.12	0.16
Household size	0.04***	0.01	-0.02	0.02
Education	0.002	0.01	0.01	0.01
FBO	0.12	0.10	-0.08	0.13
lnFarm size	0.45***	0.09	-0.23**	0.11
Extension contact	0.03***	0.01	0.02**	0.01
Credit constraints	-0.06	0.07	-0.28**	0.11
Livestock	0.02	0.02	-0.01	0.02
Hired labor	0.02***	0.005	-0.01*	0.007
Slope	-0.12*	0.07	0.11	0.11
Moderate erosion	-0.08	0.12	0.14	0.16
Severe erosion	-0.62	0.48	0.57	0.54
Fertile plot	-0.02	0.11	-0.05	0.19
Moderately fertile plot	-0.05	0.09	0.14	0.18
Upper East	-0.03	0.06		
Upper West	0.13***	0.05		
Constant	6.45***	0.17	0.31	0.37
Test of observ. heterogeneity, p -value			0.000	
Number of observations ^a = 512				

Note: Columns 1 and 2 present the estimates of the maize yield equation in the nonadoption state and the treatment effect (difference between adoption and the nonadoption states) respectively. The reported p -value test of observed heterogeneity is a test of whether the treatment effect ($\delta_1 - \delta_0$) varies across the observed covariates. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

^a The number of observations for the δ_0 outcome model is 212.

Farm size has a positive and significant effect in the untreated state, implying that a percentage increase in farm size tends to increase yields and net revenues. However, the treatment effect is negative and statistically significant on maize yields, suggesting that farmers with smaller farm sizes tend to obtain significantly higher yield gains after adoption. These

¹⁵ The coefficients (in Tables 2.3, 2.4 and 2.5) measure effects on the outcome in the untreated or non-adoption state (i.e. (δ_0), in eqn 8).

¹⁶ The coefficients (in Tables 2.3, 2.4 and 2.5) measure the difference of the effects between the treated and the untreated state (i.e. ($\delta_1 - \delta_0$) in eqn 8). In other words, they can interpreted as differences in treatment effects across covariate values, just like an interaction between treatment status and a covariate in an OLS regression (Andresen (2018)).

findings suggest that adopting CA practices helps smaller farms to catch up with large-scale farms in terms of yields. This may be due to the fact that CA practices allow smallholders to use inputs more efficiently.

Table 2.4: Farm Net Returns (log) Equation

Variable	Outcome δ_0		Outcome ($\delta_1 - \delta_0$)	
	(1)		(2)	
	Coefficient	SE	Coefficient	SE
Age	-0.01**	0.01	0.02**	0.01
Male	-0.22	0.18	0.36	0.29
HH size	0.02	0.03	-0.03	0.04
Education	-0.02	0.02	0.05*	0.03
FBO	0.20	0.19	-0.27	0.29
lnFarm size	0.31***	0.10	-0.11	0.17
Extension contact	0.02	0.02	0.03	0.02
Credit constraints	-0.49***	0.14	-0.63	0.20
lnMarket distance	0.38**	0.16	-0.48**	0.19
Livestock	0.04	0.03	0.01	0.04
Hired labor	0.02***	0.01	-0.05***	0.01
Slope	-0.07	0.14	-0.01	0.20
Moderate erosion	-0.11	0.18	0.08	0.26
Fertile plot	0.18	0.18	-0.49	0.37
Moderately fertile plot	-0.07	0.20	0.03	0.36
Upper East	-0.06	0.10		
Upper West	0.17*	0.09		
Constant	0.52***	0.55	1.98***	0.63
Test of observ. heterogeneity, p -value			0.000	
Number of observations ^a = 512				

Note: Columns 1 and 2 present the estimates of the farm net return equation in the nonadoption state and the treatment effect (difference between adoption and the nonadoption states) respectively. The reported test of observed heterogeneity is a test of whether the treatment effect ($\delta_1 - \delta_0$) varies across the observed covariates. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

^a The number of observations for the δ_0 outcome model is 212.

We also observe a similar pattern concerning hired labor. In the untreated state, farmers who are less labor endowed experience lower maize yields and farm net returns compared to those endowed with more labor. This disadvantage in benefits disappears when they adopt, implying that farmers with a smaller labor endowment are able to catch up with farmers endowed with more labor with respect to maize yields and net farm returns after adoption.

In the untreated state, farmers who are not liquidity-constrained experience 6 and 49 percentage points increases in maize yields and net returns than liquidity-constrained farmers,

respectively, although not significant in the case of maize yields. Interestingly, when those who are not liquidity-constrained adopt CA practices, they experience even higher gains of about 49 percentage points increases in maize yields than those who are liquidity-constrained. The treatment effect is however not significant in the case of net returns. The estimate of the extension variable is positive and statistically significant in the untreated state for maize yields, suggesting that farmers with more extension contacts tend to experience more yields. Similarly, the treatment effect is also positive and statistically significant, suggesting that farmers with more extension contacts tend to have higher gains in yields after adoption.

2.4.3 Heterogeneity in Treatment Effect in Observed Characteristic (Inorganic N Fertilizer Use)

Table 2.5 reports results on the treatment effect of adoption on inorganic N fertilizer use. The estimate of the variable on age is not statistically significant in the untreated state. However, the treatment effect is negative and significantly different from zero, suggesting that compared to younger farmers, older farmers tend to reduce their use of inorganic N fertilizer after adoption. In the untreated state, male-headed households tend to significantly apply more inorganic N fertilizer. At the same time, their treatment effect is negative, suggesting that compared to female-headed households, they significantly cut down on N from inorganic sources after adoption.

Farms with moderate soil erosion tend to significantly (at the 10% level), *albeit* marginal, use more inorganic N fertilizer at the untreated state. However, the treatment effect is negative, implying that, compared to farms without erosion, moderately eroded farms reduced their inorganic N use after adoption. A similar pattern emerges for moderately fertile plots. At the untreated state, moderately fertile farms tend to use more inorganic N fertilizer. Interestingly, the treatment effect shows that, compared to infertile farms, moderately fertile farms significantly cut down the use of inorganic N fertilizer after adoption.

Table 2.5: Inorganic N Fertilizer Use (log) Equation

Variable	Outcome δ_0		Outcome ($\delta_1 - \delta_0$)	
	(1)		(2)	
	Coefficient	SE	Coefficient	SE
Age	0.01	0.01	-0.03*	0.02
Male	1.01***	0.35	-1.87***	0.52
HH size	0.04	0.04	0.01	0.06
Education	-0.01	0.04	0.004	0.05
FBO	0.50	0.35	-0.59	0.51
lnFarm size	0.24	0.28	0.42	0.47
Extension contact	0.02	0.04	0.006	0.05
Credit constraints	0.06	0.28	-0.49	0.49
Livestock	0.04	0.05	-0.04	0.07
Hired labor	0.03*	0.02	-0.02	0.03
Slope	-0.19	0.26	-0.08	0.40
Moderate erosion	0.63*	0.36	-0.94*	0.57
Fertile plot	0.16	0.31	-0.75	0.59
Moderately fertile plot	0.56	0.37	-1.19*	0.62
Upper East	0.33*	0.19		
Upper West	0.29	0.19		
Constant	2.77***	0.65	2.42*	1.26
Test of observ. heterogeneity, p -value			0.000	
Number of observations ^a	= 512			

Note: Columns 1 and 2 present the estimates of the Inorganic N fertilizer use equation in the nonadoption state and the treatment effect (difference between adoption and the nonadoption states) respectively. The reported test of observed heterogeneity is a test of whether the treatment effect ($\delta_1 - \delta_0$) varies across the observed covariates. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

^a The number of observations for the δ_0 outcome model is 212.

These findings could be attributed to improvements in soil conditions due to the use of leguminous cover crops and other conservation practices, and thus highlights their importance in reducing run-off, erosion, and ensuring that soil nutrients are retained.

2.4.4 Average and Marginal Treatment Effects Estimates

An important motivation of this study is to ascertain whether farmers benefit from the adoption of CA practices and how this effect varies with respect to their unobserved characteristics. The MTE illustrates whether farmers who are more likely to adopt based on unobservable traits have higher or lower gains from adoption. Figure 2.1 displays the MTE estimates evaluated at the mean values of the observed covariates. In general, the pattern of the MTE estimates as shown

in Figure 2.1, is largely consistent with the intuition and concept of conservation agriculture as expressed earlier in this paper.

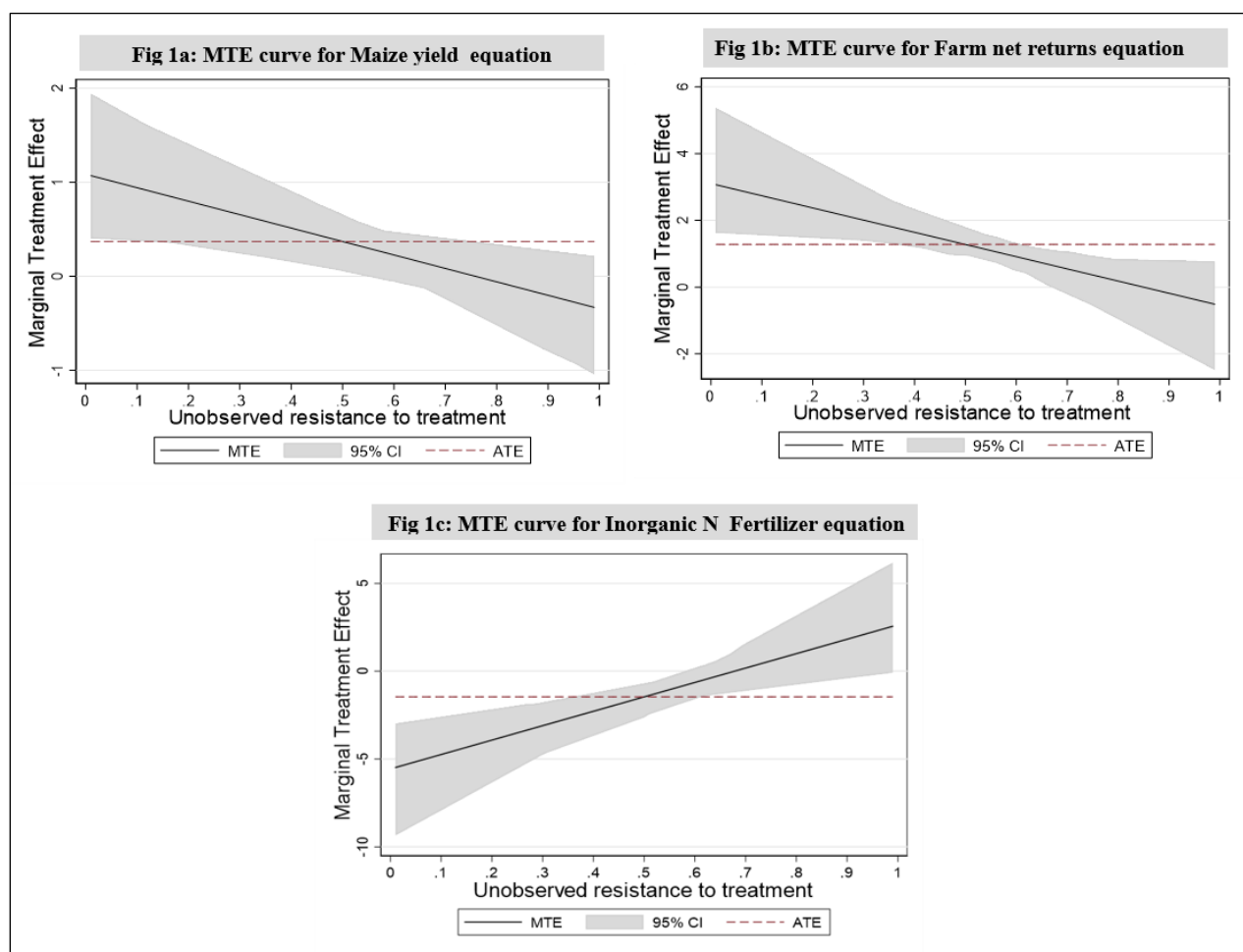


Figure 2.1: MTE curves for outcome equations.

This Figure shows the estimated MTEs of the three outcome equations estimated at the mean values of the observed covariates (X)

In particular, the MTE estimates for maize yields and farm net returns in Figure 2.1a and 1b, respectively, show a declining MTE, implying that farmers who are more likely to adopt CA practices, that is, those with low unobserved resistance to treatment (U_D), tend to benefit more from its adoption, that is, a pattern of positive selection on unobserved gains. Consistent with our findings, a recent study by Kim et al. (2019) in rural Tanzania found that the adoption of CA practices such as maize-legume intercropping and organic fertilizers (e.g. manure or compost) were associated with increases in maize yields and income, compared to nonadopters. Our results further suggest significant heterogeneity (at 10 % and 5% levels for maize yields

and farm net returns, respectively) in the returns to the adoption of CA practices, varying from approximately -0.5 for high U_D farmers (who would lose from CA adoption) to about 1.1 for low U_D farmers (who would gain from CA adoption) in the case of maize yields. Furthermore, we also observe returns to adoption from -0.5 for high U_D farmers to around 3.0 for low U_D farmers, suggesting that farmers who are less likely to adopt, would lose if they adopt. The lower gains for farmers who are less likely to adopt are corroborated by Suri (2011) who argued that farmers decide to adopt agricultural technologies on the basis of their comparative advantage.

Interestingly, in the case of inorganic N fertilizer use, a different pattern is observed. As shown in Figure 2.1c, the MTE curve exhibits an increasing function with respect to the unobserved resistance to treatment (U_D) and mirrors a pattern of reverse selection on gains, suggesting that farmers who are more likely to adopt CA practices, cut down inorganic N usage to a greater extent after adoption. The result also depicts significant heterogeneity (at the 1% level) in the use of inorganic N fertilizer ranging from approximately 2.6 for high U_D farmers (who would increase their inorganic N fertilizer use) to about -5.4 for farmers with U_D close to 0 (who would cut down greatly on inorganic N use). As argued by ten Berge et al. (2019), soil nitrogen requirement varies with respect to the level of nitrogen use efficiency. Minimizing nitrogen losses through the use of organic soil amendments, cover cropping and maize-legumes rotation improve soil fertility over time and build up nitrogen capital in the soil, thus requiring relatively less N from inorganic fertilizers (Ma et al., 2018).

On the other hand, farmers with lower adoption desires would not cut down on inorganic N fertilizer usage by an equivalent amount even if they chose to adopt. Intuitively, the pattern observed implies positive selection on gains, since farmers who adopt CA practices tend to cut down on inorganic N fertilizer usage, because of the adoption of alternative soil nitrogen

enhancing practices such as maize-legumes rotation, compost, organic manure, and cover cropping.

Table 2.6 presents the average gains from the adoption of CA practices for different categories of farmers. We show the estimates of the different treatment effect parameters as weighted averages of the MTE: the ATE (average treatment effect), TT (effect of treatment effect on the treated), and TUT (effect of treatment effect on the untreated). The estimated ATEs are 0.37 and 1.28 for maize yields and net returns, respectively, (See columns 2 and 3 of Table 2.6), implying that for a farmer picked at random from the population of farmers, adopting CA practices raises the yields by 37 percentage points and net returns by 128 percentage points. In the case of the TT, which places more weight on farmers with high propensity scores, the gain from adoption for the average farmer who adopts is significantly higher, at 65 percentage points for maize yields and 193 percentage points for farm net returns. However, the findings for the TUT are not statistically significant in the case of either maize yields or farm net returns. The different treatment effect parameters suggest that the return to adoption for adopters is higher than for either the random farmer or for nonadopters ($TT > ATE > TUT$), implying a positive selection on gains from CA adoption.

Column 3 of Table 2.6 presents the estimates of the treatment effect parameters for inorganic N fertilizer use. The results depict the following sequence; $TT (-288) > ATE (-142) > TUT (62)$, suggesting that the average farmer who is more likely to adopt significantly cuts down the usage of N from inorganic sources to a larger extent after CA adoption, compared to a non-adopter. These findings show a pattern of positive selection on gains, implying that adoption tends to build up soil nitrogen capital and thus requires less nitrogen from inorganic sources.

Further, the findings in Table 2.6 as well as the MTE curves (see Figure 2.1) also imply that the adoption of CA practices would bring little benefits (and at some point, even result in

negative effects) for nonadopters if they decided to adopt. It is significant to indicate that nonadopters are generally less endowed due to a number of structural and institutional factors.

Table 2.6: Estimates of Treatment Effects Parameters

Parameter	Maize yields (log) (1)	Farm net returns (log) (2)	Inorganic N Fertilizer use (log) (3)
ATE	0.37*** (0.13)	1.28*** (0.27)	-1.46*** (0.51)
TT	0.65*** (0.25)	1.93*** (0.55)	-2.96*** (0.97)
TUT	-0.02 (0.18)	0.36 (0.31)	0.65 (0.78)
Test of observable heterogeneity, p -value	0.000	0.000	0.000
Test of essential heterogeneity, p -value	0.072	0.042	0.008
Number of observations = 512			

Note: This table presents the estimates of different treatment effects parameters; ATE (average treatment effect), TT (effect of treatment on the treated), TUT (effect of treatment on the untreated). The reported test of observed heterogeneity is a test of whether the treatment effect ($\delta_1 - \delta_0$) varies across the observed covariates. The p -value for the test of essential heterogeneity, which is a test for a nonzero slope of the MTE curve is presented. Bootstrapped standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

First, CA practices are knowledge and management-intensive, requiring a considerable amount of training and on-farm extension support to provide the needed backstopping (Faltermeier and Abdulai, 2009; Jayne et al., 2019). However, this category of farmers are faced with limited extension contacts and training opportunities, which are key to realizing the needed benefits from conservation agriculture. Second, CA practices demand precision as to the timing of tasks. However, farms of nonadopters are more likely to be located at greater distances from the homesteads. This setting at hand leads to longer journeys and shortens the time required to work on the farm. Thus, labor intensity (person-hours per day/season) is likely to decrease as farm distance increases (Ali et al., 2019).

Our results generally reveal that, the average farmer with a high propensity to adopt (low U_D) cuts down on the usage of N from inorganic sources to a greater extent and experiences significant increases in maize yields and farm net returns when compared to those with low propensity to adopt. Conservation agriculture practices such as maize-legume rotations, cover

cropping, manure, and compost tend to improve organic matter, build up nitrogen capital, and in turn have direct and positive effects on soil fertility, which inorganic fertilizer does not, but indirectly through crop output. Farmers, therefore cannot rely on inorganic N fertilizer alone, due to nutrients deficit arising out of nutrients extraction through crop harvest, and removal of crop residues, which decrease soil organic matter content.

To test the sensitivity of the baseline estimation results, we conduct robustness checks that include using different functional forms of $K(P)$ such as cubic, quartic and semiparametric approaches, allowing for a more flexible pattern of the MTE curve such as the U-shaped (Cornelissen et al., 2018). The shapes of these curves from the alternative specifications are identical to that of our baseline MTE curves (see Figure 2.A4 in the supplementary appendix). Further, we use a quadratic term of the farm distance variable and its interaction with the variable on the distance to the nearest extension office as an instrument in separate estimations. The resulting estimates (Table 2.A4 in the supplementary appendix) are of a similar pattern and corroborates our baseline results.

2.4.5 Policy Simulations

To the extent that farmers who are less likely to adopt conservation agriculture practices (high U_D) have lower returns or even losses suggests that appropriate policy changes could induce (change in propensity scores) them into adoption. We therefore, estimate the mean effect of two policy alternatives by computing the policy-relevant treatment effects (PRTE)¹⁷ (see Heckman and Vytlačil, 2001; Carneiro et al., 2017) as a weighted average over the MTE curves. The first policy alternative addresses the fact that many CA practices have high implementation costs, which limits their adoption (Petersen and Snapp, 2015). Thus, well-endowed farmers are more

¹⁷ We compute the PRTE as follows: $PRTE(x) = \int MTE(X, U_D) f_{U_D|X}(U_D|X, C(p) = 0, C(\bar{p}) = 1) dv$ (9)

where P (policy instrument) does not affect the outcome equations and shift from $P=p$ to $P = \bar{p}$.

It is also important to note that, in situations where the policy instruments are not the same as the excluded instrument used to identify the baseline models, as in this study, the former should also affect adoption, but should not enter directly into the outcome equations. These instruments were not included in the baseline estimations because the baseline results for the treatment effect parameters were not different from that of the PRTEs (see appendix Tables 2.A5 and 2.A6).

likely to adopt CA practices, raising concerns about potential endogeneity. We therefore compute the average village-level cost of implementation. If we had used the farmer's actual value, the result would have been biased toward well-endowed farmers. We therefore simulate the impact of reducing the cost of implementing CA practices by 50%.

The second policy alternative acknowledges that CA practices are knowledge and management intensive. Mockshell and Villarino (2019) highlighted the limited policy and institutional support (e.g., training and research) for their upscaling. To promote widespread adoption, farmers need to be exposed to further training that includes field demonstrations and advisory services. Capacity building for farmers (e.g., training and field demonstrations in the study area) is usually organized in groups at the village or community level. We therefore simulate a policy change that increases the average community-level training days on CA practices (including field demonstrations) by approximately 50% (i.e., 4.1 to 6.2 days).

Table 2.7: Policy-Relevant Treatment Effects Estimates

Outcome Variable	Implementation cost			Training days		
	Propensity scores		Policy effect	Propensity scores		Policy effect
	Baseline (1)	Policy (2)	PRTE (3)	Baseline (4)	Policy (5)	PRTE (6)
Maize yields (log)	0.58	0.67	0.19 (0.16)	0.58	0.69	0.22* (0.13)
Farm net returns (log)	0.58	0.67	0.93*** (0.22)	0.58	0.70	0.58** (0.24)
Inorganic N fertilizer (log)	0.58	0.65	-0.89** (0.43)	0.58	0.70	-0.83** (0.45)

Number of observation = 512

Note: This table presents the PRTE (columns 3 and 6) per farmer induced to adopt based on the two policy alternatives (increasing training days and reduction in implementation cost). Column 1 and 4 reports the propensity scores from the baseline line specifications of the policies. Columns 2 and 5 report the increases in the propensity score as a result of the policy changes. Bootstrapped standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figures 2.A1 and 2.A2 (in the supplementary appendix) show the PRTE weights for the two policy measures with the estimates reported in Table 2.7. Columns 1 and 4 of Table 2.7 show the propensity scores for the baseline specifications. As shown in columns 2 and 5, both policies induce nonadopters into adoption. In particular, reducing the cost of implementation

increases the probability of adoption by 9 percentage points for both the outcome equations of maize yields and farm net returns and 7 percentage points for inorganic N fertilizer use. In addition, the returns to adoption for the average farmer induced to adopt as a result of the policy change (PRTE) is 93 percentage points for farm net returns and -89 percentage points for inorganic N fertilizer use (see column 3 of Table 2.7).

A similar pattern is observed, *albeit* with higher probabilities, in the case of the second policy measure. Increasing training and demonstration days on CA practices encourage nonadopters to adopt, increasing the probability of adoption by 11 percentage points for maize yields, and 12 percentage points for both farm net returns and inorganic N fertilizer use. The PRTEs are statistically significant for all three specifications, at 22 percentage points and 58 percentage points for maize yields and farm net returns, respectively, and -83 percentage points for inorganic N fertilizer use.

2.5 Conclusion and Policy Implication

This study uses a recent survey of farm households to examine the heterogeneity in the effect of adoption of conservation agriculture (CA) practices on farm performance and inorganic N fertilizer use in the northern Savanna regions of Ghana. We employ the marginal treatment effect (MTE) approach that allows us to estimate both the average treatment effects of adoption of CA practices, and the distribution of the impact of adoption on unobserved resistance to adoption. Understanding the heterogeneity (both observed and unobserved) in the effect of adoption has implications on policy decisions.

The empirical results reveal significant heterogeneity in the effect of adoption of CA practices on maize yields, farm net returns, and inorganic N fertilizer use, suggesting that farmers' adoption decisions are based on their comparative advantage. For the two outcome variables of maize yields and farm net returns, we find that farmers with lower resistance to adoption tend to have higher maize yields and farm net returns compared to those with higher

resistance. In the case of inorganic N fertilizer use, we find that farmers with high probability (lower resistance) of adoption tend to significantly reduce inorganic N usage after adoption. Whereas farmers with low probability of adoption use relatively higher amount of inorganic N fertilizer, the MTE estimates show that they also realize lower gains on maize yields and farm net returns.

These findings are intuitive, particularly because most farmlands in the northern Savanna regions are characterized by low organic matter, which is key for building up soil N capital and improving soil fertility (Häring et al., 2017). As argued by Poore and Nemecek, (2018), for every kilogram of inorganic N applied to crops, it is estimated that between 60 and 400g are lost into reactive forms, particularly due to inherent poor soil conditions, thereby reducing the effectiveness of inorganic N fertilizers on maize yields. Our findings further highlight the importance of CA practices in improving soil organic matter content, which is able to release available N that may correspond with the N requirement of the crop, thereby contributing to a reduction in the usage of N from inorganic sources.

Despite potentially significant gains, we also find that CA adoption could result in small gains, or even negative effects for nonadopters if they were to adopt due to a number of institutional (e.g. inadequate extension services, training) and structural (e.g. poor transportation and road networks) limitation faced by this category of farmers. As highlighted by the African Union's 2017 progress report on the *2014 Malabo Declaration*, Ghana and other countries in sub-Saharan Africa need to urgently increase the share of arable lands under conservation agriculture (African Union Commission, 2018).

Our findings provide a number of salient policy implications. First, ensuring widespread adoption and benefits for farmers would require increased capacity building for farmers through training and field demonstrations. Additionally, and as evident from our findings, CA adoption would require a more vibrant and proactive extension system with sufficient basic soil testing

tools to promote location-specific agronomic recommendations (due to the heterogeneity of soil biophysical characteristics). Second, providing incentives to implement CA practices could also boost adoption. For instance, refocusing the fertilizer subsidy program as part of the government's "Planting for Food and Jobs" Program to emphasize CA practices (e.g. cover cropping, maize-legumes rotation, and organic amendments such as animal manure and compost) could play a crucial role in promoting conservation agriculture, thereby ensuring a buildup of soil N in the medium to long-term.

Third, some of these internal inputs (e.g. crop residues, manure, compost) may not be available in sufficient quantities due to low biomass production. Thus, the government, through public-private partnerships such as the "One District, One Factory" initiative, could support the private sector in developing the value chains for these inputs. Until the markets for these organic materials and biomass are developed, it will not be possible to drastically reduce the use of inorganic N fertilizer in the short-run. Instead, there should be a conscious effort to supplement its use with CA practices as part of a comprehensive soil management strategy.

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Appendix

Table 2.A1: Test of Validity of the Excluded Instrument

Dependent Variable	Maize yield	Farm net returns	Inorganic N fertilizer use
Farm distance	-0.02 (0.02)	-0.07 (0.04)	0.01 (0.07)
Constant	6.394*** (0.436)	5.571*** (0.889)	3.112*** (0.479)
Sample size	212	212	212

Standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A2: Correlation Between Outcome and Instrumental Variables

Dependent Variable	Farm distance
Maize yield	-0.02
Farm net returns	-0.13
Inorganic N fertilizer use	0.11

Table 2.A3: Summary of descriptive statistics of CA practices

CA practices	Observations	Farm size		Average years of adoption	
		Mean	Std. Dev	Mean	Std. Dev
organic amendments (compost, manure)	144	2.79	1.55	6.59	1.68
maize-legumes rotation	222	4.76	2.94	5.84	1.80
zero tillage	196	5.15	3.32	4.16	1.45
cover cropping	236	4.81	3.15	6.47	1.54
mulching	186	4.58	2.74	5.34	1.49

^a An average farmer adopted on the average three CA practices. Due to the multiple adoption, the observations do not sum up to 512.

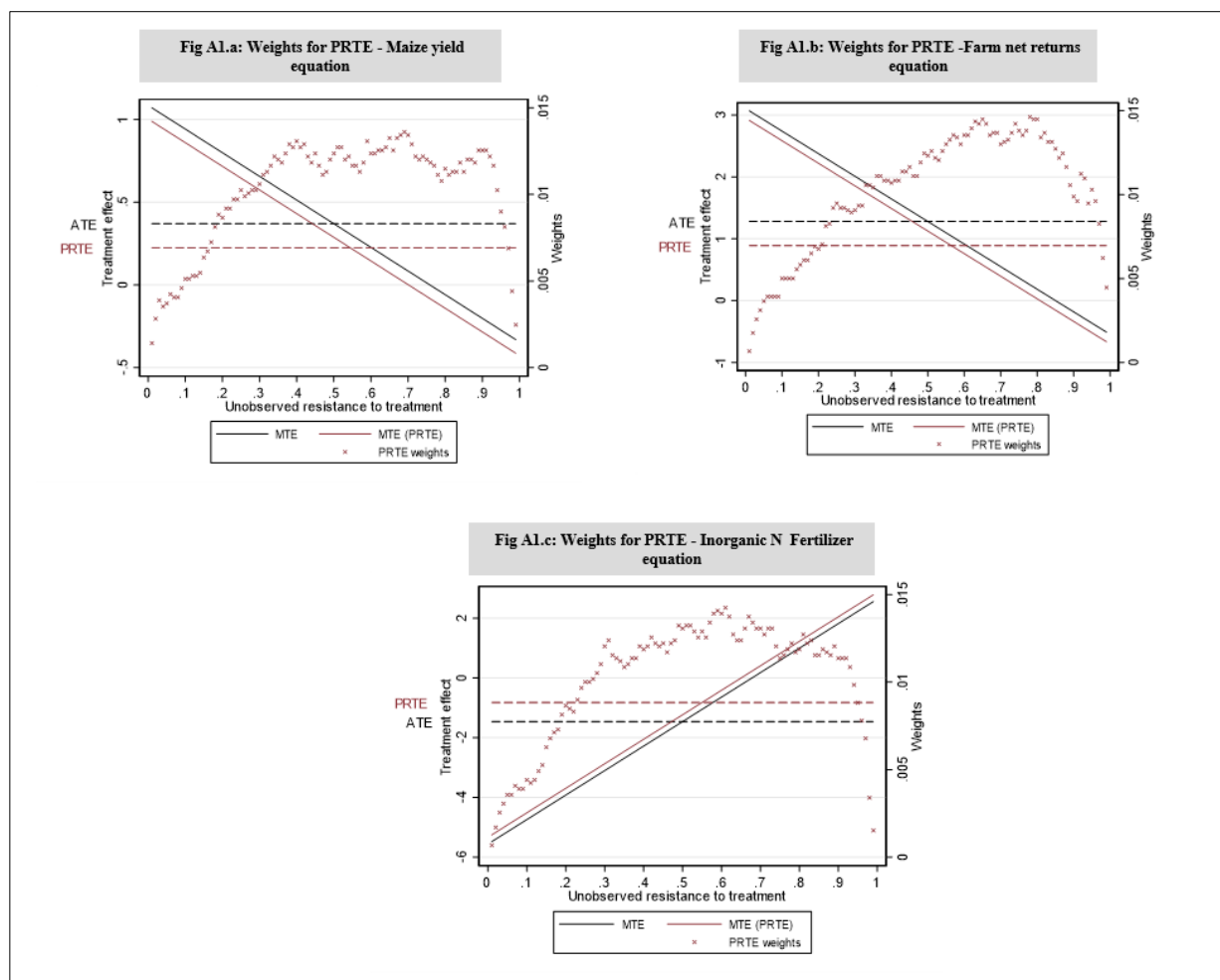


Figure 2.A1: Distribution of the PRTE weights (increasing CA training days)

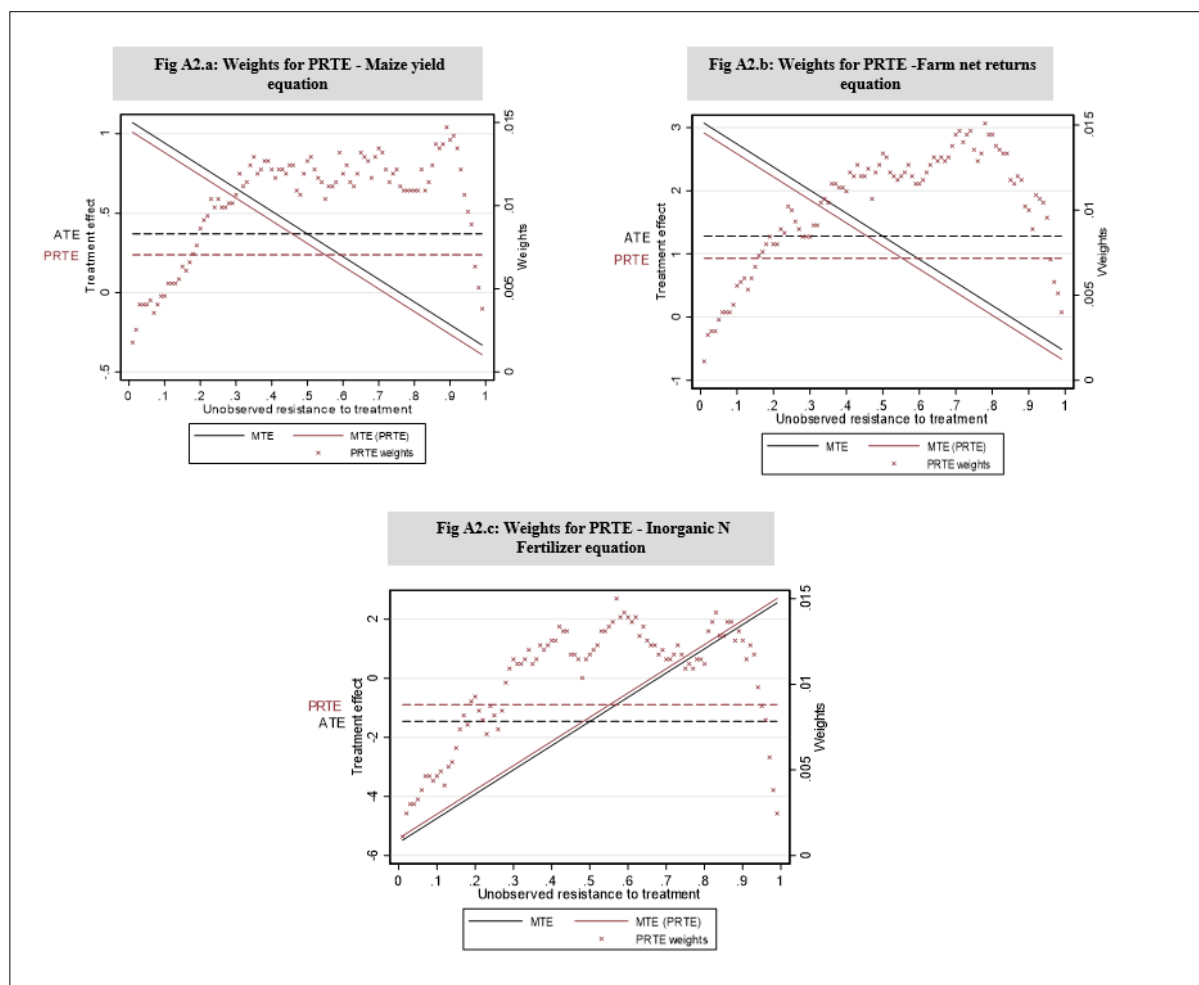


Figure 2.A2: This Figure graphs the distribution of the PRTE weights (decreasing CA implementation cost)

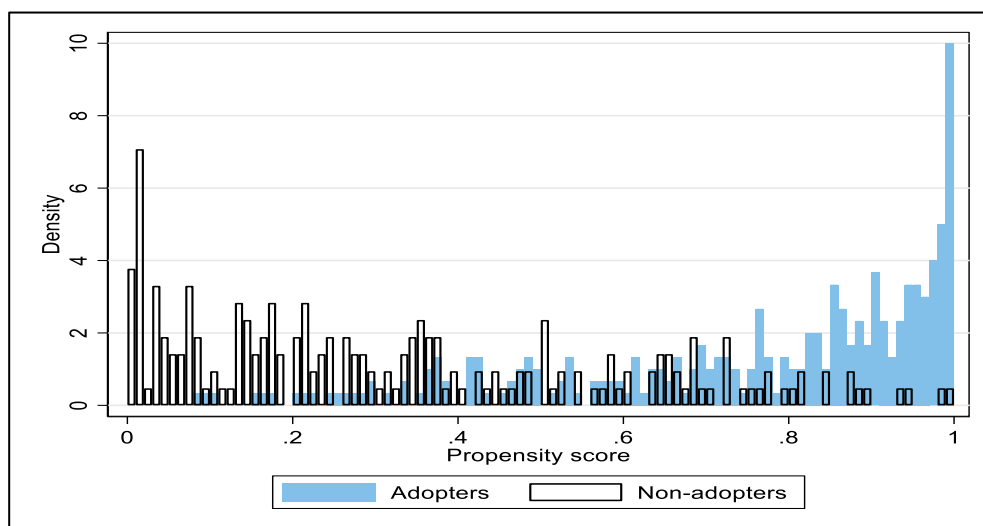


Figure 2.A3: Support of Propensity Scores P for $C=1$ and $C=0$

P is the estimated probability of adoption. The Figure shows the estimated probability of CA adoption. It is estimated from a first stage selection equation model.

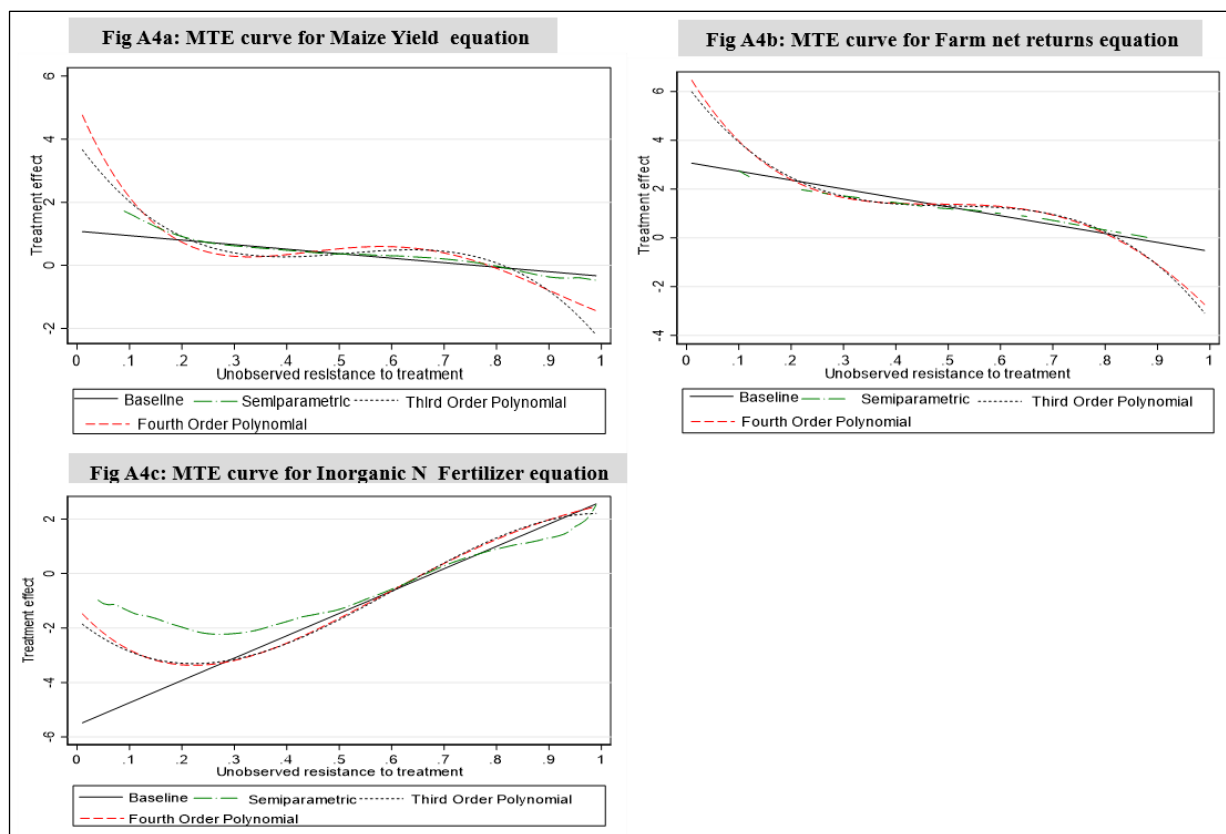


Figure 2.A4: Robustness Checks (1) of the Functional Forms.

This Figure depicts the alternative specifications of the MTEs using different functional forms such as the Third Order Polynomial (cubic), Fourth Order Polynomial (quartic), and the Semiparametric model. The solid curve denotes our baseline specification.

Table 2.A4: Robustness Checks Results (2)

Panel A Parameters	Baseline		Quadratic term		Interacted extension distance	
	Maize yields	Farm net returns	Maize yields	Farm net returns	Maize yields	Farm net returns
	(log) (1)	(log) (2)	(log) (3)	(log) (4)	(log) (5)	(log) (6)
ATE	0.37*** (0.13)	1.28*** (0.27)	0.29** (0.12)	1.09*** (0.17)	0.30** (0.12)	1.04*** (0.32)
TT	0.65*** (0.25)	1.93*** (0.55)	0.52*** (0.19)	1.53*** (0.30)	0.63*** (0.21)	1.52*** (0.66)
TUT	-0.02 (0.18)	0.36 (0.31)	-0.03 (0.16)	0.48 (0.30)	-0.16 (0.18)	0.36 (0.47)
Test for essential heterogeneity, p -value	0.072	0.042	0.041	0.035	0.026	0.221

Note: This table presents the estimates of the robustness checks. Panel A shows the robustness checks for maize yields and farm net returns. Columns 1 and 2 refer to the baseline model in table 6. In columns 3 and 4, we use the quadratic term of the instrument. In columns 5 and 6, the instrument interacts with the distance to the extension office. The p -value for the test of essential heterogeneity, which is a test for a nonzero slope of the MTE curve is presented. Bootstrapped standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B Parameters	Baseline	Quadratic term	Interacted extension distance
	Inorganic N Fertilizer use	Inorganic N Fertilizer use (log)	Inorganic N Fertilizer use (log)
	(log) (1)	(log) (2)	(log) (3)
ATE	-1.46*** (0.51)	-1.20*** (0.38)	-1.03** (0.56)
TT	-2.96*** (0.97)	-2.46*** (0.68)	-1.67** (1.04)
TUT	0.65 (0.78)	0.57 (0.81)	-0.13 (0.86)
Test for essential heterogeneity, p -value	0.008	0.008	0.283

Note: Table A4 panel B presents the estimates of the robustness checks for inorganic N fertilizer use. Column 1 refers to the baseline model in table 6 (col, 3). In column 2, we use the quadratic term of the instrument. In column 3, the instrument interacts with the distance to the extension office. The p -value for the test of essential heterogeneity, which is a test for a nonzero slope of the MTE curve is presented. Bootstrapped standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.A5: Estimates of treatment effects parameters based on PRTE (CA training days)

Parameter	Maize yields (log) (1)	Farm net returns (log) (2)	Inorganic N Fertilizer use (log) (3)
ATE	0.37** (0.15)	1.28*** (0.29)	-1.46*** (0.47)
TT	0.65*** (0.25)	1.93*** (0.59)	-2.96*** (0.94)
TUT	-0.02 (0.20)	0.36 (0.40)	0.65 (0.67)
Test of observable heterogeneity, <i>p</i> -value	0.000	0.000	0.042
Test of essential heterogeneity, <i>p</i> -value	0.064	0.071	0.011
Number of observations = 512			

Note: This table presents the estimates of different treatment effects parameters based on the PRTE (increasing CA training days); ATE (average treatment effect), TT (average treatment effect on the treated), TUT (average treatment effect on the untreated), and the *p* -values for the test of observed and essential (unobserved) heterogeneities for the three main outcome variables. Standard errors are reported in parentheses. Significance level at **p* < 0.1, ***p* < 0.05, ****p* < 0.01

Table 2.A6: Estimates of treatment effects parameters based on PRTE (cost of implementation)

Parameter	Maize yields (log) (1)	Farm net returns (log) (2)	Inorganic N Fertilizer use (log) (3)
ATE	0.37** (0.17)	1.28*** (0.30)	-1.46*** (0.48)
TT	0.65** (0.33)	1.93*** (0.56)	-2.96*** (1.04)
TUT	-0.02 (0.19)	0.36 (0.31)	0.65 (0.79)
Test of observable heterogeneity, <i>p</i> -value	0.016	0.000	0.007
Test of essential heterogeneity, <i>p</i> -value	0.163	0.036	0.026
Number of observations = 512			

Note: This Table presents the estimates of different treatment effects parameters based on the PRTE (decreasing CA implementation cost); ATE (average treatment effect), TT (average treatment effect on the treated), TUT (average treatment effect on the untreated), and the *p* -values for the test of observed and essential (unobserved) heterogeneities for the three main outcome variables. Standard errors are reported in parentheses. Significance level at **p* < 0.1, ***p* < 0.05, ****p* < 0.01

Chapter 3

Minimum Tillage as Climate-Smart Agriculture Practice and its Impact on Food and Nutrition Security

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Abstract

We employ plot-level and household data combined with geo-referenced historical weather data to provide microeconomic evidence of the impact of minimum tillage (MT) on maize yields, food and nutrition security, and farm labor demand in Ghana. We account for potential selection bias and omitted variable problems by using an ordered probit selection model to estimate two transition-specific treatment effects: from conventional tillage systems to short-term MT adoption and from short-term to long-term MT adoption. The empirical results show that transitioning into long-term MT adoption significantly increases households' food and nutrient security and contributes to a net saving in labor demand.

3.1 Introduction

There is growing consensus about the damaging effects of conventional agriculture on soil quality and ecosystem services and the need to transition and transform food production systems to become more environmentally sustainable (UNDP, 2019). Soil degradation as one of the global environmental challenges is happening at an alarming rate and has contributed to a decline in agricultural productivity and high risk of crop failure in many parts of the world. Intensive conventional tillage systems, which involve a sequence of practices, such as ploughing, ridging, and harrowing, leave the soil surface bare and loosen soil particles, causing high levels of soil surface runoff and erosion as well as decreased soil nutrients (Kassam et al., 2009). Available evidence indicates that an estimated 25 percent of the world's total land area has been degraded while 24 billion tons of fertile soils are lost every year, mainly due to unsustainable land-use practice (GEF, 2019).

The United Nations Convention to Combat Desertification (UNCCD) reports that approximately two-thirds of arable lands in sub-Saharan Africa are estimated to be subjected to soil degradation through soil compaction, soil erosion, and nutrient loss, with at least 485 million people, especially smallholder farmers and rural communities being affected (UNCCD, 2013). Thus, the agriculture sector contributes directly and indirectly to substantial emission of greenhouse gases. More precisely, Agriculture, Forestry, and Other Land Use (AFOLU) practices are responsible for about 21 percent of total greenhouse gas emissions, mainly attributable to unsustainable land-use changes such as soil degradation (FAO, 2016; Searchinger et al., 2019). Agriculture and food production systems as a whole have to contribute to stabilizing food production and global climate, through soil conservation practices, in a manner that simultaneously

increases agricultural productivity and reduces emissions, and increases carbon sequestration in biomass and soils (Ross et al., 2019).

There is a widespread recognition among policy-makers and international organizations that unless concerted efforts are made to stabilize food production through transitioning to productive and sustainable agriculture, achieving the SDG on Zero Hunger by 2030 may be jeopardized (FAO, 2016, Kuma et al., 2018). Agricultural policies and programs have over the past decades focused on promoting conservation agriculture (CA) as an option to intensify agricultural production and improve the fertility of soils. Conservation agriculture comprises a set of crop management principles, namely, minimum soil disturbance (e.g., minimum tillage), maintenance of permanent soil cover, and rotation or association with diverse crops (FAO, 2017). Minimum tillage (MT) involves shifting from conventional tillage systems that contribute to losses of soil, water, and organic matter, to a soil cultivation method that causes minimum soil disturbance or seeding directly into untilled soil. The technology has the potential to provide several ecosystem services including carbon sequestration, protection of soil surface from runoff and erosion, enhanced infiltration of rainfall water, and increased soil fertility through enhanced nitrogen and organic matter contents (Rahm and Huffman, 1984).

Despite the aforementioned benefits, uptake of minimum tillage and other conservation agriculture practices remain low, coupled with increased dis-adoption among smallholder farmers (Grabowski et al., 2016, Kuma et al., 2018; Tessema et al., 2018). This raises the question of its suitability and benefits in sub-Saharan Africa (Giller et al., 2009). One of the major trade-offs that potentially accounts for this low adoption is that productivity gains remain uncertain and controversial (Giller et al., 2009; Brouder et al., 2014; Ngoma, 2018). While some studies have observed immediate yield gains from the adoption of minimum tillage and other CA practices

(Ngwira, 2013; Tessema et al., 2018), others observed a lag period of 2–5 cropping seasons or even longer periods before any significant yield gains (Giller et al., 2009; Pannell et al., 2014). For instance, in Zimbabwe, Michler et al. (2019) found that in the short term, that is, within four years, the adoption of minimum tillage had either a negative impact or no yield benefits on cereal production. Similarly, Thierfelder and Wall (2010) observed for Zambia that the adoption of minimum tillage and crop residue retention had no impact on maize yields in the first three years of adoption. Smallholder farmers have short-term planning horizons due to a high discount rate and may see immediate tangible welfare benefits of minimum tillage as a key driver behind adoption (Pannell et al., 2014).

Thus far, previous empirical studies have examined the determinants and impacts of minimum tillage, considering smallholder farmers' adoption options to be limited to the binary choice of whether or not to transition to minimum tillage (Tessema et al., 2018; Issahaku and Abdulai, 2020). Nevertheless, the adoption decisions of smallholder farmers and benefits are more likely to be heterogeneous concerning the length of adoption (Pannell et al., 2014; Maggio et al., 2021). Transitioning from conventional tillage systems into the adoption of minimum tillage could have short-term benefits, with benefits accruing to adopters within the first few cropping seasons or long-term benefits, with benefits becoming visible only after several cropping seasons (Giller et al. 2009; Jaleta et al., 2016; Kansanga et al., 2020). Furthermore, medium to long-term adoption of climate-smart agricultural practices such as minimum tillage is expected to improve soil fertility and productivity over time, due to the gradual improvements in the biological, physical, and chemical properties of the soil (Ma et al., 2018). Thus, understanding the inter-temporal adoption decisions of smallholder farmers and the impacts of adoption are crucial in formulating targeted policies aimed at addressing their constraints to resource use (Maggio et al., 2020).

We contribute to the empirical literature on the adoption of minimum tillage as follows: First, we determine the impact of minimum tillage adoption transitions on maize yields, household dietary diversity, and household food insecurity access scores (HFIAS). We explore the temporal dimension of adopting minimum tillage by estimating two transition-specific treatment effects: one from conventional tillage to short-term minimum tillage adoption and from short-term to long-term minimum tillage adoption. Previous studies have analyzed the productivity and food security benefits of minimum tillage adoption (e.g. Grabowski et al., 2016; Teklewold and Mekonnen, 2017). However, they tend to typically estimate homogenous effects and fail to account for important treatment effect heterogeneity regarding farmers' adoption transitions. Thus, the inability to capture the trade-off between short-term and long-term welfare benefits may lead to misleading conclusions and tend to affect its widespread adoption (Shiferaw and Holden, 2001).

Second, the issue of increased labor demand under minimum tillage systems also emerges as an important point of concern. Transitioning from conventional tillage may lead to an increase in labor demand for weeding in the short-term. Thus, this increase in labor demand offsets the labor-saving gained from minimum tillage, especially in cases where herbicides are not applied (Tessema et al., 2018). However, maintaining a protective layer of crop residues on the soil surface may lead to economic benefits such as reduced total labor demand in the long-term (Giller et al., 2009). Thus, understanding the potential magnitude of the impact of labor requirements, and taking into account the heterogeneity in the length of adoption is essential to properly evaluate the broad range of benefits and potential trade-offs of minimum tillage adoption.

To the best of our knowledge, there is a paucity of empirical evidence on the heterogeneous effect of length of minimum tillage adoption on household welfare. The bulk of the evidence is mainly based on field experiments (either on-farm or on-station demonstration fields) (e.g.

Thierfelder and Wall, 2010; Ngwira et al., 2013). However, these studies may not capture the performance of the technology under heterogeneous smallholder farmers' socio-economic characteristics and site-specific conditions (such as soil type, climate, management practices, and topography).

Our study accounts for potential threats of selection bias and omitted variable problems by employing the ordered-probit selection model to distinguish between conventional tillage system, short-term, and long-term adoption of minimum tillage. We use recent survey data of maize farm households from the northern savanna zone of Ghana and geo-referenced historical weather data (rainfall and temperature) (1981-2018) to control for the effect of climatic shocks.

3.2 Household survey and data description

3.2.1 *Farm Household survey*

The data come from 489 maize farm households in the northern Savanna zone of Ghana. A survey was conducted for the 2018/2019 cropping season in 15 communities across six districts and three regions under the Sustainable Land and Water Management Project (Funded by World Bank through the Global Environment Facility) intervention areas. We purposively selected six districts from the three regions based on the operational areas of the project and the prevalence of minimum tillage technologies. Further, we randomly selected three to six communities from each district. Finally, 489 maize farm households operating approximately 886 maize plots were randomly sampled in proportion to the farmer population in the community. The survey data were collected using a structured questionnaire by trained and qualified researchers and enumerators who have good working knowledge of the farming systems in the study areas. The survey also collected household and plot-level data on production costs, prices, household demographic characteristics,

access to market information, extension contacts, and minimum tillage practices being implemented, as well as the food security situation of farm households.

Following previous literature on conservation agriculture (e.g. Abdulai and Huffman, 2014; Teklewold and Mekonnen, 2017; Michler et al., 2019; Ngoma et al., 2018; Issahaku and Abdulai, 2020), we present in Table 3.1 a detailed description of the control variables used in our empirical analysis. Concerning household-level information and demographic characteristics, we control for age, gender, education of household head, household size, and asset ownership (e.g., farm size, livestock ownership). We also control for information access (extension service), membership of Farmer Based Organizations (FBO), and resource constraints (credit access). Based on the approach of Abdulai and Huffman (2014), we define credit-constrained farmers as those who received credit but expressed a desire to borrow more at the existing interest rate, those whose credit request was denied, or those who had no access to any form of credit. Our analysis also accounts for plot-level characteristics such as soil fertility (fertile and moderately fertile), slope, and control for location, differentiating between the regions used for the study to account for location fixed effects.

In addition, we include climatic variables to show differences in seasonal mean temperature and rainfall and their influence on farmers' choices concerning the length of minimum tillage adoption. Variability in the frequency and intensity of rainfall, rising mean temperatures, and seasonal dry spells have adverse effects on food production and threaten the livelihoods of resource-poor farmers (Michler et al., 2019; UNDP, 2020). To control for the impact of rainfall shocks and increased temperatures on yields and food and nutrition security, we use rainfall and temperature data (from the Prediction of Worldwide Energy Resources data archive)¹⁸ that

¹⁸ <https://power.larc.nasa.gov/data-access-viewer>

provides global data at high-resolution (0.5x0.5 degree) to generate a gridded rainfall and temperature time series. We use household geographical coordinates to derive long-term mean rainfall and temperature data (from 1981-2018) for the months within the cropping season.¹⁹ Thus, following previous literature (Amare et al., 2018; Michler et al., 2019), we compute rainfall shocks using a dummy variable to capture the differential exposure to rainfall (negative rainfall shock²⁰).

In this paper, we define minimum tillage based on the literature and our study context as a tillage system with reduced soil disturbance, where tillage is limited only to planting stations whilst the rest of the soil remain undisturbed. These practices include Zai technique²¹, ripping, and zero tillage. Zai pits are made with hand-hoes, rip lines are constructed with ox- or tractor-drawn rippers, and zero tillage with jab planters or dibble sticks (Due to the minimum soil disturbance, crop residues from previous seasons harvests are also left on the surface of the soil. The non-adopters comprise all other farmers who used conventional tillage practices including ploughing, ridging, harrowing, and hand hoeing).

To measure the time length of adoption, we consider the heterogeneity in the length of adoption and construct our treatment variable into three different adoption states: conventional tillage, short-term minimum tillage adoption, and long-term minimum tillage adoption to provide better insights into its potential economic benefits. We constructed a dynamic adoption data set based on recall data and information from our cross-sectional survey. Smallholder farmers' recall

¹⁹ The northern Savanna zone has a unimodal rainfall pattern that usually runs from April to October.

²⁰ We compute negative rainfall shock as follows: $\underline{RS}_{kt} = \left| \frac{R_{kt} - \bar{R}_k}{\sigma_{R_k}} \right|$ if $R_{kt} < \bar{R}_k$, 0 otherwise, where R_{kt} is the observed rainfall for the previous year season, \bar{R}_k is the mean historical rainfall, and σ_{R_k} represent the standard deviation of rainfall for the same period

²¹ The zai technique is a traditional name for planting basins where seeds are sown in small planting pits and filled with organic material such as crop residues. This practice reduces soil erosion, improves microbial activities, and concentrates soil water around the base of the plant, thereby supporting plant growth during seasonal dry spells. (Ehiakpor et al., 2019).

information can be used to approximate the dynamic pattern of adoption in the absence of longitudinal data (Besley and Case, 1993). Farmers were asked when they first heard about the technology and when they first used it on their farms. Accordingly, we define short-term adoption to include plots where minimum tillage has been practiced for less than 4 cropping seasons, and medium- to long-term (henceforth referred to as “long-term”) for those where minimum tillage has been adopted for more than 4 cropping seasons.

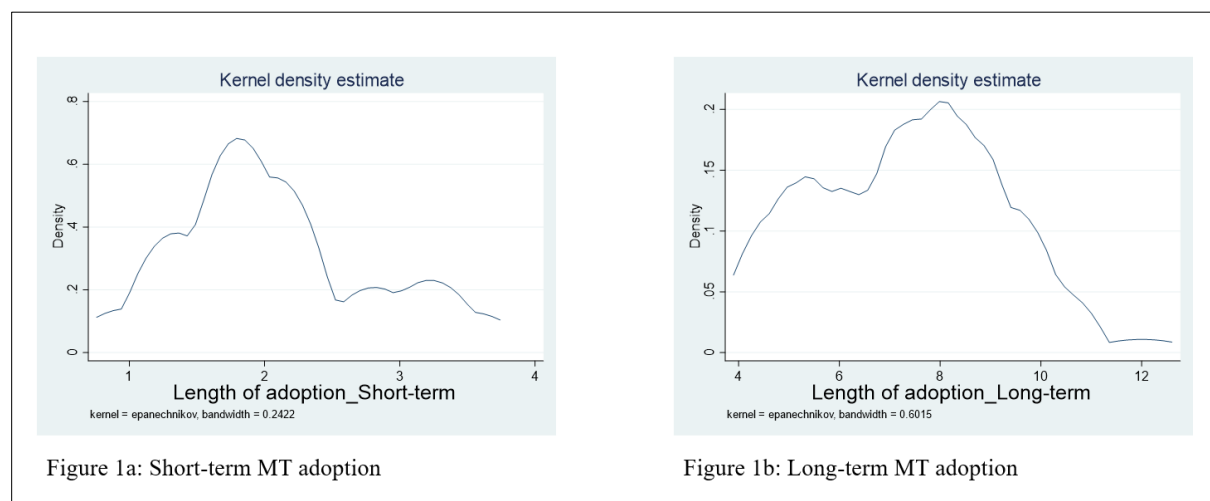


Figure 3.1: Distribution of the length of minimum tillage adoption

Figure 3.1 presents the kernel density estimates of the length of adoption. It is clear from the figure that the majority of short-term adopters are within 1-2 years of adoption, while the majority of long-term adopters are within 7-10 years of adoption. This distribution further indicates the importance of analyzing the heterogeneity in the length of adoption with respect to the expected welfare outcomes.

3.2.2 Measurement of food and nutrition security

Two important indicators of food and nutrition security are employed in the study: household dietary diversity and household food insecurity access scores (HFIAS). We compute the dietary

diversity of households using the Simpson's index (SI) of dietary diversity. This measure is a good proxy for a household's socio-economic capacity to access a variety of foods. Understanding dietary diversity is vital because nutritional levels differ between food items and food groups. A number of empirical studies (Issahaku and Abdulai, 2020; Shahzad and Abdulai, 2020) have measured dietary diversity using a count of all food groups consumed by the household. However, this approach assigns equal weights to the food groups or items regardless of the calorie and nutrition content and hence is unable to provide sufficient information on household dietary diversity.

Thus, to overcome this problem, we convert the quantity of food groups consumed into calories using food composition tables for Western Africa developed by FAO (Vincent et al., 2020) to account for the number of food items consumed and the respective magnitude (calories) of each food group (Nguyen et al., 2011; Teklewold et al., 2019). We calculate the calorie consumption using the following food items: (i) Cereals, (ii) roots and tubers, (iii) pulses (iv) oils and fats, (v) vegetables, (vi) fruits, (vii) meat (viii) egg, (ix) fish, (x) dairy products, (xi) legumes, nuts and seeds, (xii) sweets and (xiii) beverages (Swindale et al., 2006, Leroy et al., 2015). Mathematically, Simpson index can be computed as follows:

$$SI = 1 - \sum_{i=1}^n w_i^2$$

where w_i is the calorie share of food item in the total amount of calories consumed. The Simpson index is in the range of zero to one. Thus, a higher index signifies better dietary diversity.

In addition, we measure household food insecurity access scores to capture different behavioral and psychological dimensions of food security (Maxwell et al., 2014). HFIAS comprises nine occurrence questions on the prevalence of food insecurity (access) with three levels

of severity based on a recall period of the past four weeks (30 days). The maximum score for a household is 27, representing poorer access to food and greater household food insecurity; the minimum score is zero (0), which signifies that the household is food secure (Coates et al., 2006; Leroy et al., 2015).

Table 3.1: Variable Descriptions and Descriptive Statistics

Variable	Description	Mean	Std. Dev
Outcome variables			
Maize yields	The gross value of production metric ton (hectares)	1.961	1.322
HFIAS	Household food insecurity assess scores, where 0 represents a food secure HH, and 27 a food-insecure HH.	4.37	2.67
Dietary diversity	Simpson index (based on calorie share).	0.72	0.14
Labor demand	Total person-days (hectares)	58.54	57.47
Treatment variables			
Long-term MT adoption	1 indicates a continuous MT adoption for more than 4 cropping seasons, 0 otherwise	0.315	0.46
Short-term MT adoption	1 indicate a continuous MT adoption for less than 4 cropping seasons, 0 otherwise	0.262	0.44
Conventional Tillage (CT)	1 if HH practice CT on plot, 0 otherwise	0.423	0.49
Explanatory variables			
Age	Age of household head in years	42.35	12.89
Male headed	Male =1, Female =0	0.63	0.48
HH size	Size of Household	5.97	2.97
Education	Years of formal education	3.72	4.77
FBO	1 if farmer belongs to farmer-based organization, 0 otherwise	0.31	0.46
Farm size	Total farm size of plot (hectares)	1.19	1.08
Extension	Number of extension contacts per annum	10.35	6.91
Credit access	1 if farmer credit constrained, 0 otherwise	0.36	0.48
Livestock	Number of Livestock in Tropical Livestock Units	1.82	4.12
Mean_slope	Perception that plot has is moderately sloped (1=yes; 0=no)	0.66	0.47
Mean_fertile	Perception that plot has is fertile (1=yes; 0=no)	0.37	0.48
Mean_Mod. fertile	Perception that plot is moderately fertile (1=yes; 0=no)	0.51	0.50
Asset	Value of HH durable assets (‘000 GHS)	2.53	2.46
Negative rainfall shock	1 if the metrics indicate a level of rainfall with a standard deviation below the long-term mean, 0 otherwise	0.47	0.50
Mean temperature	Mean temperature in °C (1981 to 2018)	27.33	0.47
Fertilizer	Total monetary value of fertilizer used (GHS) (hectares)	311.27	284.36
Climate information	1 if HH received climate information prior to adoption; 0 otherwise	0.60	0.49
CA Training	Number of training received on conservation agriculture (CA)	3.55	3.33
Northern region	Northern region=1, 0 otherwise	0.37	0.48
Upper East	Upper East region=1, 0 otherwise	0.32	0.47
Upper West	Upper West region=1, 0 otherwise	0.31	0.46

MT: Minimum tillage

Table 3.1 presents the definitions and the descriptive statistics of the selected variables used in the analysis. The sample average household size is six persons with a mean farm size of approximately two hectares. The average level of education is approximately 3.72 years of schooling, indicating lower years of education across the study areas, compared to the national average of 7.3 years (GSS, 2012; UNDP, 2020). Table 3.A1 also presents the mean differences in the outcome variables and household characteristics across minimum tillage adoption status.

In particular, we find that long-term adopters have significantly higher maize yields (2.45 Mt/ha) compared to short-term adopters (2.14 Mt/ha) and conventional tillage farmers (1.43 Mt/ha). Also, the average HFIAS is lower for long-term adopters (2.40) compared to short-term adopters (4.42) and conventional tillage farmers (5.54), signifying that long-term minimum tillage adoption plays a significant role in improving the food security situation of households. Similarly, the average Simpson index value is higher for long-term adopters (0.89), compared to short-term adopters (0.70) and conventional tillage farmers (0.61), indicating a high level of dietary diversity for long-term adopters.

Concerning the total labor demand, short-term adopters use more labor (67.69 person-days/ha) compared to long-term adopters (45.27 person-days/ha) and conventional tillage farmers (62.37 person-days/ha). This result could be explained by the relatively large amount of labor required for manual weed control during this stage of adoption (see Table 3.A3). Generally, the estimates vary significantly between conventional tillage farmers, short-term adopters, and long-term adopters for some household and farm-level characteristics and outcome variables. However, these effects may not signify the impacts of adoption, as these comparisons do not take into account confounding factors that may affect the adoption of minimum tillage.

3.3 Conceptual framework

We consider the minimum tillage adoption decisions as a constrained optimization problem where farm households' transition into different minimum tillage adoption states depends on several factors including available information, relative costs and benefits of minimum tillage, and other socio-economic conditions. Given these constraints smallholder farm households may decide to transition into minimum tillage adoption (i.e., short-term or long-term), if the expected net benefits from transitioning are higher than the expected net benefits of conventional tillage (CT) as follows, i.e. when $\pi_i^{*MT} > \pi_i^{*CT}$ [49]:

$$\begin{aligned}\pi_i^{*MT} &= p_i Q_i^{*MT} - \sum_{j=1}^J \omega_{ji} X_{ji}^{*MT} \\ \pi_i^{*CT} &= p_i Q_i^{*CT} - \sum_{j=1}^J \omega_{ji} X_{ji}^{*CT}\end{aligned}\tag{1}$$

Where Q_i^{*MT} and Q_i^{*CT} are vectors of maize yields for minimum tillage and conventional tillage farmers; p_{it} is a vector of maize prices which is assumed to be the same for both categories of farmers; X_{ji} and ω_{ji} are vectors of input quantity and input prices; respectively.

To better understand the impact of minimum tillage on household welfare, we consider the various pathways through which transitioning into minimum tillage can potentially influence food and nutrition security, as well as labor demand. Transitioning into minimum tillage adoption would affect food and nutrition security primarily through an increase in crop productivity (maize yields) and income. Higher crop productivity can be realized from the agronomic benefits of minimum tillage such as increased soil moisture, enhanced input use efficiency, and increased soil organic matter (Rahm and Huffman, 1984; Abdulai and Goetz, 2014; Tessema et al., 2018). The resulting improvement in yields may increase household food availability from own production and contribute to relaxing household consumption constraints. However, some authors (Ball, 2000) have argued that in some drier regions, conservation tillage is mainly employed to reduce soil

degradation that is usually associated with traditional tillage systems as well as conserve soil moisture and reduce production costs rather than aiming at short-term productivity gains. Thus, whether minimum tillage contributes to higher yields is an empirical issue.

Increased household income also enhances the purchasing power of households to access diverse and micronutrient-rich foods, and thus plays an important role in enhancing their dietary diversity (Brown et al., 2017). Furthermore, switching into long-term minimum tillage adoption is expected to save time and labor (especially critical planting time) (Laukkanen and Nauges, 2011) primarily due to reduced ploughing and the suppression of weeds through crop residue retention. Thus, the labor saved could be channeled into a variety of income-generating activities that could potentially increase the quantity and diversity of food available at the household level (Kassie et al., 2020). That notwithstanding, switching into short-term minimum tillage adoption may lead to increased labor demand for weeding if herbicides are not applied, and may reduce household income and affect consumption patterns (Rahm and Huffman, 1984; Giller et al., 2009).

3.4 Empirical strategy

As stated earlier, we categorize minimum tillage adoption into multiple adoption states: conventional tillage ($j = 1$), short-term adoption ($j = 2$), and long-term adoption ($j = 3$) based on the length or duration of adoption. Thus, farm households could transition from conventional tillage into short-term minimum tillage adoption or from short-term into long-term minimum tillage adoption. Given the multivalued nature of the treatment, we model minimum tillage technology adoption as an ordered choice (Heckman et al., 2006; Chiburis and Lokshin, 2007; Cornelissen et al., 2018) under the assumption that farmers are risk-neutral and take into consideration the expected benefits derived from adoption. However, the expected benefits are not observable. Instead, all that is observed is the decision to use minimum tillage technology either

in the short-term or long-term or to practice conventional tillage. Therefore, we define the latent variable D_{ij}^* which denotes sorting of farmer i into the three adoption states ($j = 1,2,3$) of minimum tillage adoption, based on an ordered-probit selection rule as:

$D_{ij}^* = \alpha_j' \mathbf{Z}_{ij} + \theta \bar{\mathbf{Z}}_i + \mu_{ij}$, where

$$D_{ij} = \mathbf{1}[C_j(w_j) < \alpha_j' \mathbf{Z}_i + \theta \bar{\mathbf{Z}}_i + \mu_i \leq C_{j+1}(w_{j+1})], j = 1, 2 \dots \bar{J} \quad (2)$$

and the cutoff values satisfy

$$C_j(w_j) \leq C_{j+1}(w_{j+1}), \quad C_0(w_0) = -\infty, \quad \text{and } C_{\bar{J}}(w_{\bar{J}}) = \infty$$

in which D_{ij} is a multivalued treatment variable, \mathbf{Z}_i is a vector of observed variables, $\bar{\mathbf{Z}}_i$ is mean plot-level characteristics, $\alpha_j' \mathbf{Z}_i + \bar{\mathbf{Z}}_i + \mu_i$ is a latent linear index, α is a vector of estimated parameters, w_j is a vector of observed regressors, $C_j(w_j)$ are threshold parameters, which are allowed to depend on the regressors, and μ_{ij} are error terms.

We express our observed outcomes Q_{ij} , as a linear function of a vector of X_i for each of the adoption state $j = (1,2,3)$ as follows:

$$Q_{ij} = \begin{cases} \beta_1 X_i + \theta_1 \bar{X}_i + \varepsilon_{i1} & \text{if } D_i = 1 \\ \beta_2 X_i + \theta_2 \bar{X}_i + \varepsilon_{i2} & \text{if } D_i = 2 \\ \beta_3 X_i + \theta_3 \bar{X}_i + \varepsilon_{i3} & \text{if } D_i = 3 \end{cases} \quad (3)$$

where the parameter vector, β_j , of X_i depend on the treatment state j , D_i is the choice of the length of adoption, and ε_i has a zero mean and has a variance of σ_j^2 , for each $j = 1,2,3$.

Given that minimum tillage adoption is not random, smallholder farmers' decisions could be influenced by unobserved characteristics (e.g., skills, ability, and motivation) that would also correlate with the outcome variables of interest, resulting in self-selection and omitted variable problems. Furthermore, there may be heterogeneity in returns to minimum tillage adoption such that smallholder farmers with high returns to minimum tillage are most likely to practice minimum

tillage (Suri, 2011; Abdulai and Huffman, 2014). Consequently, the estimation of specification (3) with the OLS approach could potentially produce biased and inconsistent estimates. To account for the potential biases that may result from the non-randomness of selection, we employ the ordered-probit selection model (Heckman et al., 2006; Chiburis and Lokshin, 2007). The model employs full information maximum likelihood (FIML) to simultaneously estimate selection equation (2) and the outcome specification (3) for the three adoption states. We correct the selection bias and omitted variable problem by including the inverse mills ratios (IMR) from a first-stage ordered choice model (equation 1) in the second-stage outcome models (equation 3). Further, we define the correlations of these errors as $\rho_j = \text{Corr}(\varepsilon_{ij}, \mu_{ij})$, assuming joint normality of the errors in equations 2 and 3. The substantive outcome equations can be rewritten in terms of expectations as;

$$\begin{aligned}
E[\varepsilon_{i1}|D_i = 1] &= E[\varepsilon_{i1}|(C_1(w_1) - \alpha'Z_i - \theta\bar{Z}_i) < \mu_i] = \rho_1 \frac{\phi(C_1(w_1) - \alpha'Z_i - \theta\bar{Z}_i)}{1 - \Phi(C_1(w_1) - \alpha'Z_i - \theta\bar{Z}_i)} = \rho_1\lambda_1, \\
E[\varepsilon_{i2}|D_i = 2] &= E[\varepsilon_{i2}|(C_2(w_2) - \alpha'Z_i - \theta\bar{Z}_i) < \mu_i \leq (C_1(w_1) - \alpha'Z_i - \theta\bar{Z}_i)] \\
&= \rho_2 \frac{\phi(C_2(w_2) - \alpha'Z_i - \theta\bar{Z}_i) - \phi(C_1(w_1) - \alpha'Z_i - \theta\bar{Z}_i)}{\Phi(C_1(w_1) - \alpha'Z_i - \theta\bar{Z}_i) - \Phi(C_2(w_2) - \alpha'Z_i - \theta\bar{Z}_i)} = \rho_2\lambda_2, \\
E[\varepsilon_{i3}|D_i = 3] &= E[\varepsilon_{i3}|\mu_i \leq (C_2(w_2) - \alpha'Z_i - \theta\bar{Z}_i)] = \rho_3 \frac{-\phi(C_2(w_2) - \alpha'Z_i - \theta\bar{Z}_i)}{\Phi(C_2(w_2) - \alpha'Z_i - \theta\bar{Z}_i)} = \rho_3\lambda_3,
\end{aligned} \tag{4}$$

The ratios on the right-hand side of equations (4) are the Heckman-type selection correction terms, which are constructed based on predicted probabilities from the first-stage selection equation (2) and included as correction terms in the outcome equations with ρ_1 , ρ_2 and ρ_3 as the associated coefficients [33, 56];

$$Q_{ij} = \begin{cases} \beta_1 X_i + \theta_1 \bar{X}_i + \rho_1 \lambda_1 + \eta_{i1} & \text{if } D_i = 1 \\ \beta_2 X_i + \theta_2 \bar{X}_i + \rho_2 \lambda_2 + \eta_{i2} & \text{if } D_i = 2 \\ \beta_3 X_i + \theta_3 \bar{X}_i + \rho_3 \lambda_3 + \eta_{i3} & \text{if } D_i = 3 \end{cases} \tag{5}$$

Note that the statistical significance of the correlation coefficients (ρ_1 , ρ_2 and ρ_3) indicates the presence of selection bias. A positive sign of the ρ_j s indicates reverse selection on unobserved gains, while a negative sign indicates positive selection on unobserved gains.

3.4.1 Estimating treatment effects

Using equation 5, we further express the treatment effects, that is, ATE^\dagger (average treatment effect for the entire population), ATE (average treatment effect for those at one of the transition stages), TT (average treatment on the treated, or the gains for those who choose to transition), and TUT (average effect of treatment on the untreated, or the gains for those who chose not to transition) for farmer's transition between j and $j + 1$ as follows:

$$ATE_{j+1,j}^\dagger = E[Q_{ij+1} - Q_{ij}] \quad (6a)$$

$$ATE_{j+1,j} = E[Q_{ij+1} - Q_{ij} | D_i \in \{j, j + 1\}] \quad (6b)$$

$$TT_{j+1,j} = E[Q_{ij+1} - Q_{ij} | D_i = j + 1] \quad (6c)$$

$$TUT_{j+1,j} = E[Q_{ij+1} - Q_{ij} | D_i = j] \quad (6d)$$

The difference between ATE^\dagger and ATE shows the difference in the characteristics of those in the entire population and that of those at the transitions between two adoption states. The difference between the TT and ATE measures sorting on gains, while the difference between TUT and ATE measures sorting losses. Further, the relationship between equations (6b) to (6d) illustrates whether patterns of heterogeneity reflect positive ($TT > ATE > TUT$) or reverse selection ($TUT > ATE > TT$) on gains. In other words, these patterns show whether economic gains are greater among farm households most or least likely to transition into short-term or long-term adoption (Cornelissen et al., 2018; Heckman et al., 2018).

We address a potential plot-level unobserved heterogeneity problem that could arise due to farm households cultivating multiple plots using Mundlak's approach (Mundlak, 1978).

Furthermore, to ensure identification and exclusion restriction, we need to have instruments that directly affect the selection equation, but not the outcome variables of interest (Chiburis and Lokshin, 2007). Intuitively, one requires an instrument (as a source of variability) for each transition (Heckman et al., 2006). In our analysis, the three ordered choices imply two transitions (i.e., conventional tillage to short-term minimum tillage adoption, and short-term to long-term minimum tillage adoption) and thus require at least two instruments.

Following previous studies (e.g. Di Falco et al., 2011; Shahzad and Abdulai, 2020), we use past climate information and training on conservation agriculture received by farmers as the excluded instruments. Access to reliable and timely climate information (through print and broadcast media etc.) on rainfall and temperature forecasts tend to influence behavioral changes towards the adoption of minimum tillage (Pagliacci et al., 2020). Similarly, training is effective in driving the adoption of conservation agriculture technologies. Increased training assists farmers in their day-to-day operations and is crucial in enhancing and sustaining the adoption of innovations. Training on minimum tillage is usually organized in groups at the village level. Thus, farmers who receive more training days are more likely to adopt, raising concerns about potential endogeneity and biased results. As a result, we used the average village-level training days to address this.

We establish the admissibility of the instruments following Di Falco et al. (2011) by carrying out a falsification test. A variable may be a valid instrument if it affects minimum tillage adoption decisions, but not the outcome variable of interest among farmers who did not adopt minimum tillage. Our results indicate that the variables are jointly significant in affecting minimum tillage adoptions (see Table 3.2), but not the outcome variables (see Table 3.A2). A further test of correlation in Table 3.A4 shows that the instrumental variables are not correlated with the outcome variables of interest (i.e., the exclusion restriction assumption).

In addition, we check the relevance and validity of the instruments by showing test diagnostics of a generalized method of moments (IV-GMM)²² estimations of the effect of the length of minimum tillage adoption on the outcomes in Table 3.A5. The diagnostics test statistics presented in the lower part of Table 3.A5 suggest the instruments are relevant as well as good predictors of the length of MT adoption. Specifically, the Cragg-Donald F-statistic of 23.86, the Kleibergen-Paap rk Wald F-statistic of 77.75 and the corresponding Angrist and Pischke p -value ($p=0.000$) all reject the null hypothesis that the instruments are weak. Furthermore, given the Hansen J test statistic of 1.204 and the p -value of 0.2726, we cannot reject the null hypothesis of zero correlation between the instruments and the error term (reported in Table 3.A5).

3.5 Empirical results and discussions

3.5.1 *First-stage selection results*

In the interest of easing interpretation, we report the marginal effects computed after estimation of the ordered probit model in columns 1, 2, and 3 of Table 3.2, for conventional tillage, short-term, and long-term minimum tillage adoption, respectively. In particular, the marginal effects show that male-headed households are less likely to practice conventional tillage. The results also show that an increase in extension contacts significantly decreases the probability of practicing conventional tillage by about 0.008, and increases the probability of investing in long-term minimum tillage adoption by about 0.007.

The estimates of the marginal effects also show that among credit-constrained farmers, the probability of adopting minimum tillage in the short-term increases significantly by about 0.15,

²² We employ the IV-GMM estimator because of its efficiency over the conventional two-stage least squares when the equation is over-identified and its robustness to heteroskedasticity (Cameron and Trivedi, 2005).

Table 3.2: First Stage Ordered Selection Model

Variables	Conventional tillage		Short-term MT adoption		Long-term MT adoption	
	1		2		3	
	Marginal effects	S.E.	Marginal effects	S.E.	Marginal effects	S.E.
Age	-0.001	0.002	-0.002	0.002	0.004*	0.002
Male headed	-0.144***	0.054	0.128*	0.067	0.016	0.051
HH size	-0.001	0.009	0.008	0.012	-0.007	0.009
Education	0.008	0.005	-0.012**	0.006	0.042	0.004
FBO	-0.211***	0.055	0.170***	0.061	0.058	0.046
Farm size	0.029**	0.013	-0.030**	0.014	0.001	0.010
Extension	-0.008*	0.004	-0.001	0.005	0.007*	0.004
Credit access	-0.038	0.050	0.151**	0.060	-0.112**	0.048
Livestock	-0.006	0.005	0.007	0.007	-0.001	0.005
Mean_slope	0.148***	0.054	0.001	0.063	-0.150***	0.045
Mean_fertile	-0.179**	0.083	0.192**	0.096	-0.013	0.079
Mean_Mod. fertile	-0.188**	0.082	0.152	0.096	0.036	0.078
Asset (log)	-0.109***	0.023	-0.045*	0.027	0.154***	0.022
Negative rainfall shock	-0.190***	0.069	0.275***	0.088	-0.085	0.079
Mean temperature	0.205***	0.067	-0.027	0.081	-0.178***	0.056
Fertilizer (log)	0.076***	0.016	-0.066***	0.020	-0.009	0.013
Climate information	-0.398***	0.050	0.411***	0.052	-0.013	0.046
CA Training	-0.186***	0.012	0.163***	0.012	0.023***	0.006
Northern	0.537***	0.081	-0.533***	0.093	-0.040	0.080
Upper West	0.200**	0.099	0.227**	0.105	0.027	0.088
Joint significance plot- level variables $\chi(3)$	22.22***		9.41**		14.39***	
χ^2 test of instrument			77.75			
p value of instrument			0.000			
No. of obs. (plots)	391		226		269	

Note: Table 3.2 reports the marginal effects estimates of the adoption decision from a generalized ordered probit selection model for all three adoption states (conventional tillage, short-term adoption, and long-term adoption). The p -value for the excluded instruments (Climate information and CA training) is reported. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

MT: Minimum tillage

while the probability of adopting minimum tillage in the long-term decreases by about 0.11.

Anecdotal evidence suggests that smallholder farmers usually receive inputs free of charge from donor or government-sponsored projects within the first few years of adoption. Thus, credit constrained farmers may still be able to implement minimum tillage in the short-term. However,

beyond the intervention phase, credit constrained farmers encounter liquidity constraints for the purchase of agrochemicals (e.g., herbicides, fertilizers) and may not continuously adopt minimum tillage in the long-term.

In terms of the effect of climate variability on minimum tillage adoption, we find that rainfall variability, as represented by negative rainfall shocks, significantly decreases the likelihood of farmers practicing conventional tillage by about 0.19, and increases the probability of investing in minimum tillage in the short-term by about 0.27. This finding suggests that smallholder farmers perceive the practice of minimum tillage as an adaptation strategy to mitigate the risk of unpredictable weather conditions and shortage of rainfall. This is because minimum tillage has the potential to increase soil moisture by improving water infiltration and decreasing evaporation (Rahm and Huffman, 1984; Michler et al., 2019). The result agrees with previous studies [e.g., 4] that found that rainfall variability influences smallholder farmers' decisions as regards the use of soil and water conservation technologies.

We also find that increase in mean temperature increases the probability of practicing conventional tillage by 0.20 and decreases the probability of long-term adoption by about 0.17. Regarding the variables used as instruments, the results show that smallholder farmers who experience increase in the number of training on CA are more likely to adopt minimum tillage in the short-term and long-term, whereas those who receive climate information are more likely to decrease the practice of conventional tillage and adopt minimum tillage in the short-term. The findings indicate that the variables used as instruments appear to be strong predictors of either adopting minimum tillage in the short-term or long-term.

3.5.2 *Second-stage estimation results*

In this section, we present the results from the second-stage estimation in Tables 3.3, 3.4, and 3.5 for the three adoption states, on the effect of the observed variables on maize yields, HFIAS, dietary diversity, and labor demand. To highlight the importance of self-selection, we report the correlation coefficients (ρ 's) in the lower parts of Tables 3.3, 3.4, and 3.5. The estimated ρ 's are statistically significant across all three adoption states for maize yields and labor demand specifications. Further, the estimated correlations are statistically significant in both the short-term and long-term adoption states for HFIAS, and statistically significant only in the case of short-term adoption for the dietary diversity specification. These results indicate the presence of selection bias arising from unobserved characteristics, lending credence to the appropriateness of the ordered-probit selection model.

The negative signs of these correlation coefficients for maize yields and HFIAS indicate positive selection on unobserved gains, suggesting that farm households with maize yields lower than that of the average farmer or food insecurity scores higher than the average farmer have higher probabilities of transitioning into short-term and long-term minimum tillage adoption. In other words, farmers decide to transition into short-term and long-term minimum tillage adoption based on their comparative advantage (Suri, 2011). Also, the positive signs of the correlation coefficients related to dietary diversity (short-term minimum tillage adoption) signify reverse selection on unobserved gains, suggesting that farm households with Simpson index value above that of the average farmer have lower probabilities of transitioning into short-term minimum tillage adoption

Table 3.3: Second stage estimates of determinants of maize yields

Variables	Conventional tillage		Short-term MT adoption		Long-term MT adoption	
	1		2		3	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Age	-0.002	0.002	0.003	0.003	-0.002	0.002
Male headed	-0.042	0.043	-0.027	0.051	-0.055	0.055
HH size	0.028***	0.005	0.026***	0.009	0.019**	0.085
Education	-0.005	0.006	0.003	0.004	0.005	0.004
FBO	0.148***	0.056	-0.116**	0.057	-0.006	0.042
Farm size	0.045***	0.009	0.013	0.015	0.020**	0.009
Extension	0.046***	0.005	0.021***	0.005	0.037***	0.004
Credit access	-0.135***	0.040	-0.296***	0.056	-0.254***	0.050
Livestock	0.003	0.005	0.011***	0.004	0.008*	0.004
Mean_slope	-0.019	0.046	-0.041	0.080	0.007	0.041
Mean_fertile	-0.005	0.054	-0.146*	0.080	0.036	0.070
Mean_Mod. fertile	-0.0003	0.049	-0.192**	0.110	0.074	0.070
Asset (log)	0.033	0.024	0.095***	0.027	-0.021	0.024
Negative rainfall shock	-0.143**	0.065	-0.440***	0.115	-0.315***	0.088
Mean temperature	-0.067	0.061	0.007	0.063	0.062	0.057
Fertilizer (log)	0.168***	0.025	0.137***	0.020	0.085***	0.012
Northern	-0.060***	0.073	0.570***	0.128	0.338***	0.087
Upper West	0.204***	0.078	0.533**	0.113	0.299***	0.100
Constant	7.346***	1.700	6.379***	1.670	5.741***	1.514
$\rho_{\epsilon\mu}$	-1.109***	0.218	-0.534***	0.135	-1.027***	0.202
LR test of indep. eqns. ($\rho = 0$): $\chi^2(3) = 46.76$ ***						
Log pseudolikelihood = -904.32						
No. of obs. (plots)	391		226		269	

Note: Columns 1, 2, and 3 present the estimates of the maize yield equation for all three adoption states, that is, conventional tillage, short-term adoption, and long-term adoption, respectively. The estimates of $\rho_{\epsilon\mu}$ depict the correlation between the unobservables in the first-stage ordered Probit selection equation (2) and the second-stage outcome equations (3 and 5) in each of the three states. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. MT: Minimum tillage

Next, Table 3.3 presents the second-stage results on the determinants of maize yields. In particular, the household size variable is positive and statistically significant across all adoption states. In other words, larger households that normally have higher labor endowments obtain higher maize yields. Farm size shows a positive and significant impact on conventional tillage, and long-term minimum tillage adoption, suggesting that among conventional tillage farmers and long-term adopters, larger farms attain higher yields compared to smaller farms. This finding contrasts the stylized fact of an inverse relationship between farm size and productivity. The results also indicate that extension contacts significantly increase maize yields across all adoption states, highlighting the crucial role extension contacts play in enhancing productivity gains. We also find that negative rainfall shock exerts a negative and statistically significant impact across all adoption states, suggesting that conventional tillage farmers, short-term and long-term minimum tillage adopters who experience rainfall stress tend to experience decreases in maize yields.

The results in Tables 3.4 and 3.5 show the determinants of HFIAS and dietary diversity for conventional tillage farmers and both short-term and long-term minimum tillage adopters, respectively. The coefficient for household size is positive and statistically significantly different from zero in the case of HFIAS under conventional tillage and long-term minimum tillage adoption, suggesting that conventional tillage farmers and long-term adopters with larger household sizes, all things being equal, tend to be more food insecure. The variable on access to credit is positive and statistically significant in the case of HFIAS for conventional tillage farmers and long-term minimum tillage adopters, suggesting that these categories of farm households who are credit-constrained are more likely to become food insecure, partly due to their inability to purchase agriculture inputs (i.e., fertilizers, herbicides, pesticides) to increase production and farm income.

Table 3.4: Second stage estimates of determinants of HFIAS

Variables	Conventional tillage		Short-term MT adoption		Long-term MT adoption	
	1		2		3	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Age	-0.047***	0.010	-0.035***	0.010	-0.019*	0.010
Male headed	-0.504*	0.273	0.159	0.243	-0.525*	0.299
HH size	0.094**	0.037	0.035	0.037	0.146***	0.048
Education	-0.068**	0.028	-0.049	0.023	0.013	0.023
FBO	0.148	0.296	-0.691***	0.255	-0.185	0.239
Farm size	0.083*	0.049	-0.004	0.061	0.040	0.052
Extension	-0.036*	0.021	-0.014	0.022	-0.061***	0.018
Credit access	0.410*	0.245	0.323	0.252	1.021***	0.270
Livestock	0.016	0.035	-0.059**	0.024	0.028	0.028
Slope	-0.012	0.290	0.614**	0.243	-0.095	0.235
Fertile	-0.080	0.359	0.334	0.369	-0.758*	0.416
Mod. fertile	-0.078	0.346	0.168	0.362	-1.04**	0.405
Asset (log)	-0.245*	0.136	-0.123	0.118	-0.521***	0.141
Negative rainfall shock	1.863***	0.380	4.674***	0.531	1.252***	0.440
Mean temperature	0.633*	0.380	0.271	0.301	0.280	0.307
Fertilizer (log)	0.001	0.098	-0.230***	0.080	-0.070	0.058
Northern	1.029***	0.385	-0.406	0.610	-0.108	0.477
Upper West	0.284	0.521	-1.415***	0.684	-0.537	0.462
Constant	-9.603	10.230	-2.11	7.828	3.875	7.754
$\rho_{\epsilon\mu}$	-0.357	0.246	-0.333***	0.121	-0.628***	0.157
LR test of indep. eqns. ($\rho = 0$): $\chi^2(3) = 20.49$ ***						
Log pseudolikelihood = -2403.75						
No. of obs.	207		128		154	

Note: Columns 1, 2, and 3 present the estimates of the HFIAS equation for all three adoption states, that is, conventional tillage, short-term adoption, and long-term adoption, respectively. The estimates of $\rho_{\epsilon\mu}$ depict the correlation between the unobservables in the first-stage ordered Probit selection equation (2) and the second-stage outcome equations (3 and 5) in each of the three states. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
MT: Minimum tillage

The coefficient of education is positive and statistically significant in the case of dietary diversity for short-term and long-term minimum tillage adoption. In other words, more educated farm household heads are associated with higher dietary diversity. This finding is consistent with previous studies that observed a positive and significant relationship between education and dietary quality of households (Ehiakpor et al., 2019). As expected, negative rainfall shock (rainfall

deficit) tends to negatively affect food and nutrition security outcomes (i.e. significantly increases HFIAS and decreases dietary diversity) across all adoption states.

Similarly, a rise in mean temperature increases food insecurity (HFIAS) in the case of conventional tillage farming and decreases dietary diversity in the case of short-term and long-term adoption. Thus, climate variability exposes the crop production systems to extreme risk (e.g., through soil moisture stress, and dry spells) and has the potential to result in increased crop failure and thus threaten the food and nutrition security of farm households (Teklewold et al., 2019). Table 3.6 also presents the output of the second-stage regressions for labor demands. In particular, the household size variable is positive and significant under both conventional tillage and short-term minimum tillage adoption, suggesting that conventional tillage farmers and short-term adopters with larger household sizes tend to have higher farm labor supply.

Table 3.5: Second stage estimates of determinants of Dietary diversity

Variables	Conventional tillage		Short-term MT adoption		Long-term MT adoption	
	1		2		3	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Age	0.001*	0.0004	0.0005	0.001	-0.001**	0.0002
Male headed	-0.002	0.011	-0.040**	0.017	0.004	0.008
HH size	0.001	0.001	-0.003	0.003	-0.002	0.001
Education	0.002	0.001	0.004***	0.001	0.002***	0.0005
FBO	0.004	0.012	0.036***	0.013	-0.009	0.007
Farm size	0.0004	0.002	0.001	0.003	0.001	0.001
Extension	0.001	0.001	0.002	0.001	-0.001	0.0006
Credit access	-0.003	0.010	-0.020*	0.013	-0.008	0.008
Livestock	0.002	0.001	0.002	0.001	-0.0003	0.001
Slope	-0.050***	0.011	-0.068***	0.015	0.004	0.006
Fertile	-0.025*	0.014	-0.007	0.033	-0.023**	0.010
Mod. fertile	0.004	0.013	-0.023	0.031	-0.008	0.009
Asset (log)	-0.006	0.006	0.042***	0.008	0.013***	0.004
Negative rainfall shock	-0.030**	0.013	-0.062**	0.027	-0.058***	0.012
Mean temperature	0.005	0.015	-0.035**	0.016	-0.019**	0.008
Fertilizer (log)	-0.006	0.004	-0.001	0.005	0.001	0.002
Northern	-0.012	0.016	-0.027	0.035	-0.017	0.015
Upper West	0.005	0.017	0.017	0.029	0.035***	0.012
Constant	0.648	0.419	-1.544***	0.402	1.405***	0.196
$\rho_{\varepsilon\mu}$	0.225	0.431	0.377**	0.154	-0.189	0.369
LR test of indep. eqns. ($\rho = 0$): $\chi^2(3) = 8.04^{**}$						
Log pseudolikelihood = 484.70						
No. of obs.	207		128		154	

Note: Columns 1, 2, and 3 present the estimates of the HDDS equation for all three adoption states, that is, conventional tillage, short-term adoption, and long-term adoption, respectively. The estimates of $\rho_{\varepsilon\mu}$ depict the correlation between the unobservables in the first-stage ordered Probit selection equation (2) and the second-stage outcome equations (3 and 5) in each of the three states. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
MT: Minimum tillage

Table 3.6: Second stage estimates of determinants of labor demand

Variables	Conventional tillage		Short-term MT adoption		Long-term MT adoption	
	1		2		3	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Age	0.004	0.003	-0.001**	0.003	0.001	0.002
Male headed	0.894	0.725	-0.023	0.082	0.059	0.075
HH size	0.0347***	0.011	0.056***	0.014	0.002	0.010
Education	0.017	0.001	0.005	0.006	0.004	0.005
FBO	0.132	0.092	-0.138	0.109	-0.030	0.055
Farm size	0.184***	0.014	0.107***	0.016	0.043***	0.009
Extension	0.017**	0.007	0.004	0.009	0.003	0.005
Credit access	-0.140**	0.066	-0.031	0.085	-0.131**	0.064
Livestock	-0.008	0.080	0.006	0.006	0.010*	0.005
Mean_fertile	-0.083	0.095	0.130	0.139	0.007	0.097
Mean_Mod. fertile	0.064	0.086	0.080	0.162	0.106	0.089
Asset (log)	0.033	0.043	0.083**	0.042	0.121***	0.027
Fertilizer (log)	0.046	0.028	0.023	0.023	-0.039***	0.013
Upper East	-0.248***	0.086	0.068**	0.111	-0.102	0.063
Upper West	0.279***	0.084	0.281***	0.083	0.056	0.064
Constant	2.614***	0.412	3.708***	0.424	3.245***	0.361
$\rho_{\varepsilon\mu}$	1.032***	0.337	0.269**	0.122	0.996***	0.124
LR test of indep. eqns. ($\rho = 0$): $\chi^2(3) = 59.70$ ***						
Log pseudolikelihood = -1239.06						
No. of obs. (plots)	391		226		269	

Note: Columns 1, 2, and 3 present the estimates of the labor demand equation for all three adoption states, that is, conventional tillage, short-term adoption, and long-term adoption, respectively. The estimates of $\rho_{\varepsilon\mu}$ depict the correlation between the unobservables in the first-stage ordered Probit selection equation (2) and the second-stage outcome equations (3 and 5) in each of the three states. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

MT: Minimum tillage

3.5.3 Impact of minimum tillage adoption

In this section, we disentangle the heterogeneity in the duration of adoption of minimum tillage.

We present the treatment effects across transitions based on equations (6a) to (6d) in Table 3.7 for the four outcomes studied in this paper. The estimates presented in Panel A show the treatment effects of transitioning between conventional tillage and short-term adoption, while Panel B reports the treatment effects of transitioning between short-term and long-term adoption.

In particular, the ATE^{\dagger} estimates show that transitioning from conventional tillage to short-term adoption increases maize yields, dietary diversity, and labor demand by 4.88%, 13.57%, and 8.07%, respectively, and decreases HFIAS by 13.37%. For the transition between short-term and long-term adoption, the ATE^{\dagger} estimates show an increase in maize yields and dietary diversity by 5.41% and 24.66%, respectively, and a decrease in HFIAS and labor demand by 8.68% and 17.07%, respectively.

As discussed in section 4, we next present the treatment effect parameters across the outcomes and their relation to the pattern of selection. More specifically, the estimates of the ATE, which measures the average effect for those at one of the transition stages, show that for a farmer chosen at random, switching from conventional tillage to short-term minimum tillage adoption increases maize yields, dietary diversity, and labor demand by 4.40%, 10.85%, and 12.64%, respectively, and reduces food insecurity (HFIAS) by 18.86%. At the same time, transitioning from short-term to long-term minimum tillage adoption increases maize yields and dietary diversity by 5.30% and 19.54%, respectively, and decreases HFIAS and labor demand by 27.91% and 13.70%, respectively.

The TT, which measures the gains for those who chose to transition, suggests that switching from conventional tillage to short-term adoption increases maize yields, dietary diversity, and labor demand by 3.58%, 12.84%, and 12.92%, respectively. At the same time, transitioning from short-term to long-term adoption increases maize yields and dietary diversity by about 4.33% and

Table 3.7: Estimates of Treatment Effects Parameters

Panel A	Maize yields (log)		HFIAS		Dietary diversity		Labor demand (log)	
	1		2		3		4	
Conventional tillage vs Short-term MT adoption	Treatment effect	% of base category	Treatment effect	% of base category	Treatment effect	% of base category	Treatment effect	% of base category
ATE [†]	0.369*** (0.011)	4.88	-0.655*** (0.050)	-13.37	0.085*** (0.002)	13.57	0.380*** (0.017)	8.07
ATE	0.337*** (0.013)	4.40	-1.000*** (0.060)	-18.86	0.067*** (0.002)	10.85	0.567*** (0.017)	12.64
TT	0.271*** (0.047)	3.58	-0.178 (0.164)	-3.59	0.080*** (0.004)	12.84	0.573*** (0.043)	12.92
TUT	0.375*** (0.040)	4.88	-1.478*** (0.120)	-26.79	0.059*** (0.004)	9.68	0.563*** (0.043)	12.57

Note: This table presents the estimates of different treatment effects parameters; ATE[†] (Average treatment effect for the full population), ATE (average treatment effect), TT (effect of treatment on the treated), TUT (effect of treatment on the untreated). Standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B	Maize yields (log)		HFIAS		Dietary diversity		Labor demand (log)	
	1		2		3		4	
Short-term MT adoption vs long-term MT adoption	Treatment effect	% of base category	Treatment effect	% of base category	Treatment effect	% of base category	Treatment effect	% of base category
ATE [†]	0.430*** (0.007)	5.41	-0.368*** (0.071)	-8.68	0.175*** (0.002)	24.66	-0.870*** (0.012)	-17.07
ATE	0.416*** (0.010)	5.30	-1.229*** (0.084)	-27.91	0.145*** (0.003)	19.54	-0.703*** (0.014)	-13.70
TT	0.340*** (0.042)	4.33	-1.729*** (0.133)	-42.31	0.110*** (0.004)	14.22	-0.581*** (0.024)	-11.09
TUT	0.506*** (0.040)	6.45	-0.633*** (0.149)	-13.25	0.187*** (0.004)	26.52	-0.850*** (0.025)	-16.95

Note: This table presents the estimates of different treatment effects parameters; ATE[†] (Average treatment effect for the full population), ATE (average treatment effect), TT (effect of treatment on the treated), TUT (effect of treatment on the untreated). Standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

14.22%, respectively, and decreases HFIAS and demand for labor by 42.31% and 11.09%, respectively. The TUT, which measures the gains for those who chose not to transition, suggests that switching from conventional tillage to short-term adoption increases maize yields, dietary diversity, and labor demand by 4.88%, 9.68%, and 13.57%, respectively, and reduces food insecurity by 26.79%. Whereas transitioning from short-term to long-term adoption increases maize yields and dietary diversity by 6.45% and 26.52%, respectively, it reduces food insecurity and labor demand by 13.25% and 16.95%, respectively.

The results generally exhibit substantial heterogeneity in the gains from one level of transition to the other. In particular, the magnitude of the treatment effect estimates for maize yields is relatively higher for farm households transitioning from short-term to long-term minimum tillage adoption than from conventional tillage to short-term minimum tillage adoption. These results point to a gradual increase in maize yields from minimum tillage adoption over time, favoring minimum tillage adoption in the medium- to long-term. In our study context, climate-related stresses such as mid-seasonal dry spells and erratic rainfall distribution, combined with poor soil quality greatly impede crop growth (Atampugre et al., 2019).

With its capacity to conserve soil moisture, the adoption of minimum tillage over time contributes to mitigating the effect of mid-seasonal dry spells by reducing evaporation of water, increasing crop water use efficiency, and thus stabilizing yield variability (Giller et al., 2009; Tessema et al., 2018; Grabowski et al., 2019). Further, crop residue contributes to a reduction in soil erosion, and buildup of soil organic matter over time and thus decreases production risks by increasing yields (FAO, 2017). Our results corroborate other studies that show that the benefits derived from the adoption of climate-smart agriculture practices increase with the duration of adoption (e.g. Maggio et al., 2021).

Interestingly, the results also show significant evidence of a decrease in farm labor demand when transitioning into long-term minimum tillage adoption. While this observation might be surprising, it is important to underscore the fact that a substantial amount of labor is required for weeding (see *t*-test, Table 3.A1), particularly when switching to short-term adoption, as minimum tillage systems are prone to weed infestation in the first years of implementation. However, under medium to long consecutive years of adoption, there is sufficient soil surface cover, because of the continuous retention of crop residues from previous cropping seasons, which suppresses the emergence of weeds, thus contributing to a net reduction in labor requirement (Giller et al., 2009). Consistent with our findings, recent studies (e.g. Tessema et al., 2018; Laukkanen and Nauges, 2011) found that the adoption of conservation tillage decreases the use of labor.

Furthermore, our results reveal the pattern of selection on gains. In particular, we find evidence of reverse selection on gains ($TUT > ATE > TT$) between the two transitions (Panels A and B for Table 3.7) for maize yields, suggesting that disadvantaged farm households who are less likely to switch from conventional tillage to short-term minimum tillage adoption, and from short-term to long-term minimum tillage adoption tend to benefit more if they transition. Consistent with our analysis (see *t*-test, Table 3.A1), conventional tillage farmers and short-term adopters are faced with a couple of limitations (such as low extension contacts) which tend to affect their yields. Thus, switching into long-term adoption helps disadvantaged farmers to significantly close the gap in maize yields. We also observe a similar pattern in the case of farm labor demand when switching from short-term to long-term minimum tillage adoption.

Our results also show evidence of positive selection on gains ($TT > ATE > TUT$) in the case of dietary diversity (Table 3.7 Panel A), suggesting that better-resourced farm households who are most likely to transition into short-term adoption of minimum tillage tend to have higher Simpson

index value (i.e., higher dietary diversity). However, less endowed farm households or those who are less likely to transition into long-term minimum tillage adoption benefit the most (higher dietary diversity), rather than the least. In other words, this finding shows an equalizing effect of long-term adoption, implying a reverse selection on gains (Table 3.7 Panel B). We further observe a pattern of positive selection on gains in terms of HFIAS, indicating that more endowed households tend to experience better food security situations when they transition into long-term minimum tillage adoption.

Given the generally positive effects of minimum tillage adoption on food and nutrition security, we next focus on understanding the impact mechanisms. While improving food security is not, strictly speaking, a direct product of minimum tillage adoption, it can be thought of as an extension of the productivity and income-increasing effects of its adoption. A key dimension of food security is food availability which is determined by the level of food supplies. Thus, the adoption of minimum tillage is hypothesized to increase yield and this improves food availability. We further hypothesized that farm income contributes to better food and nutrition because it affects the overall household income, making food more accessible.

Also, in times of food scarcity and hunger, households are more likely to sell their farm produce to purchase food (Kuma et al., 2018). We explicitly explore these relationships in Figures 3.2 to 3.3. Each Figure illustrates the association between household food and nutrition security for the predicted counterfactuals across the three adoption status, and maize yield and farm income. Figure 3.2 further shows a positive and strong association between farm income, maize yields, and dietary diversity, while Figure 3.3 shows a negative association between farm income and maize yields on household food insecurity access scores. This observation is further corroborated by correlation analysis in appendix 3.A5.

3.6 Conclusion and Policy Implications

This study used plot-level and household data from the northern savanna zone of Ghana and geo-referenced historical weather data to examine the determinants and impacts of adoption of minimum tillage on maize yields, household dietary diversity, and household food insecurity access scores (HFIAS), and farm labor demand. The analysis accounted for heterogeneity in the length of minimum tillage adoption (i.e., conventional tillage, short-term, and long-term minimum tillage adoptions) and estimated the treatment effects of farm households' adoption transitions, which involved transitioning from conventional tillage to short-term adoption and from short-term to long-term adoption. We employed an ordered-probit selection model to account for potential selection bias arising from the non-randomness of minimum tillage adoption decisions. The empirical results revealed that several household and farm-level variables significantly affect farmers' decisions regarding the use of minimum tillage. Moreover, we observed that negative rainfall shocks result in a positive and significant impact on farmers' short-term adoption decisions, indicating farmers' responses to rainfall variability.

Overall, our results show that the adoption of minimum tillage has positive and significant impacts on maize yields and food and nutrition security across adoption transitions. In particular, and in contrast to previous studies (Michler et al., 2019), we find no evidence of yield penalties often observed during the first few years of minimum tillage adoption. However, we observe relatively higher maize yields when transitioning from short-term into medium- to long-term minimum tillage adoption, potentially due to the gradual improvement in soil health (i.e., chemical, physical, and biological properties) over time. Our results also reveal a pattern of positive selection on gains from transitioning into long-term minimum tillage adoption on HFIAS, suggesting that farm households that are more likely to transition into medium- to long-term adoption tend to

experience better food security situations. Also, we find that transitioning into medium- to long-term adoption results in economic benefits such as net savings in total labor demand, as the use of herbicides, and the prolonged retention of crop residue help maintain soil surface cover, thereby suppressing the emergence of weeds, and reducing the demand for labor for weed control.

A major conclusion from our results is that transitioning into longer cropping seasons under minimum tillage contributes to relatively higher maize yields and food security benefits. More importantly, differentiating between the duration of adoption is crucial in teasing out the heterogeneous benefits of minimum tillage technology. In particular, medium-to long-term investments in minimum tillage technology offers significant benefits of adapting crop production systems to climate variability. Thus, our findings highlight the importance of developing and implementing programs that not only promote adoption but also help smallholder farmers to sustain adoption for more cropping season. It is important to undertake enhanced institutional and policy initiatives to eliminate the bottlenecks associated with the continuous adoption of minimum tillage systems. In other words, enhancing extension delivery through redesigning and improving minimum tillage knowledge and information to suit local conditions may help smallholder farmers develop the required resilience to climate change and variability.

The findings of this study should be interpreted with caution, since we used mainly cross-sectional survey data. Furthermore, we acknowledge the fact that, since the measurement of the length of adoption relied on farmer recall, there may be potential recall bias. That notwithstanding, we do not expect systematic bias in our assessment. Therefore, this analysis is useful in deepening the understanding of the linkages between the length of minimum tillage adoption and food and nutrition security.

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Table 3.A1: Mean differences in characteristics

Variable	Conventional tillage		Diff. (t-stat.)	Short-term MT adoption		Diff. (t-stat.)	Long-term MT adoption	
	1			2			3	
	Mean	Std. Dev.	(2-1)	Mean	Std. Dev.	(3-2)	Mean	Std. Dev.
Outcome variables								
Maize yields	577.48	391.51	288***	866.46	490.84	125.36**	991.82	563.81
HFIAS	5.54	2.44	-0.72***	4.42	2.45	-2.42***	2.40	1.99
Dietary diversity	0.61	0.004	0.09***	0.70	0.01	0.18***	0.89	0.003
Labor demand	23.93	15.12	31.52***	55.45	38.42	-26.45***	28.97	17.93
Hired labor	7.65	6.47	28.24***	35.89	27.32	-23.30***	12.61	8.56
Family labor	16.28	11.57	3.28**	19.56	15.07	-3.91**	16.37	10.31
Land preparation	5.74	3.63	0.91**	6.65	4.61	-3.76***	2.90	1.79
Planting	2.87	1.81	8.22***	11.09	7.68	-6.74***	4.34	2.69
Weeding	4.79	3.02	11.85***	16.63	11.53	-11.42***	5.21	3.23
Harvesting	3.11	1.96	3.54***	6.65	4.61	2.04***	8.69	5.38
Threshing	3.59	2.27	0.85***	4.44	3.07	0.67**	3.76	2.33
Herbicide appl.	1.44	0.91	4.11***	5.54	3.84	-3.52***	2.03	1.25
Fertilizer appl.	2.39	1.51	2.04***	4.44	3.07	-2.41***	2.03	1.25
Explanatory variables								
Age	41.09	13.22	1.52	42.61	12.15	0.81	43.42	12.46
Male headed	0.44	0.50	0.29***	0.73	0.44	0.06	0.80	0.40
HH size	5.95	3.25	-0.07	5.88	2.79	0.19	6.08	2.73
Education	2.65	3.87	1.80***	4.45	5.12	0.10	4.56	5.29
FBO	0.23	0.42	0.07	0.30	0.46	0.11**	0.41	0.49
Farm size	6.18	5.46	-1.87***	4.31	2.74	0.83**	5.13	3.21
Extension	8.40	6.36	1.57**	9.98	5.59	3.30***	13.28	7.62
Credit access	0.46	0.50	-0.09*	0.37	0.48	-0.13**	0.23	0.42
Livestock	1.22	3.32	0.95**	2.17	4.21	0.14	2.31	4.87
Slope	0.68	0.47	-0.001	0.68	0.47	-0.07	0.61	0.49
Fertile soil	0.38	0.48	0.03	0.40	0.49	-0.05	0.36	0.48
Moderately fertile soil	0.45	0.50	0.08	0.53	0.50	0.02	0.55	0.50
Asset (log)	6.74	1.14	0.61***	7.36	0.07	0.58***	7.94	0.06
Negative rainfall shock	0.34	0.47	0.18***	0.52	0.50	0.07	0.59	0.49
Mean temperature	27.29	0.46	0.07	27.37	0.48	-0.02	27.34	0.48
Fertilizer	208.13	123.67	79.73***	128.39	91.50	2.47	130.87	95.73
Climate information	0.36	0.48	0.46***	0.83	0.38	-0.09*	0.73	0.44
CA Training	0.71	1.14	4.17***	4.88	3.09	0.13	5.01	2.82
No. of obs. (plots)	391			226			269	

Note: Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Exchange rate at the time of survey: 1 USD = 5.14 Ghana Cedis (GHS)

Table 3.A2: Test of validity of selection instruments

Variable	Maize yields	HFIAS	Dietary diversity	Labor demand
Climate information	0.07 (0.06)	0.16 (0.37)	-0.11 (0.28)	0.03 (0.08)
CA Training	0.03 (0.02)	0.20 (0.14)	-0.13 (0.16)	-0.004 (0.04)
F-test on instruments	1.79	1.06	0.56	0.05
p-value	0.17	0.57	0.54	0.95

Table 3.A3. Disaggregation of labor demand

Variable	Description	Mean	Std. Dev
Labor demand	Total person-days per acre	33.77	27.44
Hired labor	Hired labor (person-days) used per acre	16.60	19.27
Family labor	Family labor (person-days) used per acre	17.17	12.28
Land preparation	Labor (person-days/acre) used for land preparation	5.08	3.80
Planting	Labor (person-days/acre) used for planting	5.49	5.53
Weeding	Labor (person-days/acre) used for weeding	8.02	8.25
Harvesting	Labor (person-days/acre) used for harvesting	5.80	4.70
Threshing	Labor (person-days/acre) used for threshing	3.87	2.54
Herbicide application	Labor (person-days/acre) used for herbicide application	2.70	2.76
Fertilizer application	Labor (person-days/acre) used for pesticide application	2.81	2.21

Table 3.A4: Correlation between instrumental variable outcomes variables

Instrument	Climate information		Training	
Dependent variable	Correlation	p-value	Correlation	p-value
Maize yield	0.1248	0.0955	0.0553	0.2751
HFIAS	-0.0038	0.9397	-0.0746	0.1407
Dietary diversity	0.0589	0.2455	0.0112	0.8256
Labor demand	0.0038	0.9405	0.0324	0.5234

Table 3.A5. First-stage regressions of the IV-GMM

Variables	First-stage IV-GMM	
	Coefficient	S.E.
Age	0.002	0.002
Male headed	0.161***	0.044
HH size	-0.003*	0.007
Education	0.008	0.005
FBO	0.117***	0.044
Farm size	0.019**	0.009
Extension	0.014***	0.004
Credit access	-0.07	0.043
Livestock	0.001	0.006
Mean_slope	-0.170***	0.043
Mean_fertile	0.048	0.058
Mean_Mod. fertile	0.122**	0.055
Asset (log)	0.163***	0.018
Negative rainfall shock	0.117	0.073
Mean temperature	-0.255***	0.053
Fertilizer (log)	-0.066***	0.014
Climate information	0.244***	0.048
CA Training	0.099***	.012
Northern	-0.371***	0.070
Upper West	-0.199***	0.089
Constant	7.329	1.459
R ²	0.921	
Weak identification tests:		
Cragg-Donald F-statistic	257.63***	
Kleibergen-Paap rk Wald F statistic	77.75	
P-value of Angrist-Pischke F-test	0.0000	
Over identification test:		
Hansen J	1.204	
p-value	0.2726	

NB: the table presents first-stage estimations of the IV-GMM regression of length of adoption on the main set of controls and the instruments as in our main model reported in Table 2.

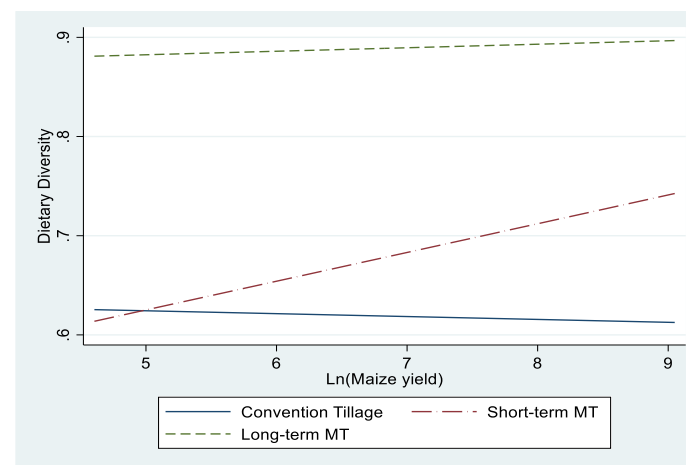
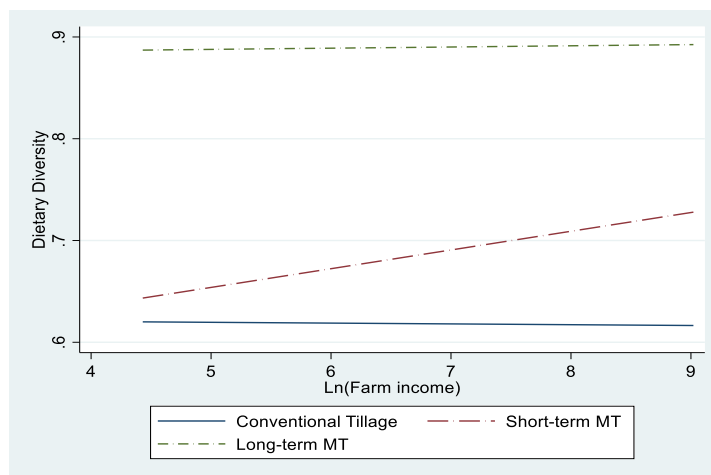


Figure 3.A1. Plot of potential outcomes by household farm income and maize yields for dietary diversity

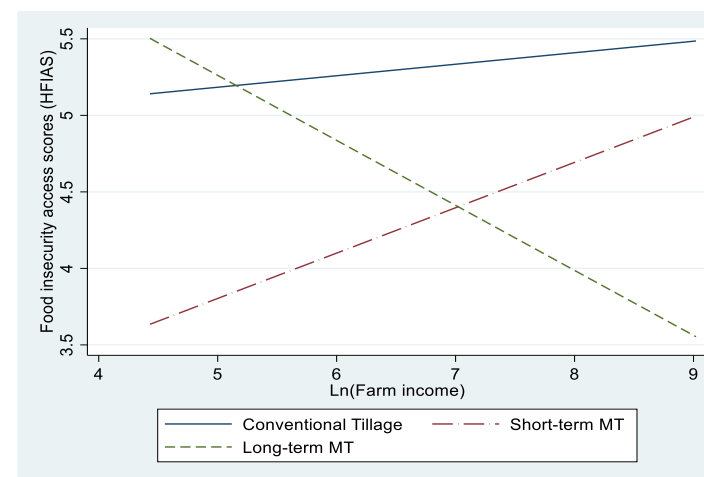
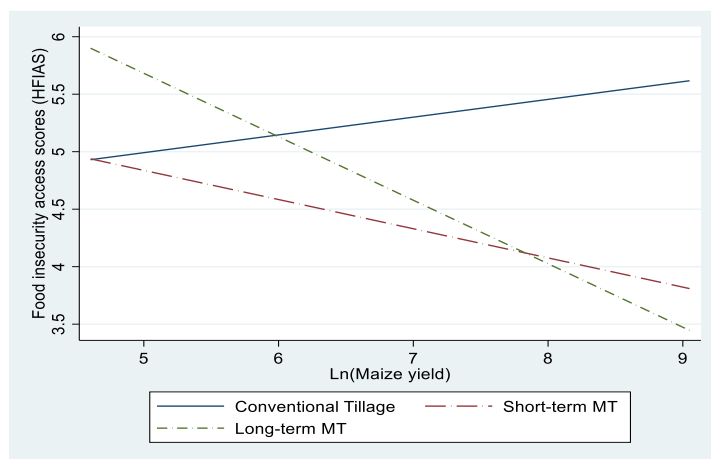


Figure 3.A2. Plot of potential outcomes by household farm income and maize yields for food insecurity access scores (HFIAS)

Chapter 4

Heterogeneous impact of crop diversification on farm performance and risk exposure.

Empirical Evidence from Ghana.

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Abstract

Increasing frequency of extreme weather events threatens the livelihoods of low-income farm households due to the heavy dependence on rain-fed agriculture coupled with the under-developed formal markets for risk management products. Thus, crop diversification is one of the widely used *ex ante* adaptation strategies to hedge against weather risk exposure. In this study, we use survey data from the northern Savanna zone of Ghana merged with historical weather data to shed light on the heterogeneous impact of crop diversification on farm net returns and risk exposure. We employ the dose response function and instrumental variable techniques to address potential endogeneity concerns. Overall, our findings show that crop diversification is a welfare-enhancing strategy that significantly increases farm net returns, lowers the probability of crop failure, and thus decreases downside risk exposure. However, the dose response function results show that crop diversification generates positive benefits at relatively lower intensities up to a threshold and tends to decline as diversification level increases. The findings also reveal that access to climate-related information and increased fertilizer usage influence the intensity of crop diversification. Thus, enhancing access to climate information, and providing tailor-made extension messages for heterogeneous landscapes of farmers could improve their livelihoods.

Keywords: climate risk management; crop diversification; dose response function

JEL classifications: D81, Q12, Q54, C31.

4.1 Introduction

Production and income risks are major source of concern in sub-Saharan Africa (SSA), particularly due to weather-induced risks—mainly long dry spells, floods, and crop pest and disease infestations; as well as to market risks such as crop price volatility (Adhikari et al., 2015; Kray et al., 2018). Climate variability and extreme weather events affect the quantity and quality of crop production, increases the volatility of farm income, and thus contribute to increased food and nutrition insecurity among marginalized households who lack adequate assets to buffer against these risks (Kray et al., 2018). The Food and Agriculture Organization (FAO) projects a decline in the global average yields across all crops by 1.1 percent by 2050 due to climate change, with the largest decline expected to occur in sub-Saharan Africa (FAO, 2018).

Farm households' decisions to diversify or specialize crop production affect their resilience, and hence their capacity to cope with these risks. Therefore, understanding the effect of their cropping decisions and risk management strategies are inevitable parts of the response to these weather-related shocks. The literature shows a myriad of *ex-ante* and *ex-post* risk management instruments, including credit, insurance, and use of drought-tolerant varieties that contribute to building the resilience of vulnerable farm households. However, imperfect credit and insurance market conditions, information asymmetry, high transaction cost, and governance challenges that characterize rural economies, particularly in sub-Saharan Africa, are compelling push factors for crop diversification as an important risk hedging option (Jensen and Barrett, 2017; Arslan et al., 2017).

There is renewed interest by development organizations and governments in promoting crop diversification as an effective strategy to minimize the risk of crop failure and to mitigate income risks for marginal and low-income farm households. For example, the FAO's 2021 State of Food and Agriculture (SoFA) report emphasizes the need to enhance the resilience of

agricultural households through crop diversification to create multiple pathways for absorbing shocks associated with climate variability and market volatility (FAO, 2021b). Moreover, in Ghana, the governments' flagship program on Planting for Food and Jobs (PFJ)²³, which is aimed at boosting agricultural production among smallholder farm households, encourages the intensification and diversification of farm enterprises for job creation and sustainable agri-food systems (Pauw, 2021).

Crop diversification in our context refers to the practice of shifting from monoculture to cultivating additional crops through, e.g., multiple cropping or intercropping within the same farming season (Chemura et al., 2020). Economic theories that study agent's behavior under uncertainty, such as the Portfolio Theory by Markowitz (2010, 1952) are useful for explaining farm households' response mechanisms to shocks. The theory assumes that if the cultivation of two crops are not perfectly correlated with each other, combining them in a portfolio under a diversified system, contributes to a reduction of the risk associated with crop production (Paut et al., 2019). Specifically, more diverse cropping systems increase the resilience of agro-ecosystems to climate-related stressors and shocks by providing different levels of susceptibility and traits such as drought tolerance, and by providing key ecosystem services such as fixation of atmospheric nitrogen, soil carbon sequestration, or disease and pest control (Altieri et al., 2015).

Thus, crop diversification tends to reduce income variability and downside risk exposure for risk-averse and low-income farm households operating under marginal farmlands and rain-fed agriculture (Bozzola and Smale, 2020). Although crop diversification may improve the adaptive capacity of farm households to weather-related and market shocks, heterogeneity in socio-economic drivers and the level of diversification decisions may shape the distribution and

²³ The Planting for Food and Jobs (PFJ) initiative, which began in 2017, provides seed and fertilizer subsidy and of boosting smallholder agricultural production and creating jobs along agricultural value chains through other complementary interventions. In addition, it provides services to smallholder farmers, such as extension advice and marketing support (MoFA, 2017).

the extent of the welfare gains among farmers (Makate et al., 2022). Therefore, unpacking possible heterogeneous effect of crop diversification across different intensities rather than a mean causal effect is an important first step in developing effective policies and programs for household risk management in sub-Saharan Africa. To this end, we employed a recent survey data of farm households from the northern Savanna zone of Ghana merged with geo-referenced historical weather data (rainfall and temperature) to examine the heterogeneous impact of crop diversification on farm performance and risk exposure.

The study contributes to the literature on crop diversification and risk exposure as follows: First, despite the extensive application of variance in measuring risk exposure, there are concerns in the literature about its limitation in distinguishing between “downside risk” and “upside risk” (Chavas and Shi, 2015). As a result, we use in addition to variance, the skewness of the farm net returns distribution in our risk analysis. The focus on skewness in measuring risk is consistent with the maximization of expected utility and gives a clearer picture of downside risks. In other words, this approach helps determine if crop diversification is beneficial for farm households that are most vulnerable to climatic shocks (Antle, 2010; Bozzola and Smale, 2020).

Second, recent studies in Ghana (Bellon et al., 2020; Dagunga et al., 2020; Martey et al., 2022), Uganda (Asfaw et al., 2018; Tesfaye and Tirivayi, 2020), and Namibia (Mulwa and Visser, 2020) have shown positive impacts of crop diversity on poverty reduction, dietary diversity and household income. Other studies in Ethiopia (Di Falco and Chavas, 2009; Michler and Josephson, 2017), Bangladesh (Moniruzzaman, 2019), and Kenya (Bozzola and Smale, 2020) also found that crop diversification tends to decrease the variance and downside risk of crop yields and farm revenues. Notwithstanding the contribution of the above-mentioned studies in understanding its impact on household welfare and risk exposure, they fail to disaggregate the effect of diversification with respect to the level of intensity. This limitation is

non-trivial because crop diversification intensity varies and provides different levels of responses to farm net returns and risk exposure. We assume that farmers are risk-averse and choose the level of intensity to maximize their expected utility. Thus, increasing climatic risks lead farm households to increase their intensity of diversification, as it may provide them with greater natural insurance (Baumgärtner and Quaas, 2010). Furthermore, and more importantly, the impact of diversification may, however, flatten or diminish once a certain threshold is reached, particularly due to competition for the same nutrients and water, thus lowering crop productivity (Kray et al., 2018).

Therefore, the present study fills the knowledge gaps by employing the dose response function (DRF) approach to evaluate the heterogeneity in the impact of crop diversification on farm net returns and risk exposure (i.e. variance, and skewness) across different intensities. Our estimation approach incorporates a zero-treatment probability mass, addresses the potential endogeneity of crop diversification in farm net returns, and thus restores the consistency of the estimates using instrumental variable (IV) estimation (Cerulli, 2015; Esposti, 2017). To the best of our knowledge, the use of dose response approach for the analysis of crop diversification is a novelty as it disaggregates the causal effect of different diversification intensities instead of a single average causal effect.

The remainder of the paper is organized as follows: The next section describes the impact pathways of crop diversification. The survey data is described in section 4.3. The conceptual framework is outlined in section 4.4. Section 5 presents the empirical strategy of the study. The empirical results and discussions are presented in section 4.6, while the final section concludes the study.

4.2 Pathways of crop diversification

The literature conceptualizes crop diversification in terms of “push” and “pull” factors that are influenced by socio-economic and institutional factors, as well as biophysical conditions. In the

absence of perfect agricultural insurance and credit markets (Jensen and Barrett, 2017), farm households faced with uncertainties of crop production are pushed to cultivate a portfolio of crops instead of specializing (Tesfaye and Tirivayi, 2020). As weather-related risks increase, crop diversification reduce the variance of production and farm incomes, and limit exposure to downside risk because of its natural insurance function (Baumgärtner and Quaas, 2010; Arslan et al., 2018). This is can be explained by the “sampling effect” hypothesis which asserts that greater diversity enables greater productivity and increases the goodness of fit between species traits and environmental conditions. Therefore, different crops occupy multitude of niches, facilitate ecosystem functioning and tend to reduce the variance of outcomes, hence, buffer against crop failure (Tilman et al., 2005). Furthermore, under a diverse cropping system, unsystematic risks, that is, those risks that do not have the same effect on crops, such as risk of crop-specific pests and diseases can potentially be reduced.

On the other hand, and depending on the market-orientation, resource endowed and more educated farm households with relatively better market access conditions are likely to be pulled into diversification as a means of smoothing their incomes, as well as reducing their exposure to market risks (e.g., fluctuations in the prices of produce) (Kray et al., 2018). In a risky context with imperfect output markets, it is assumed that farm households can reduce their exposure to price volatility by diversifying their production systems. It is worth mentioning that, farm households with low capacity to purchase agricultural inputs such as mineral fertilizers are usually motivated to cultivate crop mixes including legumes, as they provide biological nitrogen fixation and thus improve the fertility of the soil (Mulwa and Visser, 2020). Thus, in the long run, the continuous adoption of crop diversification could lead to a reduction in the cost of production as it may reduce the need to purchase expensive fertilizers.

4.3 Data and descriptive statistics

4.3.1 Data sources

The data used in the analysis come from 487 farm households in the northern savanna zone of Ghana: A survey was conducted for the 2018/2019 cropping season in 15 communities across six districts and three regions under the Sustainable Land and Water Management Project intervention areas. We purposively selected six districts from the three regions based on the operational areas of the project. Further, we randomly selected three to six communities from each district. Finally, 487 farm households were randomly sampled in proportion to the farmer population in the community. The survey data were collected using a structured questionnaire by trained and qualified researchers and enumerators with good working knowledge of the farming systems in the study areas. The survey also collected household data on crop production, household demographic characteristics, access to market information, and extension contacts.

Based on a review of the literature on crop diversification, (e.g. Di Falco and Chavas, 2009; Tesfaye and Tirivayi, 2020; Bozzola and Smale, 2020), we present in Table 1 a detailed description of the control variables used in our empirical analysis. We include household-level information and demographic characteristics. The risk management decisions of farm households depend on factors such as age, gender, education of household head, household size, and asset ownership (e.g. farm size, livestock ownership). Other factors include access to extension service, membership of Farmer Based Organizations (FBO), and access to credit. We define credit-constrained farmers following the approach of Abdulai and Huffman (2014), as those who received credit but expressed a desire to borrow more at the existing interest rate, or those whose credit request was denied, or those who had no access to any form of credit. We also include location-fixed effects. These dummy variables may capture observed covariates

that vary with the agro-ecological zones. We hypothesize that crop diversification and climate change adaptation decisions may be influenced by agro-ecological conditions.

Table 4.1: Variable Descriptions and Descriptive Statistics

Variable	Description	Mean	Std. Dev
Outcome variables			
Farm net returns	Value of crop production less variable costs (GHS) per acre	1662.31	1755.48
Variance	Second central moment of farm net returns distribution	0.73	0.92
Skewness	Third central moment of farm net returns distribution	-0.27	2.04
Treatment variables			
Diversification index ^a	Margalef index of diversification	20.41	16.10
Number of crops	Number of crops cultivated by households	3.453	1.703
Explanatory variables			
Age	Age of household head in years	42.50	12.62
Male headed	Male =1, Female =0	0.65	0.48
Household size	Size of Household	6.00	2.96
Education	Years of schooling of household head	3.80	4.80
FBO	1 if a member of Farmer Based Organization (FBO), 0 otherwise	0.32	0.46
Farm size	Total farm size of HH in acres	5.45	4.30
Extension	Number of extension contacts per annum	10.61	7.02
Credit constraint	1 if HH is credit constrained, 0 otherwise	0.35	0.48
Livestock	Number of Livestock in Tropical Livestock (TLU) Units	1.91	4.16
Market distance	Distance to the nearest market (km)	8.50	4.64
Asset	Value of HH durable assets (‘000 GHS)	2.70	2.46
Negative rainfall shock	1 if the metrics indicate a level of rainfall with a standard deviation below the long-term mean, 0 otherwise	0.46	0.50
Mean temperature	Mean temperature in °C (1981 to 2002)	27.34	0.47
Climate information	HH receives current climate information = 1, 0 otherwise	0.63	0.48
Improved seeds	1 if farmer used improved seed varieties, 0 otherwise	0.92	0.27
Fertilizer use	Quantity of fertilizer use per acre (kg)	95.75	70.99
Fertility	1 if the soil is considered moderately to fertile, 0 otherwise	0.89	0.31
Distance input dealer	Distance from homestead to the nearest input dealer (km)	2.47	1.61
Sudan	Sudan savanna zone =1, 0 otherwise	0.49	0.50
Guinea	Guinea savanna zone =1, 0 otherwise	0.51	0.50
Number of observations		487	

^a we transform the diversification index to take values in the [0, 100] range, where 0 is the treatment level of the untreated units, with 100 being the maximum dose.

4.3.2 Cropping systems

Among the most dominant crops cultivated in the study area are maize, rice, groundnut, soybean, sorghum, millet, and yam (Boansi et al., 2021). It is the case that maize dominates

crop production and is cultivated by all households in our sample. However, despite its food security and economic benefits, maize is susceptible to weather-related shocks and affects the livelihood of farm households (FAO, 2018; Kray et al., 2018; Boansi et al., 2021). Thus, diversified farm households cultivate in addition to maize, a number of crop combinations of the same kind or intercrop with different species either on the same piece of land or different plots.

To provide a common basis for our analysis, we focus on the list of major crops cultivated (i.e., cereals, legumes, and root and tubers) in the study area (see Figure 4.A1) under the Planting for Food and Jobs program (Pauw, 2021). This study categorizes these crops into three: (1) maize-monocropping; (2) legumes (i.e. groundnut, cowpea, soybean), and (3) alternative staple (i.e. millet, sorghum, rice, yam). As shown in Table 4.A1 (*see appendix*), these observed crop categories further appear in different combinations (i.e. Maize-legume, Maize-staple, Maize-legume-staple) and provide varying degrees of commercialization and agronomic benefits, as well as climate resilience.

4.3.3 Measurement of crop diversification

We define diversified farm households to include those who cultivated more than one of the above-mentioned crops. This study employs the Margalef index of richness (number of species or varieties) to measure crop diversification as follows:

$d = \frac{S-1}{\ln(A)}$, where A is the total area planted for the portfolio of crops and S is the total number of crops planted.

Several studies have used different indices such as Simpson diversification index (e.g. Bellon et al., 2020), Herfindahl index of diversity (e.g. Mulwa and Visser, 2020), Shannon-diversity index (e.g. Tesfaye and Tirivayi, 2020) to compute crop diversification among farm households. Nevertheless, Margalef provides better goodness of fit compared to the other indices and can

capture the richness of crop species. More importantly, the above-mentioned indices such as the Simpson diversification index require the computation of the area share occupied by the various crops planted by households. However, in our study area, farmers also intercrop different crops on the same piece of land, making it difficult to measure the actual area allocated to each crop. Thus, employing the Margalef index provides a more practical and consistent way of computing crop diversification in our setting. The index is between zero and one; hence, the larger the index, the greater the different crop species grown by farm households.

4.3.4 Summary statistics

In this section, we briefly present the descriptive statistics on the different cropping patterns and levels of diversification among farm households. With respect to the cropping systems, the results of the *t*-test statistics in Table 4.A1 show that maize mono-cropping is dominated by farm households with lowest average farm net returns (565.56 GHS/acre), negative skewness (-2.67) and a higher variance (1.63). This indicates that maize mono-cropping households are basically pulled into this cropping system in an attempt to meet their food consumption needs given that maize is the most widely consumed and cultivated staple crop *albeit* with limited appeal as commercial crop (Gage et al., 2012; GSS, 2018).

Moreover, the relatively higher fertilizer usage (121.02 kg/acre) further suggests a rather depleted soil nutrients due to the continuous practice of monocropping, hence increased application of inorganic fertilizer to improve fertility and support plant growth. Compared to maize-staple system, the net farm returns of legume-based systems are higher, either in combination with maize (2202.62 GHS/acre) or in a maize-legume-staple system (2016.15 GHS/acre). This heterogeneity in benefits can be explained by economic and agronomic reasons affecting these crops and their respective combinations. The commercialization potential of legumes such as groundnut and soybean may pull household to incorporate them into maize-based cropping systems (Maggio et al, 2018).

Table 4.A2 (*see appendix*) further compares the differences in mean between “non-diversified”, “somewhat diversified” (i.e. diversification index less than 50%) and “very diversified” (i.e. diversification index greater than 50%) households. In particular, the net farm returns are higher among “somewhat diversified” (1318.43 GHS/acre) and “very diversified” (2587.37 GHS/acre) households compared to non-diversified households (565.56 GHS/acre). The results also show that the average farm size is larger among “somewhat diversified” (6.8 acres) compared to “very diversified” (3.47 acres) and non-diversified households (6.23) households. Also, the amount of inorganic fertilizer use is lower among “somewhat diversified” (85.21/acre) compared to “very diversified” (96.43/acre) and non-diversified (121.2/acre) households. These significant differences in the outcome variables and the household characteristics may not indicate impact of diversification, as this comparison do not account for selection bias arising from observed and unobserved factors.

4.4 Conceptual framework

We assume that farm households are risk-averse and maximize their expected utility of farm net returns π , through optimal utilization of vector of inputs X for maize monocropping, and d which represent inputs for diversification (e.g. different crop seeds) to produce N multiple outputs $y_n = (y_1, y_2, \dots, y_N)$. The output prices are denoted as $P_n = (P_1, P_2, \dots, P_N)$ while C_x and C_d are the corresponding vector of input prices for inputs X and d , respectively. We assume that the inputs and output prices are non-random since smallholder farmers are mostly price-takers with respect to both input and output markets. Therefore, we represent φ as the vector of random variables that captures observed factors that are beyond the control of farmers (e.g. rainfall shocks, temperature variation, seasonal dry spells). The corresponding production technology can be represented by a stochastic production function $y = f(X, d, \varphi)$. Under risk aversion, farm households’ expected utility maximization problem can be expressed as follows:

$$\text{Max } E[U(\pi)] = \text{Max } E \left\{ U \left[\left(\sum_{n=1}^N P_n y_n(X, d, \emptyset) \right) - C'_x X - C'_d d \right] \right\} \quad (1)$$

where $U(\cdot)$ is the von Neumann-Morgenstern utility function. E denotes the expectation operator, and π is the farm net returns. Risk-averse farmers will thus diversify their crop production systems if the expected utility (i.e. farm net returns) to be derived $E[U(\pi^A)]$ is greater than not diversifying $E[U(\pi^N)]$, i.e. $E[U(\pi^A)] - E[U(\pi^N)] > 0$

Assuming a strictly interior solution, the first-order conditions from equation (1) for crop diversification can be specified as:

$$C_d^A = E[\partial U(\pi^A)/\partial \pi^A | C_d] = E \left[(\partial U(\pi^A)/\partial \pi^A) \cdot \frac{P(\partial y_n^A(\cdot)/\partial d^A)}{\partial d^A} \right] \quad (2)$$

Equation (2) can be reformulated to obtain the following specification:

$$\frac{C_d^A}{P} = E \left[\frac{(\partial y_n^A(X, d, \emptyset))}{\partial d^A} \right] + \frac{\text{cov}[\partial y_n^A(\cdot)/\partial d^A; \partial U(\pi^A)/\partial \pi^A]}{E[\partial U(\cdot)/\partial \pi^A]} \quad (3)$$

The term with the covariance in equation (3), which is associated with production uncertainty, is the risk premium associated with the farmer's decision problem. For a risk-neutral farmer, $\text{cov}[\partial y_n^A(\cdot)/\partial d^A; \partial U(\pi^A)/\partial \pi^A] = 0$, and the ratio $\frac{C_d^A}{P}$ would be equal to the expected marginal product of the inputs (i.e. different crop seeds) used for diversification. However, in the case of a risk-averse farmer, this term is different from zero. Risk preferences generally influence farmers' behavior and welfare, and risk-averse decision-makers are motivated to reduce their risk exposure (Di Falco and Chavas, 2009). As showed by Pratt (1964), risk-aversion can be examined using the Arrow-Pratt risk-aversion coefficient, $R^A = -\left(\frac{\partial^2 U(\pi^A)/\partial \pi^2 A}{\partial U(\pi^A)/\partial \pi^A} \right)$. When $(\partial U(\pi^A)/\partial \pi^A) > 0$ risk aversion corresponds to $\frac{\partial^2 U(\pi^A)}{\partial \pi^2 A} > 0$, and $R^A > 0$.

In line with previous studies, we use the variance and skewness to capture farmers' exposure to risks (Antle, 2010; Chavas and Shi, 2015). In a typical agrarian setting, smallholder farmers are mostly concerned about the exposure to downside risk or unfavorable risky occurrences located in the lower part of the income distribution. Exposure to downside risk often creates liquidity challenges that impact negatively on household welfare (Bozzola and Smale, 2020). Thus, we incorporate aversion to downside risk by considering this term, $\frac{\partial R^A}{\partial \pi^A} = -\left(\frac{\partial^3 U(\pi^A)/\partial \pi^{3A}}{\partial U(\pi^A)/\partial \pi^A}\right) + (R^A)^2$, where R^A represents Arrow-Pratt measure of absolute risk aversion, and decreasing absolute risk aversion means $\frac{\partial^3 U(\pi^A)}{\partial \pi^{3A}} > 0$, implying aversion to unfavorable downside risk. Smallholder farmers experiencing downside risk aversion consider management strategies such as crop diversification to reduce variability and downside risk exposure.

4.5 Econometric Framework and Empirical approach

To proceed with the estimation process, we rely on the moment-based approach of the stochastic production function (Antle, 1983) to test how different intensities of crop diversification affect farm net returns and its higher moments. Specifically, we account for the extent of risk exposure by approximating the variance and skewness of farm net returns to examine the effect of crop diversification on volatility and downside risk. Thus, we regress farm net returns on production inputs and other farm-level variables from which the residuals are generated to compute the different moments (i.e. variance and skewness) in equations 4-6.

$$E[f(X, d, \varphi) - q_1(X, d, \varphi)]^k = q_k(X, d, \varphi, \beta_k) \forall k \geq 2 \quad (4)$$

where $q_1(\cdot) = E(f(X, d, \varphi))$ denotes the mean of the production function. Given equation (4), we express the variance, which reflects the second moment of the farm net returns distribution as:

$$E[(f(X, d, \varphi) - E(f(X, d, \varphi)))^2] = \mu_2 \quad (5)$$

Similarly, the skewness (reflecting the third moment of farm net returns distribution) is given as:

$$E[(f(X, d, \varphi) - E(f(X, d, \varphi)))^3] = \mu_3 \quad (6)$$

The skewness approximates downside risks. In other words, positive skewness means a decrease in downside risk exposure and for that matter a decrease in the probability of crop failure. Thus, smallholder farmers maximize their expected utility with an increase in farm net returns, a lower variance, and a positive skewness. We focus on farm net returns because it considers the fluctuations in the quantity and quality of production, as the quality is indirectly considered in the output prices. Therefore, variability in farm net returns provides the opportunity to effectively assess the risks farmers encounter (Bozzola and Smale, 2020).

4.5.1 Econometric Framework

Given that farm households differ in the intensity of adoption and choose the level of crop diversification to maximize the expected utility, as argued in the conceptual framework, we examine the heterogeneous impact of crop diversification intensity using the dose response function (DRF) (Cerulli, 2015). The econometric puzzle in identifying and consistently estimating the dose response function and the average treatment effect (ATE) is the potential endogeneity of the crop diversification, as diversification decisions are not random. In other words, farm households' diversification decisions may be influenced by latent traits (e.g. motivation, entrepreneur skills) that could also influence the output variable and hence may lead to inconsistent estimates of the parameters.

To tackle this potential source of endogeneity, our estimation approach proposed by Cerulli (2015) accounts for the potential threat of treatment endogeneity through an instrumental variable (IV) estimation procedure. The approach further takes advantage of the continuous treatment (i.e. diversification intensity) and does not require the full normality assumption, and considers both treated (i.e. diversified) and non-treated (i.e. non-diversified)

units to identify the dose response functions and the average treatment effects, thus making use of the complete information in the dataset. Furthermore, it estimates other causal parameters of interest such as average treatment effect (ATE), average treatment effect on the treated (ATET), and average treatment effect on the untreated (ATENT).

Given that our sample contains a sizeable number of non-diversified (untreated) farmers, crop diversification intensity can be modeled by employing the type-1 Tobit model or Heckman two-step procedure (i.e. type-2 Tobit model). However, a limitation of the type-1 Tobit model is that it assumes that one set of variables and coefficients accounts for the two different behaviors in question: i.e. the adoption of crop diversification and the intensity of diversification. Hence, following Cerulli (2015), we employ Heckman's two-step procedure (or type-2 Tobit model) to model crop diversification decisions. We also use a two-stage least squares (2SLS) model to estimate the outcome equations using the predicted values computed from the type-2 Tobit model as instruments that provide consistent estimation of the model coefficients (Wooldridge, 2010; Chatzimichael et al., 2021).

4.5.2 Empirical Strategy

We represent adoption as binary treatment indicator denoted by (d_i) , with y_{i1} and y_{i0} denoting potential outcomes (i.e. farm net returns) for a diversified farmer ($d_i = 1$) and a non-diversified ($d_i = 0$), and x_i the vector of farm and household characteristics (see Table 1) for farmer $i = 1, \dots, N$; where N is the total number of observations (including diversified and non-diversified). Let $g_1(x)$ and $g_0(x)$ represent two functions as farmers' responses to x when diversified and non-diversified units, respectively; α_1 and α_0 are constants, and ε_1 and ε_0 as the error terms with zero mean and a constant variance. Lastly, the t represents the intensity of diversification, which is continuous and takes on values in the range $[0, 100]$, and $h(t)$ is a function different from zero and is a response of a given intensity or t . Given the above notations, we express the two potential outcomes as follows:

$$\begin{cases} d = 1: y_1 = \alpha_1 + g_1(x) + h(t) + \varepsilon_1 \\ d = 0: y_0 = \alpha_0 + g_0(x) + \varepsilon_0 \end{cases} \quad (7)$$

Given equation 7, we express the treatment effect (TE) as $TE = (y_1 - y_0)$ and the causal parameters of interests as the population ATEs conditional on x and t as follows:

$$ATE(x, t) = E(y_1 - y_0 | x, t)$$

$$ATET(x, t > 0) = E(y_1 - y_0 | x, t > 0) \quad (8)$$

$$ATENT(x, t = 0) = E(y_1 - y_0 | x, t = 0)$$

Assuming a linear parametric form for $g_1(x_i) = x\delta_1$ and $g_0(x_i) = x\delta_0$, the ATE conditional on x and t can be expressed as follows:

$$ATE(x, t, d) = d * [\alpha + x\delta_1 + h(t)] + (1 - d) * [\alpha + x\delta_0] \quad (9)$$

where $\alpha = (\alpha_1 - \alpha_0)$

4.5.3 Estimation procedure

The baseline regression for estimating the parameters of interest ($\alpha_1, \alpha_0, \delta_1, \delta_0, ATE$) and other treatment effect parameters (i.e. ATET, ATENT) is given as:

$$y_i = \alpha_0 + d_i * ATE + x_i\delta_0 + d_i\delta * (x_i - \bar{x}) + d_i * \{h(t_i) - \bar{h}\} + \eta_i \quad (10)$$

where $\eta_i = \varepsilon_{0i} + d_i * (\varepsilon_{1i} - \varepsilon_{0i})$ and represents the error term; \bar{h} is the sample mean of $h(t_i)$; and \bar{x} is the vector of averages of the observed covariates of farmer i .

To obtain consistent estimates of equation (10), we may assume unconfoundedness in equation (11), which indicates that both d and t are exogenous, given the observable variables in x .

$$E(y_{ji} | d_i, t_i, x_i) = E(y_{ji} | x_i) \text{ with } j = \{0, 1\} \quad (11)$$

Thus, by invoking this assumption, the ordinary least square (OLS) estimation of equation (10) could generate consistent and unbiased estimates of the basic coefficients of the model. However, in our context, this assumption might not hold because of the non-randomness of

crop diversification decisions. Consequently, d and t are potentially endogenous and might produce biased estimates. Thus, we further express equation (10) as follows (i.e. equations 12.1-12.3) consisting of outcome equation, the crop diversification equation, and the level of intensity equation:

$$y_i = \alpha_0 + x_i\delta_0 + d_iATE + d_i\delta * (x_i - \bar{x}) + ad_iK_{1i} + bd_iK_{2i} + cd_iK_{3i} + \eta_i \quad (12.1)$$

$$d_i^* = x_{id}\beta_d + z_{id}\omega_d + \epsilon_{id}, \quad d_i = 1, \text{ if } d_i^* > 0 \quad (12.2)$$

$$t'_i = x_{it}\beta_t + z_{it}\omega_t + \epsilon_{it} \quad (12.3)$$

where d_i^* is a latent variable, which is the difference between expected utility of farm net returns from crop diversification $E[U(\pi^A)]$ and without $E[U(\pi^N)]$. Farm household i will choose to diversify if $d_i^* > 0$; t_i is observed only when $d_i = 1$; $K_{1i} = t_i - E(t_i)$, $K_{2i} = t_i^2 - E(t_i^2)$, and $K_{3i} = t_i^3 - E(t_i^3)$, where these terms are the polynomial functions of the level of intensity and are different from zero when the treatment is positive. The terms x_{id} and x_{it} are two sets of observed covariates; $z_{it}\omega_t$ and $z_{id}\omega_d$ are the vectors of the instrumental variables for the crop diversification decision and level of intensity equations, respectively; and ϵ_{id} and ϵ_{it} are error terms with zero unconditional means. Equation (12.2) is the selection model with a vector of household and farm characteristics x_{id} , while equation (12.3) is the level of intensity equation.

The endogenous terms include d_i , K_{1i} , K_{2i} , K_{3i} , with the latter three being functions of the endogenous variable t . Intuitively, having two endogenous variables, that is, d_i^* and t'_i requires at least two sets of instruments (z_{id} and z_{it}) as a source of variability. We assume that these identifying instruments are directly correlated with d_i^* and t'_i , but uncorrelated with the error term of the equations estimating the impact of crop diversification on farm net returns and risk exposure, y_i (referred to as exclusive restriction). Therefore, we identify two separate sets of suitable instruments in line with the existing literature (e.g. Di Falco and Chavas, 2009; Bozzola and Smale, 2020; Tesfaye and Tirivayi, 2020).

The first set of instruments responsible for the crop diversification decisions d_i^* (z_{id}), is related to farm households' exposure to past rainfall shocks and mean temperatures over a decade preceding the data collection round. Various climate scenarios predict a rise in mean temperature by 2.1–2.4°C and wide fluctuations in rainfall patterns by 2050 in the northern Savanna zone of Ghana (World Bank, 2010). These changes are likely to have far-reaching implications on agricultural activities, especially among resource-poor farm households (Boansi et al., 2021). Thus, we draw on rainfall and temperature data (from the Prediction of Worldwide Energy Resources data archive)²⁴ that provides global data at high-resolution (0.5x0.5 degree) to generate a gridded rainfall and temperature time series. Using the farm household geographical coordinates, we generate negative rainfall shock²⁵ and mean temperature, using long-term mean rainfall and temperature data from 1981 to 2002 for the months within the cropping seasons.

We use these climatic variables as instruments only for a period (i.e. over a decade and a half) preceding the farming season in which the data was collected. Hence, we expect the past rainfall shocks and mean temperature to be correlated with crop diversification decisions at the time t but would not have a direct effect on current household farm net returns (Bozzola and Smale, 2020). By this reasoning, our instruments meet the exclusion restriction assumption, in that, they only affect farm net returns and risk exposure indirectly through crop diversification decisions. We test the relevance of the instruments²⁶ employing an F -test of the joint significance of the excluded instrument, the results of which are shown in Table 2. Furthermore, we use as instrument for the level of intensity indicator t'_i (z_{it}), the walking distance from agro-

²⁴ <https://power.larc.nasa.gov/data-access-viewer/>

²⁵ Following Michler et al. (2018), the rainfall shock is computed as follows: $\underline{RS}_{kt} = \left| \frac{R_{kt} - \bar{R}_k}{\sigma_{R_k}} \right|$ if $R_{kt} < \bar{R}_k$, 0 otherwise,

where R_{kt} is the observed rainfall for the previous year season, \bar{R}_k is the mean historical rainfall, and σ_{R_k} depict the standard deviation of rainfall for the same period

²⁶ We examine the validity of the instruments for the crop diversification decision d_i^* , following the approach of Di Falco et al. (2011) we run separately a probit model of the selection equation and OLS regression for the outcome equations of the untreated. The results show that the instruments positive and significantly affect crop diversification decisions (see the down part of Table 4.2) but did not show any statistically significant impact on the outcome variable among the untreated farm households (see first column of Table 4.A3).

input seller (Di Falco and Chavas, 2009). We argue that smallholder farm households' decision to lower risks through allocating farmlands to different crop species can be influenced by improved access to agricultural inputs (such as different crop seeds, fertilizers, etc.)²⁷. Thus, proximity to input markets is a *sine qua non* in improving access and could make a big difference concerning the intensity of diversification (Kray et al., 2018).

We then proceed to jointly estimate the crop diversification decision (12.2) and the level of intensity (12.3) using the Heckman two-step procedure (or type- 2 Tobit model), assuming that the errors are jointly normally distributed. We further estimate equation (12.1) employing a two-stage least squares (2SLS) approach using the predicted values of d_i and t_i computed from the previous Tobit estimation as instruments to obtain consistent and unbiased estimates of the basic parameters ($\alpha_0, \delta, \delta_0, a, b, c, ATE$) in equation 12.1. Based on the above estimates, we estimate the dose response function as:

$$ATE(t_i) = d_i \left(ATET + \hat{a}(t_i - \bar{t}) + \hat{b}(t_i^2 - \bar{t}^2) + \hat{c}(t_i^3 - \bar{t}^3) \right) + (1 - d_i) ATENT \quad (13)$$

where $\hat{a}, \hat{b}, \hat{c}$ are coefficients of the estimated polynomials; \bar{t}, \bar{t}^2 and \bar{t}^3 are the sample means for polynomial functions of the levels of intensity. The standard errors and confidence intervals for ATET and ATENT are correctly estimated via bootstrapping.

4.6 Empirical results and discussion

4.6.1 Drivers of crop diversification

We first report the results of the crop diversification decision equation (12.2). To ease interpretation, we report the marginal effects computed after estimation of a probit model in Table 4.2. In order to attempts to establish a causal link on the impact of crop diversification

²⁷ As argued by an anonymous reviewer, one potential threat to this identification strategy is that if firms choose to locate near the best farmers, distance to input sellers would be endogenous. However, this is not the case in our context, because the study area is typically rural and majority of input sellers normally locate close to other shops or retailers, and not farmers (Asante et al. 2021). Therefore, our context is different from the case in urban farming areas where input sellers might be sited in areas closer to best farmers. Also, the Planting for Food and Jobs program, which is an initiative of the government, has worked with private agricultural inputs providers to enhance supply at the community and district level (MoFA, 2017).

on farm net returns and its higher moments, we check the relevance and validity of these instruments by reporting test diagnostics of a generalized method of moments (IV-GMM) estimations of the effect of crop diversification on farm net returns in Table 4.A3. The diagnostics test statistics reported at the bottom of the Table (in the second column) indicate that the instruments are together relevant, and as such good predictors of crop diversification decisions. In particular, the Cragg-Donald F-statistic of 87.12, the Kleibergen-Paap rk Wald F-statistic of 70.97 and the associated Angrist and Pischke (2009) p -value ($p=0.000$) all reject the null hypothesis that the instruments are weak. In addition, given the Hansen J test statistic of 5.123 and the accompanying p -value of 0.1772, we cannot reject the null hypothesis of zero correlation between the instruments and the error term.

Consistent with our primary hypothesis, the marginal effect results show that the variable representing negative rainfall shock is positive and statistically significant driver of crop diversification, suggesting that past rainfall shocks act as a push factor for a diversified crop production system. As discussed earlier, our study area is dominated by maize farming which is sensitive to weather shocks. Therefore, as rainfall shocks and temperature increases, farmers move away from maize monocropping to a more diversified cropping system (Maggio et al., 2018) The above finding is consistent with recent empirical studies (e.g. Tesfaye and Tirivayi, 2020; Bozzola and Smale, 2020) that show a positive association between crop diversification and climate-related shocks. Also, increase in mean temperatures significantly increases the probability of crop diversification by 0.065. Further test of the relevance of our instruments rejects the null hypothesis, suggesting that the instruments are valid (see F -test below Table 4.2).

The estimates also show that the coefficient of the climate information variable is positive and statistically different from zero, indicating that farm households who receive climate information are more likely to diversify their production systems. Tailored-made seasonal

forecast information may assist farm households to plan and effectively select suitable crop species, as well as the timing of critical farming activities (e.g. land preparation, planting date, scheduling of fertilizer application). We also find that a unit increase in household assets (i.e. proxy of household wealth) increases the probability of crop diversification by 0.014. If farm households have more assets, they can either convert these to cash or use them as collateral to secure credit for the procurement of inputs such as improved seeds, fertilizers, and other inputs to enhance their diversified crop production systems. We also find that increase in distance to the main market decreases the probability of diversifying crop production systems by 0.010. As discussed in section 4.2, farm households within shorter distances to main markets are more likely to be pulled into cultivating portfolio of crops to smooth their incomes. Finally, the variable representing extension contacts is positively associated with crop diversification.

We then focus on the results from the level of intensity equation (12.3) presented in column 2 of Table 4.2. Starting with the instrumental variable of the model, the results show that walking distance to input dealer is an important driver that explains farm household's decisions on the level of crop diversification. Shorter distances to input dealers increase the level of diversified crop production systems. Focusing on the observed covariates, age has a significant and positive effect on the level of crop diversification, potentially indicating that risk aversion increases with age. Moreover, the variable measuring farm size is negative and statistically significant, while its quadratic term is also significant but has a positive sign. This finding implies that an increase in farm size decreases crop diversification intensity up to a threshold, beyond which diversification intensity begins to increase, thus suggesting a U-shaped pattern. Unsurprisingly, the coefficient associated with fertilizer use is positive and statistically significant, implying that a unit increase in the use of inorganic fertilizer increases the level of diversification. This finding is expected given that smallholder farmers normally receive subsidies on fertilizer under the Planting for Food and Jobs program.

Table 4.2: Drivers of crop diversification: First stage regression

Variables	Marginal effects	Standard Error	Diversification Level	Standard Error
	1		2	
Age	0.001	0.0005	0.099*	0.057
Male headed	0.025	0.017	-0.589	1.461
Household size	-0.002	0.002	-0.256	0.261
Education	0.001	0.001	-0.066	0.133
FBO	0.038**	0.016	-1.462	1.376
Farm size	0.009**	0.004	-4.345***	0.455
Farm size quadratic	-0.0003*	0.000	0.169***	0.022
Extension	0.005***	0.002	-0.099	0.109
Credit constraints	0.012	0.010	0.648	1.467
Market distance	-0.010***	0.004	0.093	0.162
Livestock	0.001	0.002	-0.139	0.144
Asset (log)	0.014**	0.006	0.362	0.608
Negative rainfall shock	0.080***	0.025		
Mean temperature	0.065***	0.0225		
Climate information	0.054**	0.022	2.889**	1.413
Improved seeds	0.153**	0.076	0.827	2.975
Fertilizer use (log)	-0.010**	0.005	0.696**	0.360
Fertility	-0.000	0.016	1.242	2.077
Distance input dealer			-1.694***	0.464
Sudan	0.019	0.014	0.842	1.439
Constant			34.055***	6.989
χ^2 test of instrument	47.48			
p value of instrument	0.000			
Number of observations		487		

Note: Table 4.2 reports the marginal effects estimates of the crop diversification decision from the probit selection model in column 1. In column 2, we report the estimates on the drivers of the level of crop diversification using the Margalef index of diversification. The p –values for the excluded instruments (Negative rainfall shock, mean temperature) are reported. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6.2 Determinants of farm net returns, variance, and skewness: Second-stage estimation

results

In this section, we present the estimation parameters of the outcome equations (12.1) in Table 4.3. Focusing first on the farm net returns equation (reported in column 1, Table 4.3), our results indicate that climate information has a positive and statistically significant effect on farm net returns, suggesting that receiving adequate climatic information enables farmers to adopt diversified cropping systems that enhance their farm net returns. In the regression model, we

include in addition to farm size, its quadratic term to detect whether its influence on farm net returns has a positive or negative curvature.

Interestingly, the coefficient of farm size is negative and statistically different from zero, however, its quadratic term is positive and statistically significant and follows a U-shaped pattern. In other words, the effect of farm size on farm net returns is not linear, indicating that increasing farm size leads to decreasing farm net returns up to a threshold, after which further increases in farm size results in increasing net returns. The coefficient of the variable representing extension is positive and statistically significant, indicating the positive effect of increased extension contacts on increasing farm net returns. The importance of agriculture extension as a mechanism for knowledge transfer has become necessary due to increasing demands by smallholder farmers to adapt their production activities to changing climatic conditions, to manage soil degradation, and above all to increase farm net returns.

The regression results for the variance and the skewness equations are shown in columns 2 and 3 of Table 4.3, respectively. The coefficient of the variable representing climate information is negative and statistically significant in the case of variance and positive in the case of skewness, indicating that receiving climate information (e.g. rainfall, temperature) contributes to decreasing the volatility of farm net returns, as well as decreasing downside risk exposure. These findings are consistent with the notion that receiving climate information is a decisive determinant for crop choice and leads to greater diversification to ward off risks (Kray et al., 2018).

Table 4.3: Second stage estimates of determinants

Variables	Farm net returns (log)		Variance		Skewness	
	1		2		3	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Age	-0.007**	0.003	-0.008	0.011	-0.001	0.009
Male headed	0.114	0.079	-0.092	0.100	0.286**	0.204
HH size	0.017	0.014	0.003	0.039	-0.014	0.035
Education	0.007	0.007	0.052	0.045	-0.020	0.018
FBO	0.343	0.337	-0.178	0.412	0.575	0.873
Farm size	-0.221**	0.093	-0.131	0.157	-0.020	0.241
Farm size quadratic	0.009**	0.004	0.006	0.006	0.001	0.011
Extension	0.035***	0.008	0.009	0.011	0.060***	0.021
Credit constraints	0.096	0.088	0.024	0.116	0.506	0.228
Market distance	0.007	0.027	0.001	0.037	-0.045	0.071
Livestock	-0.060	0.048	0.018	0.067	-0.040	0.144
Asset (log)	-0.082	0.031	-0.001	0.079	-0.055	0.338
Climate information	0.372***	0.084	-0.519***	0.103	1.052***	0.217
Improved seeds	0.338**	0.129	-0.021*	0.303	0.502**	0.334
Fertilizer use (log)	0.010	0.033	-0.139	0.156	-0.015	0.086
Fertility	0.146	0.101	-0.040	0.126	-0.555**	0.215
Sudan	0.010	0.087	-0.001	0.108	-0.071	0.224
Constant	7.618***	0.930	3.254**	1.213	-2.920	2.411
R-squared	0.495		0.462		0.341	
Number of observations			487			

Note: The table shows the estimates of the outcome equation 9.1 for farm net returns, variance and skewness. S.E reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.6.3 Impact of Crop Diversification

An important motivation of this study is to ascertain whether farm households benefit from diversified crop production systems and how this effect varies with respect to the crop diversification decision and the level of intensity. In doing so, we present the estimation results of the key treatment effect parameters in columns 1, 2, and 3 of Table 4.4 for farm net returns, variance, and skewness, respectively, as well as illustrate the distribution of the treatment effects conditional on the covariates in Figure 4.1. We further illustrate the estimated dose response functions in Figure 4.2.

In particular, the coefficients of the binary treatment variable show a positive average treatment effect (ATE) of 1.295 and 1.367 for farm net returns and skewness, respectively,

implying that for a farmer picked at random from the population of farmers, adopting crop diversification increases farm net returns by 1.295, and contributes to a decline in downside risk exposure and crop failure by 1.367. On the other hand, the ATE of the variance of farm net returns is negative and statistically significant, suggesting a reduction in the volatility of farm net returns by 0.962. Furthermore, the estimated treatment effect on the treated (ATET), whose standard errors are computed by running 200 bootstraps, are positive for farm net returns (1.166) and skewness (1.531), and negative (-0.948) in the case of variance. The estimated treatment effects on the untreated (ATENTs) have the expected coefficients in all cases but are not statistically significant.

Table 4.4: Estimates of Treatment Effects Parameters

Parameter	Farm net return (log) (1)	Variance (2)	Skewness (3)
ATE	1.295*** (0.744)	-0.962** (0.281)	1.367** (1.857)
ATET	1.166** (0.477)	-0.948** (0.302)	1.531* (1.436)
ATENT	1.899 (3.077)	-1.023 (3.104)	0.601 (9.209)

Number of observations = 487

Note: This Table presents the estimates of different treatment effects parameters; ATE (average treatment effect), ATET (effect of treatment on the treated), ATENT (effect of treatment on the untreated). ATET and ATENT standard errors in parenthesis are obtained by 200 bootstrap simulations. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Based on the above results, we further illustrate the distribution of the causal effects given the covariates for the diversified, non-diversified, and the whole sample in Figure 4.1. Consistent with the results in Table 4.4, the distributions (see Figure 4.1) depict a larger probability mass of positive values for farm net returns (see Figure 4.1a) and skewness (see Figure 4.1c), and negative values for variance (see Figure 4.1b). Furthermore, and in the case of farm net returns the peak of ATENT appears to be shifted to the right side of both ATE and ATET, suggesting that non- diversified farm households would have obtained higher farm net returns if they diversified, *albeit* not significant. This finding shows evidence of reverse selection on gains (ATENT>ATE>ATET), suggesting that farm households who are less likely to diversify their crop production system tend to benefit more if they diversify.

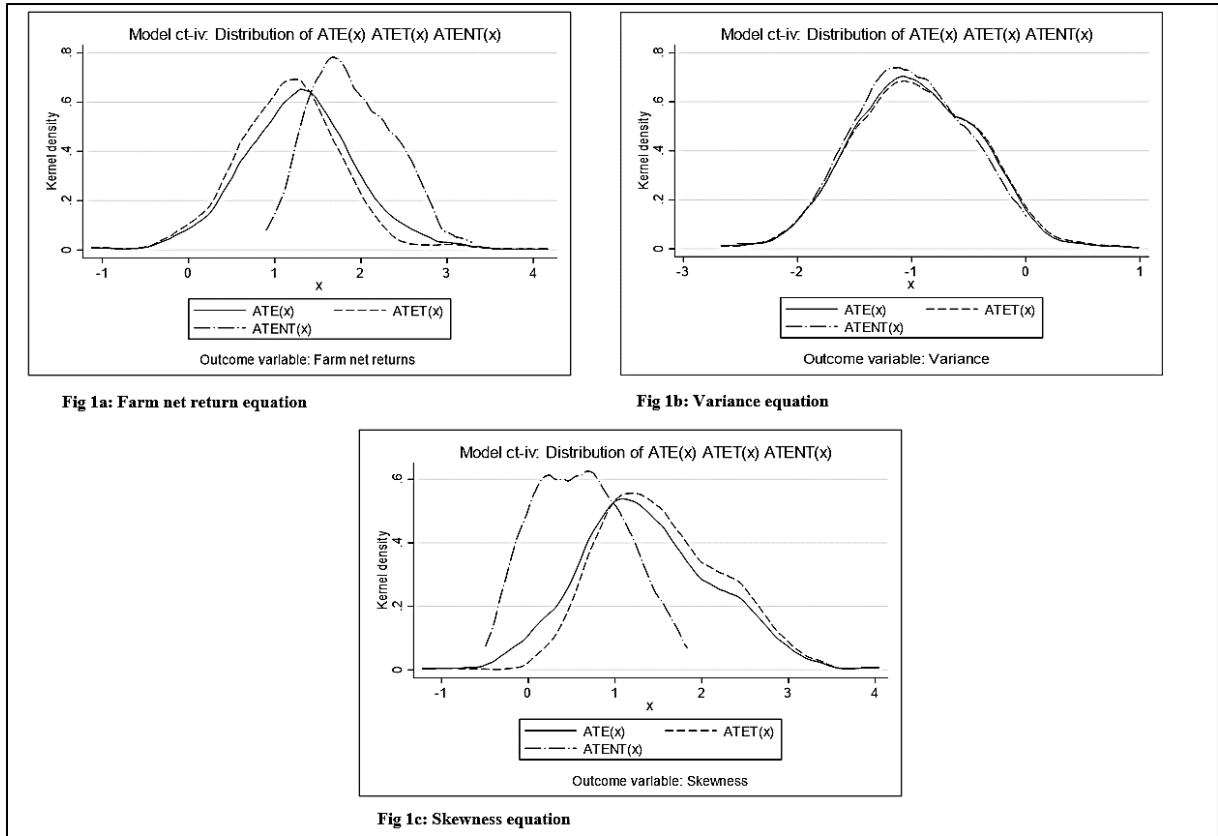


Figure 4.1: Distribution of treatment effects conditional on the covariates.

The above results show evidence of heterogeneous responses to crop diversification. In order to provide more information on this phenomenon, we illustrate in Figure 4.2 the estimated dose response functions (i.e. farm net returns, variance, and skewness) at each level of crop diversification, together with 95% confidence interval bounds. The results show average effect of crop diversification with respect to its intensities. In particular, an inverted U-shaped pattern is observed in Figure 4.2a and 4.2c with a region of positive and significant effect up to the dose of about 95 (i.e. ATE of 1.593) percent and about 90 percent (i.e. ATE of 1.499) in the case of farm net returns and skewness, respectively. The trend shows a maximum and significant effect of diversification around the dose of about 75 percent (i.e. ATE of 3.065) for farm net returns and about 70 percent (i.e. ATE of 3.550) for skewness. After these thresholds, a further increase in the intensity of crop diversification results in a decline in farm net returns and skewness, suggesting diminishing returns in the benefits from crop diversification.

Regarding the variance (see Figure 4.2b), we observe a region of negative effects up to the dose of about 70 percent (i.e. ATE of -0.015), *albeit* significant only up to 25 percent (i.e. ATE of -1.023), after which we observe increase in volatility (i.e. positive values). This implies that diversification reduces the variability of farm net returns up to a threshold and starts to increase as intensity increases.

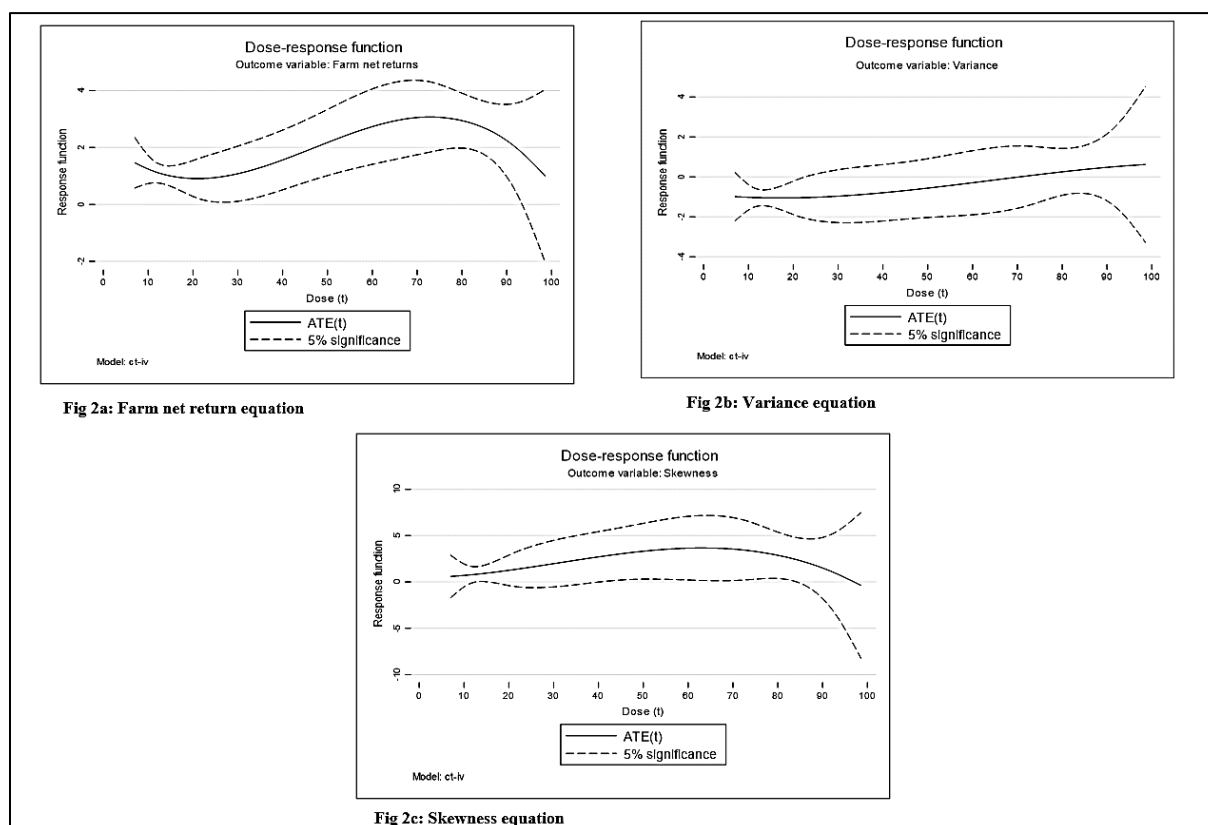


Figure 4.2: Estimated dose-response functions

The Figure shows the estimated dose-response functions (i.e. farm net returns, variance, and skewness) at each level of crop diversification together with 95% confidence interval bounds. NB: Crop diversification intensity in these Figures are scaled over $[0, 100]$ interval.

Overall, the findings highlight heterogeneous responses between crop diversification, farm performance, and risk exposure. In particular, we find that crop diversification increases farm household utility with respect to farm net returns, lowers variance (i.e. reduces farm net returns variability), and increases the skewness of farm net returns (i.e. decreases the risk of crop failure). However, far from being constant and homogeneous, our results indicate that crop diversification benefits in terms of increased farm net returns start to diminish after a certain threshold. The same pattern is also observed with respect to skewness, where crop

diversification lowers the probability of crop failure and therefore decreases the exposure to downside risk exposure up to a threshold, beyond which the effect decreases with each additional level of diversification. Similarly, the results show a non-linear relationship between crop diversification and variance, where a relatively lower diversified crop production system stabilizes farm net returns, while increased levels tends to increase the volatility of farm net returns.

A plausible explanation for these findings is the trade-off towards the allocation of resources as diversified crop production systems increase. In other words, as diversification increases and more crops are grown, there is increased competition for resources (i.e. labor, fertilizer, time, etc.) among crops and could affect the efficient allocation of resources, as well as reduce the farm-level efficiency (FAO, 2021b). Furthermore, highly diversified crop systems may result in some of the crops being cultivated at a smaller scale, thereby under-utilizing their comparative advantage. It is also worth mentioning that, the heterogeneity in the benefits of cropping systems is largely attributed to the agronomic importance and economic attributes of the crops under the diversified system. For instance, some of the alternative crops (e.g. millet, sorghum) may be less vulnerable to weather fluctuations, but are often poorly commercialized and primarily for household consumption, hence may not enhance farm income (Maggio et al., 2018).

4.6.4 Robustness check

To test the robustness of our estimation results, we employ the semi-variance approach²⁸ to approximate downside risk exposure. This approach captures losses that are below a certain threshold. The semi-variance and the variance differ when the farm net returns distribution is skewed. Further, the negative semi-variance is larger than the variance if the farm net returns distribution is negatively skewed (i.e. downside risk) (Bozzola and Smale, 2020). The resulting

²⁸ We express the semi-variance, which focuses on farm net return realization below the expected value as follows:

$$E(f(X, d, \mu) - E(f(X, d, \mu)))^2 \forall f(X, d, \mu) < E(f(X, d, \mu)) = \mu_2^- \quad (13)$$

estimates of the dose response function (see Figure 4.A4) show a U-shaped pattern, suggesting that as crop diversification increases, the downside risks significantly decrease up to a threshold (i.e. dose of about 65) and begins to increase upward. In comparison with the variance, the negative semi-variance can differentiate between upside and downside risks. Intuitively, these findings are of a similar pattern and corroborate the results of the skewness equation (which also approximates downside risks). Furthermore, the estimated treatment effect parameters (see Table 4.A4) have the expected signs and magnitude and thus affirm the robustness of our estimation results.

4.7 Conclusion and Policy Implication

This study contributes to the growing empirical literature and policy discourse by examining the heterogeneous impact of crop diversification on farm performance and risk exposure, using survey data merged with historical weather data from the northern Savanna regions of Ghana. We employed the dose response function (DRF) and instrumental variable techniques to address potential endogeneity concerns and to estimate the distribution of the impact of crop diversification across different intensities (dose). The study explored how crop diversification as a risk management mechanism could boost farm net returns and minimize risks emanating from climate-related shocks, particularly when risk-buffering instruments such as crop insurance, agricultural credit, and irrigation systems are virtually non-existent.

The empirical results revealed that past climatic shocks (i.e. rainfall shocks, mean temperature) and household-farm level characteristics such as farm size, agricultural extension, climate information strongly affect crop diversification decisions. In addition, access to input, in particular fertilizer usage, also significantly influenced the intensity of crop diversification. Our findings further showed that, in general, crop diversification is beneficial to farm households. The gains, however, are not the same as the returns to diversifying are heterogeneous across households. In particular, the results uncovered a non-linear relationship between crop diversification intensity and farm net returns as well as risk exposure. In other

words, at relatively lower levels of crop diversification, farm net returns and skewness appeared to have a positive and significant effect up to a threshold (i.e. 75 and 70 percent levels for farm net returns and skewness, respectively), beyond which further diversification resulted in a decline in farm net returns and increased downside risk exposure. Similarly, the impact of diversification on volatility of farm net returns is positive (i.e. lower volatility), particularly at lower levels of crop diversification, and slightly negative (i.e. higher volatility) as the intensity of diversification increased.

A number of policy implications emerge from our findings. First, access to climate-related information is essential, as it can create the needed awareness and enable farm households to anticipate weather-related hazards in order to adapt accordingly. Second, there is the need to develop a well-designed extension communication strategy, particularly crop diversification-related messaging. Extension communication should be tailor-made for heterogeneous landscape of farmers given that there may be a suitable level of crop diversification for different categories of farmers (Kray et al., 2018). Third, the findings of the study lend support to the current policy focus on diversified crop production systems under the Planting for Food and Jobs program. However, the non-linear effect of crop diversification on farm net returns and risk exposure stresses the need to consider factors such as farm size, crop types, and market access in the promotion of diversified crop production systems

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Appendix

Table 4.A1: Mean differences in characteristics (cropping systems)

Variables	Maize monocropping		Maize-legume		Maize-staple		Maize-legume-staple	
	1		2		3		4	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Farm net returns	565.56	1036.43	2202.62***	1865.23	1246.78***	1228.70	2016.15***	1944.78
Skewness	-2.67	3.55	0.51***	0.99	-0.16***	0.93	0.20***	0.74
Variance	1.63	1.56	0.58***	0.61	0.52***	0.55	0.51***	0.47
Age	41.82	13.71	41.67	12.07	43.64	12.71	43.19	12.55
Male headed	0.37	0.49	0.68***	0.47	0.67***	47	0.77***	0.42
Household size	6.05	6.04	5.99	2.78	5.80	2.70	6.19	2.99
Education	3.10	3.95	4.39**	5.11	3.72	4.84	3.50	4.81
FBO	0.15	.36	0.40***	0.49	0.35***	0.48	0.31***	0.46
Farm size	6.23	5.68	5.46	4.14	5.46	3.83	4.87**	3.70
Extension	7.10	4.86	13.18***	8.16	10.44***	6.47	9.56***	5.58
Credit constraint	0.44	0.55	0.27***	0.44	0.43	0.50	0.34	0.47
Livestock	1.09	2.20	2.10*	5.03	2.40**	5.15	1.83**	2.56
Market distance	11.61	3.94	7.55***	4.40	8.44***	4.50	7.74***	4.65
Asset	1180.07	1091.29	3481.95***	2875.93	2765.21***	2275.37	2633.82***	2152.42
Negative rainfall shock	0.15	0.36	0.30***	0.46	0.35***	0.48	0.36***	0.48
Mean temperature	27.12	0.32	27.42***	0.49	27.35***	0.48	27.37***	0.485
Climate information	0.43	0.50	0.74***	0.44	0.57*	0.50	0.67***	0.47
Improved seeds	0.77	0.42	0.97***	0.17	0.92***	0.27	0.95***	0.21
Fertilizer use	121.02	63.93	88.86***	59.85	96.17**	87.41	87.47***	71.52
Fertility	0.85	0.36	0.91	0.29	0.88	0.32	0.90	0.30
Distance input dealer	2.35	1.26	1.86***	1.24	2.14	1.59	2.01	1.51
observations	86		174		104		123	

Note: Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The base-category is maize monocropping.

Exchange rate at the time of survey: 1 USD = 5.14 Ghana Cedis (GHS)

Table 4.A2: Mean differences in characteristics (levels of diversification)

Variables	Non-diversified		Diff. (t-stat.) (2-1)	Somewhat diversified		Diff. (t-stat.) (3-2)	Very diversified	
	1			2			3	
	Mean	Std. Dev.		Mean	Std. Dev.		Mean	Std. Dev.
Farm net returns	565.56	1036.43	752.87***	1318.43	1324.63	1268.94***	2587.37	2016.17
Skewness	-2.67	3.55	2.96***	0.29	1.07	-0.11	0.18	0.77
Variance	1.63	1.56	-1.03***	0.60	0.60	0.12**	0.48	0.49
Age	41.82	13.71	0.82	42.65	12.38	0.00	42.65	12.43
Male headed	0.37	0.49	0.37***	0.74	0.44	-0.07	0.67	0.47
Household size	6.05	6.04	0.256	6.30	2.96	-0.66**	5.64	2.62
Education	3.10	3.95	0.285	3.389	4.59	1.22**	4.61	5.29
FBO	0.15	.36	0.28***	0.43	0.50	-0.16***	0.27	0.45
Farm size	6.23	5.68	0.57	6.80	4.07	-3.33***	3.47	2.85
Extension	7.10	4.86	6.15***	13.26	7.929	-4.15***	9.10	5.41
Credit constraint	0.44	0.55	-0.14**	0.30	0.46	-0.08*	0.38	0.48
Livestock	1.09	2.20	1.40**	2.48	5.64	0.85**	1.63	2.28
Market distance	11.61	3.94	-2.95***	8.65	4.43	-1.79***	6.86	4.41
Asset	1180.07	1091.29	2284.17***	3464.24	2744.65	-938.57***	2525.67	2185.32
Negative rainfall shock	0.15	0.36	0.22***	0.37	0.48	-0.08*	0.29	0.45
Mean temperature	27.12	0.32	0.22***	27.34	0.47	0.11**	27.45	0.50
Climate information	0.43	0.50	0.25***	0.68	0.46	-0.02	0.66	0.47
Improved seeds	0.77	0.42	0.18***	0.94	0.23	0.02	0.96	0.19
Fertilizer use	121.02	63.93	-35.81***	85.21	69.36	11.22	96.43	73.34
Fertility	0.85	0.36	0.04	0.88	0.32	0.04	0.92	0.27
Distance input dealer	2.35	1.26	-0.21	2.14	1.342	-0.18	1.96	1.49
Observation	86			218			183	

Note: “Non- diversified (i.e. maize monocropping), “somewhat diversified” (i.e. diversification index less than 50%) and “very diversified” (i.e. diversification index greater than 50%). Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Exchange rate at the time of survey: 1 USD = 5.14 Ghana Cedis (GHS)

Table 4.A3: Test of Validity of the Excluded Instrument and IV-GMM regressions

Variables	Test of Validity		First-stage IV-GMM	
	Coefficient	SE	Coefficient	Robust SE
	1		2	
Age	-0.004	0.006	-0.000	0.001
Male headed	0.137	0.152	0.051*	0.030
Household size	0.032	0.023	-0.001	0.005
Education	-0.015	0.019	0.002	0.002
FBO	-0.193	0.207	0.045*	0.024
Farm size	-0.177***	0.055	0.009	0.009
Farm size quadratic	0.008***	0.002	-0.000	0.000
Extension	0.023	0.017	0.003	0.002
Credit constraints	0.141	0.147	0.040	0.030
Market distance	0.002	0.028	-0.009*	0.005
Livestock	-0.024	0.033	0.001	0.002
Asset (log)	0.122	0.073	0.023*	0.013
Negative rainfall shock	-0.155	0.251	0.204***	0.035
Mean temperature	-0.480	0.236	0.054	0.044
Climate information	0.810***	0.173	0.030	0.027
Improved seeds	0.090	0.160	0.161***	0.058
Fertilizer use (log)	0.003	0.062	-0.006	0.006
Fertility	0.217	0.189	-0.054	0.038
Distance input dealer	0.088	0.087	-0.114***	0.009
Sudan			0.027	0.031
Guinea	-0.007	0.156		
Constant	18.557***	6.518	-0.777	1.233
R ²			0.566	
Weak identification tests:				
Cragg-Donald F-statistic			87.12	
Kleibergen-Paap rk Wald F statistic			70.97	
P-value of Angrist-Pischke F-test			0.000	
Over identification test:				
Hansen J			5.123	
p-value			0.1772	
Number of observations	86		487	

Note: The first column shows the OLS estimates of farm net returns equation by farmers that did not diversify. The second column shows the first stage IV-GMM results. SE reports the bootstrapped standard errors. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This

Table 4.A4: Estimates of Treatment Effects Parameters

	ATE	ATET	ATENT
Semi-variance	-1.453*** (0.460)	-1.357* (1.403)	-1.898 (1.079)

Note: This table presents the estimates of different treatment effects parameters; ATE (average treatment effect), ATET (effect of treatment on the treated), ATENT (effect of treatment on the untreated) for the semi-variance equation. ATET and ATENT standard errors are obtained by 200 bootstrap simulations. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

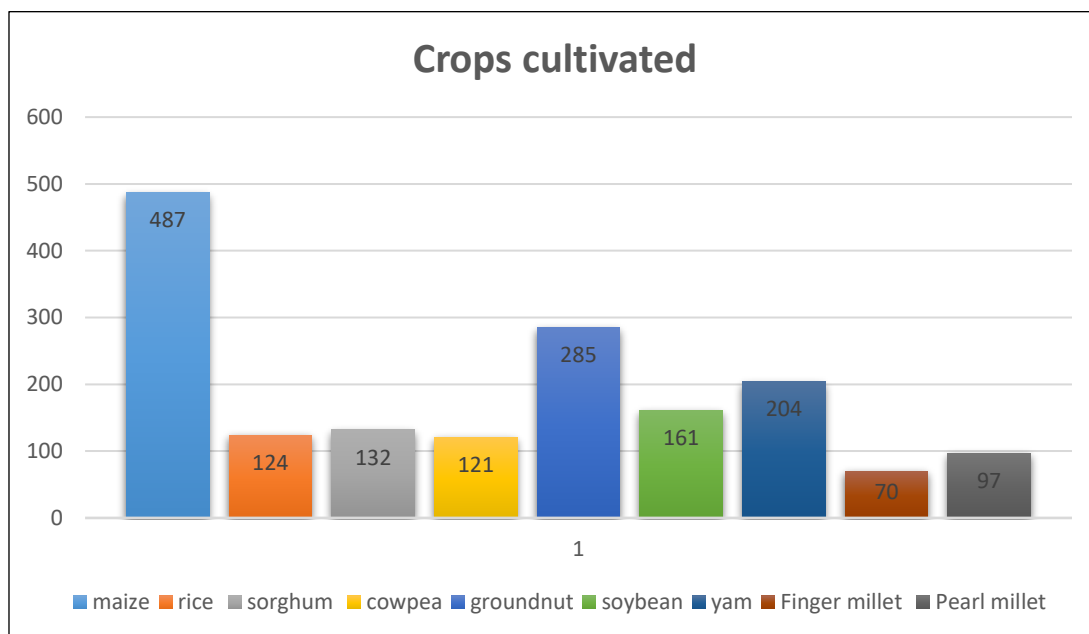


Figure 4.A1: Distribution of crops cultivated by farmers. Source: Survey data, 2019

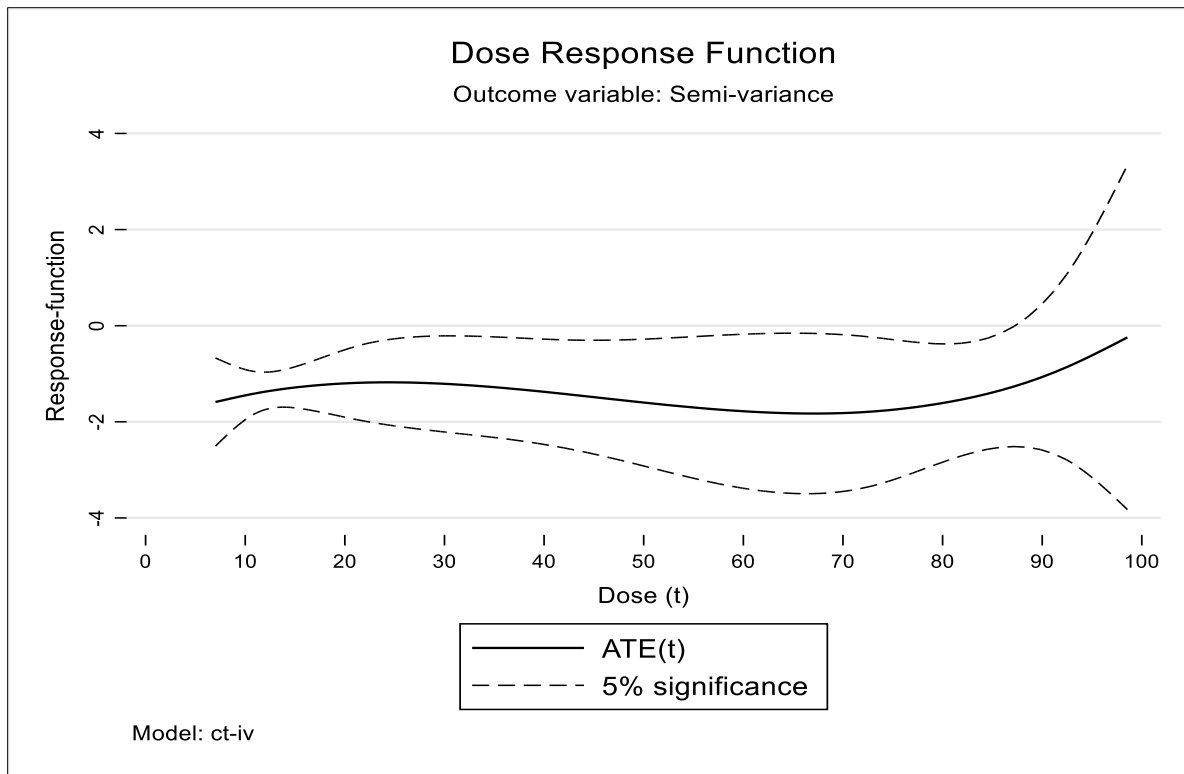


Figure 4.A2: Dose-response function (semi-variance)

The figure shows the estimated dose-response functions (Semi-variance) at each level of crop diversification together with 95% confidence interval bounds. NB: Crop diversification intensity in these figures are scaled over [0, 100] interval.

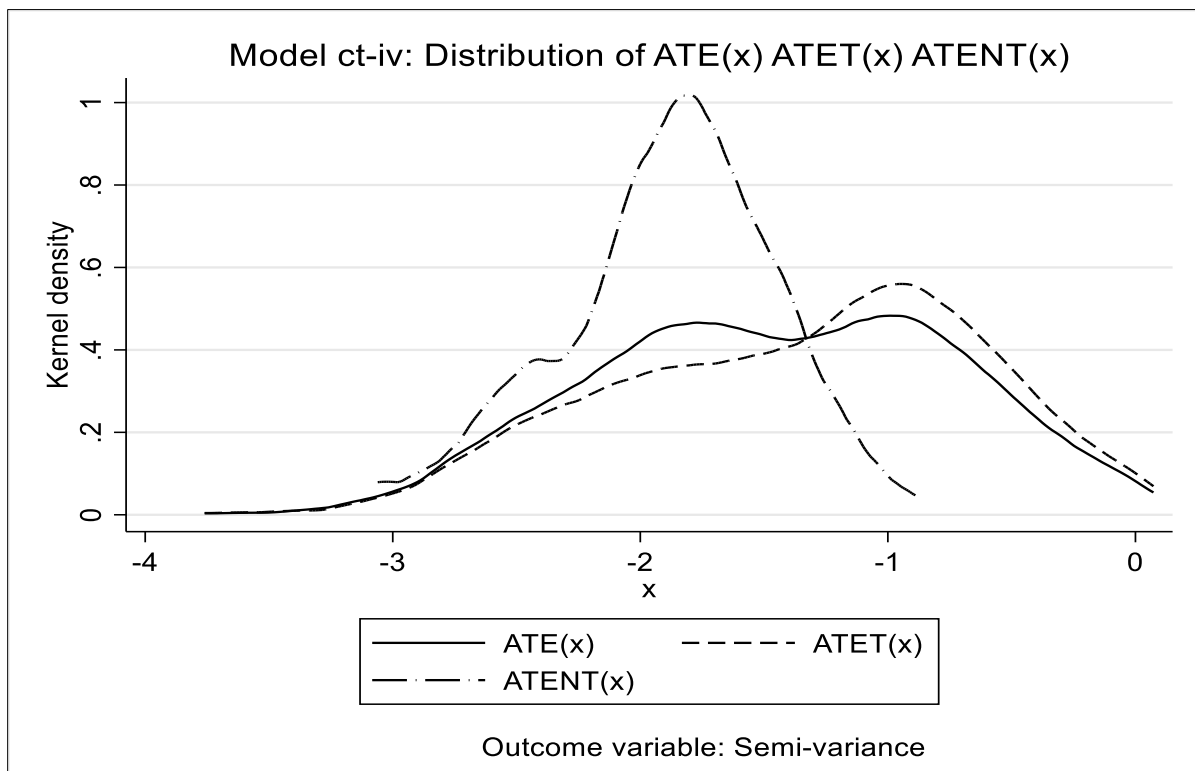


Figure 4.A3: Distribution of treatment effects conditional on the covariates (Semi-variance).

Chapter 5

Examining the impact of conservation agriculture and participation in field demonstrations on productivity and efficiency among farmers in Ghana

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Revised and Re-submitted to *Applied Economics*

Abstract

Improving the efficiency of agricultural production while promoting resilient agricultural technologies and sustainable food systems is central to achieving the SDG of zero hunger. Within the framework of this goal, smallholder farmers have been reached out through various policies and interventions such as conservation agriculture and field demonstrations. Thus, to better understand the effectiveness of these interventions, we use a stochastic frontier model with an endogenous treatment status and mediator, using two instrumental variable methods to address potential endogeneity concerns. We employ plot-level data from the northern Savanna zone of Ghana matched with historical rainfall data to decompose the treatment effects into production frontier and inefficiency components, and further, examine the direct effects of conservation agriculture (CA) and the indirect effects via a mediator (i.e. field demonstrations). The empirical results reveal that rainfall shocks within the cropping season significantly reduce the level of technical efficiency. Further, the mediation analysis shows that most of the effects are driven by participation in field demonstrations. We conclude that improving access to climatic information and embedding field demonstrations in CA activities could shift the technology frontier upward and improve the level of efficiency.

Keywords: Treatment effect, Stochastic Frontier Model, Conservation Agriculture, Mediation Analysis, Field Demonstrations

JEL CLASSIFICATION: C26, O13, Q12 Q16,

5.1 Introduction

The need to improve the efficiency of food production systems has gained considerable attention in recent policy discourse as crop yields continue to decline in many parts of the world, particularly in sub-Saharan Africa (Jayne et al., 2019). The adverse effects of soil degradation and climate variability have contributed to a decline in soil fertility, crop yield reduction, and rising food prices, leading to increased food insecurity in the region (Mu et al., 2017; Lungarska and Chakir, 2018; FAO et al., 2020). In particular, yields of primary staple crops are substantially lower than what could potentially be achieved, resulting in what is widely known as ‘yield gap’ (i.e., the difference between the potential yield and the actual yield) (Leitner et al., 2020). In Ghana, for example, average maize yield is approximately 2.26 Mt/ha, which is lower compared to 5.5 Mt/ha under improved and efficient agricultural production systems (MoFA, 2018). Thus, substantial investments in soil and water conservation technologies would be required to improve efficiency and ultimately close the yield gaps.

To tackle the challenges of low agricultural productivity, the Government of Ghana and its development partners have implemented policies and programs²⁹ intended to expand the production possibility set (i.e., upward shifts in the production frontier), enhance human capital through the provision of technical assistance and extension advisory services (Ambler et al., 2020; Bravo-Ureta et al., 2020a). In particular, conservation agriculture (CA)³⁰ has been promoted to build up soil organic matter and carbon pool, enhance soil moisture retention, and thus improve soil fertility over time (FAO, 2017).

²⁹ These include the USAID Feed the Future Agricultural Technology Transfer program, World Bank funded Sustainable Land and Water Management Practice Project (SLWMP), the Ghana Strategic Investment Framework (GSIF) for Sustainable Land Management (SLM) 2011–2025, Ghana Agricultural Sector Investment Program (GASIP) (June 2015 - June 2019), and the Ghana National Climate Change Master Plan Action Program for Implementation: 2015–2020.

³⁰ CA is a cropping system based on three agronomic management principles: (1) minimum mechanical soil disturbance (e.g. minimum tillage); (2) permanent soil organic cover (e.g. crop residue retention, mulch, cover cropping); and (3) species diversification (e.g. crop rotation, intercropping) (FAO, 2017).

Given the institutional challenges (i.e., technical and logistical) of agricultural extension services (Jayne et al., 2019), one key feature of these projects has been the use of field demonstrations as a medium to speed up the technology transfer process among widely dispersed smallholder farmers. This approach is one of the most effective extension tools that enable smallholder farmers to improve their existing knowledge, learn first-hand, and observe innovative farming technologies in operation (Kijima et al., 2012; Sutherland and Marchand, 2021; Cai et al., 2022). It further enhances their managerial capacities in order to move closer to the production frontier (Bravo-Ureta et al., 2020a). Despite the importance of the link between participation in field demonstrations and production efficiency in a context of low farm productivity (Bravo-Ureta et al., 2020a), it is surprising to see the lack of rigorous assessments on its impact. Understanding its effectiveness on production efficiency contributes to the ongoing efforts to sustainably improve agricultural productivity and competitiveness of the sector in Ghana and the sub-region. To the best of our knowledge, our paper is the first attempt to simultaneously analyze the impact of conservation agriculture adoption and farmers' participation in field demonstrations on productivity and efficiency.

Stochastic frontier models have been extensively applied in policy-related studies to analyze agricultural efficiency as the production potential of the agricultural sector (Centorrino et al., 2020). The approach enables the decomposition of observed output into the maximum possible output given the technology and the level of input (i.e., production frontier) and the gap relative to the frontier (inefficiency component) (Chen et al., 2020). The application of stochastic production frontier models continues to be a dynamic area of research in the literature (Bravo-Ureta et al., 2012). Yet, only few studies have been carried out within the context of an impact evaluation framework. Dinar et al. (2007), for example, looked into the impact of agricultural extension on farm performance in Greece. The authors found that extension significantly closes both the technology and management gaps. Also, employing propensity

score matching to construct a matched sample of treated and non-treated plots, Gebregziabher et al. (2012) investigated the efficiency of irrigated plots in the Tigray region of Ethiopia. The study concluded that agricultural productivity was comparatively higher on irrigated plots.

A major shortcoming of the above-mentioned studies is their inability to take into account potential selection bias often intrinsic to these agricultural interventions. The adoption decisions of farmers are not random and may be influenced by unobserved attributes such as motivation, skills, leading to potential selection bias. Thus, failure to account for these issues could lead to bias and inconsistent estimates, and hence spurious conclusions. Recent empirical studies such as (e.g., Bravo-Ureta et al., 2012; Abdulai and Abdulai, 2017; Abdul-Rahaman and Abdulai, 2018) have employed various approaches to address the selectivity bias stemming from observed and unobserved attributes in the stochastic production frontier models. That notwithstanding, these studies do not consider the direct and indirect impacts that heterogeneous production systems have on both the technology frontier and efficiency functions.

Therefore, this paper attempts to address this empirical puzzle following the approach of Chen et al. (2020) by bringing together methodological elements from the mediation analysis in treatment effect setting and the stochastic production frontier literature. We further address the endogeneity that could separately and simultaneously affect the technology frontier and the production inefficiency model, using an instrumental variable approach. Employing a unique dataset of maize producers from the northern Savanna zone of Ghana matched with geo-referenced historical weather data (i.e., rainfall) (1981-2018), this paper contributes to the empirical literature as follows: First, to understand the importance of the mediating effect of participation in field demonstration in more detail, we examine the impact of conservation agriculture adoption directly on the technology frontier and technical inefficiency and indirectly via a mediator. Further, we decompose the treatment effect into four different parts: direct

effects on the technology frontier, indirect effects on the technology frontier through a mediator, direct effects on technical inefficiency, and indirect effects on inefficiency through a mediator.

Second, although weather conditions (e.g., rainfall) are significant drivers of agricultural productivity (Bravo-Ureta et al., 2020b; Plastina et al., 2021), the vast majority of empirical studies on technical efficiency usually ignore them and instead treat them as random shocks. Weather conditions typify the production environment in a manner that can affect the ability of farmers to convert farm inputs into outputs, thereby affecting production efficiency (Chen et al., 2021). Previous studies have shown that maize is highly susceptible to rainfall shocks and is projected to even worsen in the future (Lobell et al., 2008; IPCC, 2021). As a result, efficiency analyses that do not account for weather variability as a source of production inefficiency may result in biased estimates, potentially leading to misleading conclusions (Chen et al., 2021). Thus, given that weather variability and uncertainty affect production efficiency, we explicitly incorporate rainfall volatility in the inefficiency function.

The remainder of the paper is organized as follows: The survey data and descriptive statistics are described in section 5.2. Section 5.3 discusses the conceptual and econometric framework of the model respectively. The empirical results and discussions are presented in section 5.4, while the final section concludes the study.

5.2 Household survey and descriptive statistics

5.2.1 *Farm household survey*

To apply the above-mentioned model, we use data from 512 maize producers in the northern Savanna zone of Ghana: A survey was carried out for the 2018/2019 cropping season in 15 villages across six districts and three regions under the Sustainable Land and Water Management Project intervention areas. We purposively selected six districts from the three regions based on the operational areas of the project and the prevalence of conservation agriculture practices. Further, three to six villages from each district were selected at random.

Finally, in proportion to the farming population in the areas, 512 maize producers were randomly sampled. The data was collected using a structured questionnaire by trained and qualified researchers and enumerators with a thorough understanding of the farming systems in the study areas. The dataset contains information on household and plot-level production costs, prices, household demographic characteristics, access to market information, extension contacts, and conservation agriculture practices.

Table 5.1 presents the definition and summary statistics of variables used in the empirical analysis. The list of control variables includes age, gender, education of household head, extension visits, farm size, and credit access. We define credit-constrained farmers as those who received credit but expressed the desire to borrow more at the existing interest rate, those whose credit request was denied, or those who had no access to formal and informal lenders (Abdulai and Huffman, 2014). We controlled for location-fixed effects to capture exogenous variables that may vary with the agro-ecological zones. Furthermore, climatic variables such as rainfall are important factors of maize production, hence, we included a rainfall variable that measures the amount of rainfall during the cropping season in the production frontier function.

In addition, given the technology and inputs, weather variability (e.g., rainfall shock) may impede the extent to which the production potential may be achieved and thus affect production efficiency (Chen et al., 2021). We therefore included rainfall shock in the inefficiency function. Our rainfall data is obtained from the Prediction of Worldwide Energy Resources data archive³¹. It provides global data at high-resolution (0.5x0.5 degree) to generate a gridded rainfall time series. We matched household geographical coordinates with the rainfall data to obtain long-term mean rainfall data (from 1981-2018) for the months within the cropping season.³² Thus, following Michler et al. (2019), we measured rainfall shock as a normalized deviation in a

³¹ <https://power.larc.nasa.gov/data-access-viewer>

³² The northern Savanna zone has a unimodal rainfall pattern that usually runs from April to October.

single season's rainfall from expected seasonal rainfall over 37 years (i.e., 1981-2018) as follows:

$$\frac{RF_{kt}}{\sigma_{R_k}} = \left| \frac{R_{kt} - \bar{R}_k}{\sigma_{R_k}} \right| \quad (1)$$

where R_{kt} is the observed rainfall for the previous year's season, \bar{R}_k is the mean historical rainfall, and σ_{R_k} represents the standard deviation of rainfall for the same period. In our econometric model, the outcome variable is maize yields in kilograms. The inputs used in the analysis include farm size measured in acres, total labor, amount of inorganic fertilizer used, and the chemicals used. Following the approach of Battese (1997), we take into account the zero values of inorganic fertilizers in the model by introducing their dummies, so that the logarithm of the zero-valued inputs is taken if it is positive, and zero otherwise (Villano et al., 2015).

5.2.2 Conservation agriculture technologies and field demonstrations in the study

Even though the three main pillars of conservation agriculture are in principle of global nature, their adoption usually varies among smallholder farmers due to heterogeneity of farming systems, socio-economic, and agri-environmental factors (Corbeels et al., 2014). In our study area, the conservation agriculture practices adopted by farm households include crop rotation (i.e., maize-legumes rotation), minimum tillage, cover cropping, mulching, and organic amendments (i.e., animal manure and compost) (Dalton et al., 2014; Ambler et al., 2020). Crop diversification including crop rotation is a key part of the conservation agriculture system, and various approaches underscore the use of cereal (e.g., maize)-legumes rotations (Giller et al., 2009). Legumes commonly cultivated include soybean (*Glycine max* (L.) Merrill), groundnut (*Arachis hypogaea* L.), beans (*Phaseolus vulgaris* L.), and cowpea (*Vigna unguiculata* (L.) Walp.). Combining legumes with maize in a rotation facilitates the buildup of soil organic matter pool and nitrogen that contribute to maize productivity. In addition, permanent soil cover

using crop residues and plant biomass, and reduced soil disturbance through minimum tillage (e.g., Zai technology³³) increases soil organic carbon content and soil moisture content and enhances water use efficiency (FAO, 2017; Ehiakpor et al., 2019). We define CA adopters to include at the very least, smallholder farmers who implement one of the above-mentioned practices.

Conservation agriculture has often been described as knowledge and management-intensive agricultural technology, which makes its adoption among smallholder farmers more challenging (Giller et al., 2009; Mockshell and Villarino, 2019). As a result, showcasing conservation agriculture through smart approaches such as field demonstrations accelerates its adoption, helps smallholder farmers to learn how to implement them effectively on their fields, and thus enhance their managerial ability. Therefore, as part of its strategy, the Sustainable Land and Water Management Project established 344 field demonstrations to effectively show productivity increases and facilitate upscaling of CA technologies. These demonstration fields were established in project communities to serve as both training sites and reference points for the promotion of the technology and to build the capacity of farmers.

The fields demonstrations provided farmers the opportunity to observe the application of these technologies in local contexts and to directly learn from experts and other actors in the extension delivery chain. Field days and training sessions were also organized regularly on the fields to highlight the benefits of these technologies. The field days proved to be effective in terms of sharing results and best practices among a large group of smallholder farmers including project beneficiaries and non-beneficiaries (World Bank, 2021). Therefore, in our study, we

³³ The zai technology is a minimum tillage practice where seeds are sown in small planting pits and filled with organic material such as crop residues. This practice reduces soil erosion, improves microbial activities, and concentrates soil water around the base of the plant, thereby supporting plant growth during seasonal dry spells (Ehiakpor et al., 2019).

define participation in field demonstrations to include those who participated at least once in these activities to gain knowledge and skills.

5.2.3 Descriptive statistics

Table 5.1 provides the descriptive statistics of the variables employed in our econometric analysis. As shown in the Table, the means of most variables between treated (i.e., $D = 1$) and untreated (i.e., $D = 0$) units are statistically different from zero. In particular, rainfall amount in the cropping season was higher for the treated units compared to the untreated units. Concerning rainfall shock, treated units had negative rainfall shock (-0.09) while untreated units had positive rainfall shock (0.03). This result possibly explains the reason behind the adoption of conservation agriculture practices by the former units as a mechanism to mitigate against mid-seasonal dry spells.

Intuitively, the treated units use more labor (76.37 per person-days) compared to the untreated (48.66 per person-days). We also observed that treated units have more extension contacts relative to the untreated. Regarding the instrumental variables, the treated units appear to travel comparatively shorter distances to the field demonstration plots and received past information on weather variability. As regards fertilizer use, the untreated units used significantly more inorganic fertilizer (273.07 kg/acre) compared to the treated (139.91 kg/acre). This could potentially be attributed to the adoption of practices such as manure, leguminous cover cropping, compost which complement inorganic fertilizer application. In terms of herbicide use, the untreated units use 32.08 litres/per acre more than the treated units. Furthermore, treated units obtained an average maize yield of 928.46 kg/acre, which is higher than the 602.61 kg/acre for the untreated units. The significant difference in maize yields between the treated and untreated units may not imply impacts of adoption, as this comparison does not take into account confounding factors that influence the adoption of conservation agriculture technologies.

Table 5.1: Definition of variables and descriptive statistics

Variable	Definition	All	Std. dev	D=1	D=0	Diff (t-stats)
Maize yields	Quantity of Maize output per acre (kg)	788.11	532.22	928.46	602.61	324.44***
CA Adoption	1 if farmer adopted conservation agriculture, 0 otherwise	0.569	0.495			
Field demonstration	1 if a farmer participated in field demonstrations activities, 0 otherwise	0.598	0.490			
Age	Age of household head in years	42.44	12.66	43.42	41.07	2.35**
Male	Male =1, Female =0	0.63	0.48	0.77	0.44	0.33
Education	Years of schooling of household head	3.63	4.74	4.33	2.64	1.69***
Farm size	Total farm size of HH in acres	5.41	4.37	4.80	6.27	-1.47***
Extension	Number of extension contacts per annum	10.38	7.00	11.56	8.72	2.85***
Credit constraint	1 if farmer is credit constrained, 0 otherwise	0.37	0.48	0.31	0.45	0.14***
Labor	Total labor per acre (man-days)	64.45	56.24	76.37	48.66	27.71***
Fertilizer	Total amount of inorganic fertilizers used (kg/acre)	197.26	162.92	139.91	273.07	-133.15***
Fertilizer_dummy	1 if farmer applies inorganic fertilizer, 0 otherwise.	0.92	0.26	0.90	0.97	-0.071***
Chemicals	Total amount of chemicals used (litre/acre)	36.27	81.14	22.46	54.53	-32.08***
Slope	1 if plot has portions of steep slopes, 0 otherwise.	0.61	0.49	0.57	0.66	-0.09***
Rainfall amount	Total amount of rainfall over the cropping season (mm)	1017.60	63.03	1005.81	1033.19	-27.37***
Rainfall shock	Normalized deviations in a single season's rainfall from expected seasonal rainfall (1981-2018)	-0.03	0.88	-0.09	0.03	-0.90**
Climate information	1 if farmer received weather information prior to adoption, 0 otherwise	0.64	0.48	0.88	0.29	0.58***
Distance to demo farms	Distance to demonstration farms (km)	2.23	1.26	1.72	2.95	-1.22***
Agro-ecological zone	Sudan=1, 0 otherwise	0.48	0.50	0.55	0.40	0.14
Number of Households		512		300	212	

The exchange rate at the time of the survey: 1 USD = 5.14 Ghana Cedis (GHS)

5.3 Conceptual and empirical framework

Let Y represent the potential output under a given intervention and X , the vector of observed exogenous characteristics. We express the conventional stochastic frontier model (Kumbhakar and Lovell, 2000) as:

$$Y = Y^* - u, \quad u \geq 0, \quad (2)$$

$$Y = h(X, \beta^h) + v$$

Where Y^* is the unobserved stochastic frontier that may be influenced directly by the conservation agriculture technology and indirectly via participation in field demonstrations, $u \geq 0$ is the unobserved production inefficiency usually assumed to be random, $h(\cdot)$ is a frontier function with parameter vector β^h , and v is a pure random error. In the model framework of stochastic frontier analysis, equation 2 shows that Y^* and u are two unobserved and distinct random components of output. We thus express the conditional means of the random component as follows:

$$E[v|X] = 0, \quad (3.1)$$

$$E[Y^*|X] = h(X, \beta^h), \quad (3.2)$$

$$E[u|X] = g(X, \beta^g), \quad (3.3)$$

Where $g(\cdot)$ is a non-negative inefficiency function with parameter vector β^g . In the stochastic production frontier literature, the parameters of the frontier and inefficiency functions can be identified separately by way of imposing restrictions on the vectors of their respective parameters or through a distinctive parametric form of $h(\cdot)$ and $g(\cdot)$, or even both. Thus, we express the conditional mean representation of equation 2 as follows:

$$E[Y|X] = h(X, \beta^h) - g(X, \beta^g). \quad (4)$$

In principle, the impact of an intervention on farmers can be determined from the difference between the potential outcomes with intervention (Y_1) and without intervention (Y_0). The average treatment effect (ATE) can be expressed as:

$$ATE = E(Y_1 - Y_0 | D = 1) = E(Y_1 | D = 1) - E(Y_0 | D = 1) \quad (5)$$

5.3.1 Treatment effects

We follow the approach of Imbens and Angrist (1994) to divide the whole population into four different subpopulations in terms of four outcomes of $(D(1), D(0))$: always takers if $D(1) = D(0) = 1$, compliers if $D(1) > D(0)$, defiers if $D(1) < D(0)$ and never takers if $D(1) = D(0) = 0$.

The conditional local average treatment effect ($CLATE_x$) is further identified by focusing on the subpopulation of farmers who are compliers in equation (6):

$$CLATE_x \equiv E[Y(1, M(1)) | X = x, C] - E[Y(0, M(0)) | X = x, C] \quad (6)$$

and the local average treatment effect ($LATE$):

$$LATE = E[CLATE(X) | C] = E[Y(1, M(1)) | C] - E[Y(0, M(0)) | C] \quad (7)$$

The model allows the decomposition of the $CLATE$ into conditional direct and indirect effects for the mediation analysis as follows:

$$CDLATE_x = E[Y(1, M(1)) | X = x, C] - E[Y(0, M(1)) | X = x, C] \quad (8.1)$$

$$CILATE_x = E[Y(0, M(1)) | X = x, C] - E[Y(0, M(0)) | X = x, C] \quad (8.2)$$

Further, the decomposition of the local average treatment effect is as follows:

$$DLATE = E[CDLATE(X) | C] = E[Y(1, M(1)) | C] - E[Y(0, M(1)) | C] \quad (9.1)$$

$$ILATE = E[CILATE(X) | C] = E[Y(0, M(1)) | C] - E[Y(0, M(0)) | C] \quad (9.2)$$

The $CLATE_x$ in our study denotes the total effect of conservation agriculture for compliers with $X = x$, while $CILATE_x$ is linked to the indirect effect obtained via participation in field demonstration, and $CDLATE_x$ the remaining direct effects. Similarly, $LATE$ signifies the total effect of conservation agriculture among compliers, while $ILATE$ is the indirect effect derived via participation in field demonstration, and $DLATE$ the remaining direct effect. As mentioned earlier, these treatment effects are further decomposed into the production frontier and the inefficiency functions.

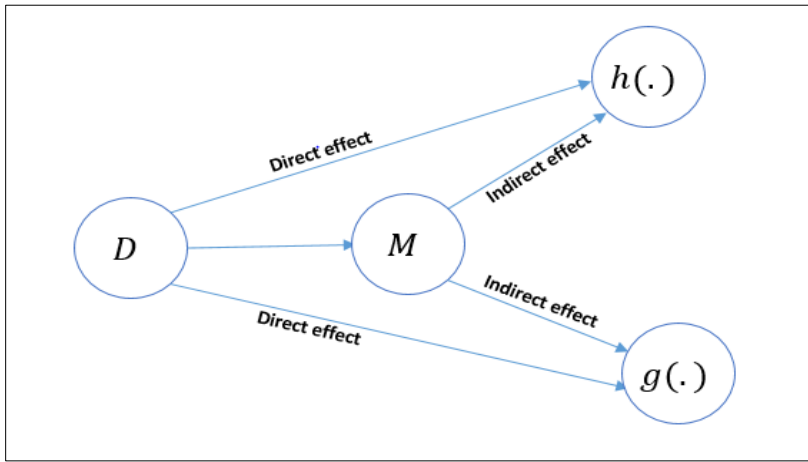


Figure 5.1: Causal pathways of the model.

Note: D and M represent the treatment and mediator binary indicators, respectively.

While $h(.)$ and $g(.)$ denote the technology frontier and inefficiency functions

Source: Adapted from Chen et al., 2022

5.3.2 Model set-up

We first depict the causal pathway of the model framework in Figure 5.1, and consider the structural model in equation 10 for $(Y, M, D)|Z_1, Z_2, X$, following a new stochastic frontier model³⁴ as follows:

$$Y = \tilde{h}(D, M, X) - \tilde{g}(D, M, X) + U_Y \quad (10)$$

We assume that farmers are risk-neutral in their decision to adopt conservation agriculture and take into account the net benefit (D^*) to be derived from adoption, such that a farmer will adopt

³⁴ $Y(d, M(d')) = \tilde{h}(d, M(d'), X, \beta_{dj}^h) - \tilde{g}(d, M(d'), X, \beta_{dj}^g) + U_Y(v(d, M(d'))) + \tilde{u}(d, M(d'))$ (12)

if the expected utility gained from adoption is greater than not adopting. Since D^* is the latent propensity to adopt and cannot be observed, we specify it as a function of exogenous variables (X) in the following latent variable discrete model:

$$D^* = \gamma_{z1}Z_1 + \gamma_x X + U_D, \text{ with } D = 1 \text{ if } D^* \geq 0, \text{ and } D^* = 0 \text{ otherwise} \quad (11)$$

where D is a binary adoption indicator, with $D = 1$ is representing adoption and 0 otherwise, unobserved component (U_D), and parameter of interest γ . In this framework, we further consider a mediator M to be a function of D in the following equation:

$$M^* = \alpha_d D + \alpha_{z2} Z_2 + \alpha_x X + U_M, \text{ with } M = 1 \text{ if } M^* \geq 0, \text{ and } M^* = 0 \text{ otherwise} \quad (13)$$

where M is a binary indicator with outcomes (0, 1), with $M = 1$ if a farmer participates in field demonstrations, and 0 otherwise, unobserved component (U_M), exogenous variables (X), and parameter of interest α .

In our study, we consider M , which denotes participation in field demonstrations as a post-treatment mediator. Field demonstrations have been extensively used over several decades as a well-established method of agricultural extension delivery, primarily to introduce and promote innovative technologies, but also to share experiences in a farmer-to-farmer context, and to support knowledge co-creation among smallholder farmers and other actors (e.g. scientists, extension agents). More recently, field demonstrations have followed a wide range of approaches and are designed with multifaceted objectives in mind. Moreover, the integration of field demonstration activities within broader learning programs and agricultural knowledge and information sharing activities makes it difficult to assess its specific outcomes (Sutherland and Marchand, 2021). In our study context, we hypothesize that quite a number of these conservation agriculture technologies (e.g., compost application, mulching, manuring, crop rotation) may have been in existence and adopted by smallholder farmers prior to the setting up of these demonstration fields. Therefore, in our view, participation in these fields demonstration

activities offers an important opportunity to among other things strengthen the managerial performance and build the capacity of smallholder farmers to improve their efficiency, which indicates moving towards the production frontier (Bravo-Ureta et al., 2020a; Ojo et al., 2021; Cai et al., 2022).

In this model framework, we assume that both the treatment assignment D and the mediator M are endogenous. In other words, the treatment and the mediator variables are allowed to be endogenously related to unobserved confounders, and identification is thus achieved through two separate instrumental variables (IV) (Chen et al., 2020; Salm et al., 2021). In particular, we let Z_1 be a binary variable for the treatment indicator D and equals 1 if a farmer received past climate information prior to adoption and 0, otherwise. We argue that access to past weather information tends to influence behavioral changes towards the adoption of conservation agriculture (Di Falco et al., 2011; Pagliacci et al., 2020).

Concerning the endogenous mediator variable M , we employ the method of Frölich and Huber (2014) which considers a continuous IV, Z_2 . We use distance from homestead to demonstration sites for the parameter identification. Due to mobility challenges, smallholder farmers may not be able to travel long distances to the demonstration sites. Thus, we hypothesize that longer distance to demonstration sites may negatively affect participation. We further posit that the identifying instruments are statistically independent (see Table 5.A1) of the unobserved components of the outcome and may satisfy the exclusion restriction assumption because conditional on X , the instruments Z_1 and Z_2 could only affect the outcome variable (maize yields) through their influence on D and M (Chen et al., 2020).

5.3.3 Model estimation

We define a bivariate response model for the joint decisions on adoption of conservation agriculture and participation in field demonstrations, which is specified as $P(M, D|Z_1, Z_2, X, \eta)$ and set the distribution $F_{U_{M,D}}(\dots, \rho_{md})$ as a bivariate normal distribution in equation 14.

$$\begin{bmatrix} U_M \\ U_D \end{bmatrix} | (Z_1, Z_2, X) \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{md} \\ \rho_{md} & 1 \end{bmatrix} \right) \quad (14)$$

We obtain the estimates of the parameter vector $\eta \equiv (\alpha_d, \alpha_{z2}, \alpha_x, \gamma_{z1}, \gamma_x, \rho_{md})$ by a first-stage maximum likelihood (ML) method. Following the new stochastic frontier model in equation (12), we express the conditional mean representation as follows:

$$E[Y(d, M(d')) | X, C] = h_{d'}(X, \alpha_m, \beta_{d1}^h, \beta_{d0}^h) - g_{d'}(X, \alpha_m, \beta_{d1}^g, \beta_{d0}^g) \quad (15)$$

We further estimate the parameters of vector β_d in equation (15) using a second-stage weighted non-linear least square estimator $\hat{\beta}_d = (\hat{\beta}_{d1}^h, \hat{\beta}_{d0}^h, \hat{\beta}_{d1}^g, \hat{\beta}_{d0}^g)$ for $d \in \{0, 1\}$ based on equation 16.

$$\beta_d \equiv \argmin_{b_d \in \beta_d} \sum_{d'=0,1} E[w(d, d', \alpha_w)(Y - h_{d'}(X, \alpha_m, b_{d1}^h, b_{d0}^h) + g_{d'}(X, \alpha_m, b_{d1}^g, b_{d0}^g))^2] \quad (16)$$

Where $w(d, d', \alpha_w) \equiv w(1, 1, \alpha_w), w(1, 0, \alpha_w), w(0, 1, \alpha_w), w(0, 0, \alpha_w)$ is a weighted function of (D, Z_1, Z_2, X) with parameter vector α_w obtained from the first-stage ML estimation. Given $\hat{\alpha}_m$ and $\hat{\beta}_d$, we obtain the *CLATE* component estimators following the formulae in section 3.1.

5.4 Empirical results and discussion

We discuss in this section the results from the empirical analysis. Before presenting the main results, we first show the estimates from the bivariate probit model in Table 5.A1. The model accounts for selection bias and identification of the instrumental variable regression. As shown in the Table, the p -value for the null hypothesis shows that ρ_{md} is statistically significant, suggesting that both the CA adoption model (i.e., treatment model) and the participation in field

demonstrations (i.e., mediation model) are correlated due to unobserved heterogeneities, lending credence to the appropriateness of using this model.

Regarding the instrumental variables used for the identification of the model, the Table shows that both climate information (i.e., Z_1 for the treatment model) and distance to field demonstrations plots (i.e., Z_2 for the mediation model) are statistically significant (at the 1% level). More specifically, access to past climate information increases the probability of adopting CA technology. Furthermore, the variable on distance to field demonstration plots is negative and statistically different from zero, suggesting that a unit increase in the distance decreases the likelihood of participating in field demonstrations by 15.5%. In other words, field demonstration plots should rather be located on plots that are easily accessible to a wide range of smallholder farmers, particularly due to mobility limitations (e.g., bad roads) in most parts of the study areas.

To check the validity of our instrument, we follow Di Falco et al. (2011) to establish the admissibility of the instruments by carrying out a falsification test. As discussed earlier, a variable is considered a valid instrument if it affects adoption or participation decisions, but not the outcome variable of interest among farmers who did not adopt or participate. We therefore run OLS regression for the outcome equation on the untreated units. We find that Z_1 (access to climate information) and Z_2 (distance to field demonstration sites) did not have any statistically significant effect on the outcome variable among the untreated units ($F\text{-stat.} = 0.01, p = 0.93$) (see Table 5.A2).

5.4.1 Determinants of technology and inefficiency frontiers

We now present the estimates of the weighted non-linear least square estimator (WNLSE) estimated using the generalized method of moments procedure. The estimates $(d, M(d')) = (1, M(d'))$ represent the treated units ($D = 1$), and $(d, M(d')) = (0, M(d'))$ for the untreated units ($D = 0$) in Tables 2 and 3, respectively. Specifically, column 1 of Table 5.2

shows the results of CA adoption scenario with mediation (henceforth referred to as $D^1 - M^1$), while column 2 represents the case of CA adoption without mediation (henceforth referred to as $D^1 - M^0$). We further present in column 1 of Table 5.3, the case scenario of farmers who did not adopt CA but participated in the field demonstrations (henceforth referred to as $D^0 - M^1$). The results in column 2 of Table 5.3 also represent the case scenario of farmers who neither adopted CA nor participated in field demonstrations activities (henceforth referred to as $D^0 - M^0$).

In particular, the variable on fertilizer is positive and statistically significant (at 1% level of significance), across farmers in $D^1 - M^1$, $D^1 - M^0$, and $D^0 - M^0$ categories, suggesting that a unit increase in the quantity of fertilizer use shifts the production frontier upward by 0.280%, 0.763%, and 0.549%, respectively, a finding that has been corroborated by Asante et al. (2019). The estimated coefficient of credit is negative and statistically significant for the $D^1 - M^0$ and $D^0 - M^0$, indicating that liquidity-constrained farmers tend to experience a downward shift in the production frontier by 0.630% and 0.868%, respectively. These results show the importance of credit access in enhancing yield. Surprisingly, liquidity constrained farmers in the $D^0 - M^1$ category tend to experience an increased upward shift in the frontier.

Regarding the rainfall variable, our results are consistent with those found in the literature (e.g., Bravo-Ureta et al., 2020b; Chen et al., 2020; Tirkaso and Hailu, 2022). Indeed, we find that mean seasonal rainfall is positive and statistically significant (at 1% level of significance) for smallholder farmers in the $D^1 - M^0$ and $D^0 - M^1$ categories, signifying that 1% increase in rainfall amount within the cropping season significantly pushes the production frontier upward by 0.836% and 0.375%, respectively. This finding is corroborated by Boansi et al. (2021) who found a significant positive effect of increasing rainfall amount on staple groups such as maize in the northern Savanna zone of Ghana. The coefficient of the extension variable is positive and statistically significant for the $D^1 - M^1$ category, implying that a unit increase

in the number of extension contacts significantly shifts the production frontier upward by 0.799%.

Table 5.2: Weighted non-linear least square estimates for the treated unit

Variable	$D^1 - M^1$		$D^1 - M^0$	
	$(d, M(d')) = (1,1)$		$(d, M(d')) = (1,0)$	
	(1)		(2)	
	Coefficient	Std. err.	Coefficient	Std. err
Frontier function (h)				
Age	0.253	0.336	0.121	0.148
Male	0.421	0.267	0.278	0.196
lnEducation	-0.284**	0.144	0.386	0.261
Farm size	-0.006	0.092	0.103	0.159
lnExtension	0.799**	0.317	0.440	0.289
Credit constraint	0.359	0.297	-0.630***	0.199
lnLabor	0.461**	0.218	-0.175	0.281
lnFertilizer	0.280***	0.093	0.763***	0.194
Fertilizer_dummy	2.140***	0.307	2.142***	0.098
lnChemicals	0.072	0.243	0.150	0.360
Slope	-0.165	0.376	-0.329*	0.196
lnRainfall amount	0.131	0.275	0.836***	0.114
Agro-ecological	0.410	0.319	-0.739***	0.282
Constant	2.319***	0.051	0.785***	0.019
Inefficiency function (g)				
$\beta_{RF\ shock}^g$	2.345***	0.212	0.104***	0.017
β_0^g	-3.310***	0.211	-3.415***	0.002
Number of observations:	300			

Note: Columns 1 presents the estimates of farmers who adopted conservation agriculture and participated in field demonstrations ($D^1 - M^1$), while column 2, shows the estimates of farmers who adopted conservation agriculture but did not participate in field demonstrations ($D^1 - M^0$). The standard errors are bootstrapped from 500 re-samples. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The estimated coefficient of age is positive and statistically significant, indicating that additional increase in age pushes the production frontier upward by 0.631% and 1.027% for the $D^0 - M^1$ and $D^0 - M^0$ categories, respectively. We also observe that the estimated coefficient of the variable on chemicals is positive across all categories but only statistically significant among farmers in the $D^0 - M^1$ category, implying that a percentage increase in the use of chemicals results in an upward shift of the production frontier by 1.637%.

Table 5.3: Weighted non-linear least square estimates for the untreated unit

Variable	$D^0 - M^1$		$D^0 - M^0$	
	$(d, M(d')) = (0,1)$		$(d, M(d')) = (0,0)$	
	(1)		(2)	
	Coefficient	Std. err	Coefficient	Std. err
Frontier function (h)				
Age	0.631***	0.205	1.027**	0.415
Male	0.519*	0.311	0.050	0.337
lnEducation	-0.288	0.440	0.196	0.269
Farm size	0.076	0.175	0.136	0.125
lnExtension	-0.080	0.406	-0.554	0.388
Credit constraint	1.178***	0.416	-0.868***	0.305
lnLabor	-0.236	0.439	-0.441*	0.248
lnFertilizer	0.265	0.262	0.549***	0.204
Fertilizer_dummy	1.178***	0.113	2.036***	0.253
lnChemicals	1.637***	0.360	0.187	0.279
Slope	-2.360***	0.203	0.414	0.472
lnRainfall amount	0.375*	0.237	-0.111	0.190
Agro-ecological	1.617***	0.383	-0.815**	0.331
Constant	2.299***	0.035	4.905***	0.038
Inefficiency function (g)				
$\beta_{RF\ shock}^g$	0.582***	0.023	0.214	0.385
β_0^g	-2.950***	0.017	-0.863**	0.515
Number of observations:	212			

Note: Columns 1 presents the estimates of farmers who participated in field demonstrations but did not adopt conservation agriculture ($D^0 - M^1$), while column 2, shows the estimates of farmers who neither participated in field demonstrations nor adopted conservation agriculture ($D^0 - M^0$). The standard errors are bootstrapped from 500 re-samples. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, we shift attention to the results of the inefficiency model in the lower parts of Tables 5.2 and 5.3. As would be expected, the estimated coefficients of the rainfall shock variable in the inefficiency function are positive and statistically significant (at 1% level of significance) in all categories (i.e., $D^1 - M^1$, $D^1 - M^0$, $D^0 - M^1$) except for $D^0 - M^0$. Though we cannot provide a direct marginal effect interpretation of the estimated coefficients due to the non-linearity of the inefficiency function (Chen et al., 2020), the positive signs of the coefficients suggest that rainfall shocks adversely affect the full realization of the production potential, thus increasing the level of inefficiency. These results are not surprising since the *t-statistics* in Table 5.1 show among other things that CA adopters experience negative rainfall shocks, a

phenomenon that has also been highlighted in the study area by Boansi et al. (2021). Intuitively, increased volatility of rainfall poses a huge threat to efficient maize production among smallholder farmers, particularly due to over-reliance on rain-fed agriculture and susceptibility of maize to weather variations. Notwithstanding the potential of irrigation in significantly stabilizing maize productivity, only 0.3 percent of the total arable lands are under irrigation (FAO, 2021). Therefore, low amount of seasonal rainfall potentially reduces maize productivity as a result of increased water stress.

Conversely, extreme amount of rainfall adversely affects the efficiency of maize production due to waterlogging, inhibition of oxidation, leaching of nutrients, and influx of pests and diseases. Based on the IPCC's (2021) sixth assessment report, several regions in sub-Saharan Africa are projected to experience increases in the frequency of agricultural droughts (IPCC, 2021), therefore, interventions and investments in climate-friendly production technologies such as conservation agriculture are needed to counteract unfavorable climatic conditions and to improve among other things the nutrients and the water holding capacity of soils.

5.4.2 Impact of conservation agriculture and field demonstrations on production frontier and inefficiency

We now report the treatment effects in Table 5.4. The estimates show the local average treatment effects (LATE) and its components. Columns 1, 2, and 3 of Table 5.4 present the estimates of the treatment effects of CA adoption and participation in field demonstrations on output (maize yields), production frontier, and the inefficiency functions, respectively. The first row reports the total treatment effects of the output, frontier, and inefficiency functions, while the second and the third rows provide the results of the mediation analysis (i.e., the direct and indirect effects of CA adoption on the output, production frontier, and inefficiency functions).

Table 5.4: Estimates of Local Average Treatment Effects (LATE)

	Maize outputs	Frontier	Inefficiency
Total effect	<i>LATE</i>	<i>LATE_h</i>	<i>LATE_g</i>
	0.707***	0.542***	-0.165***
	(0.031)	(0.029)	(0.004)
Mediation analysis	<i>DLATE</i>	<i>DLATE_h</i>	<i>DLATE_g</i>
	0.196***	0.129***	-0.067***
	(0.034)	(0.033)	(0.004)
	<i>ILATE</i>	<i>ILATE_h</i>	<i>ILATE_g</i>
	0.511***	0.413***	-0.098***
	(0.015)	(0.015)	(0.001)

Note: This table presents the estimates of the treatment effects. The *LATE* is the local average treatment effect which presents the total treatment effects of both conservation agriculture adoption and participation in field demonstration. *DLATE* is the direct treatment effect directly from the adoption of conservation agriculture (i.e. through other channels other than participation in field demonstration). *ILATE* represents the indirect treatment effect derived via participation in field demonstration. Standard errors are reported in parentheses and are from 1000 re-sample. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

More specifically, in column 1, the results indicate that adoption of conservation agriculture tends to have a positive and statistically significant (at 1% level of significance) total effect on maize yields with an effect of 70.7% (i.e., $LATE = 0.707$). The mediation analysis shows that participation in field demonstrations results in a relatively larger and statistically significant (at 1% level of significance) treatment effects, contributing to 51.1% increase in the total maize yields (i.e., $ILATE = 0.511$). The remaining direct effect (i.e., 19.6%) is also positive and statistically significant (i.e., $DLATE = 0.196$), suggesting that the total effect is comparatively driven by the indirect effect. We further decompose the treatment effects into two main components, that is, production frontier and inefficiency components in columns 2 and 3 of Table 5.4. The estimates paint a picture of greater impact of the interventions on each of the components. In particular, the total effect of CA adoption tends to be positive and statistically significant (at 1% level of significance), indicating an upward shift in the production frontier by 54.2% (i.e., $LATE_h = 0.542$). Decomposing the total treatment effect, the mediation estimates further point to an upward shift in the production frontier by (12.9%) which

is a direct effect ($DLATE_h = 0.129$) of CA adoption, and comparatively greater indirect effect ($ILATE_h = 0.413$) of about (41.3%) via participation in field demonstrations.

Focusing on the impact on technical inefficiency, our results are generally consistent with the notion that the adoption of new technologies improves the technical efficiency of smallholder farmers. In particular, the estimate of the total treatment effect (the first row of column 3, Table 5.4) points to a statistically significant reduction in the level of technical inefficiency as a result of the intervention, indicating that smallholder farmers who adopt CA tend to experience 16.5% improvements in technical efficiency ($LATE_g = -0.165$). In other words, for the subpopulation of compliers (i.e., those who have access to climate information), adopting CA may contribute to reducing technical inefficiency. Furthermore, the mediation estimates show that the indirect effect mediated through participation in field demonstration results in a relatively greater reduction in technical inefficiency by 9.8% ($ILATE_g = -0.098$). On the other hand, the direct effect obtained through other channels other than participation in field demonstrations is 6.7% ($DLATE_g = -0.067$).

In line with the hypothesis motivating this study, these findings highlight the importance of taking into account potential treatment effect heterogeneity by disaggregating the impact of technology adoption into direct and indirect effects. In particular, the results generally reveal that the adoption of conservation agriculture and participation in field demonstrations significantly improve maize productivity, push upward the maize production frontier and reduce the level of technical inefficiency. It is interesting to note that, even though the magnitudes of the direct effects (i.e., through other channels other than participation in field demonstrations) are not trivial, the indirect effects derived via participation in field demonstrations are significantly greater.

These findings make a strong case for encouraging participation in field demonstrations as it improves smallholder farmers' practical knowledge on the use of innovative technologies

and provides them the opportunity to get hands-on and visual knowledge on their application and benefits, thereby contributing to improving their managerial performance (Ehiakpor et al., 2020; Bravo-Ureta et al., 2020b). While the above findings highlight the benefits of conservation agriculture, it is also worth noting that the study's focus is on compliers, on whom the impact of conservation agriculture are likely to be more pronounced. Therefore, expanding access (via radio, TV, mobile phone, etc.) and providing timely information on weather variability (e.g., rainfall, dry spells) could further enhance its adoption, thereby contributing to improving maize productivity.

5.4.3 Policy simulation and robustness

So far, our findings have shown that the adoption of conservation agriculture mediated via participation in field demonstration contributes significantly to increased output, pushes the production frontier upwards, as well as improves the level of efficiency. This suggests that policy interventions that seek to overcome structural barriers and induce farmers to participate in field demonstrations can be very beneficial. In particular, a policy instrument or intervention that addresses mobility concerns (e.g., travel distance to demonstration sites) has the potential to increase participation and by extension improve the productivity of smallholder farmers.

Using the policy-relevant treatment effects (PRTE)³⁵ in the marginal treatment effect literature, we calculate a PRTE for a counterfactual policy that manipulates the propensity scores. Thus, the estimated results represent the treatment effect for a farmer who is shifted into treatment by the new policy relative to the baseline propensity scores (Heckman and Vytlačil, 2001; Andresen, 2018). Specifically, we simulate a policy effect of making field demonstrations more accessible to farmers by siting them closer to their homesteads (i.e., reducing the average travel distance to demonstration sites by 50 %).

³⁵ We compute the PRTE as follows: $PRTE(x) = \int MTE(X, U_D) f_{U_D|X}(U_D|X, C(p) = 0, C(\bar{p}) = 1) dv$ (17)
where P (policy instrument) does not affect the outcome equations and shift from $P=p$ to $P = \bar{p}$.

Table 5.5: PRTE and Robustness

Maize yields (log)		Distance to demonstration sites		
	1	2		3
		Propensity scores		Policy effect
	LATE	Baseline	Policy	PRTE
	0.706*** (0.069)	0.572	0.680	1.201*** (0.183)

Note: This Table presents the PRTE (column 3) per farmer induced to adopt based on decreasing distance to field demonstration sites by 50%. Column 2 reports the propensity scores from the baseline line specifications of the policy and the propensity score because of the policy changes. We further report the robustness result for LATE (local average treatment effect) based on the MTE model. The number of observations is 512. Bootstrapped standard errors are reported in parentheses. Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column 2 of Table 5.5 shows the propensity scores for the baseline specifications and that of the policy. As evident from the results, our policy induces non-participants of field demonstration into participation by 15.88%. In addition, we observe in column 3, a positive and significant treatment effect (i.e., PRTE = 1.201) for those induced to participate. These findings are instructive and underscore the need for policymakers and programs to take into account the proximity of these demonstration sites to farmers to achieve sustained adoption and improvement in farm productivity. To ensure the robustness of our findings, we further estimate LATE employing the marginal treatment effect model (MTE) which also generates various treatment effect parameters including the LATE (Heckman and Vytlačil, 2007). As it is evident from the result, column 1 of Table 5.5 shows a total effect of 70.6% ($LATE = 0.706$) which corroborates the result of our main model in column 1 of Table 5.4 (i.e., $LATE = 0.707$).

5.5 Conclusion and Policy Implication

This study contributes to the growing empirical literature by examining the direct and indirect impacts of conservation agriculture and participation in field demonstrations, using household data matched with historical rainfall data from the northern Savanna regions of Ghana. We employed a stochastic frontier model with an endogenous treatment status and mediator and address the endogeneity concerns using two instrumental variable methods. This model, in particular, decomposes the treatment effects into technology frontier and inefficiency components. In the mediation analysis, we disentangled the total effects into direct effects

obtained through other channels other than participation in field demonstrations, and indirect effects mediated by participation in field demonstrations. From a policy perspective, the analysis conducted in this study is relevant to the extent that it contributes to shedding light on the potential causal mechanisms of conservation agriculture.

The empirical results revealed significant production potential and that the adoption of conservation agriculture technologies shifts the technology frontier upward and improves the level of efficiency. Our mediation analysis estimates further showed that even though we observed a significant direct effect through the adoption of conservation agriculture, a larger share of the total effect was driven by the indirect effects via participation in field demonstrations. These findings thus illustrate the policy relevance and the complementary effect of field demonstrations in improving farm productivity. The findings also established statistically significant differences in key determinants of the production and inefficiency functions. In particular, we found positive and statistically significant relations between variables such as fertilizer, extension contacts, and seasonal rainfall on the technology frontier. Furthermore, rainfall shocks during cropping seasons, according to our findings, are detrimental to technical efficiency, making it difficult for vulnerable farm households to automatically adjust to such exogenous shocks.

Our finding generates important policy implications. Policymakers must strengthen and support the agricultural extension service delivery, including investing and integrating field demonstrations in technology adoption programs to achieve impacts and economies of scale. This effort could improve smallholder farmers' managerial capacity, particularly given the complementary role of demonstration plots in shifting upward the technology frontier and improving efficiency. However, longer travel distances to demonstration plots are a major barrier to its participation. It is therefore critical to fashion out measures to ensure that they are located closer to homesteads.

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Appendix

Table 5.A1: CA adoption and field demonstration participation decisions (First-Stage Bivariate Probit Estimates)

Variables	CA adoption (D)		Demonstration participation (M)	
	Coefficient	S.E	Coefficient	S.E
Age	0.079	0.164	0.824***	0.217
Male	-0.030	0.116	0.930***	0.130
lnEducation	-0.066	0.049	0.116*	0.060
Farm size	-0.041*	0.022	-0.061**	0.031
lnExtension	0.356***	0.103	1.123***	0.114
Credit constraint	-0.366***	0.102	-0.006	0.136
lnLabor	0.246***	0.083	0.830***	0.108
lnFertilizer	0.229**	0.108	1.138***	0.104
Fertilizer_dummy	0.991*	0.589	5.391***	0.623
lnChemicals	0.267**	0.116	0.633***	0.153
Slope	0.263	0.204	0.942***	0.273
lnRainfall amount	-4.290***	1.473	-9.673***	1.810
Rainfall shock	0.225**	0.110	0.412***	0.128
Climate information	1.036***	0.123		
Distance to demo farms			-0.155***	0.040
CA Adoption	0.858***	0.286		
Agro-ecological	-0.021	0.125	0.253	0.161
Constant	27.434***	10.141	58.019***	12.350
ρ_{md}	0.368**	0.157		
Wald test of $\rho_{md} = 0$	4.76**			
Wald test Chi2	446.29***			
Log-likelihood	-747.55			
Number of observations	512			

Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.A2: Test of Validity of the Excluded Instrument

Variables	Coefficient	Standard Error
Age	-0.000	0.002
Male	0.048	0.044
Education	0.004	0.006
Farm size	0.104***	0.012
Extension	0.047***	0.004
Credit constraint	-0.106**	0.045
Labor	-0.001***	0.000
lnFertilizer	0.001***	0.000
Fertilizer_dummy	0.037	0.132
lnChemicals	0.000*	0.000
Slope	0.205***	0.051
Rainfall amount	-0.002***	0.001
Rainfall shock	0.098*	0.053
Climate information	0.050	0.047
Distance to demo farms	-0.021	0.016
Agro-ecological	0.114**	0.058
Constant	8.315***	0.699
F-test	0.01	
Number of households	212	

Significance level at * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 6

Conclusion and Policy Implications

6.1 Concluding remarks

The impacts of climate-related shocks on agriculture and the implications for food and nutrition security are already alarming and are projected to intensify over time, and become heterogeneous across regions, particularly in sub-Saharan Africa. In addition, degradation of arable lands and agro-ecosystem conditions are contributing to a decline in food production. These long-term stresses compromise agriculture's ability to feed the rapidly growing global population, impeding progress towards achieving the sustainable development goals (SDGs) on eradication of hunger, undernourishment, and poverty by 2030. Rather than exacerbating climate variability and depletion of soils and ecosystems, agrifood systems need to shift to a more sustainable and resilient production pattern to secure the livelihoods of low-income farm households. The adoption of cover crops, intercropping, crop rotation, and minimizing soil disturbance through conservation agriculture (CA) has the potential to restore and conserve soil, boost the capacity of soils to sequester carbon dioxide, improve nitrogen use to reduce emissions, and increase agricultural productivity.

However, widespread adoption of these technologies may be hampered by policy, institutional, and socio-economic constraints that must be overcome. Thus, this study contributes to the literature on technology adoption and provides a comprehensive understanding of the constraints and opportunities associated with its adoption. First, the study investigated the heterogeneity in conservation agriculture adoption and the implication on farm productivity and inorganic nitrogen fertilizer use. Second, the study assessed the food and nutrition security potential of conservation agriculture by examining how medium to long-term adoption of minimum tillage (MT) impacts dietary diversity and household food insecurity access scores (HFIAS).

Third, in the absence of adequate formal financial instruments to mitigate weather-related shocks, the study further investigated the role of crop diversification in improving household welfare and risk exposure. Furthermore, the study underscored the important role of a mediator in shifting the technology frontier upward and improving efficiency by analyzing the dual impact of participation in field demonstrations and conservation agriculture adoption on farm productivity and efficiency, decomposing the total effects into direct effects through all channels other than participation in field demonstration and indirect effects through participation in field demonstrations. The next sections summarize the empirical methods, main findings of the study and the policy implications of the study.

6.2 Summary of empirical and econometric methods

Several empirical challenges are often encountered in impact assessment studies when using observational data. This study employed state of the art econometric methodologies that are robust and address the potential endogeneity and identification issues. This section presents an overview of the major issues, and how they were addressed. More details are provided in the individual papers.

To contribute to the literature, chapter 2 employed the marginal treatment effects (MTE) approach to investigate the heterogeneous treatment effects of CA on farm performance and inorganic fertilizer use. The approach considers the treatment effect heterogeneity due to observed and unobserved characteristics. The framework estimates a continuum of treatment effects along with the whole distribution of farmers' unobserved resistance to adoption. It further shows the pattern of selection and allows a number of economically important parameters of interest to be estimated: the average treatment effects (ATE), average treatment effects on the treated (TT) and the average treatment on the untreated (TUT). The policy relevant treatment effect (PRTE) estimates the effects of reducing the cost of implementing CA technologies or increasing the average training days on CA.

Chapter 3 examined the impact of minimum tillage on maize yields, food and nutrition security, and labor demands considering the heterogeneity in the duration of adoption. Specifically, because of the ordered nature of the treatment variable, the study accounts for potential selection bias and omitted variable problems using an ordered probit selection model to estimate two transition-specific treatment effects: from conventional tillage systems to short-term MT adoption and from short-term to long-term MT adoption. This is a parametric model that employs full information maximum likelihood procedure to jointly estimate a first-stage ordered-Probit of the length of adoption, and a second-stage outcome model for the three different adoption states of minimum tillage (conventional, short-term, and long-term MT adoption). The model addresses selection bias and omitted variable concerns by including the inverse Mills ratios obtained from a first-stage ordered choice model into the second-stage outcome models.

In the fourth chapter, the study analyzed the heterogeneous impact of crop diversification on farm net returns and risk exposure, employing the dose response function and instrumental variable techniques to address potential endogeneity concerns. This method allows for the estimation of a causal response between the outcome variables and each level of the dose applied (i.e. levels of diversification). The approach further incorporates a zero-treatment probability mass, addresses the potential endogeneity of crop diversity in farm net returns, and thus restores the consistency of the estimates using instrumental variable (IV) estimation. It further estimates other causal parameters of interest such as average treatment effect (ATE), average treatment effect on the treated (ATET), and average treatment effect on the untreated (ATENT).

Finally, the study employed the stochastic frontier treatment effect with endogenous mediator model to estimate the impact of CA adoption and participation in field demonstrations. The model addresses potential endogeneity from selection and omitted variable bias in both the

adoption decision and the participation decision models, using binary recursive probit analysis in the first stage. In the second stage, the framework used the generalized method of moment (GMM) approach to estimate stochastic frontier regression that considers the treatment heterogeneities among production units. The treatment effects are decomposed into production frontier and inefficiency components, as well as direct effects of CA and the indirect effects via a mediator (i.e. participation in field demonstrations).

6.3 Summary of main findings

The results in chapter two revealed significant heterogeneity in the impacts of adoption of CA practices on maize yields, farm net returns, and inorganic nitrogen (N) fertilizer use, signifying that farmers' adoption decisions are based on their comparative advantage. We further found that farmers with higher propensity to adopt experienced higher maize yields and net returns compared to those with lower propensity to adopt. Regarding the use of inorganic N fertilizer, the findings further demonstrated that farmers with high propensity to adopt significantly reduced inorganic N usage after adoption. Whereas farmers with low propensity to adopt use comparatively more inorganic N fertilizer. The results also indicated that age, gender, education, livestock, farm size, extension contacts, farmer-based organization (FBO), and soil erosion significantly influence CA adoption decisions. Further, the PRTEs revealed that increasing training sessions and supporting farmers to reduce the cost of implementation could increase adoption.

The empirical results in chapter three generally showed significant impacts of minimum tillage across different transitions. Specifically, transitioning into short-term and long-term minimum tillage adoption increases maize yields, dietary diversity and decreases household food insecurity access scores. However, the study found that switching to short-term and long-term minimum tillage increases and decreases total labor demands, respectively. The findings further illustrated substantial heterogeneities in gains. We found positive selection on gains in

transitioning between conventional tillage and short-term minimum tillage in the case of dietary diversity, indicating that more endowed farmers who are more likely to transition tend to experience higher dietary diversity. A similar pattern was observed when transitioning between short-term to long-term minimum tillage. The findings showed that age, extension contacts, rainfall shocks, temperature, and credit significantly affect farmers' decisions regarding the adoption of minimum tillage.

In chapter four, the empirical results primarily showed that cultivating a wider diversity of crops helps to increase farm net returns and reduce downside risk exposure. The findings illustrated substantial heterogeneity in the impact of crop diversification. In the case of farm net returns and skewness, the results showed evidence of reverse selection on gains ($ATENT > ATE > ATET$), indicating that farmers who are less likely to diversify tend to experience greater gains if they diversify. The dose response function results revealed an inverted U-shaped pattern with a maximum and significant effect around the dose of about 75 percent (i.e. ATE of 3.297) for farm net returns and about 70 percent (i.e. ATE of 4.983) for skewness. However, beyond these thresholds (doses), further increases in the level of diversification resulted in a decline, indicating diminishing returns. A similar pattern was observed in the case of the variance, with lower diversified crop production system stabilizing farm net returns whereas higher levels increased farm net return volatility.

The findings in chapter five showed that the adoption of conservation agriculture and participation in field demonstrations significantly improved maize productivity, pushed upward the production frontier, and reduced the level of technical inefficiency. In particular, the adoption of conservation agriculture had a positive and significant total effect on maize yields with an effect of 69.9%, whereas the mediation analysis showed that CA directly contributed to 19.4% increase in total output and the remaining 50.5% indirectly through participation in field demonstrations. Further, CA led to an increase in technology frontier with an effect of

55.7% of the total output. The mediation analysis showed that the upward shift in the frontier is largely derived via participation in field demonstrations. As for the impact on technical inefficiency, the effect amount to 14.3% increase in total output. Furthermore, the mediation analysis illustrated that the inefficiency-reducing effect is largely derived indirectly via participation in field demonstrations.

6.4 Policy Implications

This dissertation explored the role of conservation agriculture in improving household welfare among smallholder farmers in Ghana. Several key elements emerge from the analysis contained in the individual chapters. The first important point that emerges from the study is that conservation agriculture as a climate-smart agriculture technology has the potential to significantly improve farm productivity, and food and nutrition security, manage the use of nitrogen from inorganic sources, as well as reduce downside risk exposure. Despite this potential, our findings indicated that a number of barriers including access to information and credit, extension, training, and labor demands might hamper its widespread adoption. It is particularly challenging for smallholder farm households to sustain the adoption of these technologies because of the difficulties they encounter in accessing credits. Conservation agriculture is labor and cost-intensive and would require substantial investments in order to achieve the expected benefits. In addition, gaps in climate information need to be addressed. Investment is required to assist smallholder farmers with timely and accurate weather and seasonal forecast. This information must be user-friendly and accessible through collaboration between Ghana meteorological agency, research institutions, and the agricultural extension service. Therefore, instead of undertaking a blank promotion of the technology across farming systems, policymakers should provide tailor-made solutions to address these specific constraints.

The second point is that conservation agriculture technology is typically management and knowledge-intensive. Thus, the policy simulations revealed that increasing capacity building through training has the potential to increase adoption and farm productivity. Further, the mediation analysis demonstrated that by providing opportunities for effective farmer-to-farmer learning and exchange with scientists and extension agents through field demonstrations, the technology frontier could be shifted upward and inefficiency reduced. The third point is that crop diversification can significantly improve household welfare and risk exposure, suggesting that policies and programs such as the Planting for Food and Jobs must continuously integrate crop diversification as an essential component, and facilitate its adoption by providing low-income farm households with incentives through improved access to seeds and fertilizers, weather information and extension service.

Last but not least, the findings of the study will support policy processes and re-orient farming systems in a manner that facilitates, rather than hinders, the transition to conservation agriculture in order to improve the livelihoods of low-income farm households and build the resilience of the agrifood systems, especially under a changing climate. Ghana has made progress in integrating climate-smart agriculture into national economic development plans and agricultural policies and initiatives through the National Climate Change Policy (NCCP) and has further aligned its policies and programs to a number of sub-regional climate change initiatives such as the Climate Change, Agriculture and Food Security (CCAFS). These concerted efforts aim to address the bottlenecks associated with the adoption of these climate-smart technologies. More importantly, the country has incorporated in its Nationally Determined Contributions (NDCs) framework a section on mitigation and adaptation to climate change in the agriculture sector. These climate actions are important for building the resilience of smallholder farmers and reducing emissions from the sector, as well as creating synergies with other sustainable development goals, such as ending hunger and reducing poverty. Thus,

the present dissertation provides microeconomic evidence on the impacts of conservation agriculture in order to improve policy formulation and guide project implementation.

Appendices

Appendix 1: Household survey questionnaire



Christian-Albrechts University of Kiel, Germany
The Institute of Food Economics and Consumption Studies

Contribution of Conservation Agriculture to Household Welfare in Ghana

Thank you for participating in this interview. We are researchers from the University of Kiel, Germany. This research is being conducted as part of PhD research on sustainable agriculture. In the course of the interview, you would be asked questions about the characteristics of your farm and the household. Specifically, we are interested in learning more about the sustainable agricultural practices you carry out on your maize farms. Additionally, we would like to understand your production and sales of maize as well as any other non-farm activities of your household. Kindly note that all information provided is for research purposes only and shall be kept strictly confidential. Thank you for agreeing to participate in this interview.

Survey Identification		General information	
Questionnaire number		Region	
Name of enumerator		District	
Code of enumerator		Name of village/town	
Date of interview		Language of interview	
Time started		Agro-ecological zone	1. Sudan Savannah
Village location	1. Treatment area 2. Control area		2. Guinea Savannah
GPS coordinates of the homestead			3. Transitional zone
GPS coordinates of the plot			

Section A: Socio-demographic characteristics of respondents

A.1 Name of respondent	
A.2 Age	
A.3 Sex 1= Male 2= Female	
A.4 Relationship to household head 1= Head 2= Spouse 3= Son/Daughter 4= Son/Daughter in law 5= Father/Mother 6= Father/Mother in law 7= Brother/Sister 8= Grandchild 9= Other relative 10= Non-relative	
A.5 Marital status 1= Married (monogamous) 2= Married (polygamous) 3= Single, 4= Divorced, 5= Widowed	
A.6 Family type 1= nuclear 2= extended 3= other (specify)	

A.7 Household size			
A.8 Number of children			
A.9 Years of education			
A.10 Religion 1= Islam 2= Christianity 3= Traditional 4= Others specify			
A.11 Ethnicity/Tribe 1.=Hausa 2. = Dagomba 3. = Mamprusi 4. = Gonja 5.= Grussi/Frafra 6.= Dagarti 7.= Kusasi 8.=Kassena-Nankani 9.= Konkomba 10.=Nanumba 11.= Builsa 12.= Akan 13.= Guan 14. other, specify			
A.12 Status in the locality 1= chief 2= village executive 3= member 4= Migrant 5= Religious leader 6= political party leader 7=other (specify)			
A.13 Highest level of formal education completed (years)			
A.14 Occupation (List main and secondary occupation according to time spent) 1= Farmer (other crops, livestock, and aquaculture) 2=Non-farm owned business (e.g. tailoring, etc); 3=Casual laborer on another farm 4=Civil/public servant; 5. =Housewife 6=Unemployed; 7= Student; 8.=Retired; 9.= Other, specify			
a. Main occupation		b. Secondary occupation	
A.15. Other sources of income: Please specify			
A.16. Please specify if A 14 includes option 2 (non-farm business)			
A.17 Experience in own farming activities (years)			
A.18 For how many years have you been cultivating maize?			
A.19. Are you a member of any organization/group? 1= Yes 2= No			
A.20. If yes, which organization/group do you belong to? 1=FBO; 2=Saving and loans; 3=religious group; 4= Others specify...			
Please indicate the total number of household members in their respective category as in the table below			
Household member	Gender		Age
	Male	Female	

Section B. Land tenure

We would like to ask some questions about all the land which the household used either free of charge or rented in 2018. Please record all information per plot (maximum of 5 plots).

Plot ID	Size 1. Acre 2. Pole 3. Hectare	Household member responsible for this plot 1=Household head 2=Spouse 3=child	Land tenure See code below	Years of ownership if the farmer owns the land	Years of usage	If rented, what is the cost of renting per year (per acre)? (if option 6 is chosen)	Did the household have a deed on this plot? 1. Yes 2. No	What kind of deed? 1. Certificate (deed from Lands Commission) 2. Letter from village chief 3. Contract of sale 4. Other, specify	Did the household have the right to sell the plot or to use it as collateral? 1. No 2. Sell 3. Collateral 4. Both	If the plot were to be sold now, how much would it be worth? (GHS)	Main land use See code below		What is the distance from the homestead to the plot? 1=walking minutes 2=KM 3=Miles
	LT1	LT2	LT3	LT4	LT5	LT6	LT7	LT8	LT9	LT10	a	b	LT13
1													
2													
3													
4													
5													

Code LT 3

1. Owned by respondent
2. Owned by other household members
3. Owned by family
4. Community land, distributed by the chief
5. Land made arable by the household
6. Rented-in for fixed pay
7. Sharecropper (Abunu)
8. Sharecropper (Abusa)
9. Other, specify

Code LT11/LT12

(up to 2 answers per plot)

1. Rented-out for maize cultivation
2. Rented out for cultivation of other crop production
3. Sharecropped-out for maize cultivation
4. Sharecropped-out for other crop production
7. Forest
8. Pasture
9. Bushland/wetland
10. Fallow
11. Cultivation of cash crops
12. Cultivation of maize
13. Cultivation of other food crops
14. Other, specify

SECTION C: Plot-level Characteristics

Make sure to include all the plots owned/operated by the HH. Please record information per plot.

Plot ID	Slope of this plot See code below.	Vegetation before you started farming on the plot? See code below	What is the Current vegetation See code below.	What is the major type of soil of this plot? 1=sandy 2=loamy 3=clay 4=laterite 5=other, specify	Rank the level of erosion of the plot See code below	Soil quality (fertility) 1=infertile, 2=moderately fertile 3=fertile 4=highly fertile	Which crops do you plant on this plot? See code below	What was the use of this plot prior to planting maize? See code below		Were there trees on the plot before? (1=yes, 2=no)	If yes what type of trees? 1=Cashew 2=Timber 3=Dawadawa 4=Mango 5=Cocoa 6=Timber 7=others.....	Have you cut down some of the trees since you started farming on the plot? (1=yes, 2=no)
								2018 farming season	2017 farming season			
	PL1	PL 2	PL 3	PL 4	PL 5	PL 6	PL 7	PL 9	PL 10	PL 11	PL 12	PL 13
1												
2												
3												
4												
5												

Code for PL 1

1=flat
2=moderate
3=steep

Code for PL 3

1=forest,
2= semi forest,
3= savanna

Code for PL 9-10

1=rented-out
2=fallow
3=tree plantation
4=virgin land
5=grazing
6=maize
7=rice

8=cereals other than maize/rice

9=legumes10=root/tuber

11=vegetables 12=fruits

13=banana 14=flower

15=other crop (specify)

16=borrowed-out

Code for PL 2

1=forest (>200 trees),

2=semi-forest (200 to 50 tree)

3=savanna (<50 trees)

Code for PL 5

1=no erosion

2=minimal erosion

3=moderate erosion

4=eroded

5=severe erosion)

Code for PL 7

1. Maize

2. Cashew

3. Cotton

4. Groundnut

5. Sorghum

6: Mango

7. Millet

8. Rice

9. Soybeans

10. Yam

11. Vegetables

12. Other, specify

Section D: Adoption of Sustainable Agricultural Strategies (SASs)

This section intends to know your current usage of sustainable agricultural strategies

Sustainable Agricultural Strategies (SASs)	Have you ever used this technology for your maize production? If yes, in which year did you use it for the first time? If not, why have you never adopted this technology?				Did you discontinue the use of SASs at any point? If yes, in which year did you discontinue? If there are several times of discontinuation, please answer about the last one. If yes, why did you discontinue these SASs?		Did you re-adopt the SAS? If yes, in when (year) did you re-adopt? If there are several times of re-adoption, please answer about the last one after the last discontinuation.		How did you acquire knowledge on SASs? (Code SA10)	
	1=yes 2=no	If 1=yes, in which year?	Extent of adoption (in terms of plot size)	If 2=no, the reason for non-adoption. See code below	1=yes 2=no	If 1=yes, in which year?	If 1=yes, the reason for discontinuation. See code below	1=yes 2=no	If 1=yes, in which year?	
	SA1	SA2	SA3	SA4	SA5	SA6	SA7	SA8	SA9	SA10
Conservation Agriculture										
Minimum/zero tillage										
Cover cropping/Mulching										
Use of leguminous crops										
Crop rotation										
Intercropping										
Ripping										
Others, specify.....										
Crop diversification										
Using improved /drought-resistant varieties										
Changing planting date										
Cultivating more crops										
Changing crops										
Other, specify.....										

Soil and Water Conservation											
Grass stripping											
Contour ploughing											
Terracing											
Stone bunding											
Earth bunding											
Zai technique											
Others, specify.....											
Soil Fertility											
Application of manure											
Compost Application											
Organic fertilizer											
Others, specify.....											

Code for SA4/SA7: 1=not aware of this technology
2=lack of technical know-how 3=lack of cash/credit
4=not profitable. 5=unavailability of labor
6=unavailability of the product
(herbicide/fertilizer/improved

variety seed) 7=unavailability of service (tractor)
8=others, specify.
Code for SA10: 1=own experimentation 2=observation
of neighboring farmers (without direct instructions)

3=taught by neighboring farmers 4=government
extension agents 5=media 6=non-government agencies
7=private institutions 8=others, specify

Sustainable Agricultural Strategies (SASs)	SA11. Why do you practice these strategies? <i>You can select more than one reason.</i>				
	SA11a	SA11b	SA11c	SA11d	Codes SA11
Conservation Agriculture					1=Improve production 2=Reduce, prevent, restore land degradation (soil, water, vegetation) 3=Conserve ecosystem 4=protect a watershed/ downstream area – in combination with other Technologies 5=Preserve/ improve biodiversity 6=Reduce risk of disasters (e.g. droughts, floods, landslides) 7=Adapt to climate change/ extremes and its impacts (e.g. resilience to droughts, storms) 8=Mitigate climate change and its impacts (e.g. through carbon sequestration) 9=Create beneficial economic impact (e.g. increase income/ employment opportunities) 10=create beneficial social impact (e.g. reduce conflicts on natural resources, support marginalized groups) 11=other purpose (specify).....
Minimum/zero tillage					
Cover cropping/Mulching					
Use of leguminous crops					
Crop rotation					
Intercropping					
Ripping					
Others, specify.....					
Crop diversification					
Using improved /drought-resistant varieties					
Changing planting date					
Changing crops					
Other, specify.....					
Soil and Water Conservation					
Grass stripping					
Contour ploughing					
Terracing					
Stone bunding					
Earth bunding					
Zai technique					
Others, specify.....					
Soil Fertility					
Application of manure					
Compost Application					
Organic fertilizer					
Others, specify.....					

SA12. Have you ever increased your farm size in the last two farming seasons? 1=yes; 2=no

SA13. If yes, why did you increase your farm size?.....

SA14. If SA12 is yes, by how many acres have you increased your farmland?

SA14. If SA12 is no, why haven't you increased your farm size?.....

Section D.1: Perception of sustainable agricultural strategies

First, tick relevant impacts (tick boxes on the left, several answers possible). Then, for each selected impact, tick the extent and specify/ quantify if possible.

P1. Socio economic impacts

Production	decreased	1	2	3	4	5	6	7	increased
crop production	decreased								increased
crop quality	decreased								increased
production area (new land)	decreased								increased
Income and costs	decreased								increased
expenses on agricultural inputs	decreased								increased
farm income	decreased								increased
diversity of income sources	decreased								Increased
Other socio-economic impacts									

P2. Sociocultural impacts

food security/ self-sufficiency	decreased	1	2	3	4	5	6	7	increased
health situation	worsened								improved
Network among members	worsened								improved
Migration	decreased								improved
Other sociocultural impacts									

P3. Ecological impacts

Soil	decreased	1	2	3	4	5	6	7	increased
soil moisture	decreased								increased
soil organic matter	decreased								increased
soil loss	increased								decreased
Biodiversity: vegetation,									
vegetation cover	decreased								increased
pests/ diseases	decreased								increased
External inputs									
Inorganic fertilizer	increased								decreased
Pesticides	increased								decreased
Herbicides	increased								decreased

1=Very negative (− 50-100%); 2=Negative (− 20-50%) 3=slightly negative (− 5-20%);

4=Negligible impact; 5=slightly positive (+5-20%); 6=Positive (+20-50%);

7=Very positive (+50-100%)

SECTION E. Maize crop budget

E.1. Input use for Maize Production.

The questions below refer to the 2018 farming season. Please name all external inputs (inorganic fertilizer, herbicides, pesticides) applied on the maize plots between January and December 2018. *Please refer to Section C.*

Plot ID	Planting							Inorganic fertilizer Use						Herbicide			Other Chemical		
	What was the area planted to maize? (acre)	Name of the Maize Variety See code below	How did you obtain the seed? See code below	From whom did you obtain the seed? See code below	Quantity of seed used on this plot (kg)	Total Cost of seed (kg) used in GHC	How did you sow this crop on this plot in farming season 2018? See code below	Did you apply fertilizer? 1=Yes 2=No	If yes to MP08				If MP08=1 Total cost of fertilizer	Did you use herbicide for weeding during this crop growing stage? 1=Yes 2=No	If MP14=1 what is the quantity used?	If MP14=1 Total cost of herbicide used (GHC)	Did you use insecticide/fungicide? 1=Yes 2=No	If MP17=1, what is the quantity used?	If MP16=1 Total cost of other chemicals (GHC)
									1 st application		2 nd application								
									Type of fertilizer See code below	Quantity used (kg)	Type of fertilizer See code below	Quantity used (kg)							
	MP01	MP02	MP03	MP04	MP05	MP06	MP07	MP08	MP09	MP10	MP11	MP12	MP13	MP14	MP15	MP16	MP17	MP18	MP19
1																			
2																			
3																			
4																			
5																			

1=Obatanpa;
2=Golden Jubilee;
3=Mamaba (hybrid);
4=Abelechi
(Abelechi);
5=Dorke SR;
6= Okomasa;
7=Etubi (hybrid);
8=Dodzi;
9=Omankwa;
10=Akposoe;

11=Abontem;
12=Golden Crystal
13=Sanzal sima
14=Ewul buoyo
15=Wang data
16=Agric;
17=local/traditional/;
18= do not know;
19=imported hybrid
(specify _____);
20=Other(specify_____

Code for MP03
1=Purchased without
subsidy
2=In-kind credit
3=Gifted 4=Own
production;
5=Purchased through
subsidy

Code for MP04
1=Extension worker
2=Other farmers in the
village
3=Other farmers outside
the village
4=Own production
5=Local market
6=Trader
7=Other(specify)

Code for MP07
1=broadcasting before
ploughing
2=broadcasting after
ploughing
3=dibbling randomly
4=dibbling in a line
5=drilling

6=transplanting
(exclude cases
Where transplantation was
used for only a small part of
the plot)
Code for MP09/MP11
1=NPK
2=Urea
3=ammonium sulfate
4=other, specify

MP 20. Do you have access to agro-input shops in your village or community? 1=yes; 2=no

MP 21. If yes, how far is it from your homestead? 1=walking minutes.....2=KM.....3=Miles.....

E.2. Input costs – hired and family labor

L1. What was the wage rate per man-day during the 2018 farming season?.....

L2. Was the male wage rate different from that of female workers? 1=Yes 2=No

L3. If yes, what was the rate for females?.....

L4. Please count all hired and family laborers during the 2018 farming on the farmer's maize plots. Please count working days for each task for each plot for the whole year 2018. Please include cash and in-kind payments when calculating the average pay per day by task. Please repeat these questions for each plot if possible.

Plot ID	Activity	L5. Did you hire any workers? 1. Yes 2.No	L6. Type 1=Permanent 2=temporary)	L7. Number of hired workers			L8. Total number of man-days	L9. Did you use family labor? 1. Yes 2.No	L10. Number of family labor			L11. Total number of man-days per worker	L12. Cost of family per man-day.
				L7a. male	L7b. female	L7c. Total no. of laborers			L10a. Adult Men	L10b. Adult Female	L10c.Children Under 15 yrs.		
	Land preparation and ploughing or ripping												
	Harrowing												
	Planting												
	Applying agrochemical inputs												
	Fertilizer												
	Insecticide/pesticide												
	Herbicide/weedicide												
	Weeding control												
	1 st weeding												
	2 nd weeding												
	3 rd weeding												
	Sustainable agricultural strategies												
	Harvesting												
	Shelling												
	Bagging and weighing												
	Storing												

E.3. Maize input costs – other expenditures

Please list all other expenditures related to maize cultivation on the farmer's plot incurred during the 2018 farming season.

		Total amount spent in 2018 (GHS)
OE1	Cost of implementing sustainable agricultural strategies	
OE2	Purchase or rental of agricultural equipment (e.g. spaying machines, hand tools, bags, drying mats)	
OE3	Transportation costs (e.g. for buying inputs, bringing maize from farm to home, bringing maize to point of sale)	
OE4	Other farm-related expenditures, specify	

Section F: Use of external inputs

	External input use	Herbicide	Fertilizer	Pesticide	Others
EI1	In which year did you start using external input (s)?				
EI2	Have you been applying external inputs(s) on your farm in the last 3 farming seasons? 1=Yes 2=No				
EI3	If yes, why are you using it?.....				
EI4	If not, why are you not using it?.....				
EI5	Name of external input(s) you are using currently				
EI6	Have you reduced the amount of external inputs used? 1=Yes 2=No				
EI7	If yes, by how much? Please quantity in percentage terms.				
EI8	What is your recommended dosage (lit./Kg /acre)				
EI9	Were you using another one before 1=yes, 2=No				
E20	If yes, why did you stop using it?				
E21	Who recommended to you what you are currently using?				
E22	Who applies it to you on your farm?				
E23	If self, are you trained on the use 1=yes; 2=No				

Section G. Maize Harvest

Please indicate the quantity of maize harvested with the corresponding plot ID, as well as the distribution of the harvests during the 2018 farming season.

Plot ID	Quantity of maize harvested (kg)	Quantity consumed (kg)	Quantity sold (kg)	Quantity stored as seed (kg)
	MH1	MH2	MH3	MH4
1				
2				
3				
4				
5				

Section H. Maize sales

MS1. How do you access market information?

1=neighbor, 2=FBO, 3=Mobile phone, 4=Radio, 5=Extension agents, 6=others specify...

Please ask for all maize sales of the respondent for the produce harvested in the 2018 farming season. One maize sale includes all the maize sold to the same buyer at the same price. In case you sell to the same buyer later for a different price, it is counted as another sale. Please ask these questions for each plot.

Sale ID	MS2. Maize revenue			To whom did you sell? 1. Farmer; 2. local trader 3. Institution/company 4. Other, specify	Where did you sell the produce? 1-Farm gate 2-Local village 3-Neighboring town/village 4-big town market 5. Other, specify	When did you sell? [month, aggregate several sales to one buyer within one month]	What is the distance to the nearest market? 1=walking distance 2=KM; 3=Miles; 4=Others specify
	Quantity sold (refer to Section G, MH3)	Unit	Price per unit (GHS)				
	MS2a	MS2b	MS2c	MS3	MS4	MS5	MS6
1							
2							
3							
4							
5							

SECTION I. Other crop production

OC1. Do you cultivate other crops apart from maize? 1=Yes 2=No

If yes, please complete the table below.

The following questions refer to other crops which the household cultivated during the 2018 farming season on all plots that the household owns or has access to. This also includes crops that are intercropped with maize on the respondent's plots. Please only record crops (from the 2018 harvest) that are sold and not only grown for home consumption.

Pl ot ID	Crop type			What is the area (in the specified unit) planted to these crops?			What is the main purpose of cultivating this crop?			Total yield (please specify the unit) See code below			How much was sold? (kg)			Price per unit (kg) (GHS)			What is the total cost of planting seeds (GHS)			What is the total expenditure for agrochemical inputs (fertilizer, Insecticides)?			Please state other expenditures if any		
				Unit 1. Acres 2. Plot 3. Pole			1. Home Consumption 2. For the market																				
	O C2	OC 3	O C 4	O C5	O C6	O C7	O C8	O C9	OC 10	OC 11	OC 12	OC 13	OC 14	OC 15	OC 16	OC 17	OC 18	OC 19	OC 20	OC 21	OC 22	OC 23	OC 24	OC 25	OC 26	OC 27	OC 28
1	a	b	c	a	b	c	a	b	c	a	b	c	a		b	c		a	b	c	a	b	c	a	b	c	
2																											
3																											
4																											
5																											

Code OC2-OC4

1. Cashew
2. Cotton
3. Groundnut
4. Sorghum
- 5: Mango
6. Millet
7. Rice
8. Soybeans
9. Yam
10. Other, specify

Code OC11-13

1. Bowl
2. Hundred
3. Kg
4. Maxi bag
5. Metric ton
6. Mini bag
7. Pound
8. Other, specify

SECTION J: Migration

M1. Were you born in this village/community? 1. Yes; 2. No	
M2. If not, when did you move to this village/community? (year)	
M3. Place of birth 1=Outside this village, same district; 4=Outside Ghana 2=Outside this district, same region; 3=Other region in Ghana	
M4. Why did you move to this village/community instead of somewhere else? [PLEASE LIST ORDER OF IMPORTANCE] 1 High production and productivity of agriculture 2. Availability of fertile lands /high soil fertility 3. High level of income 4. Employment, seasonal employment 5. Small sized land holdings 6. Good educational facilities 7. Adequate health-care services 8. Lack of infrastructural facilities 9. Evil social customs and practices 10. Others.	
M5. Have you ever lived outside this area [DISTRICT/TOWN/CITY] in the last 3 years? 1. Yes; 2. No	
M6. If yes, where did you go? 1=Outside this village, same district 4=Burkina Faso 7=Nigeria 2=Outside this district, the same region 5=Côte d'Ivoire 8=Togo 3=Other region in Ghana 6=Mali 9=Other, specify	
M7. If yes, for how long?	
M8. Has any household member ever lived outside this area [DISTRICT/TOWN/CITY] in the last 3 years? 1=Yes; 2=No	
M9. If yes, how many?	
M10. How long did they stay?	
M11. What were the reasons for migrating? [PLEASE LIST ORDER OF IMPORTANCE] 1 Low production and productivity of agriculture 2. Scarcity of fertile lands /low soil fertility 3. Low level of income 4. Unemployment, under-employment, seasonal unemployment 5. Small sized land holdings 6. Act of proper educational facilities 7. Lack of health-care services 8. Lack of infrastructural facilities 9. Evil social customs and practices 10. Others.	
M12. Do you are any member of your household plan migrating to any other town/city? 1=Yes; 2=No	
M13. If yes, how long?	
M14. If yes, what is the reason for the planned migration? 1=Access to fertile land; 2=off farm labor; 3=education; 4=others specify.....	

SECTION K: Household Assets

Asset		A1. Number of items solely by owned HH	A2. Total value (GHC) (current value)	In the past 12 months		Asset		A1. Number of items solely owned by HH	A2. Total value (GHC) (current value)	In the past 12 months	
				A3a. Number of items purchased	A3b. Number of items sold					A3a. Number of items purchased	A3b. Number of items sold
Farm implement						Other Items					
Tractor	1					Bicycle	14				
Plough	2					Radio	15				
Carts	3					Iron	16				
Wheelbarrows	4					TV	17				
Harrow	5					Mobile Phone	18				
Motorized spraying machine	6					Satellite dish/ Multi TV/DSTV	19				
Knapsack sprayer	7					Chair/Sofa	20				
Water tanks	8					Table	21				
Beehives	9					Bed/ mattresses	22				
Trailers	10					Refrigerator	23				
Grinders	11					Motorbike	24				
Hand hoe	12					Vehicle	25				
Husking machine	13					Tricycle	26				
Other agricultural equipment, specify	50										

A4: Is this house your own? **1= yes 2=no**

A5: How old is this house ?.....years old

A6: What is the worth of your house now?.....GHC

(approximation). **A7:** Roof material (multiple responses applicable).

1=grass thatched; 2= iron sheet; 3=roofing tile; 4=wood; 5=cement/concrete;

6=other

A8: Wall material?.....1=mud;

2=bricks/stones; 3=wood; 4=iron sheet;

5=other.....

A9: Floor Material?.....1=cement; 2=earth;

3=other.....

SECTION L: Livestock

Livestock Type	Livestock Code	Oct 2017			Sept 2018			Change in Number in the last 12 months		
		Number Owned by HH members		Total value in GHC	Number Owned by HH members		Total value in GHC	Number Consumed at home	Number bought	Number sold
NAME	LI CODE	LI1a. Male	LI1b. Female	LI2	LI3a. Male	LI3b. Female	LI4	LI5	LI6	LI7
Cows	1									
Goats	2									
Sheep	3									
Chicken	4									
Pigs	5									
Donkeys	6									
Guinea Fowls	7									

Section M: Consumption and Expenditure on Major Items (Non-Durable Goods) in the Past 12 Months

Product Consumed	Total consumption including from own production/gift and purchase. Then, the respondent estimates its total value in the market.			Product Consumed	E1. Total expenditure (GHC)	
	C1a. Quantity	C1b.Unit (code)	C1c. Total Value (GHC)			
LAST ONE WEEK				LAST ONE MONTH		
Maize grain	1		kg	Salt	24	
Maize meal/flour	2		kg	Coffee/Tea: powder	25	
Millet/Sorghum	3		Kg	Drinks (including alcohol)	26	
Wheat flour	4		Kg	Tobacco/Cigarettes	27	
Rice	5		Kg	Electricity	28	
Cassava (Fresh form)	6		Kg	Cellular phone charge	29	
Cassava (Processed)	7		Kg	Firewood	30	
Sweet potatoes	8		Kg	Cow dung	31	
Irish potatoes	9		Kg	Charcoal	32	
Yam	10		Kg	Kerosene/Gas	33	
Beans	11		kg	Soap/washing products	34	
Bread	12		Loafs	Last 12 MONTHS		
LAST ONE MONTH				School fee, textbooks, etc	35	
Ground nuts	13		Kg	Medical care	36	
Green Peas	14		Kg	Transportation	37	
Chicken	15		Kg	Clothing/Shoes	38	
Meats (any)	16		Kg	Contributions		
Fish	17		Kg	Susu	39	
Eggs	18		Number	Remittances to relatives	40	
Milk	19		Tin	Mosques/Churches	41	
Vegetable	20		Kg	Credit repayments	42	
Fruit(specify).....	21		Number	Mutual support group (funeral)	43	
Sugar	22		Kg	Mutual support group (non-funeral)	44	
Cooking oil/Butter	23		liters	Other local organizations	45	

Unit Code for C1b	6=kgs	12=wheelbarrow
1=90 kg bag	7=grams	13=cart load
2=50 kg bag	8=litres	14=crate
3=25 kg bag	9=tones	
4=10 kg bag	10=numbers	15=head load
5=2 kg bag	11=bunch (banana)	16=other (specify)

SECTION N: FOOD SECURITY

FS0. Was the Household able to provide adequate food for its members during the year 2018? **0=No 1=Yes**

FS1. Which months of the year does the household have food in abundance (multiple choice) 1=Jan 2=Feb 3=Mar 4=Apr 5=May 6=Jun 7=Jul 8=Aug 9=Sept 10=Oct 11=Nov 12=Dec

FS2. Which months of the year does the household have just adequate food? (Multiple choice) 1=Jan 2=Feb 3=Mar 4=Apr 5=May 6=Jun 7=Jul 8=Aug 9=Sept 10=Oct 11=Nov 12=Dec

FS3. Which months of the year does the household barely have enough food (lean period) (multiple choice) 1=Jan 2=Feb 3=Mar 4=Apr 5=May 6=Jun 7=Jul 8=Aug 9=Sept 10=Oct 11=Nov 12=Dec

FS4: Did you or any household member go hungry within a whole day and night without eating anything because there was not enough food? 1=yes, 2=no

FS5: If yes, how often did it occur in 2018?

If No, how did you manage food distribution in the household?

	Abundance period	Period of average availability	Lean period
Number of meals per day (on average)			
If less than 3, give reasons			
Number of days per month you took only two meals per day because of lack of money/food			
Number of days per month you took only one meal per day because of lack of money/food			
Number of days without food in the period because of lack of money/food			
Number of months in which you did not have enough food to meet your family's needs (cut the size of your meals)?			

FS 6: Dishes eaten and ingredients for each dish by period

	Major food ingredient				
Abundance period	Food groups for HDDS		Code	No. days consumed within a week	Quantity (kg) per day
	Cereals, roots, and tubers	Fruits			
	Pulses and legumes	Meats, fish and seafood, and eggs			
	Vegetables	Dairy products			
		Oils and fats			
Period of average availability	Cereals, roots, and tubers	Fruits			
	Pulses and legumes	Meats, fish and seafood, and eggs			
	Vegetables	Dairy products			
		Oils and fats			
Lean period	Cereals, roots, and tubers	Fruits			
	Pulses and legumes	Meats, fish and seafood, and eggs			
	Vegetables	Dairy products			
		Oils and fats			

Code for food groups

1=rice, 2=maize, 3=millet, 4=sorghum, 5=cassava, 6=groundnut, 7=cowpea, 8=onion, 9=tomato, 10=sweet potato, 11= eggplant, 12=okra, 13=banana, 14=mango, 15=Pineapple, 16=orange, 17=cashew nut, 18=potatoes, 19=yam, 20=bambara beans, 21=beans, 22=leafy vegetables, 23=peanuts, 24=okra, 25=palm nut, 26=cowpea (leaves), 27=fish and seafood, 28=meat, poultry, guinea fowl, 29=snail, 30=egg, 31=oil/fats, 32=milk and milk products, 33=lettuce, 34=Other specify

SECTION O: Extension and Training

HH See code below	Did any member of HH receive any extension visits in the last two years? 1=yes 2=no	Extension service provider See code below	Frequency of visit See code below	How satisfied are you with the content of the information provided by the extension service?	Did any member receive training 1=yes 2=no	Provider of training See Code below	What kind of training?	Number of days of training in the last 2 seasons	How satisfied are you with the content of training provided by the extension service?
	EX1	EX2	EX3	EX4	EX5	EX6	EX7	EX8	EX9

Code for EX2/EX6: 1=agricultural extension agents, 2=extension worker from NGO, 3= private extension agents, 4=Farmer based organization, 5=other (specify)

Code for EX3: 1=weekly, 2=monthly, 3=once in 3 months, 4=once every 6 months, 5= Once a year, 5=others, specify.....

HH: 1. Household head 2. Spouse 3.Children (Male adults) 4.Children (Female adults);

Code for EX7: 1=Sustainable Agricultural Strategies, 2=Maize production; Farming as a business, 3= Records Keeping, 4=others, please specify.....

Code for

EX4/EX9: 1=very satisfied, 2=somewhat satisfied, 3=not satisfied, 4=totally unsatisfied

Section P. Participation in field demonstrations

FD1: Did any member of HH participated in field demonstration activities? 1=yes; 2=no

FD2: If yes, how often have you participated in the last 5 years?

FD3: What activities are carried out on the demonstration field? P1= Demonstrating SAS technologies (refer to SAS in Section D), P2= Meeting with extension agents, P3= Meeting with scientists, P4= Meeting with project staff, P5= Farmer to farmer learning, P6= Hands-on practical training, P7= other (specify)

FD4: Were you already adopting SAS before participating? 1=yes; 2=no

FD5: Are/is the demonstration field(s) located in your village? 1=yes; 2=no

FD6: If yes, how far is it from your homestead?.....

FD7: If FD1 is no, why haven't you participated in any field demonstration activity?.....

Section Q. Climate information access.

Q1. Do you receive timely weather/climate information? 1=yes; 2=no

Q2. If yes, from whom do you receive this information? 1. Radio. 2. TV. 3. SMS. Extension agent. 4. Neighbors. Social media. Weather stations.

SECTION R: Access to credit

AC1. Do you face credit constraints in your farm operations? 1=yes; 2=no

AC2: If yes, do you source credit to finance your farm operations?..... 1=yes; 2=no

AC3: If no, please state the reasons for not sourcing credit?

AC4: If yes, please indicate the name of the credit agency.....

AC5: What are your other sources of finance for your farm operations?.....

AC6: Did you source credit for your farm business in the 2018 farming season? ----- 1=yes; 2=no

AC7: If yes, what form was it 1=cash; 2= in-kind (3) Other (specify).....

AC8: Did you pay with interest?..... 1=yes; 2=no

AC9: What was the interest rate?..... (in percentage)

AC10: what was the average repayment periodmonths?

AC11: Are you aware of other farming credit sources in your locality? 1=yes; 2=no

AC12: If yes please name them.....

AC13: Have you sourced credit from them before?.....1=Yes; 2=No

AC14: If yes, do you still source credit from them and why?.....

AC15: Did you enjoy any input subsidies from the government in the 2018 farming season?

AC16: If yes to AC15, on which inputs,

AC17: If yes to AC15, how much per input?.....

AC18: If yes to AC15, what was the repayment plan?.....

Section S: Access to Insurance

AI1. Are you aware of agricultural insurance? 1=Yes 0= No

AI2. If yes, have you ever purchased insurance products to cover your maize farm? 1=Yes 0= No

AI3. If No to AI2, why have you not purchased insurance products? 1=Lack of funds, 2=No idea of how it works,

3=It doesn't pay, 4. Other, specify_____

If you have ever purchased an insurance product, please answer the following questions

AI4. What type of product did you purchase?..... 1=Area yield; 2=Multi-Peril; 3=Drought Index

AI5. Give reasons why you purchased this product(s)?.....

AI6. Which year did you purchase your first product? _____

AI7. If you purchased insurance product(s) in the previous farming season, did you repeat the purchase in the subsequent seasons? 1=Yes 0=No

AI8. If Yes to **AI7**, why did you repeat the purchase? 1=Had pay-out when I bought the insurance previously; 2=Had a good harvest; 3=Other_____

AI9. If No to **AI7**, why did you not repeat the purchase in the subsequent seasons? 1. Did not get a payout when I suffered a loss; 2. High premium rate; 3. Lack of money; 4. I didn't see the benefits of having insurance 5. Other_____

AI20. Which other crop did you purchase insurance to cover?.....1=Rice; 2=Sorghum; 3=Millet; 4=Others, specify.....

Section T: Social Networks

T1: Relationship and characteristics

Please I want to understand your relationship and interactions with farmers in this community/village.

Farmer s	HH ID	Do you know (X)?	Since when (year) have you known (X)?	What is the age of (X)? (in years)	What is the educationa l level of (X)? (in years)	In what way is (X) related to you? (<i>Relationshi p code</i>)	Are you in the same religious congregatio n with X?	Are you in the same associatio n with (X)? <i>See code below</i>	Have you ever spoke n to (X)? 1=Yes 2=No	If SN9 is yes, how often within a month on averag e do you speak to (X)?	Have you ever been to the hous e of (X)?	If SN9 is yes, how many times withi n a mont h do you visit the house of (X)?	If SN9 is yes, what is the distanc e betwee n the HH	Is (X)'s farm adjacen t to yours?	Have you ever passe d by the farm of (X)?	If yes to SN12 , how often withi n a mont h do you pass by (X)'s farm	Does X interact with village officials ?
	SN 1	SN2	SN3	SN4	SN5	SN6	SN7	SN8	SN9	SN10	SN1 1	SN12	SN13	SN14	SN15	SN16	
Farmers from same /community/village																	
1																	
2																	
3																	
4																	

Relationship Codes 1=Parent; 2=Child; 3=Brother/sister; 4=Grandparent; 5=Grandchild; 6=Nephew/Niece; 7=Uncle/aunt; 8=Cousin; 9=Same family lineage; 10=Mother/father in-law; 11=Brother/sister in-law; 12=Other relative; 13=Fellow villager/Neighbour; 14=Attend same church/ mosque; 15=Professional/business colleague; 16=Other, specify..... **Codes SN8:** 0=No; 1=FBO; 2=Self-help group; 3=Merry go round; 4=Savings and Credit; 5=Other (Specify)..... **Codes SN17** 1= No, 1=chief, 2=assemblymen/women, 3=village/committee chairman, 4=others specify.....

T2: Information sharing and adoption process

Farmers	HH ID Do you discuss/ Share SASs issues with X?	Does (X) inform you of upcoming extension meetings	Who first told you about sustainable agricultural strategies? (refer to section D for examples of SASs)?	Who convinced you to adopt any of the sustainable agricultural strategies?	When did X adopt the SASs? (years)	Do you exchange more than farming information with X? 1=Yes, 2=No	If yes to SN6, which other information do you share?	How many blood relatives do you have in the community	Do you belong to a royal family	Are/were your parents leaders?
	SN1	SN2	SN3	SN4	SN5	SN6	SN7	SN8	SN9	SN10
Farmers from the same village										
1										
2										
3										
4										

Code SN5: 1=Not yet, 2=Before me, 3=At the same time as me, 4=After me **Code SN7:** 1=credit, 2=labour, 3=marketing, 4=access to inputs, 5=insurance, 6=others
specify.....

U. Shocks and coping mechanisms

Please list all shocks that hit the household during the past 2 years (2017 and 2018).

	U.0 Shock	U.1. Did the HH experience any of the following shocks in the last 2 years? 1=yes; 2=no	U.2. If S1 is yes, How many times did it occur in the last 2 years?	U.3 If S1 is yes, which year did it occur? (month/year)	U.4 How much time did it take to economically recover from the shock? 1. < 1 month 2. 1-3 months 3. 4-6 months 4. 7 months-1 year 5. > 1 year 6. Not yet recovered	U.5 What is the likelihood that these shocks will happen again (1-2 years)? 1. Very likely 2. A bit likely 3. Fifty/fifty 4. Not so likely 5. Completely unlikely 6. I don't know
1	Flooding					
2	Long dry spells					
3	Erratic rainfall pattern					
4	Windstorm					
5	Pest and disease					
6	Livestock disease					
7	Bushfire					
8	Increase in prices of farm inputs					
9	Very low market/farm gate price for produce					
10	High unemployment					
11	Sickness of household member					
12	Death of household member					
13	Very low yields					
14	Crop failure					
15	Others, specify					

U.6 How did your HH deal with the shocks?

Please list (4) in order of importance

- | | | |
|--------------------------------|---------------------------------------|--|
| 1. Prayed to God | 7. Took children out of school | 12. Purchased insurance product |
| 2. Hardworking | 8. Sent children to relatives/friends | 13. Borrowed money from family/ friends/ neighbors |
| 3. Diversification | 9. Adult household member migrated | 14. Borrowed money from informal financial institution (pawnshop, moneylender, susu collectors, traders) |
| 4. crop diversification | 10. Sold assets | 15. Borrowed from formal financial institution (bank, microfinance) |
| 5. Inputs substitution | 11. Used savings | 16. Government/NGO support |
| 6. Reduction in HH expenditure | | 17. Support from social networks |
| 7. Use of weather information | | 18. Other, specify |

S.7. What measures have you (HH) put in place to reduce or prevent these shocks if they reoccur? Please list 4 in order of importance

- | | |
|--------------------------------|--|
| 1. Prayed to God | 9. Hold savings at formal institution (bank, microfinance) |
| 2. Hardworking | 10. Hold savings at informal institution (Susu, etc.) |
| 3. Diversification | 11. Participate in network activities |
| 4. crop diversification | 12. Purchase insurance |
| 5. Inputs substitution | 13. Other, specify |
| 6. Reduction in HH expenditure | |

Appendix 2: Curriculum Vitae

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Persönliche Daten

Name, Vorname:	Adam Baba
Geburtsdatum/-Ort:	23.09.1985 / Accra, Ghana
Berufserfahrung	
10/2018 – heute	<p>PhD Fellow : Institut für Ernährungswirtschaft und Verbrauchslehre, Christian-Albrechts-Universität zu Kiel, Kiel</p> <ul style="list-style-type: none"> • Datenerhebung und -auswertung • Erstellung von wissenschaftlichen Publikationen und Präsentationen auf Fachtagungen
01/2016- 07/2018	<p>Berater: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) (Integriertes Klimarisikomanagement-Wetterversicherungen)</p> <ul style="list-style-type: none"> • Verwaltung des Bereichs "Agricultural Climate Risk Management" (Präventions- und Anpassungsmaßnahmen) sowie landwirtschaftliche Versicherungen • Beratung des Ministeriums für Ernährung und Landwirtschaft in allen entwicklungspolitischen Fragen rund um das Thema Klimawandel im Kontext landwirtschaftlicher Produktion. • Entwicklung von Überwachungs- und Evaluierungswerkzeugen für das Projekt
01/2018 – 07/2018	<p>Berater: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) (Integrated Climate Risk Management (ICRM) Project, Ghana)</p> <ul style="list-style-type: none"> • Durchführungsverantwortung für eine NDCP (Nationally determined contribution) -Ländermaßnahme"Entwicklung von Überwachungs- und Evaluierungswerkzeugen für das Projekt
05/2015 – 12/2017	<p>Fachberater: Centrum für Evaluation (CEval GmbH) und German Institute for Global and Area Studies (GIGA)</p> <ul style="list-style-type: none"> • Überprüfung der Datenerhebungsinstrumente • Unterstützende Datenerhebung • Logistische, koordinative und organisatorische Tätigkeiten
05/2014 – 12/2014	<p>Wissenschaftlicher Mitarbeiter: Universität Hohenheim, Stuttgart, Germany (Institute of Production Theory and Resource Economics)</p> <ul style="list-style-type: none"> • Bearbeitung der Vorlesungsunterlagen
02/2014 – 03/2015	<p>Fachberater: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) Market-Oriented Agricultural Programme in Ghana (MOAP)</p> <ul style="list-style-type: none"> • Profitabilitätsanalyse von Agrar Service-Banden • Datenerhebung und -auswertung
12/2010 – 12/2013	<p>Berater: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) Market-Oriented Agricultural Programme in Ghana (MOAP)</p> <ul style="list-style-type: none"> • Organisation von GAPs (Good Agricultural Practices), Farming as Business, Records Keeping und Organisationsentwicklungsschulungen für Bauen • Beratung und Austausch von Berichten mit dem Ministerium für Ernährung und Landwirtschaft und den mitwirkenden Bauernverbänden

06/2009 – 11/2010	<ul style="list-style-type: none"> • Verantwortlich für alle Projektaktivitäten zur Entwicklung der Wertschöpfungsketten <p>Praktikant (National Service): Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) Market-Oriented Agricultural Programme in Ghana (MOAP)</p> <ul style="list-style-type: none"> • Datenerhebung auf Haushalts- und institutioneller Ebene und –auswertung • Förderung von Wertschöpfungsketten
06/2009 – 10/2009	<p>Praktikant: Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) Market-Oriented Agricultural Programme in Ghana (MOAP)</p> <ul style="list-style-type: none"> • Datenerhebung auf Haushalts- und institutioneller Ebene und –auswertung
12/2008 – 02/2009	
06/2008 – 08/2008	
06/2007 – 07/2007	

Studium

10/2018 – heute	<p>PhD Agrarwissenschaften, Institut für Ernährungswirtschaft und Verbrauchslehre, Christian-Albrechts-Universität zu Kiel</p> <p>Thema der Doktorarbeit</p> <p>Contribution of Conservation Agriculture to Household Welfare in Ghana</p>
10/2013 – 03/2016	<p>M.Sc. Agricultural Economics, Universität Hohenheim</p> <p>Thema der Masterarbeit</p> <p>Cost-Benefit Analysis of Climate Change Adaptation Measures in Ghana</p>
08/2005 – 05/2009	<p>Bachelor of Science (Hons) Agriculture, University of Cape Coast, Ghana</p> <p>Thema der Bachelorarbeit</p> <p>Analysis of Farmer-Based Organizations in Central Region, Ghana</p>

Weiterbildung

07/2016	<p>Klima- / Katastrophenrisikomanagement</p> <p>Seminar für Ländliche Entwicklung (SLE)</p> <p>Humboldt-Universität Zu Berlin</p>
07/2016	<p>Gender-sensibles Projektmanagement</p> <p>Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ)</p> <p>Ghana</p>

Publikationen

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Sprachkenntnisse

Sprache:	
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