The Institute for Food Economics and Consumption Studies

of the Christian-Albrechts-Universität Kiel

Coordination and Impact of Agrifood Value Chains on Farm Performance: Evidence from Smallholder Rice Farmers in Northern Ghana

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutrition Sciences

of the

Christian-Albrechts-Universität Kiel

Submitted

M.Sc. Awal Abdul-Rahaman

born in Ghana

Kiel, 2019

The Institute of Food Economics and Consumption Studies

of the Christian-Albrechts-Universität Kiel

Coordination and Impact of Agrifood Value Chains on Farm Performance: Evidence from Smallholder Rice Farmers in Northern Ghana

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutrition Sciences

of the

Christian-Albrechts-Universität Kiel

Submitted

M.Sc. Awal Abdul-Rahaman

born in Ghana

Kiel, 2019

Dean:	Prof. Dr. Dr. Christian Henning
1. Examiner:	Prof. Dr. Awudu Abdulai
2. Examiner:	Prof. Dr. Martin Schellhorn

Day of Oral Examination: 23rd January, 2019.

Gedruckt mit der Genehmigung der Agrar- und Ernährungswissenschaftlichen

Fakultät der Christian-Albrechts-Universität zu Kiel

Diese Arbeit kann als pdf-Dokument unter http://eldiss.uni-kiel.de/ aus dem Internet geladen werden.

Dedication

I dedicate this Thesis to my family for their support and prayers throughout the study

Acknowledgement

First of all, I give thanks to Almighty Allah, the great Architect of the universe, for granting me good health, strength, and wisdom to successfully go through this programme. I extend sincere thanks and appreciation to my supervisor Prof. Dr. Awudu Abdulai for his valuable support and mentorship towards the production of this thesis. I will never forget his fatherly advice and encouragement throughout this journey. My special thanks also go to the Deutscher Akademischer Austauschdienst (DAAD) and the government of Ghana for the financial support granted me throughout the study period. I also thank all my family members for the encouragement, dedicated prayers and support towards the realization of this dream. Not forgetting the enumerators who assisted me during the field data collection. May Allah richly bless you for the dedicated and quality work executed. I also express my profound gratitude to all my colleagues at the Department of Food Economics and Consumption Studies: Dr. Sascha Stark, Gazali Issahaku, Yazeed Abdul-Mumin, Sadick Mohammed, Caroline Dubert, Johanna Scholz, Muhammad Faisal Shahzad, Williams Ali, Jiajia Zhao, Asrezu Yitayew, Christoph Richartz and Baba Adam for the valuable contributions and support during the departmental seminars. Same goes to the Secretary, Anett Wolf, and all the Hiwis for their assistance throughout the study period.

Kiel, January, 2019 Awal Abdul-Rahaman

Table of Contents

List of Tables

List of Figures

Abstract

Agrifood value chains in developing countries including Africa have been undergoing rapid transformation driven by continued population growth, rising urbanization, increasing incomes, shifts in consumer dietary requirements and demand for quality food. Although this transformation presents considerable opportunities for smallholder farmers, their integration into these value chains still remains a major challenge due to myriad constraints including, but not limited to, high transaction costs associated with inputs and output markets, inadequate access to inputs, finance, and services such as extension and transportation. However, horizontal and vertical coordination have been recognized as effective mechanisms for smallholder farmers' participation in these chains. They serve as avenues for increasing bargaining power, sharing risk, reducing transaction costs, and ensuring economies of scale, as well as smallholder access to services such as inputs and technologies, extension, credit, and output markets. This study therefore contributes to the growing literature on agrifood value chains by exploring the role of these mechanisms on the production and market performance among smallholder farmers in northern Ghana. In particular, the study first examines the impact of vertical coordination mechanisms-written contracts, verbal contracts and spot market transactions – on farm performance outcomes such as net farm income, total farm income, total household income, labor productivity and price margins, using multinomial BFG model to account for selectivity bias. Second, the study employs an endogenous switching regression model to examine the impact of farmer groups and collective marketing on farm net revenues of smallholder rice farmers. It also examines the relationship between farmer group and collective marketing participation decisions. Third, propensity score matching and sample selection stochastic production frontier approaches are employed to examine the impact of farmer groups on farm yields and technical efficiency of smallholder farmers. Finally, the study also explores the role of inclusive value chains and social networks on smallholder market performance outcomes: prices received, quantity of paddy sold and net returns, using a treatment effects model to account for selection bias stemming from observed and unobserved factors. The empirical results reveal that participation in vertical coordination mechanisms is associated with increased farm performance outcomes relative to spot market transactions, with the highest gains stemming from written contract participation. Moreover, access to credit, association membership and labor significantly influence vertical coordination participation decisions. Furthermore, farmers who are members of farmer groups and participated in collective marketing obtained higher output prices, and also incurred lower input costs. The empirical results also show that farmer group and collective market participation decisions are significantly influenced by mobile phone ownership, access to credit, distance to markets and road status. Also, farmers who participated in farmer groups and collective marketing earned significantly higher farm net revenues than non-participants. The study further reveals that farmer groups play significant role in improving farm yields and technical efficiency, relative to farmers who produce and market paddy individually. The positive impacts of inclusive value chains and social networks on smallholder market performance have also been revealed by this study. Inclusive value chain participating farmers received significantly higher paddy prices, traded higher quantities of paddy and earned higher net returns, compared to non-participants. Similarly, farmers who are members of horizontal social networks benefit from improved market performance. The estimates further reveal that inclusive value chain participation decisions and market performance outcomes are significantly influenced by social networks, distance to markets, mobile phone ownership and access to credit. These findings call for development policy measures to promote contractual engagement in smallholder output transactions, formation and development of farmer groups and encouraging collective marketing, as well as strengthen social networks for improved value chain competiveness and efficiency.

Zusammenfassung

Die Wertschöpfungsketten für Agrarerzeugnisse in Entwicklungsländern, einschließlich Afrika, befinden sich in einem rasanten Wandel, der durch anhaltendes Bevölkerungswachstum, steigende Urbanisierung, steigende Einkommen, veränderte Ernährungsgewohnheiten der Verbraucher und die Nachfrage nach hochwertigen Lebensmitteln angetrieben wird. Obwohl diese Veränderungen für Kleinbauern erhebliche Chancen bieten, bleibt ihre Integration in die Wertschöpfungsketten eine große Herausforderung. Die Begründung hierzu liegt in den zahlreichen Restriktionen, wie den hohen Transaktionskosten im Zusammenhang mit Input- und Outputmärkten, unzureichenden Zugangsmöglichkeiten, Finanzen und Dienstleistungen sowie Expansion und Transport. Horizontale und vertikale Koordinierungsmaßnahmen werden jedoch als wirksame Mechanismen für die Beteiligung der Kleinbauern an den Wertschöpfungsketten angesehen. Sie dienen als Mittel zur Stärkung der Verhandlungsmacht, zur Risikoteilung, zur Senkung der Transaktionskosten und zur Sicherstellung von Größenvorteilen. Außerdem dienen sie der Sicherstellung des Zugangs der Kleinbauern zu Produktionsmitteln, Technologien sowieso zu Expansions-, Kredit- und Absatzmärkten. Diese Studie trägt daher der stets wachsenden Literatur über landwirtschaftliche Wertschöpfungsketten bei, indem sie die Rolle dieser Mechanismen für die Produktion und Marktleistung von Kleinbauern im Norden Ghanas untersucht. Insbesondere untersucht die Studie zunächst die Auswirkungen vertikaler Koordinierungsmechanismen - schriftliche Verträge, mündliche Verträge und Spotmarkttransaktionen - auf die landwirtschaftlichen Leistungsergebnisse wie landwirtschaftliches Nettoeinkommen, landwirtschaftliches Gesamteinkommen, Haushaltseinkommen, Arbeitsproduktivität und Preisspannen. Hierbei wird das multinomiale BFG-Modell zur Berücksichtigung der Selektivitätsverzerrung verwendet. Als zweites verwendet die Studie ein endogenes Switching-Regressionsmodell, um die Auswirkungen von Bauernvereinigungen und Kollektivvermarktung auf die landwirtschaftlichen Nettoeinnahmen

von Reisbauern zu untersuchen. Darüber hinaus wird der Zusammenhang zwischen den Bauernvereinigungen und den Entscheidungen über die gemeinsame Marketingbeteiligung untersucht. Drittens werden das Propensity Score Matching und Ansätze der Stochastischen Production-Frontier Analysis unter Berücksichtigung der Sample Selection-Problematik verwendet, um die Auswirkungen von Bauerngruppen auf die landwirtschaftlichen Erträge und die technische Effizienz von Kleinbauern zu untersuchen. Schließlich untersucht die Studie auch die Rolle integrativer Wertschöpfungsketten und sozialer Netzwerke für die Performance-Ergebnisse der Kleinbauern: Erhaltene Preise, Menge des verkauften Rohreises und Nettoerträge. Hierbei wird ein Behandlungseffektmodell verwendet, um Auswahlverzerrungen zu berücksichtigen, die sich aus beobachteten und unbeobachteten Faktoren ergeben. Die empirischen Ergebnisse zeigen, dass die Teilnahme an vertikalen Koordinierungsmechanismen mit einer Steigerung der landwirtschaftlichen Leistung bezüglich Spotmarkttransaktionen verbunden ist, wobei die höchsten Gewinne aus der schriftlichen Vertragsbeteiligung resultieren. Darüber hinaus beeinflussen der Zugang zu Krediten, die Mitgliedschaft in Verbänden und die Arbeitskraft maßgeblich die Entscheidungen über die Teilnahme an der vertikalen Koordination. Zudem erhielten Landwirte, die Mitglied in Bauernvereinigungen waren und an der gemeinsamen Vermarktung teilnahmen, höhere Produktionspreise und auch niedrigere Inputkosten. Die empirischen Ergebnisse zeigen auch, dass die Entscheidungen der Bauerngruppen und der kollektiven Marktbeteiligung maßgeblich von Mobiltelefonbesitz, Zugang zu Krediten, Entfernung zu Märkten und Straßenzustand beeinflusst werden. Außerdem erzielten Landwirte, die an Bauernvereinigungen und Kollektivvermarktungen teilnahmen, deutlich höhere Nettoeinnahmen als Nichtteilnehmer. Die Studie zeigt ferner, dass die Bauernvereinigungen eine wichtige Rolle bei der Verbesserung der landwirtschaftlichen Erträge und der technischen Effizienz im Vergleich zu Landwirten spielen, die ihren Reis einzeln produzieren und vermarkten. Die positiven Auswirkungen von integrativen Wertschöpfungsketten und sozialen Netzwerken auf die Marktperformance von Kleinbauern wurden in dieser Studie ebenfalls aufgezeigt. Landwirte, die an der Wertschöpfungskette teilnahmen, erhielten im Vergleich zu Nichtteilnehmern deutlich höhere Rohreispreise, verkauften höhere Rohreismengen und erzielten höhere Nettoerträge. Ebenso profitieren Mitglieder dieser horizontalen sozialen Netzwerke von einer verbesserten Marktleistung. Die Analysen zeigen ferner, dass integrative Entscheidungen über die Beteiligung an der Wertschöpfungskette und die Ergebnisse der Marktleistung maßgeblich von sozialen Netzwerken, der Entfernung zu den Märkten, dem Besitz von Mobiltelefonen und dem Zugang zu Krediten beeinflusst werden. Diese Ergebnisse erfordern entwicklungspolitische Maßnahmen zur Förderung des vertraglichen Engagements bei Kleinbauern, der Bildung und Entwicklung von Bauerngruppen und der Förderung des kollektiven Marketings sowie zur Stärkung sozialer Netzwerke zur Verbesserung der Wettbewerbsfähigkeit und Effizienz der Wertschöpfungskette.

Chapter 1

General Introduction

1.1 Agrifood value chain systems in Africa

Agriculture plays important role in reducing poverty and ensuring economic growth in developing countries including Africa. The sector employs over half of the continent's population, and contributes more than 32% of the continent's gross domestic product (Veras, 2017). However, African agriculture is still characterized by low productivity, over reliance on rainfall, with limited irrigation facilities, as well as basic infrastructural problems such as access to markets and financing (Babu and Shishodia, 2018). In view of these challenges, African governments have increasingly made strides towards advancing the agricultural transformation agenda, leading to significant progress in agricultural productivity growth in the first decade of the 21st century (Barrett et al., 2017). This productivity growth is partly attributed to the lunch of the Comprehensive Africa Agriculture Development Programme (CAADP) in 2003 at Maputo, Mozambique, where most African heads of states registered their commitments to promoting and improving the agricultural sector by pledging to invest a minimum of 10% of budgetary allocation to the agricultural sector (Benin, 2016; Barrett et al., 2017).

The CAADP initiative was aimed at increasing investment in agriculture for economic growth through promoting uptake of improved agricultural technologies for increased productivity, improving smallholder market access, combating inequality and promoting regional integration (Benin, 2016). Similarly, the G-8 meeting held in 2009 in Italy got participating nations renew their funding commitments to the CAADP (AU-NEPAD 2014; Yumkela et al. 2011). For Africa to fully achieve the impact of this initiative, requires transformation of the entire agrifood sector in terms of structural change in farming, agro-industry and marketing. Structural transformation through reallocation of economic resources from low productive activities to more productive ones stands the chance of providing the needed agricultural-led economic growth expected in Africa. A rapid response could involve increasing the productivity of activities at each stage of the different agrifood value chains, as well as work towards effective coordination of the various links within the agrifood chains.

In the past two to three decades, agrifood value chain transformation has been typically recognized as crucial for accelerating poverty reduction, improving food and nutrition security, as well as ensuring overall economic growth (Vandercasteelen et al., 2018; Bachewe et al., 2018; Ecker, 2018). A considerable body of literature has identified factors such as rising incomes, rapid population growth, increasing urbanization, and changing consumer dietary preferences among others, as the main drivers of the agrifood value chain transformation (Swinnen and Miet Maertens, 2007; Reardon et al., 2009; Ouma et al., 2013). Undoubtedly, all these transformational drivers have contributed to a growing demand for food and agricultural products, and thus present greater opportunities for smallholder farmers' integration into such diversity of agrifood value chains in Africa. However, smallholder farmers in Africa and other developing countries are unable to take advantage of the agrifood value chain transformation due to vicissitudes of challenges including, but not limited to, high transaction costs in both input and output markets, and inadequate access to services such as productivity-enhancing innovations, credit, extension services, and transportation (Kilelu et al., 2017), resulting in low crop yields, minimal use of modern inputs, and increased post-harvest losses (Rapsomanikis, 2015).

In the last one and half decades, some studies have suggested that an agriculture-led approach to development with strong focus on productivity growth in the entire agrifood value chains, offers the best opportunity for rapid and inclusive economic growth in Africa (Partnership to Cut Hunger and Poverty in Africa 2002; World Bank 2007; Staatz and Dembélé, 2008). Agrifood value chain development approach has been recognized by African governments, donor agencies, NGOs, and the private agribusiness companies as a promising tool for addressing smallholder production and marketing challenges, and facilitating their inclusion in these chains for improved welfare (Ton et al., 2011). The value chain approach is regarded as an integrated approach in the production setup with harmonized collaboration by various actors along the chain from input supply through production, processing to marketing (Humphrey and Schmitz, 2002). It focuses on coordinating the various chain activities for enhanced efficiency and competitiveness.

The literature has broadly categorized coordination in agrifood value chain into horizontal and vertical coordination (Bijman et al., 2006). Horizontal coordination occurs among value chain actors who are into the same line of agribusiness activity (e.g., farmer groups or cooperatives), with the objective of fostering collective action to address shared constraints associated with value chain participation (Kilelu et al., 2017). Vertical coordination on the other hand occurs between actors at different levels of the value chain (e.g., the link between farmers and traders or processors) for effective alignment of activities between these actors (Bijman et al, 2011). It is regarded as institutional and value chain innovation, which can take various forms ranging from spot market transactions (0% coordination) to full ownership integration (100% coordination), within which are various coordination forms such as contracting, outgrower schemes, and partnerships (Swinnen and Maertens, 2007; Barrett et al., 2012). The most common and widespread vertical coordination mechanism in Africa is contracting (written or verbal), wherein smallholder farmer(s) or farmer groups enter into agreement with buyers for the production and supply of an agricultural commodity under forward agreements, mostly at predetermined prices (Bijman, 2008; Bellemare, 2018).

As argued by Bijman et al. (2011) and Poulton et al. (2010), effective and efficient coordination of the horizontal and vertical relationships among agrifood value chain actors- smallholder farmers, inputs and service providers, buyers and processors among others- as well as facilitating goodwill, trust and cooperation amongst them will be particularly important for improved governance and chain efficiency. Both types of coordination stand to overcome the above-noted challenges facing smallholder farmers. For instance, horizontal coordination through formation of farmer groups, cooperatives or similar forms of farmer collective action serves as avenue for increasing bargaining power, sharing risk, reducing transaction costs, and ensuring economies of scale, as well as consolidating their vertical relationships with buyers for improved efficiency and efficacy of the agrifood value chains (Bijman, et al., 2006; Reuben et al., 2006). Vertical coordination through contracts is important in ensuring smallholder access to inputs and technologies, extension services, credit, and output markets. This study tries to comprehensively investigate the role of these coordination mechanisms within the context of agrifood value chains and their related implications on both farm and market performance in northern Ghana, using rice as a case following the renewed interests of government and other stakeholders in revamping the rice value chain for improved efficiency and welfare of smallholder farmers.

1.2 Problem setting and motivation

Multiple production and marketing challenges hindering linkages of smallholder farmers in developing countries to agrifood value chains that have, in recent times, undergone tremendous transformations require all-inclusive stakeholder intervention to improve smallholder welfare and ensure rural economic transformation (Reardon et al., 2009). Exacerbation of these challenges is driven by changes in the procurement systems of produce buyers such as traders, aggregators, and processors among others, which have not only created strict technical requirements but also compliance costs, making it difficult for such resource-constrained farmers to effectively participate in these formalized agrifood chains (Bijman et al., 2011). Moreover, changes in consumer dietary requirements resulting from several factors such as increasing incomes, urbanization, as well as other socio-demographic transformations have increased the demand for food and the need for smallholder farmers to follow strict food safety and quality standards, which jointly serve as drivers for smallholder exclusion in agrifood value chains in developing countries including Africa (Swinnen and Maertens, 2007). However, governments, donor agencies, and the private sector have collaboratively rolled out agrifood value chain development interventions in their quest to ameliorate the state of affairs in smallholder agriculture in developing countries. Under these interventions, smallholder farmers are linked to produce buyers in the value chains through horizontal and vertical coordination mechanisms. These mechanisms facilitate access to input and output price information, finance, uptake of productivity-enhancing technologies for improved productivity and farm output, as well as promoting market access and welfare.

A plethora of empirical evidence has highlighted smallholder farmers' welfare gains associated with both horizontal and vertical coordination in agrifood value chains in developing countries including Africa. For example, horizontal and vertical coordination tend to increase smallholder farmers' incomes (e.g., Bellemare, 2012; Schipmann & Qaim, 2010; Fischer and Qaim, 2012; Maertens and Vende Velde, 2017; Mojo et al., 2017), farm yields, profits, and efficiency (e.g., Ma and Abdulai, 2016; Abate et al., 2015; Rao and Qaim, 2012), technology adoption (e.g., Ainembabazi et al., 2017; Wossen et al., 2017), household asset holdings (e.g., Michelson, 2013; Mojo et al., 2017), and household food security (e.g., Bellemare & Novak, 2017). This study contributes to this growing literature by examining the role of farmer groups, collective marketing, and contracting in improving smallholder farm and market performance outcomes: farm net revenues, household income, prices received, price margins, labor productivity, farm yields and technical efficiency, using data from a recent survey of smallholder rice farmers from selected districts in northern Ghana: Tolon, Kumbungu, Sagnarigu districts, Savelugu Nanton Municipal and Tamale metropolis. The specific objectives of this study are presented in the next section. Findings from this study could inform development policy in respect of the design and implementation of agrifood value chain development interventions in the cereal staple sector for the benefit of smallholder farmers in Ghana.

1.3 Objectives of the study

The main objective of this study is to examine the role of coordination mechanisms in improving smallholder farm and market performance in the rice value chain in northern Ghana. The specific objectives of the study are:

1. To evaluate the impact of vertical coordination mechanisms on farm performance amongst smallholder farmers in the rice value chain in northern Ghana.
2. To examine the role of farmer groups and collective marketing in improving the livelihood of smallholder farmers in the rice value chain in northern Ghana.
3. To examine the impact of farmer groups on farm yield and technical efficiency of smallholder rice farmers in northern Ghana.
4. To assess the role of inclusive value chain participation and social networks on market performance among smallholder rice farmers in northern Ghana.

1.4 Review of Ghana's agriculture sector

Agriculture plays a major role in Ghana's sustainable long term economic growth and development. The sector accounts for about 20% of Ghana's gross domestic product and majority of the poorest households derive their livelihoods from agriculture and its linkage with agribusinesses, as it provides employment to about half of the working population (SRID-MoFA, 2016). Between 2008 and 2015, Ghana's annual growth rate averaged about 4.2%, which is below the targeted rate of 6%, and was projected by the statistical service to further slow down to about 3.3% in 2016 (Ibid, 2016). Agricultural production in Ghana is predominantly on smallholder basis with about 90% of landholdings being less than two hectares (MoFA, 2017).

In Ghana, Agriculture is categorized into four broad sub-sectors namely crops, livestock, fisheries, and forestry (MoFA, 2017). Crops sub-sector is the dominant one, accounting for about 75%, while the other sub-sectors constitute the remaining 25% (SRID-MoFA, 2016). The cash crops grown in Ghana include cocoa, palm oil, fruit, coconut, rubber, cashew, cotton, and horticulture, with the dominant sub-sector being cocoa. Available statistics indicate that Ghana is the second largest producer of cocoa in the world after Ivory Coast, accounting for about 20% of global exports (World Bank, 2017). The cocoa sub-sector, which is operated under a controlled marketing system by Ghana COCOBOD, accounts for about 7% of Ghana's GDP, 12% of total agricultural value added, as well as about 25% of export earnings (Ibid, 2017). The major staple crops produced include cassava, yam, plantain, maize, rice, soybeans, sorghum, cowpea, and millet. The livestock sub-sector is characterized by the production of poultry, sheep, goats, cattle and pigs. The poultry sector constitutes the largest source of animal protein, and currently experience the highest growth in the livestock sector. Statistics indicate that about 80% of the broiler meet are supplied by smallholder farmers. In the fisheries sub-sector, Ghana has the natural conditions for fisheries (marine and inland) development, and majority of the inland fish comes from the Volta Lake (MoFA, 2017).

Despite the important role of agriculture in the Ghanaian economy, the sector is still beset with several challenges including, but not limited to, inadequate extension services and low uptake of productivity enhancing technologies, limited access to inputs such as improved seed and fertilizer, lack of access to credit especially, among smallholder farmers, inadequate access to both domestic and international markets, limited storage and irrigation facilities, particularly in northern Ghana, and insecure land tenure system. These challenges result in low yields for both the staples and cash crops, and stagnated overall agricultural growth rates. Currently, the average yield of cocoa in Ghana stands at estimated 400-450kg/ha, which is among the lowest in the world (Ghana COCOBOD, 2015). The yields of cereal crops are estimated at 1.7 tonnes/ha compared to the average yield of 2.0 tonnes/ha and the 5.0 tonnes/ha potential yield (WDI, 2016). Similarly, Ghana has recorded about 43-66% yield gap for the staple commodities

(World Bank, 2017). Over the last decade, available statistics indicate that staple yield growth rate has lagged behind output growth (GSS, 2016). In particular, between 2005 and 2015, Ghana recorded about 4% annual output growth for cereals and 10% for roots and tubers, and an average yield growth of 1.7% for cereals and less than 5% for roots and tubers over the same period (World Bank, 2017). This suggests that in Ghana, output growth of staples is mainly driven by area expansion.

These low yields coupled with continued population growth, increasing consumer incomes, and high rates of urbanization have resulted in Ghana's inability to meet its food needs, and has become a net importer of both raw and processed foods such as rice, poultry, sugar, and vegetable oil among others. According to World Bank's (2015) global merchandize imports statistics, Ghana's food imports in 2015 accounted for about 17% of total merchandize imports, which is estimated at US$ 13.3 billion dollars, and have been projected to increase fourfold over the next 20 years. This has undoubtedly called for all-inclusive stakeholder policy initiatives to ameliorate the state of affairs and stimulate substantial increase in domestic agricultural production.

To this end, the Ghana government has over the years intensified efforts to spur agricultural transformation through increase in agricultural investment for improved productivity and growth rates of the sector. For instance, under the Ghana Shared Growth and Development Agenda (GSGDA: II-2014-2017), the government focused mainly on accelerated agriculture modernization as one of its economic development priorities. This effort is part of the ECOWAS action and its regulatory policy, and also well-articulated in the Medium-Term Agricultural Sector Investment Plan (METASIP) of Ghana's Ministry of Food and Agriculture. With World Bank support of US$ 64.5 million, the Ghana Commercial Agriculture Project (GCAP) has also been launched by government in its quest to further the agriculture commercialization agenda. The GCAP mainly aims at developing inclusive Public-Private

Partnerships (PPPs), increasing investment in infrastructure, securing access to productive land, and strengthening smallholder value chain linkages for increased on-farm productivity and value addition in selected agrifood value chains (MoFA, 2018). This initiative is complemented with other policies such as the Private Sector Development Strategy (PSDS II), which also has a major bearing on Ghana's agriculture sector outcomes through highlighting agricultural productivity and value chain development by supporting both private and public initiatives.

The government of Ghana through MoFA, has also recently launched a new flagship program known as the Planting for Food and Jobs (PFJ), which focuses on maize, rice, soybean, sorghum and vegetables value chains, aims to increase food production and achieve food self-sufficiency and job creation. The implementation of the five-year PFJ program is built on five pillars: provision of improved seeds, supply of fertilizers, provision of agricultural extension services, facilitation of market arrangements, post-harvest loss reduction, and monitoring and evaluation of program implementation through an electronic platform (MoFA, 2017). The program targets about 200,000 farmers across all the districts in Ghana, and intends to create over 750,000 jobs within the targeted agrifood value chains (Ibid, 2017). Other agricultural development initiatives include the USAID-funded Feed the Future (FtF) programs such as Agriculture Technology Transfer (ATT), Agricultural Development and Value Chain Enhancement (ADVANCE II), Resiliency in Northern Ghana (RING), Financing Ghanaian Agriculture Project (FinGAP) among others.

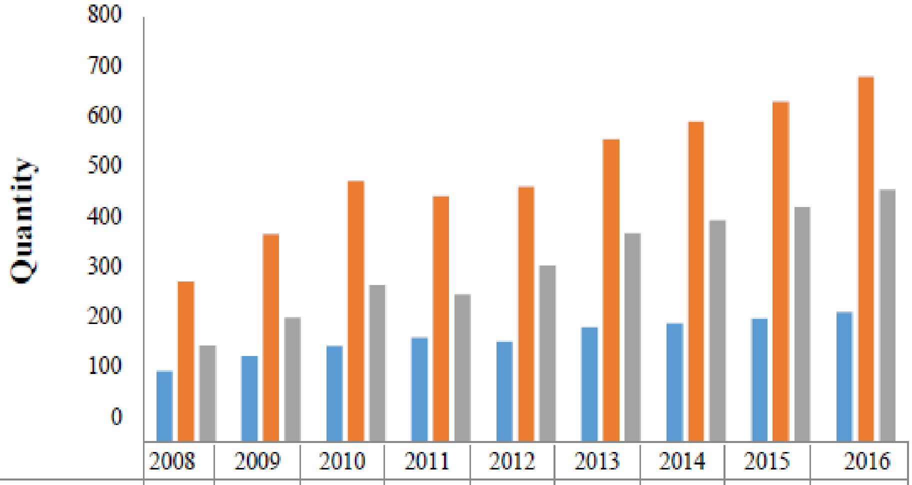
These agricultural development initiatives contribute to revamping the agriculture sector in Ghana through facilitating the provision of extension services and facilitating access to inputs, which could promote the uptake of productivity-enhancing innovations, as well as adoption of drought-tolerant and fast growing crop varieties. This leads to increased yields, output quality, and opportunities for value-addition (World Bank, 2017). The GCAP is utilizing outgrower scheme approach where nucleus farmers complement the efforts of agricultural extension agents in transferring improved technologies to smallholder farmers. Increased investment in irrigation facilities is also important in promoting long-term agricultural productivity growth in Ghana. However, irrigation development lags behind it full potential, and only 3% of public agriculture spending is channeled into irrigation investment (GIDA/IWMI, 2015). Currently, Ghana has a total of area of 206,868 hectares of land under irrigation, which represents about 2.6% of total land area under cultivation and about 41% of irrigable land (GIDA/IWMI, 2015). Investments in the rehabilitation of the irrigation facilities is ongoing under the GCAP in collaboration with Ghana Irrigation Development Authority (GIDA), which is to enable farmers to adapt their production to unpredictable climate (Choudhary *et al*., 2015).

Promoting smallholder market access is one of the policy priorities of Ghana government under the above mentioned development initiatives. Facilitating farmers' linkage to markets is crucial to agricultural development and rural poverty reduction. Smallholder farmers' integration into agricultural value chains can facilitate technology transfer for improved productivity, boosts income levels, stimulate agribusiness investments, as well as supports diversification (World Bank, 2017). Several opportunities still abound Ghana's agricultural sector for accelerated transformation. The rapidly thriving middle-class resulting from the country's lower to medium income status and the emerging oil economy implies a growing consumer consciousness on food safety standards, and demand for quality food. This presents an opportunity for farmers and other actors in the agrifood value chains to adopt production intensification strategies to meet this rapidly changing market requirements, and stimulate import substitution. Given that considerable percentage (35-40) of the youth form the Ghanaian population, government policies to promote youth employment especially in agribusiness value chains would be important to achieving inclusive and sustainable economic growth (SADA, 2016). In addition, continuous implementation of reforms such as strengthening research institutions for the generation of improved technologies, promoting transparent land tenure systems and governance, as well as improving the overall regulatory framework is a promising option for raising agricultural productivity and economic growth in Ghana.

1.5 Review of the rice sector in Ghana

Rice plays an important role in ensuring food and nutrition security among rural and urban households in Ghana. It trades behind maize as the second most important cereal staple in Ghana. Rice cultivation covers about 233,000 hectares, with an annual average production of 641,000 metric tonnes (SRID-MoFA, 2016). In Ghana, the primary rice producing areas are Volta, Ashanti, Eastern, Upper East, and Northern regions, although it is grown throughout all the regions in Ghana (GAIN, 2018). Rice cultivation is done under three ecosystems: rainfed lowland (78%), rainfed upland (6%), and irrigation system (16%) (MoFA, 2009). Commonly grown varieties include Agra rice, Jasmine 85, TOX 3109, Nerica 1, and Nerica 2 (Ragasa et al., 2013). Available statistics presented in figure 1.1 show that domestic rice production has increased steadily over the last decade compared to the area expansion cultivated to rice.

Fig. 1.1: Area cultivated versus domestic rice production in Ghana



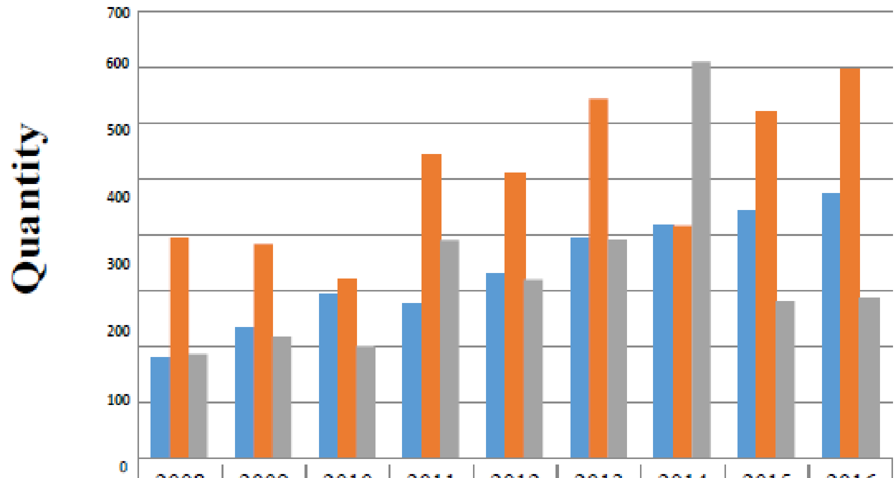
	2008	2009	2010	2011	2012	2013	2014	2015	2016
Area ('000Ha)	133	162	181	197	189	216	224	233	244
Domestic production paddy ('000 MT)	302	391	492	463	481	570	604	641	688
Domestic production milled ('000 MT)	181	235	295	278	332	393	417	442	475

Source: MoFA Statistics, 2017.

In the same vein, rice consumption continue to increase steadily, attributable to Ghana's growing population and entrepreneurial middle-class, increasing incomes, rising urbanization among other factors (MoFA, 2017). The total rice consumption in 2017/18 stands at an estimated 1.0 million metric tonnes, while the per capita consumption of 35kg in 2016/17 is expected to reach about 40kg by 2020 (GAIN, 2018). This increasing consumption is boosting domestic demand for rice in Ghana.

However, domestic rice production in Ghana falls short of the consumer demand, and the deficit (70%) is offset by imported rice making Ghana a net importer (MoFA, 2017). Ghana rice imports slightly declined from 580,000 metric tonnes in 2016/17 to 550,000 metric tonnes in 2017/18 (GAIN, 2018), suggesting that domestic rice production and quality is increasing, and meeting consumer demand. Rice importation to Ghana has also steadily increased over the years, and so does the value of the rice import bill (see figure 1.2). The inability of Ghana's domestic rice production to meet the growing domestic demand is attributable to several challenges confronting the sector. Rice production is dominated by smallholder farmers, cultivating an average of less than two hectares of farm size, and often faced with limited access to improved technologies, extension and advisory services, production inputs, finance, irrigation facilities, processing facilities, and output markets. These challenges result in low paddy yields, poor quality and uncompetitive rice compared to the imported ones. Most of the rice produced stems from low-quality seed often mixed with other varieties resulting in uneven maturity during harvest and differences in shapes and sizes of rice grains (FAO, 2013). However, the government and its development partners have over the years intensified efforts in developing the rice sub-sector through implementing agricultural interventions with the objective of increasing rice productivity and quality to match with the imported ones. Rice is one of the major food security crops well-articulated in Ghana's Medium Term Agriculture Sector Investment Plan (METASIP). The Ghana's Ministry of Food and Agriculture (MoFA) with support from Coalition for African Rice Development (CARD) developed the National Rice Development Strategy (NRDS) to boost the rice sub-sector.

Fig. 1.2: Total domestic rice production versus Imports



	2008	2009	2010	2011	2012	2013	2014	2015	2016
Domestic production milled ('000 MT)	181	235	295	278	332	393	417	442	475
Total imports ('000 MT)	395	384	320	543	509	644	417	620	698
Import value (US$ Million)	187	219	201	391	320	392	710	282	289

Source: MoFA statistics, 2017.

The CARD initiative is spearheaded by Japan International Cooperation Agency (JICA), New Partnership for Africa's Development (NEPAD), and Alliance for a Green Revolution in Africa (AGRA). The initiative aims at doubling rice production in Sub-Saharan Africa within a span of 10 years (2008-2018) through rationalizing and increasing investment in the rice sector, developing the existing rice-growing ecologies, building capacities for effective sector management, and coordinating rice development interventions through NRDS. The NRDS operates within several thematic areas, namely, quality seed system development, improved fertilizer marketing and distribution, Post-harvest and rice marketing management, irrigation and water control investment, access and maintenance of modern equipment, development of research and technology, formation and development of Farmer Based Organizations (FBOs), and credit management.

Some other rice sector interventions include the government flagship Planting for Food and Jobs program and Ghana commercial agriculture project (GCAP). The Planting for Food and Jobs program facilitates technology adoption by providing 50% subsidy on rice seed and fertilizer to increase application rates for increased productivity (MoFA, 2017). The government aims at reducing rice importation by 10% under the flagship program (MoFA, 2017). The GCAP is also promoting both rain-fed rice and irrigation cultivation especially in Northern Ghana through provision of matching investment grants, and expanding irrigation access for smallholder rice farmers (World Bank, 2017). The USAID-Feed the Future program is another important intervention implemented particularly in the northern part of Ghana. Components of the program include the Agricultural Development and Value Chain Enhancement (ADVANCE II), Agricultural Technology Transfer (ATT), Resiliency in Northern Ghana (RING), Strengthening Partisanships, Results and Innovations in Nutrition Globally (SPRING), Financing Ghanaian Agriculture Project (FinGAP), Agricultural Policy Support Project (APSP) among others. These agricultural interventions have adopted facilitative value chain approach to address key constraints in relation to the development, availability and adoption of agricultural technologies, finance, and output markets for the benefit of smallholder farmers in the rice, maize and soya value chains in Northern Ghana. These government and donor funded rice interventions work closely with the Ghana Rice Inter-professional Body (GRIB), Ghana Grains Council, and Peasant Farmers Association of Ghana (PFAG), umbrella bodies effectively furthering the rice value chain transformation agenda in Ghana.

1.6 Brief profile of Northern Ghana

Northern Ghana constitutes three regions namely Northern, Upper East and Upper West regions, which together is referred to as the Northern Savannah Ecological Zone (NSEZ). Figure 1.3 presents the map of northern Ghana. It is a high agricultural potential area endowed with abundant and fertile land (6 million hectares) for the commercial cultivation of a variety of crops such as cereals/grains, cassava, cotton, shea and raising aquaculture and livestock (World Bank, 2017). Despite the fact that farmers predominantly depend on rainfall for food production, the region has significant irrigation potential, as about 23 large and medium, and 104 small dam sites are available and can be developed to command over 547,000 hectares of irrigable land (SADA, 2016). It is estimated that the agricultural potential of northern Ghana could attract private investment in agriculture especially in the areas of irrigation and down-stream processing infrastructure development and job creation along the agrifood value chains in the area.

Despite the potential, northern Ghana lags behind the south of Ghana in terms of development and other socio-economic indicators, and houses majority of Ghana's poor whose major occupation is farming (World Bank, 2011). The region trades behind in terms of access to education, health care (including maternal and child health), safe and portable water among others in the country (GSS, 2016). Farmers in northern Ghana are highly vulnerable to shocks (floods, drought, diseases, conflicts etc.) due to limited income diversification sources. The region is highly susceptible to environmental degradation, and also characterized by low intensity and poorly distributed rainfall leading to low productivity. It is noted as the least developed region in Ghana although it covers over 40% of the country's land area and contains about 30% of the population (GSS, 2016). The government of Ghana rolled out the Savannah Accelerated Development Authority (SADA) together with other development interventions to implement a comprehensive long-term development plans for northern Ghana, and for bridging the north-south development gap. SADA is a key government authority for furthering the development agenda of northern Ghana. The authority coordinates, facilitates, and implements development projects in collaboration with both public and private players, to ensure successful investments vis-à-vis job creation and social impacts on the people (SADA, 2017).

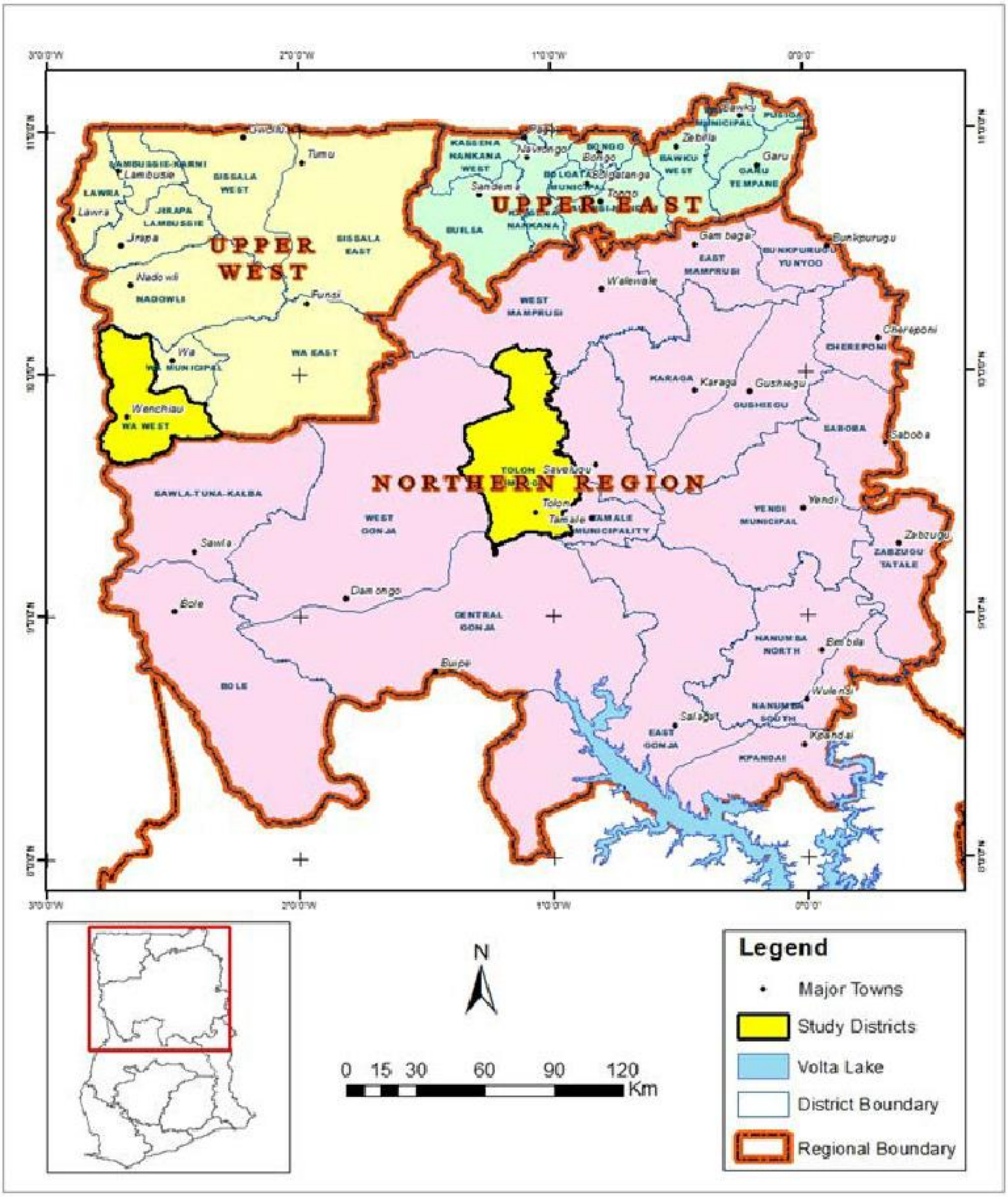


Fig. 1.3: Map of Northern Ghana. Source: Antwi *et al.* (2014).

1.7 Structure of the thesis

This thesis consists of a collection of journal articles organized as follows. Chapter one presents the general introduction of the study, chapters two to five are a collection of journal articles while conclusions and policy implications are presented in chapter six. Specifically, chapter two explores the vertical coordination mechanisms:-written contracts, verbal contracts, and spot market transactions- and their impacts of farm performance outcomes such as net farm income, total farm income, total household income, labor productivity and price margins among smallholder rice farmers. Chapter three examines the role of farmer groups and collective marketing in improving smallholder rice farmers' net revenues. In this chapter, the relationship between farmer group membership and collective market participation is explored. In chapter four, the impact of farmer groups on farm yields and technical efficiency among smallholder rice farmers is examined, using sample selection stochastic production frontier approach to account for selection bias arising from unobserved attributes. Chapter five explores the role of inclusive value chain participation and social networks in improving smallholder rice farmers' market performance outcomes such as paddy prices, quantity traded, and farm net returns. The final chapter presents the conclusions and policy implications from the study.

References

Abate, G.T., Francesconi, G.N., Getnet, K. (2014). Impact of cooperatives on smallholders' technical efficiency: Evidence from Ethiopia. *Annals of Public and Cooperative Economics* 85(2), 11-21.

Ainembabazi, J.H., van Asten, P., Vanlauwe, B., Ouma, E., Blomme, G., Birachi, E.A., Nguezet, P.M.D., Mignouna, D.B., Manyong, V.M., 2017. Improving the speed of adoption of agricultural technologies and farm performance through farmer groups: evidence from the Great Lakes region of Africa. *Agricultural Economics*, 48, 241-259.

African Union and NEPAD. (2004). Implementing the Comprehensive Africa Agriculture Development Programme and Restoring Food Security in Africa: The Roadmap, Midrand, South Africa: NEPAD Secretariat.

Antwi, E. K., Otsuki, K., Saito, O.,…Takeuchi, K. (2014). Developing a community-Based Resilience assessment model with reference to northern Ghana. *Journal of Integrated Disaster Risk Management*, 4 (1), 73-92.

Babu, S.C., Shishodia, M. (2018). Measuring Agribusiness Competitiveness: An Application to African Countries. In: Adeleye, I., Esposito, M. (eds) *Africa's Competitiveness in the Global Economy*. AIB Sub-Saharan Africa (SSA) Series. Palgrave Macmillan, Cham.

Bachewe, F. N., Berhane, G., Minten, B, Taffesse, A. S. (2018). Agricultural trasformation in Africa? Assessing the evidence in Ethiopia. *World Development*, 105,286-298.

Barrett, C. B., Christiaensen, L., Sheahan, M., Shimeles, A. (2017). On the structural transformation of rural Africa. *Journal of African Economies*, 26, 11-35.

Barrett, C.B., Bachke, M.E., Bellemare, M.F., Michelson, H.C., Narayanan, S., Walker, T.F. (2012). Smallholder participation in contract farming: Comparative evidence from five countries. *World Development*, 40, 715-730.

Bellemare, M. F., Bloem, J. R. (2018). Does contract farming improve welfare? A review. *World Development*, 112, 259-271.

Bellemare, M.F., Novak, L. (2017). Contract farming and food security. *American Journal of Agricultural Economics*, 99 (2), 357-378.

Bellemare, M.F. (2012). As you sow, so shall you reap: The welfare impacts of contract farming. *World Development*, 40, 1418-1434.

Benin, S. (2016). Returns to agricultural public spending in Ghana – cocoa versus non-cocoa Subsector. Discussion Paper # 01503, International Food Policy Research Institute, Washington D.C., USA.

Bijman, J., Muradian, R., Cechin, A.(2011). Agricultural cooperatives and value chain coordination. In *Value Chains, Inclusion, and Endogenous Development: Contrasting Theories and Realities*, 82-101 (Eds B. Helmsing and S. Vellema). New York: Routledge.

Bijman, J. (2008). Contract farming in developing countries: an overview. Working paper.

Bijman, J., Omta, S.W.F., Trienekens, J. H., Wijnands, J.H.M., and Wubben, E.M.F. (2006). Management and organization in international agri-food chains and networks. In *International agri-food chains and networks, Management and organization*. *Wageningen Academic Publishers* 15-28.

Choudhary, V., Christienson, G., Josserand, H., D'Alessandro, S. (2015). *Ghana Agricultural Sector Risk Assessment: Risk Prioritization*. World Bank, Washington, DC. Report No. 94228. https://openknowledge.worldbank.org/handle/10986/22498 License: CC BY 3.0 IGO.

Ecker, O. (2018). Agricultural transformation and food and nutrition security in Ghana: Does farm production diversity (still) matter for household dietary diversity? *Food policy*, 79, 271-282.

Fischer, E. and Qaim, M. (2012). Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya, *World Development*, 40 (6): 1255–1268.

Ghana Cocoa Board. (2015). The future of Ghana's cocoa sector. Building in robustness and resilience to What IF? Scenario Planning Report. Accra, Ghana.

Ghana Statistical Service (GSS). (2016). Revised 2015 Annual Gross Domestic Product.

Global Agricultural Information Network-GAIN. (2018). Grain and feed update in Ghana. USDA Foreign Agricultural Service.

Humphrey, J., Schmitz, H. (2002). How does insertion in global value chains affect upgrading in industrial clusters?, *Regional Studies*. 36 (9), 1017-1027.

Kilelu, C. W., Klerkx, L., Leeuwis, C. (2017). Supporting smallholder commercialization by enhancing integrated coordination in agrifood value chains: experiences with dairy hubs in Kenya. *Experimental Agriculture*, 53(2), 269-287.

Ma, W., Abdulai, A. (2016). Does cooperative membership improve household welfare?

Evidence from apple farmers in China. *Food Policy*, *58*, 94–102.

Maertens, M., Vande Velde, K. (2017). Contract farming in staple food chains: The case of rice in Benin. *World Development*, 95, 73–89.

Michelson, H. C. (2013). Small farmers, NGOs, and a Walmart world: welfare effects of supermarkets operating in Nicaragua. *American Journal of Agricultural Economics*, 95, 628-649.

MoFA. (2018). Investment guide for the agriculture sector in Ghana.

MoFA. (2017). Agricultural sector progress report. Accra, Ghana.

MoFA. (2017). Planting for food and Jobs: strategic plan for implementation (2017-2020). Ministry of Food and Agriculture, Accra, Ghana.

MoFA. (2009). National Rice Development Strategy (NRDS). Coalition for African Rice Development, Accra, Ghana.

Mojo, D., Fischer, C., and Degefa, T. (2017). The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. *Journal of Rural Studies*, 50 (2017): 84-94.

Mul, M., Obuobie, E., Appoh, R., Kankam-Yeboah, K., Bekoe-Obeng, E., Amisigo, B., Logah, F. Y., Ghansah, B., McCartney, M. (2015). Water resources assessment of the Volta River Basin. Colombo, Sri Lanka: International Water Management Institute (IWMI). 78p. (IWMI Working Paper 166). doi: 10.5337/2015.220.

Ouma, S., Boeckler, M., Linda, P. (2013). Extending the margins of marketization frontier regions and the making of agro-export markets in northern Ghana. *Geoforum*, 48, 225-235.

Partnership to Cut Hunger and Poverty in Africa. (2002). *Now is the Time: A Plan to Cut Hunger and Poverty in Africa*, Washington D.C.: Partnership to Cut Hunger and Poverty in Africa.

Poulton, C., Dorward, A., Kydd, J. (2010). The future of small firms: New directions for services, institutions, and intermediation. *World Development*, 38(10), 1413-1428.

Ragasa, C., Dankyi, A., Acheampong, P., Wiredu, A. N., Chapoto, A., Asamoah, M., & Tripp, R. (2013). Patterns of adoption of improved rice technologies in Ghana. IFPRI working Paper 35, *International Food Policy Research Institute (IFPRI)*, Washington DC.

Rapsomanikis, G. (2015). The economic lives of smallholder farmers; an analysis based on household data from nine countries. Food and Agriculture Organization, Rome.

Reardon, T., Barret, C.B., Berdegué, J.A., &Swinnen, J.F.M. (2009). Agrifood industry transformation and small farmers in developing countries. *World Development*, 37, 1717-1727.

Ruben, R., Slingerland, M, Nijhoff, H., 2006. Agro-food chains and networks for development: Issues, approaches and strategies. In *The Agro-food chains and networks for development*, 1-25 (Eds R. Ruben, M. Slingerland and H. Nijhoff). Netherland: Springer.

SADA. (2017). Commercial Agriculture Investment Guide: The Northern Savannah Ecological Zone of Ghana. Volume 1.

SADA. (2016). Toward inclusive agriculture-led economic transformation of the northern savannah zone of Ghana.

Staatz, J.M., Dembélé, N. N. (2008). Agriculture for Development in Sub-Saharan Africa. *Background Paper for the World Development Report 2008*. Washington D.C.: The World Bank.

Statistics, Research and Information Directorate (SRID)., 2016. Agriculture In Ghana: facts and figures (2015). Ministry of Food and Agriculture, October, 2016, Accra.

Swinnen, J.F.M., Maertens, M. 2007. Globalization, privatization, and vertical coordination in food value chains in developing and transition countries. *Agricultural Economics*. 37, 89–102.

Schipmann, C., Qaim, M. (2010). Spillovers from modern supply chains to traditional markets: Product innovation and adoption by smallholders. *Agricultural Economics*, 41, 361–371.

Ton, G., Vellema, S., de wildt, M. R. (2011). Development impacts of value chain interventions: how to collect credible evidence and draw valid conclusions in impact evaluations? *Journal on Chain and Network Science*, 11(1), 69-84.

Veras, O. (2017). Agriculture in Africa: Potential versus reality. https://www.howwemadeitinafrica.com/agriculture-africa-potential-versus-reality/57635/

Vandercasteelen, J., Beyene, S. T., Minten, B., Swinnen, J. (2018). Citis and agricultural transformation in Africa: Evidence from Ethiopia. *World Development*, 105, 383-399.

World Bank. (2017). Transforming agriculture for economic growth, job creation, and food security in Ghana. Agriculture Sector Policy Note. Agriculture Global Practice AFR01.

World Bank. (2007). Agriculture for Development, *World Development Report 2008:* Washington, D.C.

World Development Indicators (WDI). (2016). World Bank, Washington DC, United States of America.

World Bank. (2015). World Development Indicators (WDI), global merchandise imports.

World Bank. (2015). Tackling Poverty in Northern Ghana. *World Development Report*, Report No. 53991-GH, Washington, D.C.

Wossen, T., Abdoulaye T., Alene, A., Mekbib G. Haile, M. G., Feleke, S., Olanrewaju, A., Victor Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, 54, 223-233.

Yumkella K. K., Kormawa, P. M., Roepstorff, T. M., Hawkins, A.M. (2011). Agribusiness for Africa's Prosperity UNIDO ID/440.

Chapter 2

Vertical coordination mechanisms and farm performance amongst smallholder rice farmers in northern Ghana

Awal Abdul-Rahaman and Awudu Abdulai

Department of Food Economics and Consumption Studies, University of Kiel, Germany

Revised and Resubmitted to *Agribusiness: an International Journal*

Abstract

Despite the fact that contracting facilitates farmer participation in agrifood value chains, evidence on farmers' participation in different forms of contracts and the impact on farm performance is still limited. This study examines the determinants and impacts of vertical coordination mechanisms- spot market transactions, written, and verbal contracts- on farm performance of rice farmers in northern Ghana, using a multinomial BFG model to account for selectivity bias. The findings indicate that vertical coordination participation decision is significantly influenced by age, access to credit, labor, association membership and sales to institutional buyers. The empirical results also reveal significant gains in farm performance outcomes from participating in written and verbal contracts, relative to spot market transactions, with the highest gains associated with the use of written contracts. (JEL Classifications: C34, C35, D23, Q12, Q13)

Keywords: Vertical coordination mechanisms, farm performance, multinomial BFG model, rice farmers, Ghana.

2.1 Introduction

Agrifood value chains in developing countries continue to undergo rapid transformation due to increasing incomes, urbanization and consumer consciousness in food quality and safety (Minot & Sawyer, 2016). The expansion of agricultural commodity markets, supermarkets, agribusiness firms, and their requirements for food grades and standards drive the need for vertical coordination in agrifood value chains (Barrett, Bellemare, Michelson, Narayanan, & Walker, 2012; Henderson & Isaac, 2017). Some recent studies have shown that participation in agrifood value chains is associated with improved smallholder farmers' welfare (eg. Rao & Qaim, 2011; Saenger, Terero & Qaim, 2014). However, challenges such as underdeveloped market systems and infrastructure, limited access to financial capital and technology, high transaction costs associated with input and output markets, among others, limit smallholder participation in agrifood value chains in developing countries (Abdulai & Birachi, 2009; Otsuka, Nakano, & Takahashi, 2016). These challenges are still somehow unresolved, and often make it difficult for farmers to take advantage of prevailing market opportunities (Swinnen & Maertens, 2007).

However, contracting is recognized as the dominant form of vertical coordination mechanism that facilitates smallholder farmers' participation in agrifood value chains (Otsuka et al., 2016; Bolwig, Gibbon, & Jones, 2009). It falls between spot market transaction (0% vertical coordination), and full vertical integration (100% vertical coordination), and addresses constraints related to inadequate access to credit and extension, market imperfections, and high transaction costs (Bellemare, 2012). Smallholder farmers enter into contractual agreements with downstream buyers to reduce transaction costs and obtain other benefits associated with using contracts (Barrett et al., 2012). Such agreements can involve specification about the transaction only such as product quality, delivery times, as well as sales price (marketing contract), or specifications related to production process, product quality, seed variety, chemicals used among others (production contract) (Maertens & Vande Velde, 2017; Roussy, Ridier, Chaib, & Boyet, 2018). Contracting is important in facilitating farmers' access to inputs, credit, and technology, as well as reduces risks associated with prices and markets (Mishra, Kumar, Joshi, & Dsouza, 2018; Kariuki & Loy, 2016). Buyers can pre-finance smallholder farmers, by providing them with inputs, technology and cash credit, and costs associated with these provisions are deducted from the final produce at point of product delivery (Bellemare, 2012).

Contracting in smallholder output markets has received considerable attention in development economics literature. In particular, some authors have modeled contracting in a dichotomous framework, involving farmers' decisions to enter into contracts with agribusiness firms and supermarkets, or supply produce in spot markets (eg. Bellemare, 2012; Michelson, 2013; Maertens & Vande Velde, 2017). Recent empirical evidence in developing countries has highlighted positive welfare impacts associated with smallholder participation in agrifood value chain through contracting (eg. Rao & Qaim, 2011; Michelson, 2013). In the vegetables sector in Kenya, Rao and Qaim (2011) show positive impact of value chain participation on household income, while Michelson (2013) found that farmer participation in supermarket channels through contracts increases household productive asset holdings in Nicaragua. In output markets, evidence on smallholder farmers' participation in different forms of vertical coordination mechanisms such as written contracts, verbal contracts and spot market transactions, and their related impacts on farm performance is still limited in the empirical literature. To the best of our knowledge, only the studies by Ma & Abdulai (2016), and Trifković (2016) investigated the impacts of different forms of vertical coordination mechanisms on smallholder farm performance. In particular, Ma & Abdulai (2016) found significant increase in net returns associated with written and verbal contracts participation by apple farmers in China. The study by Trifković (2016) revealed that in the catfish sector in

Vietnam, vertically integrated and contract farms achieve higher yields and farm revenues than independent farms. Some previous studies investigated the determinants of farmers' market participation decisions, quantities of produce transacted and choice of market place for output transactions (eg. Abdulai & Birachi, 2009).

The present study contributes to the growing literature on vertical coordination mechanisms and their impacts on farm performance in three ways. First, we assess the factors influencing farmers' decisions to participate in written contract, verbal contract and spot market in output transactions, as well as highlight the impact of these factors on farm performance. Second, we examine the causal effects of written and verbal contracts participation on farm performance outcomes such as net farm income, total farm income, and total household income, relative to spot market transactions. Finally, we decompose net farm income into margins (price margins) and yield effects (labor productivity), and examine the impact of the coordination mechanisms on these performance outcomes. This will provide policy makers with insights into the multi-dimensional effects of participating in the vertical coordination mechanisms, as well as which mechanism is of substantial benefits to smallholder farmers in agrifood value chains.

We use data from a recent survey of smallholder rice farmers in five districts of northern Ghana. In recent times, the Ghana government has intensified collaborative efforts with donor agencies and agribusiness firms to upgrade the domestic cereal food staples including rice by implementing value chain interventions. The interventions aim at increasing efficiency of these value chains for the benefit of large number of smallholders. The findings from this study can also enhance stakeholder policy targeting efforts towards addressing multiple market failures facing smallholder farmers in Ghana. Given the fact that participation in vertical coordination mechanisms is non-random, we employ the selectivity approach for the multinomial logit (MNL) model introduced by Bourguignon, Fournier & Gurgand (2007) to account for selection bias associated with observed and unobserved attributes. We also compare the estimates from this approach to Lee's (1983) selection bias correction model, which computes only one selectivity correction term for all vertical coordination choices, to provide further insights into the differential impacts of coordination mechanisms on farm performance in the rice value chain.

The rest of this paper proceeds as follows: section 2 presents an overview of rice production and marketing in Ghana. Section 3 captures the data and summary statistics of the variables used in the analysis. Conceptual framework is captured in section 4, followed by empirical specification in section 5. The empirical results are presented in section 6, while the final section concludes.

2.2 Overview of rice production and marketing in Ghana

Rice has become the second most important cereal staple in Ghana after maize, and its production is done under three ecosystems: rainfed lowland (78% of arable area), rainfed upland (6%), and irrigation (16%) systems (MoFA, 2009). The major rice producing areas in Ghana include Volta, Ashanti, Eastern, Northern, and Upper East regions (MoFA, 2009). Domestic rice production increased from 390,000 MT in 2016/2017 to 450,000 MT in 2017/2018 (GAIN, 2018). Rice forms an important part of Ghanaian diet and contribute to food security among rural and urban households. Rice consumption is increasing, driven by population growth, urbanization and changing habits of consumers, which creates a gap between demand and local supply. The consumption of rice in 2017/2018 is estimated at 1.0 million MT, and the per capita rice consumption in 2016/2017 stood at 35kg, and is estimated to reach about 40kg by 2020 (GAIN, 2018). Domestic rice production still covers about 30-40% of consumer demand, allowing for imports of larger quantities to address both quantity and quality differences between local production and demand (Angeluci *et al*., 2013).

Other major cereal staples in Ghana include Maize, wheat, and sorghum. Maize is considered the most important cereal staple in Ghana mainly produced in the middle-southern part and northern regions. Statistics indicate that maize production increased from 1.75 million MT in 2016/2017 to 1.8 million MT in 2017/2018, with an estimated consumption of 1.9 million MT in 2017/2018 (GAIN, 2018). Ghana does not grow wheat domestically, and relies on imports for all its wheat needs. Wheat is mostly processed into flour for making bread, cakes and other pastries. Wheat consumption is estimated at 590,000 MT in 2017/2018, with per capita consumption of 20kg per year (GAIN, 2018). Sorghum is also one of the fundamental cereal crops mostly produced in northern Ghana. Statistics indicate that sorghum production in Ghana declined (12%) from 262,000 MT in 2015 to about 229,000 MT in 2016 (MoFA, 2016). Consumption of sorghum was 199,756 MT in 2016, with an estimated per capita consumption of about 5kg (SRID-MoFA, 2016).

The share of rice production in total cereal output in Ghana is about 16% (maize 62%, sorghum 14%). Recent increase in the production of rice and other cereal staples in Ghana is attributed to the renewed commitment of government and donor agencies to revamp the cereal staple chains by initiating a number of interventions[1]. For instance, under government's five-year Planting for Food and Jobs (PFJ) flagship program, 50% subsidy on seed and fertilizer was introduced to make it affordable for smallholder farmers for increased application rates and yields (GAIN, 2018). In northern Ghana, rice is grown by over 279, 000 households with average farm size of about two hectares, and cultivating about 70% of total land area (USAID, 2009). Majority of smallholder farmers grow improved rice varieties, although some still grow traditional varieties (Ragasa et al., 2013). Examples of improved rice varieties commonly grown by farmers in northern Ghana include Jasmine 85, AGRA rice, Togo marshal, Digang, Nerrica 1, Nerica 2, and Nabogo rice. The traditional varieties include GR 18, TOX 3108 (GR 22), and Mandii (Ragasa et al., 2013). Smallholder rice farmers produce and supply paddy rice

[1] Other interventions in northern Ghana include Feed the Future-USAID/ATT, Ghana Commercial Agriculture Project (GCAP), ADVANCE II, GHASIP projects etc.

to buyers, using vertical coordination mechanisms such as spot market transactions, written and verbal contracts. These buyers are institutions or private companies[2], aggregators and processors mostly located in the regional capitals of northern Ghana and some parts of southern Ghana. They usually enter into seasonal marketing contracts with smallholder rice farmers at the beginning of the growing season, and then travel to the contracted farmers after harvest to mobilize the paddy for onward processing and sales. These contractual arrangements, although not without challenges, have been found useful, because they provide assured markets for farmers and provide buyers with regular supply of paddy for their agribusinesses. However, some smallholder rice farmers do not get the opportunity to enter into marketing contracts with these private companies and other buyers, compelling them to sell paddy in spot markets, by either selling at farmgate to buyers who randomly travel to the rice growing areas during harvest period, or transport to market centers for sale. In other cases, local rice processors in the communities also provide markets for this category of farmers.

2.3 Data and Summary Statistics

This study uses data from a recent farm household survey conducted from June to August, 2016 in five districts of northern Ghana; Tamale metropolis, Savelugu Nanton Municipal, Tolon, Kumbungu and Sagnarigu districts. A multistage sampling approach was employed in selecting the sample for this study. First, we used purposive sampling technique to select these five districts based on the intensity of rice production, as well as their position as some of the major beneficiary areas of rice value chain interventions in northern Ghana. Second, in consultation with officials of development projects (FtF-USAID-Ghana[3]) and MoFA extension agents, we randomly selected two to three communities from each district in proportion to size of the

[2] Examples of the private companies that contract with smallholder rice farmers in northern Ghana include premium foods limited, AMSIG Resources, SAVBAN limited, BUSAKA enterprise, Investment Protocol Services Limited (IPSL) etc.

[3] The project components under the FtF-USAID-Ghana programme include Agriculture Technology Transfer project (ATT), Resiliency in Northern Ghana (RING), Agricultural Development and Value Chain Enhancement (ADVANCE), Strengthening Partnerships, Results and Innovations in Nutrition Globally (SPRING) projects.

district. Finally, we randomly sampled smallholder rice farmers in proportion to the farmer population in each area. In total, 458 rice farmers were sampled and interviewed, using structured questionnaire with the help of trained research assistants, and under the supervision of one of the authors. The data collected covered information related to 2015 production season. The survey gathered information from farmers on personal, household and farm-level characteristics, asset ownership, and access to credit and marketing activities such as vertical coordination mechanisms.

Table 2.1 presents the definition and summary statistics of the variables used in the analysis. The dependent variables are the vertical coordination mechanisms (spot market, written and verbal contracts) such that the chosen mechanism is assigned a value of one, and zero otherwise. The study sample constitutes 43% of farmers who supply paddy in spot markets, 33% use written contracts, and 24% use verbal contracts. The outcome variables include the net farm income, total farm income, and total household income. Table 2.1 shows that net farm income from rice production and sales constitute about 31% of total farm income, and 28% of total household income. Table 2.2 reports systematic differences in farmer characteristics with respect to the vertical coordination mechanisms, and associated *t*-tests results. Significant age differences exist between farmers who use verbal contracts in output transactions and those who carry out spot market transactions. In particular, farmers who supply paddy in spot markets and those who use written contracts are relatively younger than rice farmers who engage buyers with verbal contracts, suggesting that older farmers are more likely to choose verbal contracts for output transactions. Again, vertical coordination mechanism users significantly vary in terms of education. The results show that farmers who use written contracts for output transactions are more educated than farmers who use verbal contracts and spot market supply. However, there are no significant differences in education between farmers who supply in spot market and those who use verbal contracts.

Table 2.1: Variable definition and summary statistics

Variable	Definition	Mean (Std. Dev.)
Spot market	1 if farmer chose spot market, 0 otherwise	0.43(0.49)
Written contract	1 if farmer chose written contract, 0 otherwise	0.32(0.47)
Verbal contract	1 if farmer chose verbal contract, 0 otherwise	0.24(0.42)
Net farm Income	Gross revenue from rice production less variable input cost (GH¢/ha)	1,152.29(1,816.18)
Total farm income	Gross revenue from all crops including paddy rice less input cost (GH¢)	3,723.59 (4,056.53)
Total household income	Annual household income including off-farm earnings and remittances (GH¢)	4,102.50 (4,294.30)
Age	Age of respondent (years)	37.46(11.65)
Education	Education of respondent (years)	2.71(4.40)
Gender	1 if farmer is male, 0 otherwise	0.88(0.32)
Farm Size	Size of farm (hectares)	1.14(1.26)
Access to credit	1 if farmer is not credit constraint, 0 otherwise	0.40(0.49)
Mobile phone	1 if farmer owns a mobile phone, 0 otherwise	0.45(0.49)
Market perception	Farmer perception of paddy rice demand in previous year prior to the survey (1=low, 0=high)	0.35 (0.47)
Road status	1 if market road is motorable, 0 otherwise	0.73 (0.44)
Distance to market	Distance to market (km)	6.57(4.08)
labor	Total labor used in rice production (worker – days/ha)	55.86 (23.58)
Importance of legal contracts	1 if farmer considers legal contracts important, 0 otherwise	0.51(0.50)
Institutional buyer	1 if farmer sells to institution, 0 otherwise	0.21(0.41)
Association	1 if farmer belongs to farmer group, 0 otherwise	0.50(0.50)
Farm vehicle	1 if farmer owns farm vehicle, 0 otherwise	0.07(0.26)
Sagnarigu	1 if farmer is located in Sagnarigu district, 0 otherwise	0.12(0.33)
Tolon	1 if farmer is located in Tolon district, 0 otherwise	0.22(0.41)
Kumbungu	1 if farmer is located in Kumbungu district, 0 otherwise	0.24(0.42)
Savelugu Nanton	1 if farmer is located in Savelugu Nanton Municipal, 0 otherwise	0.20(0.40)
Tamale	1 if farmer is located in Tamale metropolitan area, 0 otherwise	0.20(0.40)

Note: GH¢ is Ghanaian currency: US$1 = GH¢ 4.19 in 2016, Std. Dev.: Standard Deviation

Table 2.2: Differences in characteristics among users of vertical coordination mechanisms

Variable	Spot market		Written contract		[a]Diff.	Verbal contract		[b]Diff.
	Mean	Std. Dev.	Mean	Std. Dev.	(t-stat.)	Mean	Std. Dev.	(t-stat.)
Age	36.451	11.534	37.370	10.789	0.75	39.427	12.828	2.08 **
Credit access	0.289	0.454	0.516	0.501	4.41***	0.463	0.500	3.10***
Education	2.269	4.153	3.046	0.366	1.66 *	3.054	4.648	1.52
Gender	0.888	0.315	0.887	0.317	0.02	0.872	0.334	-0.40
Farm Size	1.071	0.941	1.190	1.592	0.86	1.207	1.252	1.07
Labor	50.304	21.794	62.540	24.474	4.92***	56.663	23.139	2.39**
Dist. to market	6.545	3.925	6.465	3.607	0.19	6.788	4.940	0.473
Mobile phone	0.299	0.459	0.582	0.494	5.51***	0.563	0.498	4.68***
Road status	0.705	0.456	0.761	0.427	1.16	0.736	0.442	0.572
Import. of legal contract	0.355	0.479	0.728	0.446	7.41***	0.527	0.501	2.96***
Market perception	0.208	0.406	0.556	0.498	7.17***	0.327	0.471	2.32**
Association	0.187	0.391	0.774	0.419	13.44***	0.718	0.451	10.75***
Farm vehicle	0.086	0.281	0.039	0.195	1.73 *	0.100	0.301	0.39
Institutional buyer	0.101	0.302	0.364	0.482	6.20***	0.218	0.414	2.82***
Net farm income	929.992	1,365.047	1,223.066	1,690.430	1.78 *	1,453.282	2,521.677	2.36 **
Total farm income	3,237.234	3,331.721	4,210.974	4,737.583	2.24**	3,925.582	4,164.990	1.58
Total household income	3,392.254	3,468.399	4,898.470	4,942.842	3.34***	4,281.855	4,499.133	1.93**
Sample size	**197**		**151**			**110**		

Note: *, **, *** mean significant at 10%, 5%, and 1% levels, respectively.
[a] Differences in characteristics between written contract and spot market users.
[b] Differences in characteristics between verbal contract and spot market users.

We also observe that farmers who use written contracts and those who engage in transactions via verbal contracts constitute higher proportion of farmers who are not credit constrained, as well as generate higher net farm incomes, total farm income, and total household income relative to farmers who supply in spot markets. We also observe that farmers who use written contracts and those who use verbal contracts mostly own mobile phones, attach greater importance to legal contracts, mostly belong to farmers' associations, employ higher amount of labor, and mostly sell paddy to institutional buyers, as compared to farmers who supply paddy in spot markets. It is important to mention that the differences in outcomes by coordination mechanisms cannot be interpreted as impacts since other confounding factors are not accounted for in the means.

2.4 Conceptual Framework

2.4.1 Vertical coordination mechanism choice decision

In this section, we present a conceptual framework in relation to farmers' decisions to participate in vertical coordination mechanisms for output transactions. Following the concepts presented in Ma and Abdulai (2016), and Ito, Bao, & Su (2012), we assume that farmers are risk neutral in order to simplify our model. Given that a rice farmer engages a buyer in an output transaction involving quantity of paddy at a given price, and associated input cost, using a coordination mechanism j among M coordination mechanisms, farmer's objective would be to maximize net farm income, specified as:

$$V_{max}^{*} = pQ(\omega, Z) - W\omega, \tag{1}$$

where p is output price per kg, Q is the output (paddy) quantity in kg, W is the input prices, ω is a vector of input quantities (eg. fertilizer, herbicide, and labor), and Z is a vector of farm and household level characteristics. Net farm income can be expressed as a function of input and output prices, the choice of vertical coordination mechanism (V), and farm and household level characteristics as follows:

$$V^* = V^*(P, W, V, Z) \tag{2}$$

For any well-behaved profit function, applying Hoteling's lemma directly to equation (1) yields a reduced form of the following rice output supply function:

$$Q = Q(P, W, V, Z) \tag{3}$$

Equations (2) and (3) suggest that net farm income from rice production (V^*) and rice output (Q) are influenced by the input and output prices, choice of vertical coordination mechanism, and farm and household level characteristics. In line with Ito et al. (2012), we also decompose net farm income into labor (L) productivity (Q/L) and price margin ($p - W\omega/Q$) to evaluate the contribution of vertical coordination mechanisms to these farm performance outcomes, which is one of the objectives of the present study.

We assume that a farmer chooses coordination mechanism that yields maximum net farm income (V_{ij}^*) compared to the net farm income from any other coordination mechanism ($V_{i\tau}^*$). The expected net farm income associated with each coordination mechanism cannot be directly observed. What is observed is the actual participation in vertical coordination (V). However, the expected net farm income can be expressed as a function of observable factors in a latent variable (V_{ij}^*) model as:

$$V_{ij}^* = Z_{ij}\beta_j + \eta_{ij} \qquad V = \begin{cases} 1 & if\ V_{i1}^* > \max\limits_{\tau \neq 1}(V_{i\tau}^*)\ or\ \varepsilon_{i1} < 0 \\ \vdots & \\ M & if\ V_{iM}^* > \max\limits_{\tau \neq M}(V_{i\tau}^*)\ or\ \varepsilon_{iM} < 0 \end{cases}, \tag{4}$$

where β_j is the parameter to be estimated and η_{ij} is the error term; and Z_{ij} is a vector of farm and household level factors influencing vertical coordination choices. These variables include age, gender, education, access to credit, farm size, association membership, labor, road status ownership of mobile phone, farm vehicle, distance to markets and location variables. The variables are included in the analysis based on the existing literature (eg. Abdulai & Birachi, 2009; Winter-Nelson & Temu, 2005; Ito et al., 2012).

It is also assumed that the observed covariates in Z_{ij} are uncorrelated with the unobserved stochastic component η_{ij}, i.e. $E(\eta_{ij}|Z_{ij}) = 0$. In addition, assuming that η_{ij} are independently and identically Gumbel distributed, the selection equation (4) leads to a multinomial logit (MNL) model (McFadden, 1973). The probability that vertical coordination mechanism j is chosen by farmer *i* is specified as:

$$P_{ij} = P\left(\varepsilon_{ij} < 0 \middle| Z_{ij}\right) = \frac{\exp(Z_{ij}\beta_j)}{\sum_{\tau\neq 1}^{m}\exp(Z_{ij}\beta_\tau)},\ j = 1, 2, 3 \tag{5}$$

As stated earlier, the three vertical coordination mechanisms examined in this study include spot market transactions ($j = 1$), written contract ($j = 2$), and verbal contract ($j = 3$). Note that farmers who supply paddy in spot market are the base group for comparison in the present analysis. The multinomial logit (MNL) model constitutes the first stage, and is estimated with maximum likelihood method to obtain coefficients associated with each coordination mechanism. However, we compute marginal effects of the coefficients to allow for better interpretation of the results (Wooldridge, 2010). We also test the MNL model for the IIA assumption by conducting suest-based Hausman test, which is a modification of Hausman and McFadden test (Long & Freese, 2005).

2.4.2 Impact evaluation and selection bias

This study also investigates the impact of each coordination mechanism j on a set of farm performance outcomes. Given that the vector of outcome variables is a linear function of household and farm level factors X_{ij} and a coordination mechanism choice dummy (V_{ij}), the outcome equation is specified as:

$$Y_{ij} = X_{ij}\gamma + V_{ij}\delta + \mu_{ij}, \tag{6}$$

where Y_{ij} is a vector of outcome variables, γ and δ are vectors of parameters to be estimated; μ_i is the error term and satisfies $\mu_i \sim N(0, \sigma)$. It is worth noting that the parameter δ captures the impact of vertical coordination mechanism on the outcomes. However, given that farmers self-select into choice of coordination mechanisms for output transactions, using OLS method could result in selectivity bias. In this case, the error terms in the coordination choice model η_{ij} and the outcome equations μ_{ij} are correlated, and the expected values of μ_{ij} conditional on sample selection are nonzero, which leads to inconsistent estimates. To account for the potential selectivity bias, we consider the methods proposed by Lee (1983), Dubin & McFadden (hereinafter DMF, 1984), and the approach developed by Bourguignon et al. (hereinafter BFG, 2007).

Lee makes restrictive assumptions and fails to take into account the risk of multi-collinearity, which is considered in the DMF's approach. Moreover, Lee's (1983) approach estimates only one selectivity term, even when there are multiple alternatives (Bourguignon et al., 2007). The DMF approach is also restrictive because it only extends the number of correction parameters to *M*-1 for *M* alternatives. Given the limitations of the two approaches, Bourguignon et al. (2007) proposed an approach to account for selectivity bias with multiple outcomes, while accounting for the limitations of the Lee and DMF's approaches. It relaxes the restrictive assumption by estimating different selectivity correction terms for each coordination mechanism alternative. That is, the number of selectivity correction terms is equal to the number of vertical coordination alternatives. It also identifies the direction and sources of the bias (Park, Mishra, & Wozniak, 2014). In this study, we use the selectivity bias correction method by Bourguignon et al. (2007), which we refer to as "Multinomial BFG Model", as it provides deeper insights into the impact of coordination mechanisms on farm performance.

2.5 Empirical specification

2.5.1 Multinomial BFG model

The multinomial BFG model is a two-stage impact assessment procedure. In the first stage, we estimate MNL model (eq. 5) to examine the determinants of coordination mechanism participation, and then compute selectivity correction terms, which are included in the second stage, to estimate the outcomes consistently. To estimate the impact of coordination mechanisms on the outcomes in the second stage, we specify the following three regimes of outcome equations:

$$\text{Regime 1 (Spot Market):} \quad Y_{i1} = X_{i1}\gamma_1 + \mu_{i1} \quad if\ V = 1 \tag{7a}$$

$$\text{Regime 2 (written contract):} \quad Y_{i2} = X_{i2}\gamma_2 + \mu_{i2} \quad if\ V = 2 \tag{7b}$$

$$\text{Regime 3 (Verbal Contract):} \quad Y_{i3} = X_{i3}\gamma_3 + \mu_{i3} \quad if\ V = 3 \tag{7c}$$

where Y_{i1}, Y_{i2} and Y_{i3} are outcomes such as net farm incomes, total farm income, and total household income from participating in spot markets, written and verbal contracts, respectively; X is a vector of household and farm level factors; γ is a vector of parameters to be estimated, and μ is the error term. We identify the model since variables in Z in eq. (4) and X in eqs. (7a-7c) are allowed to overlap during estimation. In such cases, at least one variable in Z should not feature in X (see section 6.1). Therefore, to obtain unbiased and consistent estimates of γ in the outcome equations, we estimate the following regimes of selection bias corrected outcome equations (Bourguignon *et al*., 2007):

$$\text{Regime} \quad 1: \; Y_{iSM} = X_{i1}\gamma_1 + \sigma_1\left[\rho_1 m(P_{i1}) + \sum_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right] + \nu_{i1} \quad \text{if } V = 1 \quad (8a)$$

$$\text{Regime} \quad 2: \; Y_{iWC} = X_{i2}\gamma_2 + \sigma_2\left[\rho_2 m(P_{i2}) + \sum_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right] + \nu_{i2} \quad \text{if } V = 2 \quad (8b)$$

$$\text{Regime} \quad 3: \; Y_{iVC} = X_{i3}\gamma_3 + \sigma_3\left[\rho_3 m(P_{i3}) + \sum_j \rho_j m(P_{ij})\frac{P_{ij}}{(P_{ij}-1)}\right] + \nu_{i3} \quad \text{if } V = 3 \quad (8c)$$

where P_{ij} is the probability that farmer i chooses coordination mechanism j, ρ_j represents the correlation between μ_{ij} and η_{ij}, and $m(P_{ij})$ is the conditional expectation of η_{ij}, used to correct for selection bias, σ_j is the standard deviation of μ_{ij}, ν_{ij} is the error term. Note that a significant selectivity correction term $m(P_{ij})$ associated with any coordination specification indicates the presence of selection bias, and insignificant term suggests that selection bias is absent and OLS method could produce consistent estimates.

2.5.2 Treatment Effects of Vertical Coordination Mechanisms

The average treatment effects on the treated (ATT), which is the causal effect of vertical coordination mechanisms can also be estimated using the multinomial BFG model. Farmers who participate in written contracts and those who use verbal contracts constitute the treatment groups and separate predictions of the treatment effects are carried out, relative to farmers who supply paddy in spot markets. In particular, the conditional expectations of the outcomes from written contract ($j = 2$) and verbal contract ($j = 3$) participation, with spot market as base, is specified as (Bourguignon *et al.*, 2007):

$$E(Y_{i2}|V=2) = X_{i2}\gamma_2 + \sigma_2\left[\rho_2 m(P_{i2}) + \rho_1 m(P_{i1})\frac{P_{i1}}{(P_{i1}-1)} + \rho_3 m(P_{i3})\frac{P_{i3}}{(P_{i3}-1)}\right] \qquad (9a)$$

$$E(Y_{i3}|V=3) = X_{i3}\gamma_3 + \sigma_3\left[\rho_3 m(P_{i3}) + \rho_1 m(P_{i1})\frac{P_{i1}}{(P_{i1}-1)} + \rho_2 m(P_{i2})\frac{P_{i2}}{(P_{i2}-1)}\right] \qquad (9b)$$

The conditional expectations of the outcomes of farmers who participate in written contracts and those who use verbal contracts in output transactions in the counterfactual case that they sell in spot market is specified as;

$$E(Y_{i1}|V=2) = X_{i1}\gamma_1 + \sigma_1\left[\rho_1 m(P_{i2}) + \rho_2 m(P_{i1})\frac{P_{i1}}{(P_{i1}-1)} + \rho_3 m(P_{i3})\frac{P_{i3}}{(P_{i3}-1)}\right] \qquad (10a)$$

$$E(Y_{i1}|V=3) = X_{i1}\gamma_1 + \sigma_1\left[\rho_1 m(P_{i3}) + \rho_2 m(P_{i1})\frac{P_{i1}}{(P_{i1}-1)} + \rho_3 m(P_{i2})\frac{P_{i2}}{(P_{i2}-1)}\right] \qquad (10b)$$

The ATT is computed as the difference between equations $(9a)$ and $(10a)$, and $(9b)$ and $(10b)$, respectively. If we represent the inverse mills ratios in the brackets of equations $(9a)$ and $(10a)$, and $(9b)$ and $(10b)$ by λ, the ATTs for written contract $(11a)$ and verbal contract $(11b)$ can be respectively specified as:

$$ATT_{WC} = E(Y_{i2}|V=2) - E(Y_{i1}|V=2) = X_{i2}(\gamma_2 - \gamma_1) + \lambda_{i2}(\sigma_2 - \sigma_1) \qquad (11a)$$

$$ATT_{VC} = E(Y_{i3}|V=3) - E(Y_{i1}|V=3) = X_{i3}(\gamma_3 - \gamma_1) + \lambda_{i3}(\sigma_3 - \sigma_1). \qquad (11b)$$

2.6 Empirical Results and Discussion

2.6.1 Drivers of vertical coordination mechanism choices among rice farmers

The marginal effects of factors affecting farmers' coordination mechanism choices are presented in table 2.3. Note that farmers who supply paddy in spot market constitute the base group for comparison in the analysis. The results from diagnostic tests, such as the suest-based Hausman tests of Independence of Irrelevant Alternatives (IIA) and Wald test for combining alternatives indicate that the null hypotheses fail to be rejected, implying that the farmers have been appropriately categorized based on the coordination mechanism participation (see Table 2.A3 in the appendix). We also identified the multinomial BFG model to ensure unbiased and consistent outcome estimates, by including in the coordination choice model, two valid instruments that significantly influence coordination choice decisions but are uncorrelated with the outcomes. In particular, we use variables representing farmers' perceptions about paddy market demand and importance attached to legal contracts as instruments. In a two-stage procedure, these instruments are included in both stages of the multinomial BFG model and their significance levels tested in each stage (Dimova & Gang, 2007). The chi-square tests indicate the significance of these instruments at 1% level in the coordination choice model and insignificant in the outcome models for all the three coordination specifications, suggesting that the instruments are valid (see Table 2.A3 in appendix). As shown in table 2.3, farmers with perception of low paddy market demand are more likely to engage buyers via written contracts, and less likely to supply paddy in spot markets. This finding is consistent with the notion that contracting is used to deal with sluggish markets through providing smallholder farmers with guaranteed markets. In addition, farmers who consider legal contracts important in output transactions are more likely to engage buyers with written contracts, and less likely to supply in spot market. This suggests that the farmer sensitization on contracting and output market management in value chain interventions is yielding positive results in the study area.

It is important to point out that some of the variables in the coordination choice model such as access to credit and association membership are potentially endogenous. Access to credit is an important determinant of vertical coordination choice for output transactions in the study area. Farmers who are resource-constrained require sufficient financial capital to purchase inputs and pay for labor expenses. In this study, access to credit variable was constructed by seeking responses from a farmer on whether he/she needed credit, and if so whether he/she obtained the amount of credit required (Jappelli, 1990; Baydas, Meyer, & Aguilera-Alfred, 1994; Jappelli, Pischke, & Souleles, 1998). Therefore, a farmer who did not require credit, or demanded credit for paddy production and marketing, applied for it, and received the required credit amount is assigned a value of one, and zero otherwise. Agribusiness companies and other produce buyers in supply contract agreement with farmers may advance credit to these farmers, which is deducted from produce at point of delivery. On the other hand, farmers who received credit from financial institutions may choose to enter into contracts with buyers to ensure guaranteed market for their produce, as well as facilitate timely credit repayment. Therefore, farmers' decisions to participate in contract, and access credit may be jointly determined, making access to credit variable potentially endogenous in coordination choice model. In the same vein, smallholder farmers often join associations to enter into contractual arrangements with a buyer, reduce transaction costs, and improve their bargaining power in output markets (Bolwig et al., 2009; Ragasa & Golan, 2014). In that case, belonging to a farmer association could be regarded as a precondition for participating in vertical coordination. This makes association membership potentially endogenous in the vertical coordination model.

We account for the endogeneity of access to credit and association membership variables using a two-stage control function approach outlined in Wooldridge (2015). The first stage involves estimating separately access to credit and association membership variables as functions of all other explanatory variables in the vertical coordination choice model, including a set of valid instruments. These instruments should significantly influence access to credit and association membership, but not participation in vertical coordination. For access to credit, we use farmers' knowledge of credit sources as an instrument, which significantly influences access to credit, but not vertical coordination choice. The available credit sources in the study area include commercial banks, rural banks, financial NGOs (FNGOs), and microfinance companies, although farmers may also obtain credit from informal sources including friends and relatives, as well as other informal money lenders. In this study, the farmers' knowledge of credit sources variable is captured as a dummy variable, where one is assigned to a farmer who is aware of these existing credit sources, and zero otherwise. The results indicate that farmers with knowledge of credit sources are more likely to apply for credit, a finding that is consistent with the result reported by Dutta & Magableh (2006) for Jordan. However, having knowledge of credit sources does not appear to influence farmers' decisions to participate in vertical coordination in output transactions.

With regards to membership in farmers' associations, we used distance from a farmer's home to meeting venue of the association as instrument. We argue that further distance to association's meeting point discourages potential members from joining the association, as they may not effectively take part in meetings and other group activities. The results reveal that farmers who reside further away from association's meeting venue are less likely to be members of farmers' associations. However, distance to association's meeting venue did not have significant influence on vertical coordination participation. The results of the first stage regression estimates are presented in table 2.A2 in the appendix. In the second stage, both the observed access to credit and association membership variables and their respective predicted residuals from the first stage are included in the vertical coordination choice model (MNL). Table 2.3 shows that the access to credit and association membership residuals for all the coordination specifications are not statistically significant, implying that the model has been estimated consistently (Wooldridge, 2010).

The marginal effect of observed access to credit variable is positive and significant for written contracts and significantly negative for spot market specification, suggesting that rice farmers who had access to enough credit, and not credit constrained are more likely to engage buyers using written contracts, and less likely to supply paddy in spot markets. Association membership exhibits a positive and significant impact on written contracts and verbal contracts choices but negative and significant impact on spot market transactions, suggesting that farmers who belong to farmer associations are more likely to engage paddy buyers in output transactions, using written contracts and verbal contracts, but less likely to supply paddy in spot markets. This finding is consistent with Bellemare & Novak (2016), and Maertens & Vande Velde (2017). Farmers belonging to farmers' associations normally benefit from collective action through collective marketing, bulk input purchase, and other group activities, which enable members to enjoy economies of scale, increased bargaining power, and reduced transaction costs.

Table 2.3: Determinants of vertical coordination mechanism choices: MNL model

Variable	Spot market		Written contract		Verbal contract	
	Marginal effects	S.E	Marginal effects	S.E	Marginal effects	S. E
Age	-0.002	0.003	-0.003	0.002	0.005 **	0.002
Credit access	-0.206***	0.067	0.147 **	0.062	0.058	0.058
Education	-0.012	0.008	0.004	0.006	0.008	0.006
Gender	0.026	0.105	0.039	0.085	-0.065	0.092
Farm Size	-0.036	0.027	-0.016	0.023	0.019	0.022
Labor	-0.003 **	0.001	0.002 **	0.001	0.001	0.001
Dist. to market	0.002	0.008	-0.007	0.007	0.005	0.006
Mobile phone	-0.214 **	0.089	0.112	0.081	0.101	0.075
Road status	-0.067	0.098	0.066	0.084	0.001	0.081
Import. of legal contract	-0.330***	0.088	0.349***	0.076	-0.019	0.075
Market perception	-0.223***	0.074	0.287***	0.075	-0.063	0.065
Association	-0.560***	0.047	0.305***	0.049	0.254 ***	0.048
Farm vehicle	0.120	0.128	-0.178 **	0.078	0.058	0.109
Institutional buyer	-0.340***	0.065	0.354***	0.090	-0.013	0.078
Sagnarigu	0.055	0.169	0.189	0.165	-0.245***	0.065
SaveluguNanton	-0.200 **	0.085	0.342***	0.102	-0.141***	0.068
Tolon	-0.104	0.103	0.173	0.114	-0.068	0.081
Kumbungu	0.079	0.112	0.100	0.107	-0.179 **	0.068
Credit residual	-0.041	0.247	0.175	0.220	-0.133	0.213
Association residual	0.508	0.505	-0.588	0.469	0.079	0.413

Note: Based group is spot market; **, *** mean significant at 5% and 1% levels, respectively.

Age exhibits positive effect on verbal contract choice, suggesting that relatively older farmers are more likely to choose verbal contracts in output transactions, and are less likely to choose written contracts and spot market transactions. The results also show that farmers who engage more labor in farm activities are more likely to choose written contracts in output transactions, and less likely to supply in spot market. Mobile phone ownership shows a significant negative effect on spot market transactions, and positive but insignificant effect on written and verbal contracts, suggesting that farmers who own mobile phones are less likely to sell in spot markets, and more likely to engage buyers using written and verbal contracts. The use of mobile phones promotes effective communication, and facilitates acquisition of information on inputs and output prices, which could guide farmers to negotiate for better prices, as well as reduce transaction costs associated with buyer search, and setting up transactions (Akar, Ghosh, & Burrell, 2016). In addition, farmers who use written and verbal contracts already have their produce buyers, who have carried out successful business exchanges with these farmers over the past five years. This category of farmers easily contact and notify their buyers to arrange for produce pick-up, especially when paddy delivery is at farmgate. We also find that farmers who sell their produce to institutions and produce buying companies are more likely to engage these buyers via written contracts, and less likely with verbal contracts and spot market. The findings on location variables reveal that, relative to Tamale metropolis (reference area), rice farmers in Savelugu-Nanton and Kumbungu districts are more likely to use written contracts, but less likely to engage buyers through spot market and verbal contracts, implying that location fixed effects also play important role in vertical coordination choices in output markets.

2.6.2 Impact of vertical coordination mechanisms on farm performance outcomes

The multinomial BFG model is estimated for each farm performance outcome: net farm income, total farm income and total household income, labor productivity and price margins. However, we display only the net farm income estimates (table 2.4) due to space limitation, but estimates of the other outcomes are available upon request. Note that the estimator variances were bootstrapped with 100 replications to account for heteroscedasticity (Huesca & Camberos, 2010). Three selectivity correction terms related to the three coordination mechanisms have been revealed by the study, which are used to control for selection bias. According to Dimova and Gang (2007), for each net farm income specification, a negative (positive) selectivity correction term related to any coordination mechanism indicates lower (higher) net farm income than those of randomly chosen farmers, suggesting that farmers with better (worse) unobserved attributes switch from using the given coordination mechanism into using the alternative coordination mechanism.

The results show significant selectivity correction terms for spot market and written contract specifications, indicating the presence of selection bias, and lending support to the estimation of the multinomial BFG model. In particular, the selectivity correction term related to verbal contract in the spot market specification is found to be negative and statistically significant at 5% level, suggesting that net farm income from spot market transactions are downward biased relative to randomly chosen farmers. This means that for farmers using verbal contracts, switching to spot market transactions would lead to a significantly negative impact on their net farm incomes. Also, in spot markets, farmers with unobserved attributes linked to higher net farm income have switched towards using verbal contracts in output transactions. The results also reveal a positive and significant selectivity correction term related to verbal contract in the written contract specification. In other words, net farm incomes from participating in written contracts are upward biased, because farmers with worse unobserved attributes switch from using written contracts to engaging buyers with verbal contracts.

We also present net farm income estimates when Lee's model is used in accounting for selection bias (see table 2.A1 in appendix). As previously stated, Lee's model estimates a single selectivity correction term for all coordination choices and fails to provide insight as to which coordination mechanism constitutes the source of the bias. It reveals insignificant selectivity correction term in the net farm income estimation, suggesting that the model fails to account for the fact that the net farm incomes have been influenced by farmers who move to different coordination mechanisms, because they do not perform well under other coordination mechanisms.

Table 2.4: Impact of vertical coordination mechanisms on net farm income: BFG estimation

Variable	Spot market		Written contract		Verbal contract	
	Coefficients	S.E	Coefficients	S.E	Coefficients	S.E
Constant	4.092***	0.558	7.022 ***	1.325	2.574	2.681
Age	0.011	0.010	-0.014	0.012	0.005	0.013
Credit access	-0.450	0.276	0.191	0.264	0.231	0.302
Education	-0.011	0.032	0.043**	0.022	0.055	0.038
Gender	1.045***	0.356	0.084	0.503	1.912**	0.905
Farm Size	0.224**	0.115	0.212**	0.096	0.329**	0.149
Labor	0.001	0.005	-0.007*	0.004	-0.006	0.005
Dist. to market	-0.025	0.028	-0.020	0.029	-0.010	0.030
Mobile phone	-0.173	0.346	0.511**	0.263	0.872**	0.435
Road status	0.245	0.274	-0.112	0.237	0.143	0.308
Association	-0.706	0.739	0.333	0.522	0.290	0.915
Farm vehicle	0.560 *	0.339	-0.547	0.559	1.207***	0.405
Institutional buyer	-1.077 **	0.442	0.257	0.333	0.747	0.515
Sagnarigu	-0.251	0.571	-0.167	0.684	-0.458	0.748
Savelugu Nanton	0.415	0.349	0.305	0.458	0.148	0.639
Tolon	0.115	0.275	0.157	0.421	0.654	0.398
Kumbungu	1.090***	0.382	0.808 **	0.401	0.389	0.653
m(P1)	-0.087	0.901	-0.047	1.813	-2.461	2.595
m(P2)	-1.206	1.798	-0.061	0.627	-2.478	1.895
m(P3)	-2.013**	0.904	2.906 **	1.538	-0.078	0.768

Note: The dependent variable is log of net farm income; *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Examining the determinants of net farm incomes conditional on the choice of coordination mechanisms, table 2.4 shows positive and statistically significant effect of farm size on net farm income associated with the coordination mechanism specifications. This finding suggests that farmers with relatively larger farm sizes earn significantly higher net farm incomes. While our finding is consistent with studies by Park et al. (2014), other studies found negative and statistically significant impact of farm size on net farm incomes (eg. Ma & Abdulai, 2016). Education exhibits positive and statistically significant impact on net farm incomes for the written contract specification, suggesting that better education contributes to higher net farm incomes for farmers participating in written contracts.

The results also show that farmers who own farm vehicles and participate in verbal contracts, or supply paddy in spot market tend to obtain higher net farm incomes, as revealed by the positive and significant coefficients of farm vehicle ownership for spot market and verbal contract specifications. The variable representing sales to institutional buyers has a negative and statistically significant impact on net farm incomes from spot market transactions, implying that this category of farmers earn significantly lower net farm incomes. A number of factors could be driving this finding. First, farmers who supply in spot markets may not be able to produce paddy to meet the quality requirement of institutional buyers due to resource constraints, thus resulting in lower produce prices and ultimately lower net farm incomes. In addition, this category of farmers may lack the capacity to negotiate effectively for better prices for their produce, also contributing to reduced net farm incomes.

2.6.3. Average treatment effects of vertical coordination mechanisms on farm performance outcomes

Table 2.5 reports the average treatment effects on the treated (ATT) of written and verbal contracts participation on farm performance outcomes such as net farm income, total farm income, and total household income, using the multinomial BFG method. As shown in table 2.5, participating in written contracts is associated with a significant increase in net farm income, total farm income and total household income by 8.10%, 4.38%, and 5.47%, respectively, relative to spot market supply. For rice farmers who engage buyers through verbal contracts, participation significantly increases net farm income, total farm income and total household income by 5.61%, 2.70%, and 2.85%, respectively, compared to that of farmers who supply paddy in spot market. As can be observed, the results show that the highest gain in farm performance is

Table 2.5: Average treatment effects of vertical coordination mechanisms on outcomes

Outcome variable	**Mean outcome**		**ATT**	**t-value**	**Change (%)**
Net farm income	Written contract	Spot market			
	6.559 (0.634)	6.068 (0.987)	0.491	5.144***	8.10%
	Verbal contract	Spot market			
	6.495 (0.828)	6.150 (0.847)	0.345	3.057***	5.61%
Total farm income	Written contract	Spot market			
	7.904 (0.560)	7.572 (0.922)	0.332	3.775***	4.38%
	Verbal contract	Spot market			
	7.827 (0.642)	7.621 (0.713)	0.206	2.253**	2.70%
Total household income	Written contract	Spot market			
	8.132 (0.496)	7.710(0.818)	0.422	5.424***	5.47%
	Verbal contract	Spot market			
	7.882 (0.626)	7.663 (0.723)	0.219	2.405**	2.85%
Labor productivity	Written contract	Spot market			
	3.135 (0.520)	2.977 (0.822)	0.157	1.991***	5.27%
	Verbal contract	Spot market			
	3.167 (0.485)	3.092 (0.709)	0.075	0.915	2.42%
Price margin	Written contract	Spot market			
	0.523 (0.098)	0.405 (0.153)	0.118	8.139***	29.14%
	Verbal contract	Spot market			
	0.519 (0.099)	0.457 (0.142)	0.061	3.725***	13.34%

Note: ATT: average treatment effect on the treated, the dependent variable is the log of the outcome variables. Computation of ATT is based on the log of the predictions. **, *** mean significant at 5% and 1% levels respectively.

associated with participation in written contracts, relative to verbal contacts and spot market participation. Our findings are consistent with other recent studies, which report that the use of contracts in output markets contributes significantly to promoting market access and increasing incomes of smallholder farmers (eg. Bellemare, 2012; Ma & Abdulai, 2016). As stated earlier, one of the objectives of this study is to examine the impact of vertical coordination mechanisms on labor productivity (Q/L) and price margin $(p - W\omega/Q)$. The results are shown in the lower part of table 2.5. We find that participation in written contracts increases labor productivity by 5.27% at the 1% significance level. However, verbal contract participation is associated with about 2.42% increase in labor productivity, although not statistically significant. Table 2.5 also shows that farmers who transact with paddy buyers through written contracts experience 29.14% significant increase in price margin, while verbal contract participation is associated with a significant increase in price margin by 13.34%. These findings are consistent with the results obtained by Ito et al. (2012), and suggest that output market transactions using written and verbal contracts contribute to improvement in labor productivity and price margins, relative to spot market transactions, with the highest gains associated with the use of written contracts.

To gain further insights on the impact of vertical coordination mechanisms on farm performance, we examine the differential impacts of written and verbal contracts participation on net farm income, labor productivity, and price margin for different farm sizes. Based on our data, we classify farm size into two categories (small, ≤ 1.5ha; and large, >1.5ha). The results are presented in table 2.6. As can be observed, the results show that farmers with small farm sizes participating in written and verbal contracts experience significant increase in net farm incomes by 9.64% and 5.97% respectively, relative to spot market transactions. On the other hand, gains in net farm incomes associated with written and verbal contracts participation for farmers with large farm sizes are although positive, but not significantly different from zero.

This finding is consistent with the results obtained by Ito et al. (2012), and Ma & Abdulai (2016). With respect to labor productivity, table 2.6 shows that relative to spot market transactions, participation in written and verbal contracts is associated with a significant increase in labor productivity by 9.88% and 6.06%, respectively for farmers with small farm sizes. However, for farmers with large farm sizes, participating in written and verbal contracts decreases labor productivity, although not statistically significant. This finding can be attributed to the fact that farmers with large farm sizes employ relatively higher amount of labor in paddy production, which contributes to declining marginal labor productivity.

Table 2.6: Average treatment effects of vertical coordination mechanisms on outcomes disaggregated by farm size

Outcome variable	**Mean outcome**		**ATT**	**t-value**	**Change (%)**
Net farm income	Written Contract	Spot market			
Small (≤ 1.5ha)	6.449 (0.544)	5.882 (0.869)	0.567	6.127***	9.64%
Large (>1.5ha)	7.044 (0.772)	6.885 (1.071)	0.159	0.637	2.30%
	Verbal contract	Spot market			
Small (≤ 1.5ha)	6.319 (0.766)	5.962 (0.780)	0.356	3.026***	5.97%
Large (>1.5ha)	7.128 (0.739)	6.823 (0.742)	0.304	1.424	4.45%
Labor productivity	Written contract	Spot market			
Small (≤ 1.5ha)	3.046 (0.447)	2.771 (0.502)	0.274	4.526***	9.88%
Large (>1.5ha)	3.527 (0.634)	3.883 (1.254)	-0.356	-1.340	-9.16%
	Verbal contract	Spot market			
Small (≤ 1.5ha)	3.071 (0.425)	2.896 (0.500)	0.174	2.466**	6.06%
Large (>1.5ha)	3.514 (0.538)	3.795 (0.896)	-0.281	-1.319	-7.40%
Price margin	Written contract	Spot market			
Small (≤ 1.5ha)	0.526 (0.092)	0.423 (0.135)	0.103	7.005***	24.34%
Large (>1.5ha)	0.508 (0.085)	0.325 (0.200)	0.182	4.452***	56.00%
	Verbal contract	Spot market			
Small (≤ 1.5ha)	0.496 (0.084)	0.381 (0.142)	0.115	5.322***	30.18%
Large (>1.5ha)	0.600 (0.105)	0.370 (0.182)	0.230	5.367***	62.16%

Note: ATT: average treatment effect on the treated, the dependent variable is the log of the outcome variables. Computation of ATT is based on the log of the predictions. **, *** mean significant at 5% and 1% levels respectively.

We also find that participation in written and verbal contacts tends to increase price margins, albeit more favorable for farmers with large farm sizes. In particular, farmers with small farm sizes who participate in written and verbal contracts experience significant gains in price margins by 24.34% and 30.18% respectively, while farmers with large farm sizes tend to obtain 56.00% and 62.16% increases in price margins, respectively. These results suggest that farmers with large farm sizes tend to benefit more in terms of price margins, compared to farmers with small farm sizes, which is in line with the notion of scale economies, since average fixed costs associated with written and verbal contract participantion decline with larger farm sizes. The results of the ATT generally indicate that participation in written and verbal contracts tends to improve farm performance significantly, relative spot market transactions.

6. Conclusions

This study examined the determinants of smallholder participation in vertical coordination mechanisms and their related impacts on farm performance, using multinomial BFG model to account for selection bias associated with observed and unobserved attributes. The empirical results revealed that participation in written and verbal contracts in smallholder output transactions tend to improve farm performance outcomes such as net farm income, total farm income, total household income, labor productivity and price margins, relative to farmers who supply paddy in spot markets. Farmers who participate in written contracts tend to perform better than their counterparts who engage buyers with verbal contracts. The estimates disaggregated by farm sizes indicate that farmers with small farm sizes and participating in written and verbal contracts earn higher net farm income, and labor productivity than farmers with large farm sizes. However, farmers with large farm sizes tend to benefit more from price margins.

Participation in vertical coordination is significantly influenced by access to credit, mobile phone ownership, labor, membership in farmers' associations, sales to institutional buyers, market perception, and importance attached to legal contracts. Education, farm size, mobile phone and farm vehicle ownership are found to be the important determinants of net farm incomes. Our estimates also show that accounting for selection bias using the multinomial BFG model is more appropriate, because not only does it consistently estimate the impact on farm performance outcomes, but also provides information on the source and direction of the bias. The significant selectivity correction terms associated with the spot market and written contract specifications indicate the presence of selection bias.

The findings from this study do have some policy implications, and clearly suggest that targeting output transactions with innovative marketing and risk management techniques such as contracting would improve smallholder farm performance and livelihoods significantly. This calls for promotion of contracts in smallholder output transactions, especially with the renewed interests of government and donor agencies in transforming the domestic rice value chain in Ghana. However, Government and NGOs in collaboration with private agribusinesses, aggregators, and other produce buyers should intensify their engagement with smallholder farmers on the importance and use of legal contracts in output transactions, which could be an important contributor to improved and effective participation in agrifood value chains. The positive impact of education on contractual choices and farm performance calls for government investment in rural education, which could build up and protect human capital for improved labor productivity, and other rural livelihood opportunities. Incorporating credit schemes into agricultural value chain interventions could also ease smallholder credit constraints, promote pro-poor agricultural growth and smallholder welfare in Ghana. Finally, institutional innovations such as formation of farmer associations could also be re-examined and promoted, because of its role in reducing transaction costs and enhancing market access.

References

Abdulai, A., & Birachi, E.A. (2009). Choice of coordination mechanisms in the Kenyan fresh milk supply chain. *Review of Agricultural Economics*, 31, 103–121.

Akar, J. C., Ghosh, I., & Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics,* 47(2016): 35-48.

Angelucci, F., Asante-Poku, A., & Anaadumba, P. (2013). Analysis of incentives and disincentives for rice in Ghana. *Technical notes series*, MAFAP, FAO, Rome.

Barrett, C.B., Bachke, M.E., Bellemare, M.F., Michelson, H.C., Narayanan, S., & Walker, T.F. (2012). Smallholder participation in contract farming: Comparative evidence from five countries. *World Development*, 40, 715-730.

Baydas, M., Meyer, R., & Aguilera-Alfred, N. (1994). Discrimination against Women in Formal Credit Market: Reality or Rhetoric? *World Development*, 22 (7), 1073-1082.

Bellemare, M.F. (2012). As you sow, so shall you reap: The welfare impacts of contract farming. *World Development*, 40, 1418-1434.

Bellemare, M.F. & Novak, L. (2017). Contract farming and food security. *American Journal of Agricultural Economics*, 99 (2), 357-378.

Bourguignon, F., Fournier, M., & Gurgand, M. (2007). Selection bias corrections based on the multinomial logit model: Monte Carlo comparisons. *Journal of Economic Surveys*, 2, 174-205.

Bolwig, S., Gibbon, P., & Jones, S. (2009). The Economics of Smallholder Organic Contract Farming in Tropical Africa. *World Development*, 37 (6), 1094–1104.

Dimova, R., & Gang, I. N. (2007). Self-selection and wages during volatile transition. *Journal of Comparative Economics,* 35, 612-629.

Dubin, J.A., & McFadden, D.L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica,* 52, 345-362.

Dutta, D., & Magableh, I. (2006). A socio-economic study of the borrowing process: the case of microentrepreneurs in Jodan. *Applied Economics*, 38, 1627-1640.

Global Agricultural Information Network-GAIN. (2018). Grain and feed update in Ghana. USDA Foreign Agricultural Service.

Henderson, H., & Isaac, A. G. (2017). Modern value chains and the organization of agrarian production. *American Journal of Agricultural Economics*, 99, 379-400.

Huesca, L., & Camberos, M. (2010). Selection bias correction based on the multinomial logit: an application to the Mexican labour market, 2nd Stata Users Group Meeting Mexico, Universidad Iberoamericana Campus Mexico, April 29.

Ito, J., Bao, Z., & Su, Q. (2012). Distributional effects of agricultural cooperatives in China: Exclusion of smallholders and potential gains on participation. *Food Policy*, *37*(6), 700–709.

Jappelli, T. (1990). Who is Credit Constrained in the U. S. Economy? *The Quarterly Journal of Economics*, 105 (1), 219-234.

Jappelli, T., Pischke, J., & Souleles, N. (1998). Testing for Liquidity Constraints in Euler Equations with complementary Data Source. *The Review of Economics and Statistics*, 80 (2), 251-262.

Kariuki, I. M., & Loy, J. P. (2016). Contractual Farming Arrangements, Quality Control, Incentives, and Distribution Failure in Kenya's Smallholder Horticulture: A Multivariate Probit Analysis. *Agribusiness: an International Journal*, 32 (4), 547-562.

Lee, L.F. (1983). Generalized econometric models with selectivity. *Econometrica*, 51, 507-512.

Long, J., & Freese, J. (2005). Regression models for categorical dependent variables using Stata (2nd ed.). *College Station*, TX: Stata Press.

Ma, W., & Abdulai A. (2016). Linking farmers to markets: Determinants and impacts of marketing contracts in China. *China Agricultural Economic Review*, 8 (1): 1-21.

Ma, W., &Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, *58*, 94–102.

Maertens, M., & Vande Velde, K. (2017). Contract farming in staple food chains: The case of rice in Benin. *World Development*, 95, 73–89.

Michelson, H. C. (2013). Small farmers, NGOs, and a walmart world: welfare effects of supermarkets operating in Nicaragua. *American Journal of Agricultural Economics*, 95, 628-649.

Minot, N., & Sawyer, B. (2016). Contract Farming in Developing Countries: Theory, Practice, and Policy Implications in André Devaux, Maximo Torero, Jason Donovan and Douglas Horton eds. *Innovation for Inclusive Value-chain Development: Successes and Challenges*, Washington D.C.: *International Food Policy Research Institute*, 127-155.

Mishra, A. K., Kumar, A., Joshi, P. K., Dsouza, A. (2018). Cooperatives, contract farming, and Farm size: The case of tomato producers in Nepal. *Agribusiness: an International Journal*, 2018, 1–22.

MoFA. (2016). Agricultural sector progress report. Monitoring and Evaluation Directorate.

MoFA., 2009. National Rice Development Strategy (NRDS). Coalition for African Rice Development, Accra.

Otsuka, Keijiro, Yuko Nakano and Kazushi Takahashi (2016). Contract Farming in Developed and Developing Countries, *Annual Review of Resources Economics*, 8(1), 353-376.

Park, T., Mishra, A.K., & Wozniak, S.J. (2014). Do farm operators benefit from direct to consumer marketing strategies? *Agricultural Economics*, 45, 213-224.

Ragasa, C., & Golan, J. (2014). The role of rural producer organizations for agricultural service provision in fragile states. *Agricultural Economics*, 45, 537-553.

Ragasa, C., Dankyi, A., Acheampong, P., Wiredu, A. N., Chapoto, A., Asamoah, M., & Tripp, R. (2013). Patterns of adoption of improved rice technologies in Ghana. IFPRI working Paper 35, *International Food Policy Research Institute (IFPRI)*, Washington DC.

Rao, E.J.O., & Qaim, M. (2011). Supermarkets, farm household income, and poverty: insights from Kenya. *World Development*, 39, 784-796.

Roussy, C., Ridier, A., Chaib, K., Boyet, M. (2018). Marketing contracts and risk management for cereal producers. *Agribusiness: an International Journal*, 34, 616–630.

Saenger, C., Torero, M., & Qaim, M. (2014). Impact of third-party contract enforcement in agricultural markets- A field experiment in Vietnam. *American Journal of Agricultural Economics*, 96, 1220-1238.

Swinnen, J.F.M., & Maertens, M. (2007). Globalization, privatization, and vertical coordination in food value chains in developing and transition countries. *Agricultural Economics*, 37, 89–102.

Trifković, N. (2016). Vertical coordination and farm performance: Evidence from the catfish sector in Vietnam. *Agricultural Economics*, 47, 547–557.

USAID. (2009). Global food security response, West Africa rice value chain analysis. MicroREPORT #156.

Wooldridge, J.M. (2010). Econometric analysis of cross section and panel data, MIT Press, Cambridge, MA.

Wooldridge, J.M. (2015). Control function methods in applied econometrics. *The Journal of Human Resources*, 50 (2): 421-445.

Statistics, Research and Information Directorate (SRID). 2017. Agriculture In Ghana: facts and figures (2016). Ministry of Food and Agriculture, October, 2017, Accra.

Appendix

Table 2.A1: Impact of vertical coordination mechanisms on net farm income: Lee estimation

Variable	Spot market		Written contract		Verbal contract	
	Coefficients	S.E	Coefficients	S.E	Coefficients	S.E
Constant	4.040***	0.551	6.832***	1.203	5.000**	2.826
Age	0.015*	0.008	-0.021**	0.010	-0.005	0.021
Credit access	-0.384**	0.187	0.141	0.201	0.155	0.337
Education	-0.011	0.027	0.036*	0.021	0.040	0.054
Gender	1.086**	0.482	0.158	0.478	0.862	0.564
Farm Size	0.148	0.118	0.199**	0.091	0.326**	0.146
Labor	0.001	0.005	-0.006	0.004	-0.006	0.008
Dist. to market	-0.017	0.031	-0.031	0.028	-0.023	0.067
Mobile phone	-0.115	0.229	0.239	0.207	0.188	0.353
Road status	0.214	0.200	-0.132	0.215	0.134	0.311
Association	-0.884*	0.512	0.011	0.338	0.072	0.775
Farm vehicle	0.156	0.368	-0.676	0.732	1.064**	0.469
Institutional buyer	-0.961**	0.423	0.299	0.219	0.807	0.790
Sagnarigu	-0.173	0.414	0.350	0.437	-0.001	0.960
Savelugu Nanton	0.577**	0.296	0.617	0.387	0.463	0.720
Tolon	0.193	0.376	0.417	0.389	0.800	0.514
Kumbungu	1.196 ***	0.289	1.039***	0.386	0.755	0.767
$m(P_i)$	-0.710	0.602	0.198	0.368	0.025	1.538

Note: The dependent variable is the log of net farm income; *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 2.A2: First stage estimates for addressing potential endogeneity

Variables	Credit access		Association	
	Coefficient	Std. Err.	Coefficient	Std. err
Constant	-1.752***	0.642	-2.056	0.672
Age	0.007	0.008	0.008	0.009
Education	0.000	0.023	0.020	0.024
Gender	0.050	0.350	-0.172	0.351
Farm Size	0.041	0.080	-0.153	0.095
Labor	0.006	0.004	0.008*	0.004
Dist. to market	-0.014	0.027	0.044	0.032
Mobile phone	0.104	0.220	0.555**	0.220
Road status	0.064	0.241	0.575**	0.247
Import. of legal contract	0.087	0.209	0.682***	0.212
Market perception	0.391*	0.231	0.392*	0.237
Farm vehicle	0.021	0.397	0.110	0.403
Institutional buyer	- 0.036	0.267	0.303	0.290
Sagnarigu	0.235	0.403	0.383	0.429
SaveluguNanton	0.243	0.336	0.344	0.340
Tolon	0.208	0.337	0.384	0.342
Kumbungu	0.049	0.331	0.384	0.334
Association	0.344	0.215	-	-
Knowledge of credit sources	0.661***	0.220	-	-
Credit access	-	-	0.265	0.210
Distance to association meeting venue	-	-	-0.057**	0.022
Log likelihood	-285.29		-277.92	
Number of observations	458		458	

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 2.A3: Instrument validity and other diagnostic tests

Instrument variables (market perception and importance of legal contract)		
Multinomial logit model		
	$chi-square(X^2)$	$p-value$
Vertical coordination mechanisms (VCMs) choices	22.98	0.0001
BFG Impact specifications		
VCM Specification (*net farm income*)	$chi-square(X^2)$	$p-value$
1. Open market	1.37	0.5044
2. written contract	0.68	0.7101
3. verbal contract	0.71	0.7008
VCM Specification (*Total farm income*)		
1. Open market	0.56	0.7703
2. written contract	1.14	0.5645
3. verbal contract	0.16	0.9250
VCM Specification (*Total household income*)		
1. Open market	0.25	0.8843
2. written contract	0.92	0.6306
3. verbal contract	0.22	0.8955
VCM Specification (*labor productivity*)		
1. Open market	0.31	0.8579
2. written contract	0.99	0.6106
3. verbal contract	0.30	0.8601
VCM Specification (*price margin*)		
1. Open market	0.49	0.7825
2. written contract	1.75	0.4168
3. verbal contract	0.06	0.9683

Diagnostic tests results			
Suest-based Hausman tests of IIA assumption (N=458)			
Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives			
Choice alternative	$chi-square(X^2)$	df	$P > chi2$
1	14.348	21	0.854
2	17.031	21	0.709
3	16.416	21	0.746
Wald tests for combining alternatives (N=458)			
Ho: All coefficients except intercepts associated with a given pair of alternatives are 0 (i.e., alternatives can be combined)			
Choice alternative	$chi-square(X^2)$	df	$P > chi2$
1 & 2	124.320	20	0.000
1 & 3	89.772	20	0.000
2 & 3	44.210	20	0.001

Note: A significant test is evidence against Ho; df means degrees of freedom

Chapter 3

The role of farmer groups and collective marketing in improving smallholder farmers' livelihoods in rural Ghana

Awal Abdul-Rahaman and Awudu Abdulai

Department of Food Economics and Consumption Studies, University of Kiel, Germany

Submitted to *Journal of Rural Studies*

Abstract

Rapid transformation of agrifood value chains due to population growth, urbanization, rising consumer incomes and increased demand for food quality and safety has resulted in the need for smallholder farmers to coordinate horizontally through group formation and collective marketing to improve farm performance in developing countries. In this study, we use data from a recent survey of 447 rice farmers in rural areas of northern Ghana to examine the factors that promote these collective action decisions and their related implications on farm performance. We employ an endogenous switching regression model to account for potential selection bias. The data reveal that farmers that were members of farmer groups and participated in collective marketing obtained higher prices, and also incurred lower input costs. The econometric estimates show that age, access to credit, mobile phone ownership, distance to market and road status are the main drivers of group membership and collective marketing decisions. We also find positive and significant impacts of farmer group membership and collective marketing on farm net revenues.

Keywords: Collective action, smallholder rice farmers, farm net revenue, endogenous switching regression model.

3.1 Introduction

Over the past few decades, the contribution of smallholder agriculture to economic transformation and poverty reduction in developing countries has received considerable attention in research and development (Markelova et al., 2009; Verhofstadt and Maertens, 2014). Nonetheless, several challenges still impede smallholder farmers from effectively participating in both input and output markets. The main challenges include high transaction costs due to poor infrastructure and market imperfections, as well as limited access to credit and extension services (Mojo et al., 2017; Kaganzi et al., 2009; Fischer and Qaim, 2012). These challenges have resulted in increased development efforts in developing countries to improve both production capacities and access to markets (Markelova et al., 2009).

The rapid transformation in agrifood value chains stemming from rising consumer incomes, urbanization, and increasing consumer demand for food safety has resulted in the need for actor coordination in order to improve smallholder farm performance in developing countries (Reardon et al., 2009; Rao and Qaim, 2011). Effective organization of smallholders into groups to undertake production and marketing activities would help them strengthen their position in the agrifood value chain. Farmer group formation has been recognized as one of the development strategies for promoting collective action and facilitating market linkages in agrifood chains (Bernard and Spielman, 2009). It effectively contributes to reducing transaction costs, enhancing bargaining power to ensure higher output prices, and possibly lower input prices, fostering risk sharing and ensuring economies of scale (Bijman et al., 2006; Francesconi and Wouterse, 2015). African governments and NGOs are keenly interested in promoting the formation of farmer groups as a first step to commencing the implementation of agriculture and value chain development initiatives. For example, the Ghana ministry of food and agriculture

(MoFA) in collaboration with donor agencies[4], has intensified efforts to promote farmers' group formation as a means of improving farm performance and rural livelihoods (Salifu et al., 2010).

The implications of farmer groups in developing countries have been greatly contested across various strands of the literature. Some studies reveal that farmer groups promote successful participation in agrifood markets and enhance smallholder welfare. For example, Fischer and Qaim (2012) showed that in Kenya, participation in banana farmer groups resulted in price advantages and increased household income. A recent study by Mojo et al. (2017) found that Ethiopian coffee farmer groups experienced positive gains in household incomes and assets of members. By contrasts, findings from other studies suggest that farmer groups performed poorly, and in some cases, led to dissolution of the groups (Markelova et al., 2009; Kaganzi et al., 2009; Francesconi and Wouterse, 2015). For example, Bernard et al. (2008) found that farmer groups in Ethiopia failed to improve their level of commercialization, while a study by Nkhoma and Conforte (2011) on Malawi reported that farmer groups could not enhance their welfare, which they attributed to ineffective governance and management of the groups.

These mixed findings justify efforts in further exploring conditions that trigger successful operations of farmer groups, as well as mechanisms under which substantial benefits accrue to group members. Collective marketing undertaken by farmer groups is one of the important ways of ensuring sustainability of farmer groups, since it helps in reducing transaction costs, ensuring higher output prices, and lower input prices (Fischer and Qaim, 2012). In their study on Kenya, Fischer and Qaim (2012) found that about 40% of banana group members who did not participate in collective marketing, but engaged buyers on individual basis, experienced lower household incomes. This indicates that the use of farmer groups in agricultural development

[4] The government of Ghana, through funding from the World Bank has in the past invested over US$ 9 million for the formation and development of farmer groups under the Agricultural Services Sub-sector Investment Project (AgSSIP). Feed the Future (FtF), a USAID funded program is heavily supporting farmer groups to improve coordination and performance among rural smallholders.

interventions is as important as facilitating collective marketing within such groups to ensure economic transformation and poverty reduction in developing countries.

However, an issue of great interest from rural development perspective is whether or not members of farmer groups are willing and committed to participating in collective marketing. It is worth noting that some members of farmer groups do not participate in collective marketing due to myriad reasons, including but not limited to, difficulties in meeting quality requirements, lack of trust for group leaders, as well as the notion that they receive satisfactory prices by selling individually. Moreover, some group members live relatively far from the agreed paddy collection centers or in some cases, in different communities, thus making paddy bulking a challenge for such category of farmers. Thus, an issue that has not received much attention, particularly in the empirical literature is the extent to which farmer groups commit members to collective marketing, and how farmer groups and collective marketing impact on farm performance. Most of the studies mentioned earlier focused on the determinants of farmers' participation intensity in farmer groups (eg. Gyau et al., 2016). The study by Fischer and Qaim (2012), which employed PSM approach to examine the effects of banana groups on household welfare, disaggregated by collective marketing found that, for banana production in Kenya, belonging to a farmer group improves household income through collective marketing participation. But a widely known weakness of PSM method is its failure to account for farmer unobserved attributes such as farmer's innate skills, motivation and risk perception. However, the fact that group membership and collective marketing participation decisions are not randomly assigned, but involves farmers' self-selection, means that unobserved attributes still play a role in the decision process, which could bias the PSM estimates (Smith and Todd, 2005). Therefore, group membership and collective marketing decisions for improved farm performance in smallholder agriculture still require further assessment.

This study contributes to the growing literature on the role of farmer groups on farm performance in two ways. First, we explore the factors that influence farmers' decisions to join farmer groups and to participate in collective marketing. Second, we investigate the impact of group membership and collective marketing on farm performance, such as farm net revenues. The study uses recent cross-sectional data from 447 smallholder farmers in five selected districts of northern Ghana. We employ a bivariate probit model to assess the relationship between farmer group membership and collective marketing decisions, as well as factors that influence both decisions amongst smallholder rice farmers (Greene, 2012). An endogenous switching regression (ESR) model is then used to examine the impact of group membership and collective marketing on farm net revenues (Lokshin and Sajaia, 2004) and to account for observable and unobservable factors that could bias the coefficients of the estimates.

The rest of this paper proceeds as follows: section 2 presents a review of farmer horizontal coordination in Ghana. Section 3 presents the data and descriptive statistics of the variables used in the analysis. The conceptual framework employed to guide the empirical analysis is described in section 4, followed by specification of the empirical models in section 5. Section 6 discusses the empirical results, while conclusions and policy implications are presented in the final section.

3.2 Review on farmer groups in rural Ghana

The government of Ghana in collaboration with NGOs and donor agencies have in recent times implemented series of agriculture and value chain development programs aimed at promoting the formation of farmer groups. One of such programs involved a five year US$241 million agricultural development program launched in 2007, and funded by the Millennium Challenge Cooperation (MCC) of the USA, and implemented by the Millennium Development Authority (MiDA) under the Millennium Challenge Account (MCA) Ghana compact program. The program was aimed at enhancing smallholder competitiveness in high value markets through increased productivity and quality of agrifood crops (MiDA, 2013). About 1242 farmer groups operating in the cereals, legumes, fruits and vegetables value chains were recruited and registered with both MiDA and MoFA under the commercial development of farmer organizations (CDFO) component of the program. These groups were trained on organizational, business and technical capacity development modules prior to the commencement of their various agribusiness activities.

Overall, the MiDA project contributed to significant returns on investments in a transformed and competitive agricultural sector, enhanced speedy growth of the rural economy and a lowered poverty incidence among beneficiary smallholder farmers in Ghana. However, the program had a limited impact on farmer value chain integration and the promotion of collective investments by farmer groups. The attributed reasons were that collateral security for financial credit acquisition from financial institutions by farmer groups was provided by MiDA rather than orientating them to develop collective entrepreneurship spirit and their own financial capital formation, which denied majority of the farmer groups access to credit and also resulted in high loan default rate (ISSER, 2012).

The agriculture component[5] of the Feed the Future (FtF) program, an ongoing five year (2013-2018) USAID funded program, is another important program that is heavily investing in the formation and capacity building of farmer groups to enhance technology adoption, market access and overall livelihoods of smallholders in Ghana. The program aims at improving productivity, competitiveness, and incomes of smallholder farmers in the rice, soybeans and maize value chains, as well as improve nutrition and resilience of vulnerable populations in Northern Ghana. Several NGOs also work with farmer groups in Northern Ghana to promote smallholder market access. Among others include Technoserve, Agricultural Cooperative

[5] The project components under the FtF-USAID-Ghana programme include Agriculture Technology Transfer project (ATT), Resiliency in Northern Ghana (RING), Agricultural Development and Value Chain Enhancement (ADVANCE), Strengthening Partnerships, Results and Innovations in Nutrition Globally (SPRING) projects.

Development International and Volunteers Overseas Cooperative Assistance (ACDI/VOCA), Market Development for Northern Ghana (MADE), International Fertilizer Development Center (IFDC), German Agency for International Cooperation (GIZ), Adventist Development and Relief Agency (ADRA), Netherlands Development Organization (SNV), Action Aid Ghana, and Association of Church Development Projects (ACDEP).

The capacity building and orientation of farmer groups is gradually enhancing their commitment to participating in collective activities and performance in the agrifood chain. For example, a survey of 501 farmer groups in Ghana revealed that only about 13% of them participated in collective marketing (Salifu et al., 2012). This suggests that more development efforts are still required to enhance the level of collective marketing participation for improved smallholder farm performance in Ghana.

3.3 Conceptual framework

3.3.1. Group membership and collective marketing decisions

In this section, we present a conceptual framework that is based on the assumption that rice farmers make two binary decisions; (1) to join farmers' groups or not to join, (2) to participate in collective marketing or not to participate. To simplify the framework, we assume that rice farmers are risk neutral, and compare the benefits (D_M^*) generated from rice production and marketing as a group member or collective marketing participant to the benefits (D_N^*) from non group membership or non collective marketing participation. A farmer will choose to be a group member or collective marketing participant if the net benefits (D_i^*) from group membership and non-membership or collective marketing participation or non-participation is positive, that is, $D_i^* = D_M^* - D_N^* > 0$. However, since D_i^* is unobserved, we express it as a function of observable characteristics in a latent variable framework as:

$$D_i^* = Z_i\gamma + \varepsilon_i, \;\; D_i = 1[D_i^* > 0], \tag{1}$$

where D_i is the group membership or collective marketing participation indicator, assigned a value of one, and 0 otherwise, γ denotes a vector of parameters to be estimated, ε_i is the error term assumed to be independently and identically distributed with mean zero, and variance σ_ε^2, and Z_i is a vector of observable factors such as household and farm level factors influencing group membership or collective marketing participation decisions.

The probability of a farmer being a group member or collective marketing participant is expressed as:

$$\Pr(D_i = 1) = \Pr(D_i^* > 0) = \Pr(\varepsilon_i > -Z_i\gamma) = 1 - F(-Z_i\gamma) \quad (2)$$

where *F* denotes the cumulative distribution function for ε_i. Given the relation among group membership, collective marketing participation and farm net revenues, we assume that farmers maximize net revenues from rice production and marketing, which can be expressed as:

$$\pi_{max} = [PQ(\omega, Z) - W\omega] \quad (3)$$

where *P* is the price of output, *Q* is the expected output level, *ω* is the vector of input quantities, *Z* is a vector of farm and household level factors, *W* is a vector of input prices. It is worth noting that farmers are faced with varying levels of transaction costs (proportional and fixed) in both inputs and output markets, mostly caused by information asymmetry, which explains why they behave differently in a market situation (Key et al., 2000; Barret, 2008).

Proportional transaction costs essentially reduce output prices received by farmers and increase input prices purchased by farmers (Key et al., 2000; Abdulai and Birachi, 2009). We therefore incorporate into the framework the influence of transaction costs on input and output prices, as well as farm net revenues received by farmers. Let us denote the proportional transaction costs of accessing inputs and in selling output as W_τ^c and P_q^c, respectively. The actual price paid for the inputs (W_τ') and that received for the output (P_q') can then be expressed as $W_\tau' = W + W_\tau^c$ and $P_q' = P - P_q^c$, respectively. Now, if we denote fixed transaction costs associated with purchasing inputs as F_τ^c and the fixed transaction costs incurred in setting up output transaction as F_q^c, then farmers can be assumed to maximize the following farm net revenue function:

$$\pi_{max} = \left[\left(P - P_q^c\right)Q - (W + W_\tau^c)\omega - F_q^c - F_\tau^c\right] \tag{4}$$

Equation (4) implies that the farm net revenue from rice production and marketing can be expressed as a function of variable input quantities, input and output prices, proportional transaction costs associated with input and output market participation, farm and household level characteristics, group membership and collective marketing participation decisions D. This is specified as

$$\pi = \pi(W, P, D, P_q^c, W_\tau^c, Z) \tag{5}$$

For any well-specified normalized profit function, applying Hotelling's lemma directly to equation (4) results in a reduced-form of the following rice output supply specification;

$$Q = Q(W, P, D, P_q^c, W_\tau^c, Z) \tag{6}$$

Notice that equations (5) and (6) suggest that input and output prices, farm level and household characteristics, proportional transaction costs in input and output markets, group membership and collective marketing participation decisions tend to influence the farm net revenues received by farmers.

3.3.2 Impact of group membership and collective marketing decisions on farm net revenues

Given our interest in investigating the impact of group membership and collective marketing participation on farm net revenues, we specify the farm net revenues as a linear function of group membership or collective marketing participation and a vector of variables representing farm and household characteristics as:

$$Y_i = X_i\beta + D_i\delta + \mu_i \tag{7}$$

where Y_i represents farm net revenue of farmer i; X_i denotes a vector of farm, household and transaction costs characteristics; D_i is a vector of dummy variables representing group membership and collective marketing participation decisions as defined earlier; β and δ represent unknown parameters to be estimated; and μ_i denotes a random error term. To the extent that farmers self-select into group membership or collective marketing participation, using OLS method to estimate equation (7) may result in biased estimates. Thus, when farmers self-select into group membership or collective marketing participation, the error term (ε_i) in equation (1) and the error term (μ_i) in equation (7) may be correlated, leading to selectivity bias. In a non-randomized research setting, as the case in this study, the widely employed econometric techniques used in addressing selection bias especially in farmer group membership impact studies are quasi-experimental methods such as propensity score matching (PSM), treatment effects model or endogenous switching regression (eg. Ma and Abdulai, 2016). However, as stated earlier, the major weakness of the PSM approach is that it only accounts for selection bias due to observable attributes. In this study, we account for selection bias due to both observable and unobservable attributes. In doing so, we employ the endogenous switching regression (ESR) approach to jointly estimate the impact of group membership and collective marketing participation on farm net revenues. Before we estimate the impact of group membership and collective marketing on farm net revenues, we first examine the interrelationship between group membership and collective marketing decisions to provide insight as to whether farmers who are group members are more or less likely to also participate in collective marketing. This is done using a bivariate probit model specified in the next section.

3.4 Specification of the empirical models

3.4.1 Bivariate Probit regression model

As previously indicated, for some farmer groups that undertake collective marketing and sales of their paddy, some members of such groups do not participate in such a group activity, attributable to myriad reasons mentioned earlier. However, some farmers who are not members of farmer groups also have the opportunity to participate in collective marketing and sales, especially in situations where group members are unable to meet quantity requirements. This makes group membership and collective marketing decisions potentially jointly determined. Therefore, we employ a bivariate probit model to analyze the joint determination of group membership and collective marketing decisions and the related drivers of both decisions. The approach involves a specification of a two-equation model that captures farmers' decisions to belong to farmer groups and to participate in collective marketing, expressed as (Greene, 2012):

$$G_i^* = J_i\alpha + \vartheta_i, \qquad G_i = 1[G_i^* > 0] \tag{8}$$

$$C_M^* = v_M\psi + \aleph_M \quad C_M = 1[C_M^* > 0] \tag{9}$$

where G_i^* is the latent variable that represents farmer's group membership decision; J_i is a vector of farm-level, household and transaction costs characteristics influencing group membership decision; C_M^* denotes latent variable for collective marketing decision; v_M is a vector of farm-level, household and transaction costs factors influencing farmer's collective marketing participation decision; α and ψ are vectors of unknown parameters to be estimated; the random error terms $(\vartheta_i, \aleph_M)$ are assumed to follow a bivariate normal distribution with zero means, unit variances, and correlation coefficient ρ (Greene, 2012). A significant ρ implies correlation between the error terms $(\vartheta_i, \aleph_M)$. That is, the decision to join farmer group and the decision to participate in collective marketing are interrelated, and employing the traditional univariate probit model would generate biased and inconsistent estimates. However, an insignificant ρ implies that the two decisions are unrelated, providing suitable grounds for the estimation of two separate univariate probit models to generate unbiased and consistent estimates. Maximum likelihood method is employed to estimate the bivariate probit model (Greene, 2012). We compute marginal effects to determine the probability of collective marketing participation, conditional on group membership and the exogenous characteristics. In doing so, the nonlinear conditional expectation for estimating the marginal effects is expressed as (Greene, 2012):

$$E[G_i|C_M, v_M] = \frac{\Phi(\psi J_i, (2C_M - 1)\psi v_M,\ (2C_M - 1)\rho)}{\Phi[(2C_M - 1)\psi v_M]} \tag{10}$$

where Φ is the cumulative density function for the standardized bivariate normal distribution.

3.4.2. Endogenous switching regression (ESR) model

In this section, we employ ESR method to analyze the impact of group membership and collective marketing on farm net revenues. The ESR method is a two-stage procedure that involves first estimating a selection equation (eq. 1) to examine the factors influencing farmer group membership or collective marketing decision. In the second stage, the impact of group membership or collective marketing on farm net revenues is estimated by specifying two regimes of outcome equations for group members and non-members or collective marketing participants and non-participants as follows:

$$\text{Regime 1: } Y_{1i} = X_{1i}\beta_1 + \mu_{1i} \quad if\ \ D_i = 1, \tag{11a}$$

$$\text{Regime 2: } Y_{2i} = X_{2i}\beta_2 + \mu_{2i} \quad if\ \ D_i = 0, \tag{11b}$$

where Y_i denotes the farm net revenue per hectare for group membership and non-membership or collective marketing participation and non-participation regimes, X is the vector of farm-level, household and transaction costs characteristics; β is a vector of unknown parameters to be estimated and μ is the random error term. Identification of the model requires that at least one variable (known as an instrument) in Z from equation (1) should not feature in X. The identifying instrument should characteristically influence group membership or collective marketing participation decision, but not net revenues. In this context, we used farmers' perception of rice market demand as an identifying instrument, which is hypothesized to influence group membership and collective marketing participation decisions, but not net revenues. Instrumental variable test reveals that the instrument is valid.

It is significant to note that the variables in X account for potential selection bias, taking into account only observed factors. However, because selection bias still persists due to unobserved factors such as farmer innate skills and motivation, this leads to possible correlation between the error terms in the group membership or collective marketing choice equation (1) and net revenue equations (11a) and (11b), i.e, $corr(\varepsilon_i, \mu_i) \neq 0$. The ESR model accounts for this potential selection bias as an omitted variable problem. Following Heckman (1979), we compute the inverse mills ratios for group members or collective marketing participants (λ_{i1}) and non-members or collective marketing non-participants (λ_{i2}) and the covariance terms $\sigma_{\mu 1}$ and $\sigma_{\mu 2}$, after estimating the selection equation (1), which are then included in the outcome equations (11a) and (11b) as follows:

$$Y_{i1} = X_{i1}\beta_1 + \sigma_{\mu 1}\lambda_{i1} + \xi_{i1} \quad if \;\; D_i = 1, \tag{12a}$$

$$Y_{i2} = X_{i2}\beta_2 + \sigma_{\mu 2}\lambda_{i2} + \xi_{i2} \quad if \;\; D_i = 0, \tag{12b}$$

where λ_{i1} and λ_{i2} are the selectivity correction terms used to control for selection bias caused by unobserved factors; ξ_{i1} and ξ_{i2} are the random error terms with conditional zero means. As proposed by Lokshin and Sajaia (2004), the full information maximum likelihood (FIML) is employed to simultaneously estimate the selection equation (1) and the outcome equations (11a) and (11b), using *movestay* command in STATA. The FIML method is used because of its advantage in generating consistent standard errors unlike other two-stage estimation procedures.

Next, we use the coefficients from the ESR model to derive the average treatment effects on the treated (ATT). In doing so, we compare the expected farm net revenues from group members or collective marketing participants to the expected farm net revenues of the counterfactual hypothetical cases that they did not belong to farmer groups or marketed and sold their paddy individually, respectively. In particular, the expected net revenues of group members or collective marketing participants and non group members or collective marketing non-participants, respectively are expressed as:

$$E[Y_{i1}|D = 1] = X_{i1}\beta + \sigma_{\mu 1}\lambda_{i2} \tag{13a}$$

$$E[Y_{i2}|D = 1] = X_{i2}\beta + \sigma_{\mu 2}\lambda_{i2} \tag{13b}$$

The ATT for group membership and collective marketing participation is computed as the difference between equations (13a) and (13b), expressed as:

$$ATT = E[Y_{i1}|D = 1] - E[Y_{i2}|D = 1] = X_i(\beta_{i1} - \beta_{i2}) + \lambda_{i1}(\sigma_{\mu 1} - \sigma_{\mu 2}) \tag{14}$$

3.5 Data and descriptive statistics

This study uses recent farm household data gathered from June to August, 2016 in five selected districts of northern Ghana; Tolon, Kumbungu, Sagnarigu districts; Savelugu Nanton Municipal and Tamale Metropolitan area. The sample for the study was drawn using a multi-stage sampling approach. Purposive sampling method was first employed to select the five study districts because of their geographic accessibility and the intensive rice production in these areas. After purposive sampling of the districts, series of consultations were held with the agricultural extension agents (AEAs) of the Ministry of Food and Agriculture (MoFA) and other officials of ongoing donor funded projects (eg. Ghana-USAID/FtF) to randomly select about 2-3 communities from each study district. Finally, smallholder rice farmers were sampled on proportional basis with respect to the farmer population in each area. In total, we sampled 477 smallholder rice farmers, including group members and non-members, and engaged them in face-to-face interviews, using carefully designed and structured questionnaire. The information elicited during the survey was related to 2015 growing season, and focused on household and farm-level characteristics, asset ownership, as well as production and marketing activities. The data were collected with the help of trained research assistants.

The definition and descriptive statistics of variables used in the analysis are reported in table 3.1. In our context, the dependent variables are farm group membership, collective marketing and farm net revenues. Group membership is captured as a dummy and assigned a value of one, if the famer belongs to a farmer group, and zero otherwise. As shown in table 3.1, 42% of the rice farmers interviewed belong to farmer groups. Collective marketing is also captured as a dummy variable, where one is assigned to the case where a farmer participated in collective marketing in the last 12 months prior to the survey, and zero otherwise. In this context, collective marketing refers to a case where members market and sell paddy rice through a group. About 19% of farmers in the sample participated in collective marketing. This suggests that majority of the farmers in the study area still conduct marketing and sales of their produce individually, which may influence output prices and farm net revenues received by farmers. The outcome variable is farm net revenue, which is generated from rice production and marketing, and is computed as the difference between gross farm revenue per hectare less variable costs.

We review relevant literature to identify explanatory variables used in the present study (eg. Meinzen-Dick and Zwarteveen, 1998; Fischer and Qaim, 2012; Akar et al., 2016; Mojo et al., 2017: Zanello, 2014). We include age and education in the analysis, because they are considered important measures of human capital, and influence farmers' abilities to perceive, interpret, and respond to new events (Shultz, 1982). We expect that the likelihood of group membership and

Table 3.1: Variable definition and summary statistics

Variable	Definition	Mean (Std. Dev.)
Dependent variables		
Group membership	1 if farmer belongs to rice farmer group, 0 otherwise	0.19 (0.39)
Collective marketing	1 if farmer participated in collective marketing, 0 otherwise	0.42 (0.49)
Farm net revenue	Gross farm revenue from rice production minus variable input cost (GH¢)	457.72 (638.27)
Transaction costs variables		
Mobile phone	1 if farmer owns mobile phone, 0 otherwise	0.45 (0.49)
Radio set	1 if farmer owns radio set, 0 otherwise	0.56 (0.49)
Distance to market	Distance travelled to the nearest market (km)	6.54 (4.08)
Bicycle	1 if a farmer owns bicycle, 0 otherwise	0.70 (0.45)
Road status	1 if market road if motorable , 0 otherwise	0.73 (0.44)
Household characteristics		
Age	Age of respondent (years)	37.45 (11.72)
Education	Education of respondent (years)	2.02 (3.98)
Gender	1 if farmer is male, 0 otherwise	0.88 (0.32)
Market perception	Farmer perception of market demand (1=high, 0=low)	0.32 (0.46)
Farm characteristics		
Farm size	Size of farm (hectares)	1.14 (1.27)
Access to credit	1 if farmer has access to enough credit and not liquidity constraint, 0 otherwise	0.40 (0.49)
Average price per kg	Average selling price of paddy (GH¢/kg)	1.19 (0.27)
Gross farm revenue	Total value of paddy output per hectare (GH¢)	799.42 (810.00)
Yield	Quantity of rice output per hectare (kg)	665.78 (634.56)
Fertilizer and chemical costs	Expenditure on fertilizer and chemicals (GH¢)	171.89 (164.04)
Location dummies		
Sagnarigu	1 if farmer is located in Sagnarigu district, 0 otherwise	0.12 (0.33)
Tolon	1 if farmer is located in Tolon district, 0 otherwise	0.22 (0.41)
Kumbungu	1 if farmer is located in Kumbungu district, 0 otherwise	0.23 (0.42)
Savelugu Nanton	1 if farmer is located in Savelugu nanton Municipal, 0 otherwise	0.20 (0.40)
Tamale	1 if farmer is located in Tamale metropolitan area, 0 otherwise	0.21 (0.40)

Note: GH¢ is Ghanaian currency (US$1 = GH¢ 4.19), Std. Dev.: Standard Deviation collective marketing participation decisions increase with age and education, following the argument that older and better educated farmers have more experience and skills to respond to the demands of the group, as well as buyer requirements. Some recent studies found positive and significant effects of age and education on group membership decisions (Mojo et al., 2017; Fischer and Qaim, 2012). We also account for possible effects of gender by including a male dummy in the analysis. For instance, women in northern Ghana have lower opportunities, capacities and motivation than men, to effectively engage in collective action, which is attributed to their engagement in household activities and unpaid care work in addition to their farming activities (Meinzen-Dick and Zwarteveen, 1998). Farm size plays important role because larger farm sizes lower average fixed costs associated with group membership and collective marketing decisions (Fischer and Qaim, 2012). Access to credit, a proxy for financial capital and an indicator of liquidity constraint, is seen as important in group membership and collective marketing decisions. Members of farmer groups undertake certain group commitments, such as payment of membership fees and periodic contributions for financing group activities including collective marketing. In addition, rice production and marketing require investments in inputs and labor, such that resource-constrained farmers require sufficient financial capital to undertake these activities. We included access to credit dummy in our analysis to ascertain the liquidity status of the farmers. Farmers who had access to enough credit were considered not liquidity constraint. Access to credit is expected to have positive impact on group membership and collective marketing decisions, as well as farm performance.

Measures of transaction costs are also included in the analysis to account for their possible influence on group membership and collective marketing participation decisions. These measures include distance to markets, road status, ownership of mobile phone, radio set, and bicycle. We expect a positive influence of market distance on group membership and collective marketing. That is, farmers living farther away from the market could take advantage of joining farmer groups and possibly participate in collective marketing. Road status, a proxy for overall quality of the infrastructure is also expected to have a positive influence on group membership and collective marketing. Motorable roads lower transaction costs of produce transport, as well as costs of acquiring production inputs (Dercon et al., 2009). Ownership of bicycle may enable farmers to easily transport their paddy to market centers, and as such expected to influence group membership and collective marketing decisions negatively (Zanello et al., 2014). Mobile phones and radio sets facilitate acquisition of information on input and output prices, which could serve as guide for farmers to negotiate for better prices. Using these ICT tools, farmers are able to cut down costs associated with searching for buyers, as well as setting up and negotiating transactions (Zanello, 2012; Akar et al., 2016). Mobile phones tend to promote efficient communication amongst group members for effective organization of collective marketing and other group activities (Fischer and Qaim, 2012). We expect group membership and collective marketing decisions to be positively influenced by ownership of mobile phones and radio sets. Finally, we include a set of location dummies to account for possible spatial effects and infrastructural differences of the sample districts.

As shown in table 3.1, an average farmer is 37 years old, has completed about 2 years of formal education, cultivates about 1.14 hectares of rice farm and generates a farm net revenue of Gh¢457.72 per hectare. Tables 3.2 and 3.3 report the mean differences by group membership and collective marketing participation, respectively, for the variables used in the analysis, as well as the statistical *t*-test results of these differences. As reported in table 3.2, group members constitute greater proportion of farmers who participate in collective marketing of their paddy. Specifically, about 27% and 14% of group members and non-members, respectively participated in collective marketing. We also find that group members obtain higher yields, receive higher prices, and generate higher gross farm revenues, resulting in significantly higher farm net revenues than non-members. Figure 3.1 shows that the cumulative distribution function (CDF) of farm net revenues for group members is significantly different from that of non-members, revealed by the Kolmogorov-Smirnov test statistic. Variables with insignificant mean differences between members and non-members include education, gender and farm size. However, both category of farmers differ significantly along the rest of the variables under

Table 3.2: Differences in characteristics of farmers by group membership

Variable	Members		Non-members		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	(t-stat.)
Age	40.17	11.88	35.48	11.21	4.25***
Education	1.95	4.01	2.07	3.96	-0.31
Gender	0.87	0.32	0.88	0.31	-0.33
Mobile phone	0.63	0.48	0.32	0.46	6.87***
Radio set	0.64	0.47	0.50	0.50	3.12***
Farm size	1.08	0.98	1.19	1.44	-0.88
Access to credit	0.57	0.49	0.27	0.44	6.82***
Distance to market	7.04	4.10	6.17	4.03	2.23**
Bicycle	0.65	0.47	0.73	0.44	-1.80*
Market perception	0.46	0.49	0.22	0.41	5.48***
Road status	0.84	0.36	0.65	0.47	4.57***
Sagnarigu	0.29	0.45	0.01	0.10	9.55***
Tolon	0.25	0.43	0.20	0.40	1.23
Kumbungu	0.21	0.41	0.25	0.43	1.03
Savelugu Nanton	0.08	0.27	0.28	0.45	-5.37***
Tamale	0.15	0.36	0.24	0.43	-2.24**
Collective marketing	0.27	0.44	0.14	0.35	5.20***
Farm net revenue	634.51	854.88	329.39	367.74	5.12***
Average price per kg	1.27	0.37	1.13	0.13	5.59***
Gross farm revenue	981.58	1,092.99	667.32	476.04	4.12***
Yield	773.03	841.14	587.93	410.86	3.07***
Fertilizer and chemical costs	154.66	175.50	184.40	154.34	-1.89**
Sample size	**188**		**259**		

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

consideration. In particular, we observe that, on average, group members appear older and constitute a higher proportion of farmers who are not liquidity constrained relative to non-members. In addition, group members mostly own mobile phones, radio sets, live in communities with motorable roads, travel longer distances to markets as well as possess perception of high rice market demand.

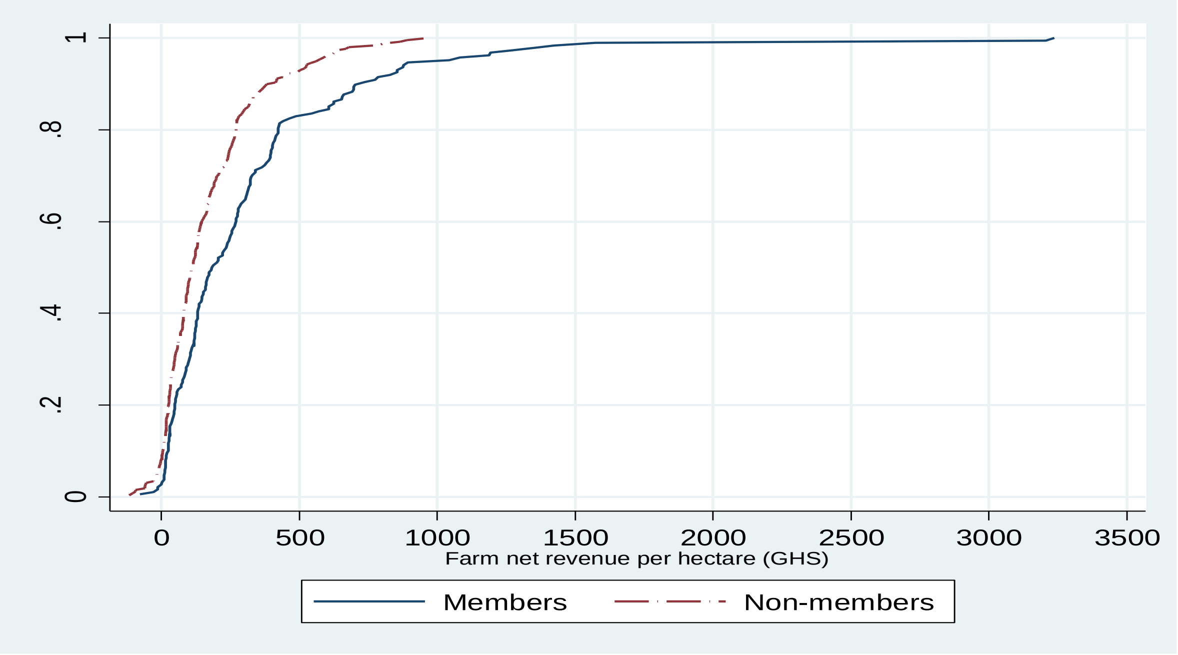


Figure 3.1: Cumulative distribution of farm net revenues by group membership. Note: the Kolmogorov-Smirnov test statistic of 0.216 indicates that the two distributions are statistically different (p = 0.000)

With regards to differences in characteristics by collective marketing participation, table 3.3, reveals that farmers who participate in collective marketing mostly access credit and are not liquidity constrained, own mobile phones and radio sets, as well as live in communities with motorable roads. However, collective marketing participants receive significantly higher paddy prices and gross farm revenues than non-participants, probably contributing to the significantly higher farm net revenues than those farmers who marketed and sold paddy individually. As shown in figure 3.2, the Kolmogorov-Smirnov test indicates that the CDF of farm net revenues, conditional on collective marketing participation, is positively and significantly different from the farm net revenue CDF for non-participants. On the other hand, collective marketing participants and non-participants do not differ along the lines of age, education, gender, bicycle ownership and farm size. However, it is important to note that these mean differences cannot

Table 3.3: Differences in characteristics of farmers by collective marketing participation

Variable	Participants		Non-participants		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	(t-stat.)
Age	37.38	11.21	37.47	11.86	-0.06
Education	2.07	4.08	2.01	3.96	0.13
Gender	0.93	0.25	0.87	0.33	1.60
Mobile phone	0.74	0.44	0.37	0.48	6.39***
Radio set	0.71	0.45	0.52	0.50	3.33***
Farm size	1.15	1.22	1.14	1.28	0.04
Access to credit	0.50	0.50	0.37	0.48	2.21**
Distance to market	5.72	3.19	6.74	4.25	2.11**
Bicycle	0.74	0.44	0.68	0.46	0.95
Market perception	0.48	0.50	0.28	0.45	3.61***
Road status	0.85	0.35	0.70	0.45	2.83***
Sagnarigu	0.11	0.31	0.13	0.34	-0.54
Tolon	0.25	0.44	0.21	0.40	0.93
Kumbungu	0.42	0.49	0.18	0.39	4.81***
Savelugu Nanton	0.10	0.30	0.22	0.41	-2.64***
Tamale	0.10	0.30	0.23	0.42	-2.84***
Farm net revenue	751.55	1,068.78	384.67	447.77	4.98***
Average price per kg	1.30	0.43	1.16	0.20	4.54***
Gross farm revenue	1109.39	1357.68	722.45	579.14	4.10***
Sample size	**89**		**358**		

Note: **, *** represent significance at 10%, 5%, and 1% levels, respectively.

be interpreted as impacts because other cofounding factors are not accounted for in the means. In this study, we analyze the drivers of farmers' group membership and collective marketing decisions, as well as the impacts of these decisions on farm performance measured by farm net revenues, while controlling for other cofounding factors.

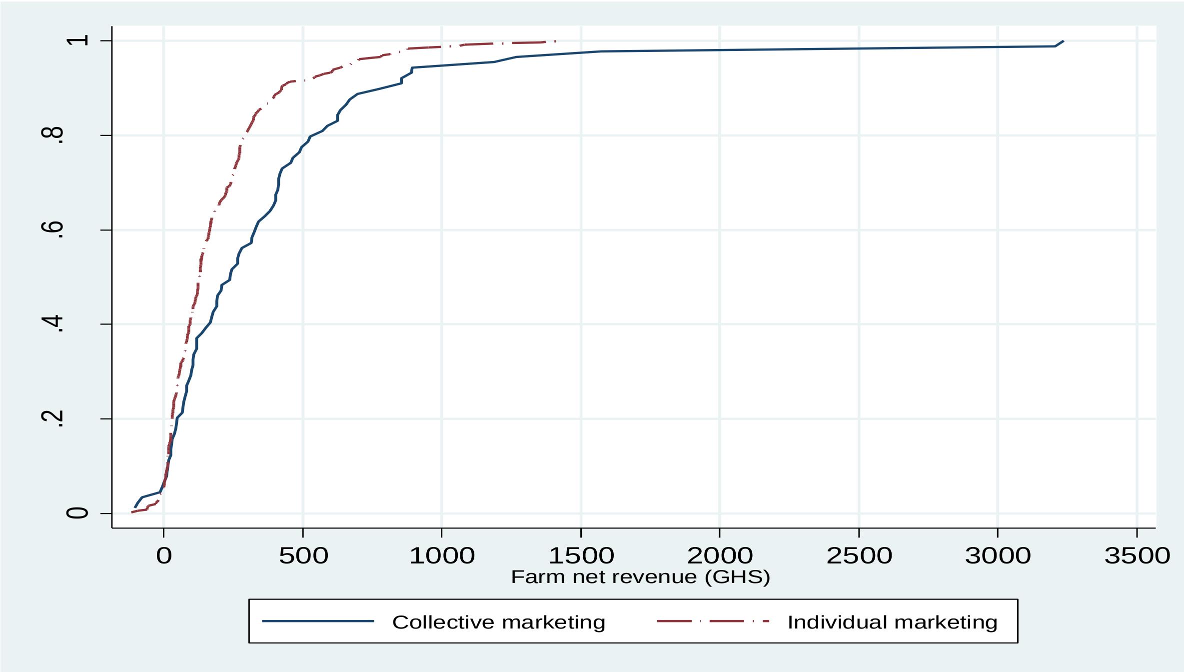


Figure 3.2: Cumulative distribution of farm net revenues by collective marketing. Note: the Kolmogorov-Smirnov test statistic of 0.262 indicates that the two distributions are statistically different (p = 0.000)

3.6 Empirical results and discussion

3.6.1 Group membership and collective marketing decisions

Table 3.4 shows the estimation results for the bivariate probit model on group membership and collective marketing participation decisions. Here, the main aim is to examine whether or not group membership and collective marketing decisions are jointly made. As reported in table 3.4, the correlation coefficient ρ is found to be positive and significant, implying that group membership and collective marketing participation decisions are not independent. This implies that employing a univariate probit regression would generate biased and inconsistent estimates.

Murphy's (2007) score test for the goodness of fit of the bivariate probit model indicates that the model is fit for the present analysis (see table 3.4). Before we begin discussion of the drivers of group membership and collective marketing decisions, it is significant to point out that some smallholder farmers in northern Ghana join farmer groups with the motive of accessing credit to undertake and/or expand their farming operations. Moreover, farmers who accessed enough credit for the growing season are also motivated to market and sell collectively with the notion of generating satisfactory farm revenues for the credit repayment. This makes access to credit potentially endogenous in both specifications, which when unaccounted for, could result in biased coefficient estimate. We address this potential endogeneity by employing the control function approach (Wooldridge, 2015). In doing so, we estimate a probit model in the first stage with access to credit as dependent variable, and including distance to credit institution as an instrument, which characteristically influences access to credit (see table 3.A1 in appendix) and not group membership or collective marketing. The observed access to credit variable and the predicted residuals are incorporated into the bivariate probit model in the second stage. The *t*-statistic of credit residual coefficient indicates that we fail to reject the null hypothesis that access to credit is exogenous (see tables 3.4, 3.5 and 3.6).

Next, we discuss the marginal effects of the exogenous variables on the probability of collective marketing participation, conditional on group membership. Table 3.4 reveals that, given group membership, farmers who have access to credit and are not liquidity-constrained have about 4.7% higher probability of participating in collective marketing. Participation in collective marketing has a higher likelihood of ensuring guaranteed markets for smallholder farmers, especially in situations where farmer groups have purchase agreements with buyers. Guaranteed markets could possibly encourage timely credit repayment. Transaction costs measures were found to also play significant roles in collective marketing participation,

Table 3.4: Maximum likelihood estimates of bivariate probit model for group membership and collective marketing

Variable	Membership		Collective marketing		Marginal effects (in %)	
	Coefficient	Std. err	Coefficient	Std. err	Coefficient	Std. err.
Constant	-3.301***	0.567	-1.886***	0.591		
Age	0.022***	0.008	-0.002	0.008	0.000	0.001
Education	0.028	0.020	-0.025	0.021	-0.001	0.002
Gender	0.087	0.290	0.243	0.309	0.033	0.019
Mobile phone	0.643***	0.158	0.920***	0.171	0.145***	0.023
Radio set	0.244	0.164	0.430**	0.172	0.064***	0.023
Farm size (log)	0.045	0.136	-0.195	0.147	-0.020	0.019
Access to credit	0.761***	0.153	0.040	0.156	0.047**	0.021
Distance to market (log)	0.423**	0.164	-0.146	0.165	0.021	0.022
Bicycle	-0.456**	0.193	-0.034	0.192	-0.029	0.029
Road status	0.467**	0.195	0.656***	0.219	0.104***	0.029
Market perception	0.499***	0.167	0.273 *	0.164	0.060***	0.022
Tolon	0.219	0.267	0.628**	0.305	0.086**	0.040
Sagnarigu	1.799***	0.390	0.365	0.341	0.143***	0.046
Kumbungu	-0.273	0.222	0.880***	0.253	0.089***	0.032
Savelugu Nanton	-0.359	0.265	-0.003	0.309	-0.020	0.040
Residual (Credit)	0.672	1.243	-2.080	1.300	-0.210	0.174
ρ	0.182*	0.103				
Log-likelihood	-374.19, $p = 0.000$					
Wald chi-sq(df =32)	193.23					
Wald test of $\rho = 0$ ($df = 1$)	3.027, $p = 0.081$					
Murphy's score test: chi-sq (9) = 8.99, $p(X^2)$ =	0.437					
Sample size	447					

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

conditional on group membership. In particular, the use of mobile phone is associated with about 14.5% higher likelihood of collective marketing participation. Mobile phones promote effective communication among group members (Fischer and Qaim, 2012). Apart from its role in searching for potential buyers, updated market information related to paddy prices is transmitted via mobile phones, and also used to facilitate interactions and negotiations with buyers over terms of sale. Again, group members who own mobile phones are easily notified via phone communication to mobilize paddy rice at community collection centers for pick up by buyers. This finding shows that the use of mobile phones undoubtedly reduces fixed transaction costs incurred by smallholder farmers, and possibly by buyers. Similarly, given group membership, farmers who own radio sets are 6.4% more likely to participate in collective marketing. Using radio sets could facilitate receipt of market information on prices of inputs and output. In the Northern regional capital, Tamale, the state-owned radio station (Radio Savanna) periodically broadcasts in local languages, regional and district market information on input prices at the beginning of growing season, and output prices at harvest, which thus serve as guide for famers to negotiate for better paddy prices with buyers during collective marketing.

Distance to markets, ownership of bicycle, and road status, which are considered measures of proportional transaction costs, also tend to influence collective marketing participation decisions. Specifically, an additional percentage increase in distance to market results in 2.1% more likelihood of collective marketing participation. This suggests that farmers who live further away from the market are more likely to participate in collective marketing. Also, as expected, farmers who own bicycles have 2.9% lower probabilities of participating in collective marketing. This is plausible, because farmers who own bicycles can easily transport their paddy to market centers, where they are likely to receive higher prices. Availability of adequate road infrastructure is also curial in rural input and output markets. It is hypothesized that good quality roads facilitates transport of produce from communities to market centers, as well as movement of produce buyers from district and regional capitals into rice growing communities at harvest period. We find that farmers who reside and farm around communities with motorable roads have 10.4% higher probability of participating in collective marketing. Communities with motorable roads are accessible to paddy aggregators and produce buying companies who normally travel from the regional capitals of northern and southern Ghana to the rice growing communities during harvest for paddy mobilization. It argued that communities with non-motorable roads discourage produce buyers from traveling to these areas to purchase produce, because they are likely to incur higher proportional transaction costs. Finally, we find that location fixed effects also play important role in farmer collective marketing participation decisions. In particular, relative to Tamale metropolis (reference district), living and farming around Tolon, Sagnarigu and Kumbungu districts, increases farmers' probabilities of participating in collective marketing by 8.6%, 14.3% and 8.9%, respectively.

3.6.2 ESR estimation results: Group membership decisions and farm net revenues

Table 3.5 presents the empirical results for the ESR model related to the determinants of group membership decisions and their impacts on farm net revenues. As stated previously, the full information maximum likelihood method is used to simultaneously estimate the group membership (selection) and farm net revenue (outcome) equations, while controlling for farmers' observed and unobserved attributes. We identified the ESR model by including in the selection equation a variable representing farmers' perceptions on rice market demand as an instrument, which strongly influences a farmer's decision to join a farmer group, but not directly on farm net revenue. The instrumental variable test confirms the validity of the instrument (see table 3.A2 in appendix). As shown in table 3.5, the results reveal negative correlation coefficients (ρ) between group membership equation (1) and the farm net revenue equations (13a and 13b), but only significantly different from zero for the correlation between group membership (1) and farm net revenue (13a). This finding indicates that selection bias caused by observed and unobserved attributes occurred in farmers' decisions to join farmer groups. It also implies that farmers who decide to be group members earn significantly higher farm net revenues than those farmers who would have been randomly assigned to group membership. This justifies the appropriateness of using the ESR approach in the estimations. The negative ρ in both the member and non-member specifications implies positive selection bias, which suggests that farmers with above-average farm net revenues have higher probabilities of joining farmer groups. The parameter estimates for the factors influencing farmers' decisions to join farmer groups are presented in the second column of table 3.5. Age is found to exhibit a positive and significant effect on group membership choice, implying that older farmers have a higher likelihood of being members of farmer groups, a finding that is consistent with the results from the study by Mojo et al. (2017). Consistent with the findings by Fischer and Qaim (2012), ownership of mobile phone appears to be an essential determinant of group membership decisions. This is revealed by the positive and significant coefficient of mobile phone ownership on group membership choice, suggesting that farmers who own mobile phones are more likely to join farmer groups. This is plausible, because an efficient communication amongst group members facilitates effective joint execution of group activities, such as collective marketing, bulk input purchase and price negotiations. Access to credit, which is an indicator of liquidity constraint, also exhibits positive and significant effect on group membership, indicating that farmers who are not liquidity-constrained are more likely to belong to farmer groups. Distance to market exerts positive significant effect on group membership, suggesting that an additional percentage increase in distance to markets increases the probability of group membership by 0.50%. As argued earlier, farther distance to markets increases proportional transaction costs, which in turn influence farmers' decisions to join farmer groups and possibly participate in collective marketing. Further, farmer group membership is positively and significantly influenced by radio set ownership and road status, implying that farmers who own radio sets and those living in communities with motorable roads are more likely to join farmer groups.

Table 3.5: Full information maximum likelihood estimates of endogenous switching regression model for group membership and impact on farm net revenue

Variable	Selection		Members		Non-members	
	Coefficient	Std. err	Coefficient	Std. err	Coefficient	Std. err
Constant	-3.634***	0.594	7.447***	0.970	4.511***	0.492
Age	0.027***	0.008	-0.021 **	0.008	-0.001	0.007
Education	0.021	0.021	-0.016	0.023	-0.000	0.018
Gender	0.118	0.314	0.231	0.318	0.591 **	0.260
Mobile phone	0.756***	0.167	-0.003	0.211	-0.047	0.171
Radio set	0.342**	0.172	0.138	0.196	-0.109	0.145
Farm size (log)	0.012	0.142	0.461***	0.157	0.502***	0.102
Access to credit	0.744***	0.167	0.823***	0.241	0.292 *	0.171
Dist. to market(log)	0.509***	0.168	-0.542***	0.201	-0.205	0.128
Bicycle	-0.421**	0.204	-0.000	0.215	0.418 **	0.181
Road status	0.628***	0.206	-0.470 *	0.267	-0.105	0.156
Tolon	0.330	0.280	-0.134	0.324	0.539 **	0.225
Sagnarigu	1.981***	0.420	-0.486	0.381	0.001	0.699
Kumbungu	-0.315	0.229	0.900***	0.303	0.920***	0.203
Savelugu Nanton	-0.525*	0.282	0.567	0.409	0.703***	0.202
Market perception	0.575***	0.169				
Residual (Credit)	-0.245	1.285				
$\ln\sigma_1$			0.185 (0.087)**			
$\rho_{\mu 1}$			-0.697 (0.342)**			
$\ln\sigma_2$					0.381 (0.052)	
$\rho_{\mu 2}$					-0.283 (0.249)	
Log likelihood:		-794.95				
LR test of indep. eqns.: $\chi^2(1)$:		40.91***				
Observations		447	188		259	

Note: The dependent variable is the log of farm net revenue; *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Next, we discuss the factors influencing farm net revenues, conditional on group membership decisions. Age exerts a negative impact on farm net revenues of both members and non-members, but significantly different from zero for group members. This suggests that relatively younger farmers earn higher farm net revenues from rice production and marketing. Non-member male farmers obtain significantly higher farm net revenues than their male counterparts who are group members. The plausible explanation for this finding is that non-members of farmer groups may not have sales commitments to buyers during harvest period, which is characterized by relatively lower paddy prices especially in the study area. This category of farmers, especially those without immediate cash needs, have the opportunity to store their paddy rice for sale at later period, when prices increase.

Farm size exhibits positive and significant impact on farm net revenue for both group members and non-members. In particular, an additional percentage increase in farm size results in 0.46% and 0.50% increase in farm net revenues for members and non-members, respectively, thus demonstrating scale effects in rice production and marketing. Access to credit positively impacts on farm net revenues received by both group members and non-members, suggesting that farmers who are liquidity-constrained tend to earn significantly lower farm net revenues from rice production and marketing. Distance to market and road status, which are proxies for proportional transaction costs, also play significant role in farm net revenue generation. In particular, an additional percentage increase in distance to market reduces net revenue by 0.54% and 0.20% for members and non-members, respectively. This finding shows the significance of transaction costs in improving farm net revenues, since rice farmers located far away tend to pay higher costs for the transport of their paddy to the markets.

3.6.3 ESR estimation results: Collective marketing decisions and farm net revenues

The estimation results for the ESR model related to the factors influencing collective marketing participation and their related impacts on farm net revenues are reported in table 3.6. Like the group membership model, we identified the collective marketing model, using a variable that represents farmers' perceptions on rice market demand as an instrument, which significantly influences farmers' decisions to participate in collective marketing, but not directly on farm net revenues. The instrumental variable test results, reported in table 3.A2 in the appendix, confirm that the instrument is valid. In table 3.6, the results show that the estimated correlation coefficient (ρ) between collective marketing equation and the farm net revenue function is negative, but statistically significant for the collective marketing participation specification. The negative ρ in both specifications indicates positive selection bias, suggesting that rice farmers with above-average farm net revenues have higher probability of participating in collective marketing. The significance of the correlation coefficient for the collective marketing participation specification indicates that self-selection, caused by observed and unobserved attributes, occurred in farmers' decisions to participate in collective marketing. It also implies that significantly higher net revenues accrue to farmers who decide to participate in collective marketing relative to those farmers who would have been randomly assigned to collective marketing participation status.

Column 2 of table 3.6 reports the parameter estimates for the factors influencing farmers' collective marketing participation decisions. As shown in table 3.6, farmers who own mobile phones and radio sets are more likely to participate in collective marketing. Moreover, road status, an indication of road infrastructure, has a positive and significant impact on collective marketing participation, suggesting that farmers who live and farm around communities with motorable roads are more likely to participate in collective marketing. Communities with motorable roads are easily accessible to paddy buyers, especially private produce buying companies who normally travel to these areas during harvest period to mobilize paddy.

With regards to the factors influencing smallholder rice farmers' net revenues, conditional on collective marketing participation, farm size exerts positive and statistically significant impact

Table 3.6: Full information maximum likelihood estimates of endogenous switching regression model for collective marketing and impact on farm net revenue

Variable	Selection		Participants		Non-participants	
	Coefficient	Std. err	Coefficient	Std. err	Coefficient	Std. err
Constant	-1.867***	0.601	7.732***	1.446	4.951***	0.409
Age	-0.010	0.007	-0.003	0.012	-0.007	0.005
Education	-0.002	0.026	0.014	0.034	-0.011	0.016
Gender	0.134	0.358	0.085	0.563	0.503 **	0.221
Mobile phone	0.582 **	0.252	0.158	0.422	-0.127	0.147
Radio set	0.292 *	0.171	-0.556 *	0.322	0.052	0.130
Farm size (log)	-0.086	0.151	0.712***	0.223	0.469***	0.096
Access to credit	0.085	0.163	0.465 *	0.272	0.806***	0.129
Dist. to market(log)	-0.167	0.160	-0503	0.310	-0.185 *	0.110
Bicycle	-0.126	0.196	0.138	0.344	0.143	0.150
Road status	0.492 **	0.250	-0.140	0.397	-0.143	0.144
Tolon	0.141	0.318	0.177	0.554	0.334 *	0.197
Sagnarigu	-0.072	0.323	1.051 *	0.601	-0.006	0.226
Kumbungu	0.704 **	0.304	0.627	0.527	0.774***	0.212
Savelugu Nanton	0.149	0.299	0.480	0.589	0.665***	0.188
Market perception	0.479 **	0.192				
Residual (Credit)	0.904	1.235				
$\ln\sigma_1$			0.365 (0.171)**			
$\rho_{\mu 1}$			-1.251 (0.425)***			
$\ln\sigma_2$					0.073 (0.040)*	
$\rho_{\mu 2}$					-0.158 (0.254)	
Log likelihood:		-790.10				
LR test of indep. eqns.: $\chi^2(1)$:		16.32***				
Observations		447		89		358

Note: The dependent variable is the log of farm net revenue; *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

on net revenues for both collective marketing participants and non-participants. Specifically, participants and non-participants respectively experience 0.71% and 0.46% significant gains in farm net revenues for any additional percentage increase in farm size. Access to credit is also found to be an important contributor to farmers' net revenue generation. We find that collective marketing participating and non-participating farmers who are not liquidity constrained received higher farm net revenues from rice production and marketing. As argued earlier, relatively higher farm net revenues could ensure timely and reliable credit repayment. The coefficient of distance to markets, which is considered to influence proportional transaction costs, is found to be negative, but significantly different from zero for non-participant specification. This suggests that conditional on collective marketing participation, farmers who failed to participate in collective marketing, but marketed and sold their paddy individually, experienced about 0.18% significant reduction in farm net revenues for any additional percentage increase in distance to market centers. Interestingly, location fixed effects also play significant role in rice farmers' net revenues, given collective marketing participation. In particular, relative to Tamale metropolitan area (reference district), participants who live and farm around Sagnarigu district receive higher farm net revenues than non-participants. However, non-participants who live and farm around Tolon, Kumbungu and Savelugu Nanton districts earn significantly farm higher net revenues than participants. This is because collective marketing and sales of paddy is usually carried out farm gates mostly during harvest period, which is characterized by relatively lower prices. However, non-participants around these areas, especially those without immediate cash needs could store their paddy to be sold at later dates (eg. lean season), when paddy prices appreciate. Again, this category of farmers may live in communities closer to the district capitals, which are characterized with good quality roads and can easily transport their paddy to the district and regional markets where there are likely to receive higher prices, hence higher farm net revenues.

3.6.4 Average treatment effects of group membership and collective marketing decisions

3.6.4.1 Group membership decisions

The results of the average treatment effects on the treated (ATT) of group membership on farm net revenues are presented in table 3.7. The ATT shows the impact of farmer group membership on farm net revenues. The ATT results reveal about 81.21% farm net revenue gain by farmers, conditional on group membership relative to non-members. To gain further insights into the impact of group membership on farm net revenues received by farmers, we disaggregated farm net revenues based on whether group members participated in collective marketing or marketed

Table 3.7: Impact of farmer group membership on farm net revenue

	Group membership			
Variable	**Members**	**Nonmembers**	**ATT**	**t-value**
	Mean outcome (farm net revenue)			
	329.84 (23.41)	182.01 (9.11)	147.82	8.671***
Farm net revenue stratification by collective marketing				
Collective marketing	387.81 (47.57)	216.03 (20.57)	171.78	5.061***
Individual marketing	307.68 (26.64)	169.01 (9.66)	138.67	7.041***
Farm net revenue stratification by farm size				
Near landless (≤ 0.5ha)	149.82 (18.43)	83.80 (6.87)	66.02	4.576***
Small (0.6 – 1.5ha)	295.60 (21.70)	171.08 (9.05)	124.52	7.750***
Medium and large(>1.5ha)	644.49 (79.62)	329.99 (22.70)	314.50	4.794***

Note: ATT: Average Treatment Effect on the Treated, The dependent variable is the log of farm net revenue. Computation of ATT is based on the antilog of the predictions, *** means significant at 1% levels.

and sold their paddy individually. Table 3.7 reveals that group members experienced 79.52% farm net revenues gain from collective marketing relative to non-members, while group members who marketed and sold their paddy individually, gained 82.04% farm net revenues than non-members. This finding reinforces the significance of group membership on smallholder farm performance and shows that group members regardless of the mode of marketing significantly benefit from improved farm performance. Further, we examine ATT of group membership on farm net revenues base on farm size in order to examine the differential impacts on farm net revenues. Interestingly, farm net revenues significantly increase by about 78.78%, 72.78% and 95.30% for nearly landless, small, and medium and large farm sizes, respectively, conditional on group membership. This indicates that group membership tends to increase the farm net revenues of all farm size categories, although the magnitude of the increase is highest with medium and large scale farmers. This finding is in line with the notion of scale economies, where the average fixed costs of group members decline with larger farm sizes, resulting in higher farm net revenues. The ATT results generally suggests that smallholder rice farmers with group membership benefit from improved farm performance than if they produce and market their paddy individually.

3.6.4.2 Collective marketing participation decisions

Table 3.8 reports the results of the average treatment effects of collective marketing participation on farm net revenues. The results show that collective marketing participation has a positive and statistically significant impact on smallholder farm net revenues. Specifically, rice farmers who participated in collective marketing experienced 62.22% significant gain in net revenues relative to non-participants. Also, we disaggregated farm net revenues based on farm size in order to gain indepth understanding and to examine the differential impact of collective marketing. As shown in table 3.8, we find that nearly landless, small, and medium and large farm size category of farmers earned 63.75%, 48.22% and 87.39% farm net revenues, respectively, conditional on collective marketing participation. This shows that farmers with larger farm sizes tend to benefit more from collective marketing as compared to farmers with smaller farm sizes. Like the impact of group membership, collective marketing also tends to improve on smallholder farm performance.

Table 3.8: Impact of collective marketing on farm net revenue

Variable	Participants	Non-participants	ATT	t-value
	Mean outcome (farm net revenue)			
	435.55 (37.71)	268.49 (18.92)	167.06	5.871***
	Farm net revenue stratification by farm size			
Near landless (≤ 0.5ha)	189.96 (29.69)	116.00 (13.14)	73.96	2.636**
Small (0.6 – 1.5ha)	409.60 (32.59)	276.33 (21.21)	133.27	4.977***
Medium and large(>1.5ha)	829.71 (123.16)	442.77 (46.61)	386.94	3.594***

Note: ATT: Average Treatment Effect on the Treated, The dependent variable is the log of farm net revenue. Computation of ATT is based on the antilog of the predictions. **, *** means significant at 5% and 1% levels, respectively.

3.7 Conclusions and policy implications

This paper has investigated the factors that influence farmers' decisions to join farmer groups and to participate in collective marketing, as well as the impact of group membership and collective marketing on farm net revenues. We used recent survey data of 447 smallholder rice farmers from five selected districts of northern Ghana in the empirical analysis. The data reveal that farmers that were members of farmer groups and participated in collective marketing obtained higher prices for their output, and also incurred lower input costs. Farmers' decisions on group membership and participation in collective marketing are shown to be jointly made, indicating that most farmers with group membership also participate in collective marketing. The empirical results support the notion that farmer group membership and collective market participation decisions in smallholder agriculture essentially enhance farm performance through improvement in farm net revenues. Specifically, both group membership and participation in collective marketing exerted positive and statistically significant impacts on farm net revenues. Farmers who belong to farmer groups regardless of the mode of marketing significantly benefit from improved farm performance. Transaction costs remain critical in group membership and collective market participation decisions. In particular, the findings revealed that group membership and collective marketing decisions are positively and significantly influenced by mobile phone ownership and road status. That is, farmers who own mobile phones are more likely to join farmer groups and participate in collective marketing. However, farmers who faced financial constraints were found to be less likely to have group membership and to participate in collective marketing.

The findings from this study show that government and donor support for the formation of farmer groups during implementation of agriculture and value chain interventions should as well incorporate strategies to facilitate smallholder collective marketing in the interventions. Both new and existing farmer groups could be trained on demand-driven capacity building modules such as group dynamics, business development as well as technical capacity development. Capacity building on group dynamics would enable farmer groups become more cohesive, and thus encourage active member participation in group activities including collective marketing. The important role of access to credit revealed by the study advocates for the need to incorporate credit schemes into agriculture and value chain development programs, as well as facilitate effective linkages between smallholder farmers and readily available financial institutions. Moreover, government investment in road infrastructure could facilitate easy access to rice growing communities by buyers and also ease produce movement to market centers.

References

Abdulai, A., and E.A. Birachi 2009. Choice of Coordination Mechanism in the Kenyan Fresh Milk Supply Chain. *Review of Agricultural Economics* 31 (1): 103–121.

Akar, J. C., Ghosh, I., and Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics*, 47(2016): 35-48.

Barrett, C. (2008). Smallholder market participation: concepts and evidence from eastern and southern Africa. *Food Policy*, 33(4):299-317.

Bernard, T., Spielman, D.J. (2009). Reaching the rural poor through rural producer organizations? A study of agricultural marketing cooperatives in Ethiopia. *Food Policy*, 34 (2009): 60-69.

Bernard, T., Taffesse, A.S., Gabre-Madhin, E.Z. (2008). Impact of cooperatives on smallholders' commercialization behavior: evidence from Ethiopia. *Agricultural Economics*, 39, 147-161.

Bijman, J., Omta, S.W.F., Trienekens, J. H., Wijnands, J.H.M., and Wubben, E.M.F. (2006). Management and organization in international agri-food chains and networks. In *International agri-food chains and networks, Management and organization*. *Wageningen Academic Publishers* 15-28.

Dercon, S., Gilligan, D. O., Hoddinott, J., and Woldehanna, T. (2009). The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian villages. *American Journal of Agricultural Economics*, 91(4): 1007-1021.

Fischer, E. and Qaim, M. (2012). Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya, *World Development*, 40 (6): 1255–1268.

Francesconi, G. N., and Wouterse, F. (2015). Promoting the role of farmer-based organizations for value chain integration: the tension between a program's targeting and an organization's investment strategy. *Agricultural Economics*, 46 (2015): 527-536.

Greene, W. H. (2012). Econometric Analysis. Prentice Hall, Upper Saddle River, NJ.

Gyau, A., Mbugua, M., and Oduo, J. (2016). Determinants of participation and intensity of participation in collective action: evidence from smallholder avocado farmers in Kenya. *Journal on Chain and Network Science*, 16(2): 147- 156.

Heckman J.J. (1979). Sample selection bias as a specification error. *Econometrica,* 47(1): 153 161.

ISSER. (2012). An impact evaluation of the MiDA FBO training. MiDA report, Accra, Ghana.

Kaganzi, E., Ferris, S., Barham, J., Abenakyo, A., Sanginga, P., and Njuki, P. (2009). Sustaining linkages to high value markets through collective action in Uganda. *Food Policy,* 34 (2009): 23-30.

Key, N., E. Sadoulet, A. de Janvry. (2000). Transaction costs and agricultural household supply response. *American Journal of Agricultural Economics*, 82(2000): 245-259.

Lokshin, M., and Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *Stata Journal,* 4(3): 282-289.

Ma, W. and Abdulai, A. (2016). Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, 58 (2016): 94-102.

Markelova, H., R. Meinzen-Dick, J. Hellin, and S. Dohrn. (2009). Collective action for smallholder market access. *Food Policy*, 34(2009): 1-7.

Meinzen-Dick, R., and Zwarteveen, M. (1998). Gendered participation in water management: Issues and Illustrations from water users associations in South Asia. *Agriculture and Human Values*, 15(4), 337-345.

MiDA. (2013). Millennium Challenge Account compact completion report. Accra, Ghana.

Mojo, D., Fischer, C., and Degefa, T. (2017). The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. *Journal of Rural Studies*, 50 (2017): 84-94.

Nkhoma, A., Conforte, D., (2011). Unsustainable cooperatives: lessons from Malawi. In: *IFAMA Symposium*, Frankfurt.

Reardon, T., Barret, C.B., Berdegué, J.A., & Swinnen, J.F.M. (2009). Agrifood industry transformation and small farmers in developing countries. *World Development*, 37, 1717-1727.

Rivers, D. and Q. H. Vuong 1988. Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, 39 (1988): 347-366.

Salifu, A., Francesconi, G.N., Kolavalli, S., 2010. A review of collective action in rural Ghana. IFPRI Discussion Paper 00998, *International Food Policy Research Institute (IFPRI)*, Washington DC.

Salifu, A., Rebecca, L. F., Meagan, K., and Shashidhara, K. (2012). Farmer Based Organizations in Ghana. IFPRI working Paper 31, *International Food Policy Research Institute (IFPRI)*, Washington DC.

Schultz, T. W. (1982). *Investing in people: The economics of population quality*. Berkeley: University of California Press.

Smith, J. A., and Todd, P. E. (2005). Does matching overcome Lalonde's critique of nonexperimental estimators? *Journal of Econometrics*,125 (1): 305-353.

Verhofstadt, E and Maertens, M. (2014). Smallholder cooperatives and agricultural performance in Rwanda: do organizational differences matter? *Agricultural Economics*, 45, 39-52.

Wooldridge, J.M. (2015). Control function methods in applied econometrics. *The Journal of Human Resources*. 50(2): 421-445.

Zanello, G. (2012). Mobile phones and radios: Effects on transactions costs and market participation for households in Northern Ghana. *Journal of Agricultural Economics*, 63(3): 694-714.

Appendix

Table 3.A1: First stage probit model estimates used for addressing credit endogeneity.

Variable	Coefficient	Std. Err.
Constant	-1.513	0.453
Age	0.005	0.005
Education	-0.036 **	0.016
Gender	0.344	0.239
Mobile phone	0.421***	0.131
Radio set	-0.038	0.136
Farm size (log)	0.170 *	0.102
Distance to market(log)	0.237 *	0.135
Road status	0.282 *	0.156
Bicycle	0.005	0.156
Tolon	0.316	0.216
Sagnarigu	0.011	0.253
Kumbungu	0.437 **	0.204
Savelugu Nanton	-0.013	0.219
Distance (km) to credit institution	-0.034 **	0.013
LR $x^2(15)$	61.30	
P-value	0.000	
Pseudo R^2	0.101	
Log likelihoods	-270.66	
Number of observations	447	

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 3.A2: Instrumental variable test for the ESR model (market perception)

Variable	Chi-square (X^2)	$p - value$
Group membership model		
Group membership	9.78	0.001
Farm net revenue (member specification)	1.76	0.184
Farm net revenue (nonmember specification)	0.05	0.903
Collective marketing model		
Collective marketing	7.59	0.005
Farm net revenue (participant specification)	0.72	0.394
Farm net revenue (non-participant specification)	0.20	0.6544

Chapter 4

Do Farmer Groups impact on Farm Yield and Efficiency of Smallholder Farmers? Evidence from Rice Farmers in Northern Ghana

Awal Abdul-Rahaman and Awudu Abdulai

Department of Food Economics and Consumption Studies, University of Kiel, Germany

Published in *Food Policy*, 81(2018): 95-105.

Abstract

Multiple production and marketing challenges facing smallholder farmers in developing countries have resulted in renewed interests of governments, donor agencies and private agribusiness companies in forming farmer groups to help address these challenges. Using recent survey data of 412 smallholder rice farmers from northern Ghana, we examine the role of farmer groups in improving yield and technical efficiency. Due to self-selection into farmer groups, we use a sample selection stochastic production frontier model to account for potential selection bias arising from observed and unobserved attributes. The empirical results reveal that participation in farmer groups is associated with increased yield and technical efficiency, relative to farmers who produce and market rice individually. Moreover, the yield and efficiency gaps between group members and nonmembers increase significantly when selection bias is taken into account in the analysis.

Keywords: Farmer groups, Yield, Technical efficiency, Selection bias, Northern Ghana.

4.1 Introduction

Despite increased research and development efforts, addressing multiple productivity and market failures, smallholder farmers in developing countries are still besieged with myriad constraints such as low crop yields, limited access to credit and extension services, and information asymmetries leading to high transaction costs associated with input and output market participation (Markelova et al., 2009; Bernard et al., 2010; Mojo et al., 2017). These constraints stimulate growing interests of governments, development agencies, and agribusiness companies in forming farmer groups as one of the essential steps in the implementation of agriculture and value chain development initiatives in developing countries. Farmer groups can enhance rural development, poverty reduction, productivity gains and food security through their role in facilitating effective and efficient smallholder participation in agrifood value chains (Verhofstadt and Maertens, 2014; Ainembabazi et al., 2017).

With the recent rapid transformation of agrifood value chains, coupled with strict food quality standards and new procurement systems of large agribusiness companies in developing countries, farmer groups' participation in these formalized chains can reduce transaction costs associated with acquiring production inputs, adoption of productivity-enhancing innovations through increased access to private and public extension services, as well as easy access to credit (Bellemare, 2012; Reardon et al., 2009). Large agribusiness companies continue to complement the efforts of government and NGOs by establishing effective vertical coordination mechanisms (e.g., contracting) with smallholder farmer groups in the form of outgrower schemes and other supplier-buyer relationships (Barrett et al., 2017; Barrett et al., 2012). Under these business relationships, smallholder farmer groups are often provided with inputs and technical backstopping services during the cropping season, and costs associated with these services are charged against the final produce (Bellemare and Novak, 2016; Wang et al, 2014; Henderson and Isaac, 2017). Undoubtedly, these inputs and technical services have direct links with yield and technical efficiency gains, which jointly indicate significant potential for improved smallholder livelihoods.

While the available literature establishes the role of farmer groups in the adoption of productivity-enhancing innovations (e.g., Spielman et al., 2011; Abebaw and Haile, 2013; Ainembabazi et al., 2017), only few studies document the role of farmer groups in improving yield and technical efficiency (e.g., Abate et al., 2014; Ainembabazi et al., 2017). Meanwhile, empirical insight on this role has policy implications, especially for governments, donor agencies, and large agribusiness companies seeking to promote smallholder productivity through farmer groups. The few studies that have investigated farmer group membership effects on yield and technical efficiency have produced mixed findings. For example, the study by Abate et al. (2014) found significant positive impact of group membership on technical efficiency of Ethiopian farmers. Ainembabazi et al. (2017) also reported positive and significant effects of farmer groups on the adoption of productivity-enhancing innovations and technical efficiency of farmers in the Great Lakes region of Africa. However, other studies found statistically insignificant impact of group membership on technical efficiency (Wollni and Brümmer, 2012; Gedara et al., 2012). These mixed findings can be attributed to the varying nature of farmer groups, as well as the analytical methods used, thus providing a reasonably firm basis for further assessment.

In the present study, the decision to participate in a farmer group is nonrandom and therefore likely to be influenced by unobserved attributes, such as farmers' risk attitude, motivation and innate skills, resulting in potential selection bias. Accounting for this bias is important in ensuring unbiased and consistent estimates. Some studies used group membership as a determinant of technical efficiency and the effect directly determined through its marginal effect (e.g., Wollni and Brümmer, 2012; Gedara et al., 2012). Such estimation procedure fails to account for selection bias associated with unobserved attributes. However, Abate et al. (2014)

and Ainembabazi et al. (2017) employed propensity score matching (PSM) method to address selection bias. Meanwhile, the limitation of the PSM method such as its failure to control for farmers' unobserved attributes is now widely known in the empirical literature.

The present study seeks to contribute to the literature by examining the role of farmer groups in sustained efforts to improve yield and technical efficiency of smallholders in Sub-Saharan Africa. Specifically, we examine the factors that influence smallholder participation in farmer groups, using data from a recent survey in five selected districts of northern Ghana. The findings from such a study can enhance stakeholder understanding of these factors for better policy-targeting efforts geared towards addressing the multiple productivity and marketing challenges confronting smallholder farmers. For example, the Ghana government, donor agencies and large agribusiness companies have collaboratively intensified efforts in revamping the rice value chain through initiating a number of agriculture and value chain development interventions[6]. These interventions generally aim at strengthening the position of smallholder rice farmer groups in the value chain, through easy access to inputs, technical services and output markets. We also examine the impact of farmer groups on the yield and technical efficiency of smallholder farmers. In doing so, we account for selection bias associated with observed and unobserved attributes, using PSM and Greene's (2010) sample selection stochastic production frontier (SPF) approaches, respectively to obtain unbiased and consistent parameter estimates (Bravo-Ureta et al., 2012).

The rest of this paper is organized as follows: section 2 presents an overview of rice production and farmer groups in Ghana. Section 3 describes the conceptual framework, as well as the empirical specification. The data and descriptive statistics of the variables used in the analysis

---

[6] Examples of the current rice sector interventions include Ghana Feed the Future (FtF) project, Ghana Commercial Agriculture Project (GCAP), Ghana Agricultural Sector Investment Programme (GASIP), Rice Sector Support Project (RSSP) etc.

are presented in section 4, followed by discussion of the empirical results in section 5. The final section presents the conclusions and policy implications from the study.

4.2 Rice production and farmer groups in Ghana

In Ghana, rice is the second most important cereal staple after maize, with a total cultivated area of about 233,000 hectares and average annual production of 641,000 metric tonnes (SRID-MoFA, 2016). Northern, Volta and Upper east regions are the main rice producing areas, with a total average production of about 467, 000 metric tonnes, constituting about 72% of the national annual average (SRID-MoFA, 2016). Rice production is done under three ecosystems namely rainfed upland, rainfed lowland and irrigated systems. The dominant ecosystem is the rainfed lowland, which covers about 78% of the arable area followed by the irrigation system (16%), and rainfed upland system covering about 6% of the arable area (MoFA, 2009). The rice sector is mostly dominated by smallholder farmers who cultivate an average of less than two hectares of rice.

Rice does not only form an integral part of Ghanaian diet, but also contributes to ensuring food security among rural and urban households. Recent increases in rice consumption, due to population growth, urbanization, and changing dietary habits of consumers, have created a wide gap between local supply and demand (MoFA, 2009). Available statistics indicate that domestic rice production covers about 30-40% of domestic demand, with the shortfall provided by large quantities of imports (Angelucci et al., 2013). To increase rice production and local supply, the government of Ghana, development agencies, and the private sector collaboratively implement agricultural value chain interventions to ensure a paradigm shift from the traditional subsistence rice production to market-oriented production. They facilitate the formation of farmer groups, an important step towards implementing these interventions to promote collective action and improve farmer welfare.

In Ghana, the interests in aggregating smallholder farmers into groups for agricultural production and marketing resumed strongly at the beginning of the 20^{th} century, and by 2010, about 10,000 farmer groups existed (Salifu et al., 2012; Francesconi and Wouterse, 2015). Ongoing development interventions in northern Ghana are the USAID funded Ghana Feed the Future (FtF) programs such as the Agricultural Development and Value Chain Enhancement II (ADVANCE II), Agricultural Technology Transfer (ATT), and Resiliency in Northern Ghana (RING) projects among others. The ADVANCE II is a four-year (2014 - 2018) project implemented by ACDI/VOCA in partnership with Technoserve Ghana, Association of Church Development Projects (ACDEP) and PAB Consult Ltd. The goal of ADVANCE II is to scale up private sector investments in agriculture to achieve food security among poor rural households, as well as improve competitiveness in the rice, maize, and soybean value chains. It focuses on three key activity components: enhancing smallholder productivity, improving market access and trade for smallholder farmers, and strengthening and building local capacity.

The project adopts a facilitative value chain approach by linking smallholder farmer groups to inputs, finance, equipment, information, and output markets through relatively larger nucleus (commercial) farmers and traders (aggregators). ADVANCE II project has been working with existing farmer groups that were formed under past interventions (eg. Millennium Development Authority (MiDA) Agriculture program), and are still in active farming business with promising growth potentials. Moreover, smallholder farmers were set up into groups and registered to participate in the project in target areas without existing farmer groups. Both existing and new farmer groups were assigned to produce and market the targeted value chain crops under larger nucleus farmers or Outgrower Businesses (OBs)[7] with demonstrable investment capacities.

[7] Nucleus farmers/OBs under the ADVANCE II project in northern Ghana include Premium Foods Ltd., Gundaa Produce company Ltd., Khama enterprise, Asawaba farms Ltd etc.

The farmer groups in our study were supported with capacity building on climate smart agricultural practices, provision of improved rice varieties, quality inputs, mechanization services (eg. tractor and threshing services), and market access. Evidence from the survey indicated that farmer groups accept membership based on the farmer's moral track record in the community, his/her willingness to participate in group activities, commitment to rice production, meeting group's obligations such as attending meetings, payment of membership fees and periodic contributions to run the group's activities, as well as contribute to achieving group's objectives. The farmer groups have at least four executive members: Chairperson, Vice Chairperson, Secretary and Organizer, mandated to manage the groups' activities. The groups facilitate input and output market linkages, as well as extension services for their members. In particular, the groups' executives negotiate on behalf of their members for lower input prices, higher paddy prices from the larger (commercial) nucleus farmers or buyers, as well as facilitate collective activities (e.g., meetings, bulk input purchase, collective sales, mutual labor support etc.), and group training and extension service delivery.

Some of the farmer groups also collaborated with the ATT project, and received similar services. However, we did not find evidence of group members not supported by any of the above mentioned projects. The ATT is a five year (2013-2018) USAID funded project implemented by the International Fertilizer Development Center (IFDC) in northern Ghana. The project is also aimed at increasing competitiveness of the rice, maize and soybean value chains. It disseminates agricultural technologies through on-farm demonstrations for increased productivity, as well as promotes market access for smallholder farmers. However, evidence on whether the farmer groups in our sample collaborated with other projects such as the RING, SPRING and GCAP could not be revealed by the survey.

4.3 Conceptual framework

In this section, we present a multi-step approach to examine the impact of farmer groups on yield and technical efficiency. We begin with a description of farmer's decision to participate in a farmer group, followed by specification of the general stochastic production frontier model, and the procedure used in accounting for potential selection bias.

4.3.1 Farmer group participation decision

We assume that a farmer makes a binary decision on whether to participate in a farmer group or not. The probability of participating in a farmer group is therefore determined by a comparison of the expected benefits (G_M^*) from participation, and the expected benefits (G_N^*) from non-participation. Intuitively, a farmer will choose to participate in a farmer group if the benefits from participation is greater than the benefits from non-participation; i.e. $G_i^* = G_M^* - G_N^* > 0$. However, G_i^* is a latent variable that is unobservable. What is observed is the actual participation in a farmer group. We thus express G_i^* as a function of observable characteristics in a latent variable framework as:

$$G_i^* = \gamma' Z_i + \omega_i, G_i = 1[G_i^* > 0], \quad (1)$$

where G_i is the farmer group participation indicator, assigned a value of one, and zero otherwise, γ is a vector of parameters to be estimated, ω is the error term with zero mean and variance σ^2, and Z_i is a vector of observable farm and household characteristics believed to influence farmer group participation decision. The probability of participating in a farmer group is specified as:

$$\Pr(G_i = 1) = \Pr(G_i^* > 0) = \Pr(\omega_i > -Z_i\gamma) = 1 - F(-Z_i\gamma), \quad (2)$$

where F is the cumulative distribution function for ω_i. In general, because farmers are heterogeneous, not all of them will belong to farmer groups. However, farmer group participation is expected to be associated with higher yield and technical efficiency, relative to farmers who produce and market paddy on their own (Abate et al., 2014; Ma et al., 2018).

4.3.2 Stochastic production frontier (SPF) model

We employ the stochastic production frontier model, with the assumption that the farmers in our context either produce paddy rice exclusively as group members or nonmembers. In general, the SPF model is specified as:

$$Y_{ij} = f(X, G_M) + \varepsilon_i, \qquad \varepsilon_i = v_{ij} - u_{ij}, \tag{3}$$

where Y_{ij} is yield of the i^{th} farmer, X denotes a vector of inputs and other explanatory variables, G_M is a dummy variable that captures the effect of farmer group participation, v_{ij} is the two-sided error term, and u_{ij} denotes the one sided error term capturing efficiency. The subscript j refers to G_M for group membership and G_N for nonmembership. Because farmers self-select into participating in farmer groups, selection bias may arise due to observed and unobserved attributes. This bias needs to be addressed when estimating the stochastic production frontier model (SPF) to obtain unbiased and consistent yield and technical efficiency estimates (Bravo-Ureta et al., 2012).

4.3.3 Addressing selection bias in stochastic production frontier (SPF) model

Given that a farmer makes a binary decision to participate in a farmer group or not, some of the factors (observed and unobserved) influencing farmer group participation decision may also influence yield and technical efficiency. In other words, the error term in the selection equation is correlated with the conventional error term in the stochastic production frontier model, leading to potential selection bias, which needs to be addressed to obtain unbiased and consistent parameter estimates associated with participation.

Some past studies have applied sample selection correction models with various assumptions to deal with selection bias stemming from unobserved attributes in SPF models (e.g., Lai et al., 2009; Kumbhakar et al., 2009; Greene, 2010). In particular, Lai et al. (2009) and Kumbhakar et al. (2009) assume that the selection bias arises from the correlation between the error term in the selection equation (ω_i) and the error terms in the conventional SPF model, ε_i and u_i, respectively. However, Greene (2010) argues that selection bias is due to correlation between ω_i and the noise term (v_i) in the conventional SPF model. Greene's (2010) approach can be seen as an extension of the Heckman's sample selection corrected linear model, as well as the nonlinear models by Terza (2009) to the stochastic production frontier model. Because the approaches by Lai et al. (2009) and Kumbhakar et al. (2009) require computationally demanding log likelihood functions (Greene, 2010), we employ the multi-step approach presented in Bravo-Ureta et al. (2012) in the present study to address selection bias stemming from both observed and unobserved attributes.

In line with Bravo-Ureta et al. (2012), we use PSM method to account for selection bias arising from observed attributes, and Greene's (2010) SPF sample selection model to correct for selection bias due to unobserved attributes. Using the PSM method, we construct a counterfactual group of farmers with similar time-invariant characteristics as those who participate in farmer groups. It is important to mention that in implementing PSM method, the variables included in the analysis should be fixed over time, especially in cases where baseline data are not available to select the appropriate variables (Caliendo and Kopeinig, 2008). The PSM method involves fitting a binary choice (in this case probit) model to generate propensity scores for group members and nonmembers. These propensity scores, which represent the probability of participating in a farmer group, are used to match group members with nonmembers, based on the observed time-invariant characteristics.

As indicated previously, to control for selection bias from unobserved attributes, we use Greene's (2010) sample selection SPF model, which along with the error structures, is specified as:

Sample selection: $G_i = 1[\gamma' Z_i + \omega_i > 0], \;\; \omega_i \sim N[0, 1]$

SPF: $y_i = \beta' X_i + \varepsilon_i, \;\; \varepsilon_i \sim N[0, \;\; \sigma_\varepsilon^2]$

$$(y_i, X_i) \text{ is observed only when } G_i = 1 \quad (4)$$

Error structure: $\varepsilon_i = v_i - u_i$

$$u_i = |\sigma_u U_i| = \sigma_u |U_i|, \text{ where } U_i \sim N[0, 1]$$

$$v_i = \sigma_v V_i, \text{ where } V_i \sim N[0, 1]$$

$$\omega_i, v_i \sim N_2[(0, 1), \ (1, \rho\sigma_v, \sigma_v^2)]$$

where G_i is a binary variable that takes on a value of one for farmer group members, and zero for nonmembers, Z is a vector of explanatory variables included in the sample selection model, and ω_i is the unobservable error term, y denotes yield, X is a vector of inputs in the production frontier model, and ε denotes the composed error term. The coefficients γ and β are the parameters to be estimated, while the elements in the error structure correspond to those normally included in the stochastic production frontier model. The parameter ρ indicates the presence or absence of selection bias associated with unobserved attributes. In particular, a significant ρ indicates the presence of selection bias on unobserved attributes (Greene, 2010). On the other hand, insignificant ρ implies absence of selection bias, in which case the maximand reduces to that of the maximum simulated likelihood estimator of the basic frontier model. Note that the standard errors are adjusted using the approach by Murphy and Topel (2002). The model parameters are estimated using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) approach, and asymptotic standard errors are obtained by employing the Berndt-Hall-Hall-Hausman (BHHH) algorithm estimator[8]. Some other recent studies have employed the sample selection SPF approach to examine impact of technology adoption (e.g., Abdulai and Abdulai, 2017; Villano et al., 2015), as well as evaluate project participation impact (e.g., De los Santos-Montero and Bravo-Ureta, 2017; Gonzalez-Flores et al. 2014). It is important to note that the Greene's (2010) sample selection SPF model is first estimated for group members and

[8] Readers interested in details of the full model and its estimation can refer to Greene (2010).

then repeated for nonmembers, in which case the dependent variable (G_i) in the selection equation is reversed, i.e G_i equals one for nonmembers, and zero for group members.

4.3.4 Empirical model specification

As stated previously, we employ the PSM method to estimate a probit model using observable farm and household characteristics to generate propensity scores, which are then used to match group members and nonmembers with similar observed time-invariant characteristics. Caliendo and Kopeinig (2008) and Khandker et al. (2010) discuss the various matching criteria used in implementing the PSM method. These include nearest neighbor matching, radius matching, kernel matching, mahalanobis matching, spline matching, as well as stratification and interval matching.

In the present study, the nearest neighbor matching algorithm is used with a maximum of five matches per group member, and a caliper of 0.025. This matching criterion produced 407 matched observations out of 412 observations, comprising 186 group members and 221 nonmembers. We also used kernel (epanechnikov option) matching method with a bandwidth of 0.05. A balancing test was conducted after both matching procedures to ascertain which of them yielded better matched sample. Mean comparisons revealed that the nearest neighbor matching yielded better matched sample than the kernel matching. Moreover, the nearest neighbor matching method is the most commonly used one in the empirical literature (e.g., Bravo-Ureta et al., 2012; Gonzalez-Flores et al., 2014). Therefore, the sample generated by the nearest neighbor matching method is used in this study.

After the matching procedure, we then estimate the SPF model with correction for selection bias. However, before doing so, we model farmer's decision to participate in a farmer group, which is described by a criterion function, and expressed as a function of exogenous farm and household characteristics (Z) influencing farmer group participation as follows:

$$G_i = \gamma_0 + \sum_{j=1}^{14} \gamma_j Z_{ij} + \omega_i \qquad (5)$$

where G_i is a binary variable assigned a value of one for a group member, and zero otherwise, γ is a vector of unknown parameters to be estimated, and ω is the error term distributed as $N(0, \sigma^2)$. The variables in Z include age, education, gender, mobile phone ownership, bicycle ownership, distance to market, total farm land, access to irrigation, access to credit, extension visits, and location variables.

However, it is important to point out that access to credit is likely to be facilitated through farmer group participation, because some farmers in northern Ghana often join farmer groups with the motive of accessing credit to undertake and/or expand their farming operations. Similarly, one would expect that a farmer receives more extension visits due to membership in a farmer group. This makes access to credit and extension visits variables potentially endogenous in predicting farmer group participation. This endogeneity needs to be addressed to obtain unbiased and consistent estimates. In doing so, we employ a two-stage control function approach outlined in Wooldridge (2015). The first-stage involves estimating, separately, access to credit and extension visits on instruments and other variables included in the farmer group participation probit model (Ainembabazi et al., 2017). These instruments should significantly influence access to credit and extension visits but not directly affect farmer group participation. We used distance to credit institution and status of farm road as instruments for access to credit and extension visits, respectively (See table A2 in the appendix). One would expect that motorable farm roads could encourage farm visits by extension officers, while farmers who live farther away from credit institution could be less likely to access credit from this source. In the second-stage estimation, the observed access to credit and extension visits variables, as well as their respective residuals predicted from the first-stage are incorporated into the farmer group participation probit model.

We evaluate the two most common functional forms used in efficiency studies: Cobb-Douglas (CD) and Translog ((TL) models (Bravo-Ureta et al., 2007; Seymour, 2017). A maximum likelihood ratio test led to the rejection of the TL in favor of the CD functional form at 5% level of significance[9]. The Cobb-Douglas (CD) functional form can be specified as:

$$\ln(Y_i) = \beta_0 + \sum_{j=1}^{5} \beta_j \ln X_{ji} + \sum_{k=1}^{8} \delta_k D_{ki} + v_i - u_i, \quad iff\ G_i = 1 \qquad (6)$$

where Y_i denotes yield of farmer i; X_{ji} is quantity of the j^{th} input; D represents dummy variables; β and δ are unknown parameters to be estimated; v and u are the elements of the composed error term, ε. The dependent variable in the SPF model is the yield of paddy rice in kilograms. The explanatory variables are represented by a total of five inputs and seven dummies. The inputs are land planted with rice (in hectares), quantity of seed (in kilograms), quantity of fertilizer (in kilogram), quantity of active ingredients in chemicals (in kilograms), and labor employed in farm activities (in worker-days). The dummy variables include access to irrigation, soil quality, rice variety and location dummies. Following Battese's (1997) approach, we account for zero values of fertilizer and chemicals by including dummies for these inputs in the SPF model, such that the logarithm of the inputs with zero values is taken only if it is positive, and zero otherwise (Villano et al., 2015). This is done to ensure unbiased and efficient parameter estimates of the SPF model.

4.4 Data and descriptive statistics

In the present study, we used recent farm household data collected from June to August, 2016 in five districts of northern Ghana: Tolon, Kumbungu, Sagnarigu districts, Savelugu Nanton municipal and Tamale metropolis. The sample for the study was drawn using a multi-stage

[9] Although the CD is restrictive and nested in the flexible TL model, it yields satisfactory parameter estimates than the TL model. Mayen et al. (2010) argue that estimation of the translog model is sometimes complicated with multicollinearity issues especially between inputs and the interaction terms.

sampling approach. First, in consultation with the Ministry of Food and Agriculture (MoFA) and some officials of ongoing donor funded projects (e.g., Ghana-USAID/FtF project), purposive sampling method was used in selecting the five study districts due to their geographic accessibility and the intensive rice production in these districts. Second, two to three communities were randomly sampled from each study district. Finally, employing proportional sampling technique, smallholder rice farmers were randomly sampled based on farmer population in each district. A total of 412 smallholder rice farmers, comprising of 186 group members and 226 nonmembers were sampled, and interviewed, using structured questionnaire. Data was gathered on several factors including farm and household characteristics, asset ownership, as well as production and marketing activities related to the 2015 production season. The field survey was conducted with the help of trained research assistants, and under the supervision of one of the authors.

Table 4.1 presents the definition and summary statistics of variables used in the empirical analysis. It shows that 45% of the farmers participate in farmer groups, whose primary focus is rice production and sales. Table 4.1 also shows that on average, a farmer in the sample is about 38 years old, has been through about 2 years of formal education, cultivates 2.8 hectares, and generates about 731.02 kilogram of rice yield. Differences in variable means between group members and nonmembers, and statistical *t*-tests for unmatched and matched samples are presented in Table 4.A1. We observe significant differences in variable means between group members and nonmembers for the unmatched sample. In particular, group members appear older, mostly own mobile phones, have better extension services, relative to nonmembers. The group members mostly plant improved rice varieties[10], apply higher amounts of fertilizer, chemicals, labor, as well as generate higher yield than nonmembers. We also observe that the

[10] Improved rice varieties commonly grown by farmers in the study area include Jasmine 85 (Gbewaa rice), AGRA rice, Togo marshal, Digang (Abirikukogu), Nerica 1, Nerica 2, Nabogo rice etc. Examples of Traditional rice varieties grown include GR 18 (Afife), TOX 3108 (GR 22) and Mandii.

Table 4.1: Variable definition and summary statistics

Variable	Definition	Mean (Std. Dev.)
Group membership	1 if farmer participates in a rice farmer group, 0 otherwise	0.45
Age	Age of respondent (years)	37.90 (11.78)
Education	Education of respondent (years)	2.05 (4.04)
Gender	1 if farmer is male, 0 otherwise	0.90
Mobile phone	1 if farmer owns mobile phone, 0 otherwise	0.32
Distance to market	Distance to market (km)	6.39 (4.03)
Bicycle	1 if a farmer owns bicycle, 0 otherwise	0.71
Total Farm land	Total farm land under farmer's control (hectares)	3.82 (3.24)
Access to credit	1 if farmer has access to sufficient credit and not credit constrained, 0 otherwise	0.44
Extension visits	Number of extension visits to farmer in a year (2015) previous to the survey	1.56 (2.75)
Access to irrigation	1 if farm is under irrigation, 0 otherwise	0.22
Variety	1 if farmer planted improved rice variety, 0 if farmer planted traditional rice variety	0.69
Farm road status	1 if farm road is motorable, 0 otherwise	0.69
Sagnarigu	1 if farmer is located in Sagnarigu district, 0 otherwise	0.14
Tolon	1 if farmer is located in Tolon district, 0 otherwise	0.24
Kumbungu	1 if farmer is located in Kumbungu district, 0 otherwise	0.26
Savelugu Nanton	1 if farmer is located in Savelugu nanton Municipal, 0 otherwise	0.18
Tamale	1 if farmer is located in Tamale metropolitan area, 0 otherwise	0.16
Input and output variables used in SPF model		
Rice yield	Total yield of rice harvested (kg/ha)	731.02 (752.80)
Land	Area of land planted with rice (ha)	2.80 (3.05)
seed	Quantity of seed planted (kg/ha)	41.16 (38.84)
Fertilizer	Total quantity of fertilizer applied (kg/ha)	80.12 (84.73)
Chemical	Total amount of active ingredient of chemical applied (kg/ha)	2.39 (2.68)
Labor	Total labor used in rice production per hectare (worker-days/ha)	55.64 (24.89)
Soil quality	1 = fertile soils, 2 = infertile soils	0.20
Fertilizer dummy	1 if farmer did not apply fertilizer, 0 otherwise	0.09
Chemical dummy	1 if farmer did not apply chemicals, 0 otherwise	0.12

Note: Std. Dev.: Standard Deviation

proportion of farmers with access to credit is significantly higher for group members than nonmembers. In this study, we construct the access to credit variable by eliciting responses from a farmer on whether he/she needed credit for rice production and marketing, and if so whether he/she received the amount of credit required. A farmer who did not need credit, or demanded credit, applied for it, and received the required amount is assigned a value of one, and zero otherwise (Jappelli, 1990).

In the matching process, a trimming procedure was employed to establish a region of common support (see figure 4.A1 in appendix), which is defined by the area of positive density within $G = 1$ and $G = 0$ distributions (Smith and Todd, 2005). In the region of common support, the estimated propensity scores range between 0.039 and 0.995. As observed in figure 4.1, almost all the propensity scores generated fall within the area of common support, though some few observations are off the common support region. This suggests that the nonmembers form a reasonable counterfactual for the group members. It is useful to mention that the PSM method accounts for the differences in observed attributes. As shown in table 4.A1, we observe no significant mean differences in terms of the observed characteristics between the two groups aside Savelugu Nanton (location dummy) after matching, suggesting that the balancing condition of the variables is fulfilled (Leuven and Sianesi, 2003; Bravo-Ureta et al., 2012). The next section discusses the sample selection SPF estimates, which accounts for selection bias due to unobserved attributes.

4.5 Empirical results and discussion

4.5.1 Farmer group participation decision

Table 4.2 presents estimates of the factors influencing a farmer's decision to participate in a farmer group. Marginal effects are computed to allow for a better interpretation of the results (Greene, 2012). The parameter estimates are jointly significant at 1% level, as revealed by the chi-square test statistic (LR $X^2(14) = 158.71$). Table 2 also reports the residual coefficients of the potential endogenous variables that include access to credit and extension visits predicted from the first-stage. The results show that these residuals are not statistically different from zero, suggesting that the access to credit and extension visits variables are not endogenously determined in farmer's decision to participate in a farmer group. We find that the decision to participate in a farmer group is positively and significantly influenced by farmer's age. In particular, an older farmer has about 0.6% probability of participating in a farmer group, which is consistent with the finding by Mojo et al. (2017). The results also show that farmers who have access to sufficient credit, and are not credit constrained are about 24.2% more likely to participate in farmer groups, as revealed by its positive and significant marginal effect. Apart from the fact that farmers with access to sufficient credit are able to fulfill their group commitments such as payment of membership fees and periodic cash contributions, they can procure production inputs such as fertilizer and chemicals, and as well pay for labor expenses. The marginal effect of extension visits variable is also found to be positive and significant, suggesting that a farmer who receives extension visits has about 1.6% higher probability of participating in a farmer group. Similar finding is reported in other recent studies (e,g., Ma and Abdulai, 2016).

Distance to market also exhibits positive and significant effect on farmer group participation decision. In particular, additional percentage increase in market distance is positively and significantly associated with about 1.1% probability of participating in a farmer group. Intuitively, farther distance to market raises transaction costs, which tend to encourage participation in farmer groups, and probably paddy sales to agribusiness companies at farmgate. The results also reveal that a farmer with access to irrigation is about 20.8% more likely to participate in a farmer group. Table 4.2 also shows that relative to Tamale (reference district), farmers located around Sagnarigu district have about 55.3% higher probability of participating in farmer groups, while farmers located in Savelugu Nanton are about 13.8 % less likely to participate in farmer groups, suggesting that location fixed effects also influence farmers' decisions to participate in farmer groups.

Table 4.2: Probit model estimates of factors influencing farmer group participation decision

Variables	Probit coefficients		Marginal effects	
	Coefficient	Std. Err.	Coefficient	Std. err
Constant	-1.559***	0.478		
Age	0.024***	0.007	0.006***	0.002
Education	0.012	0.019	0.003	0.005
Gender	-0.154	0.292	-0.042	0.080
Mobile phone	0.213	0.236	0.058	0.064
Distance to market	0.035*	0.021	0.009**	0.005
Bicycle	-0.097	0.218	-0.026	0.060
Total farm land	0.012	0.037	0.003	0.010
Access to credit	0.866***	0.151	0.238***	0.036
Extension visits	0.050*	0.027	0.013*	0.007
Access to irrigation	0.757***	0.242	0.208***	0.064
Tolon	0.185	0.257	0.050	0.070
Sagnarigu	2.011***	0.613	0.553***	0.163
Kumbungu	-0.229	0.298	-0.063	0.081
Savelugu Nanton	-0.502**	0.265	-0.138**	0.072
Credit residual	-1.242	1.185		
Extension residual	0.297	0.690		
LR $x^2(14)$	158.71			
Log likelihood	-204.27			
Number of observations	412			

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

4.5.2 Stochastic production frontier (SPF) estimates

Tables 4.3 and 4.4 present estimates of the conventional and sample selection SPF models for the unmatched and matched samples, respectively. The likelihood ratio (LR) test led to the rejection of null hypothesis of homogeneous technology between group members and nonmembers at 5% level for the unmatched ($LR = 43.42, X^2 = 27.02, df = 13$) and matched ($LR = 42.92,\ X^2 = 27.02, df = 13$) samples, lending support for the estimation of separate SPF models for members and nonmembers. This finding is further confirmed by the positive and significant effect of farmer group participation dummy on yield. As shown in tables 4.3 and 4.4, the null hypothesis test of no technical inefficiency ($\lambda = 0$) is also rejected at 1% level in all cases, implying that technical inefficiency is an important contributor to variability in observed yield.

The results of sample selection SPF model have established statistical support for the presence of selection bias associated with unobserved attributes, as revealed by the significant ρ for the group member specification. What this means is that a farmer who decides to participate in a farmer group obtain higher yield and technical efficiency (TE) compared to that of a randomly chosen farmer in our sample. This is probably due to better unobserved attributes such as production skills, motivation and good risk management behavior influencing farmers' decisions to be members of farmer groups. This finding is consistent with the findings of other recent studies on smallholder rice farmers (e.g., Rahman et al., 2009; Rahman, 2011; Villano et al., 2015). The evidence of selection bias on unobserved attributes in this study justifies the use of separate sample selection SPF models for group members and nonmembers, and the parameter estimates and TE scores from the conventional SPF model are bias and inconsistent (Bravo-Ureta et al. 2012; Gonzalez-Flores et al. 2014).

As expected, all the estimated models present positive partial production elasticities, which measure the percentage contribution of each input to percentage change in yield. With regards to the conventional inputs, the results show that land and chemicals make the highest contribution to rice yield for both categories of farmers, as revealed by the expected positive and significant effects of these inputs at least at 5% level. Similar results have also been reported

Table 4.3 Parameter estimates for the conventional and sample selection SPF models: Unmatched sample

Variables	Conventional SPF						Sample selection SPF			
	Pooled		Members		Nonmembers		Members		Nonmembers	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Constant	4.204***	0.245	4.467***	0.395	4.190***	0.338	4.363***	0.495	4.215***	0.445
ln land	0.227***	0.049	0.261***	0.084	0.226***	0.063	0.273***	0.105	0.241***	0.068
ln seed	0.054*	0.031	0.022	0.044	0.125***	0.047	0.024	0.054	0.131**	0.060
ln fertilizer	0.150***	0.049	0.188***	0.072	0.092	0.072	0.196**	0.085	0.085	0.088
ln chemical	0.291***	0.066	0.291***	0.096	0.292***	0.096	0.282**	0.122	0.315***	0.121
ln labor	0.004	0.055	0.053	0.081	0.030	0.077	0.070	0.084	0.071	0.102
Fertilizer dummy	0.663***	0.225	0.486	0.371	0.564*	0.309	0.540	0.473	0.533	0.376
Chemical dummy	0.312***	0.111	0.141	0.179	0.313**	0.148	0.123	0.191	0.345**	0.169
Soil quality	0.260***	0.065	0.353***	0.108	0.225***	0.083	0.365***	0.126	0.235***	0.087
Variety	0.416***	0.062	0.427***	0.096	0.370***	0.085	0.422***	0.112	0.377***	0.093
Irrigation	0.256***	0.074	0.347***	0.104	0.268**	0.109	0.307**	0.135	0.244**	0.121
Tolon	0.165**	0.072	0.153*	0.092	0.237**	0.116	0.159	0.118	0.240*	0.125
Savelugu	0.415***	0.082	0.356**	0.144	0.478***	0.111	0.451**	0.219	0.533***	0.133
Kumbungu	0.359***	0.079	0.233**	0.113	0.463***	0.112	0.283*	0.170	0.493***	0.122
G. membership	0.313***	0.064	-	-	-	-	-	-	-	-
L. Likelihood	-328.02		-166.34		-183.39		-240.86		-276.72	
λ	1.706***	0.188	1.794***	0.299	1.467***	0.230	-	-	-	-
σ^2	0.748***	0.001	0.712***	0.003	0.729***	0.002	-	-	-	-
$\sigma_{(u)}$	-	-	-	-	-	-	0.544***	0.196	0.588***	0.152
$\sigma_{(v)}$	-	-	-	-	-	-	0.393***	0.095	0.430***	0.070
$\rho_{(w,v)}$	-	-	-	-	-	-	-0.388**	0.173	0.277	0.414
N	412		186		226		186		226	

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 4.4 Parameter estimates for the conventional and sample selection SPF models: Matched sample

Variables	Conventional SPF						Sample selection SPF			
	Pooled		Members		Nonmembers		Members		Nonmembers	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Constant	4.166***	0.247	4.467***	0.395	4.095***	0.342	4.363***	0.495	4.167***	0.442
ln land	0.222***	0.049	0.261***	0.084	0.221***	0.064	0.273***	0.105	0.242***	0.069
ln seed	0.057*	0.032	0.022	0.044	0.129***	0.047	0.024	0.054	0.134***	0.060
ln fertilizer	0.148***	0.050	0.188***	0.072	0.092	0.075	0.196**	0.085	0.077	0.089
ln chemical	0.304***	0.067	0.291***	0.096	0.321***	0.097	0.282**	0.122	0.348***	0.121
ln labor	0.010	0.055	0.053	0.081	0.018	0.078	0.070	0.084	0.061	0.102
Fertilizer dummy	0.638***	0.231	0.486	0.371	0.550*	0.323	0.540	0.473	0.474	0.383
Chemical dummy	0.329***	0.112	0.141	0.179	0.348**	0.149	0.123	0.191	0.378**	0.170
Soil quality	0.249***	0.066	0.353***	0.108	0.205**	0.084	0.365***	0.126	0.220**	0.089
Variety	0.421***	0.063	0.427***	0.096	0.372***	0.086	0.422***	112	0.374***	0.094
Irrigation	0.256***	0.074	0.347***	0.104	0.271**	0.110	0.307**	0.135	0.251**	0.122
Tolon	0.166**	0.073	0.153*	0.092	0.239**	0.116	0.159	0.118	0. 231*	0.125
Savelugu	0.399***	0.084	0.356**	0.144	0.469***	0.114	0.450**	0.219	0.506***	0.138
Kumbungu	0.359***	0.079	0.233**	0.113	0.467***	0.112	0.283*	0.170	0.488***	0.121
G. membership	0.311***	0.065	-	-	-	-	-	-	-	-
L. Likelihood	-324.45		-166.34		-179.57		-240.66		-271.98	
λ	1.665***	0.184	1.794***	0.299	1.394***	0.224	-	-	-	-
σ^2	0.744***	0.001	0.712***	0.003	0.720***	0.002	-	-	-	-
$\sigma_{(u)}$	-	-	-	-	-	-	0.544***	0.196	0.578***	0.158
$\sigma_{(v)}$	-	-	-	-	-	-	0.393***	0.095	0.430***	0.071
$\rho_{(w,v)}$	-	-	-	-	-	-	-0.391**	0.172	0.294	0.411
N	407		186		221		186		221	

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

in other past studies (e.g., Abate et al., 2014; Rahman, 2011). We also find that fertilizer makes significant contribution to the yield of group members, while quantity of rice seed plays a minor role. Labor contributes insignificantly to the yield of both members and nonmembers, which may be due to its decreasing marginal productivity resulting from abundance of labor force (Gonzalez-Flores et al. 2014; Rahman et al., 2009). The coefficients of soil quality, rice variety and irrigation are positive and significant for both member and nonmember specifications, indicating their importance in enhancing yield. Finally, we included location dummies to account for environmental, biophysical, and other aspects of socio-economic conditions such as neighbor effects in adopting new technologies, access to information and inputs, which are known to contribute to crop yield. In particular, relative to Tamale (reference district), farmers who live and farm around Tolon, Savelugu, and Kumbungu districts obtain significantly higher rice yield.

4.5.3 Yield and technical efficiency scores

The mean technical efficiency (TE) scores derived from the conventional and sample selection SPF models for the pooled sample, group members and nonmembers for unmatched and matched samples are presented in table 4.5. In addition, the table reports statistical *t*-test of mean TE differences between members and nonmembers. Table 4.5 reveals significant TE differences between group members and nonmembers for both SPF models. For the unmatched sample, the conventional SPF model results show that group members and nonmembers, respectively operate at mean TE levels of 69% and 63%, relative to their group frontiers. The sample selection SPF model, respectively yields mean TE scores of 74% and 65% for members and nonmembers, relative to their group frontiers, suggesting that group members perform better by operating closer to their own group frontier than nonmembers. For the matched sample, the results also show that group members operate closer to their own production frontier than nonmembers, as revealed by the higher mean TE scores associated with the conventional

SPF model (69% versus 64%), and the sample selection SPF model (74% versus 66%), respectively.

Table 4.5 Technical efficiency levels across the SPF models

SPF Model	Pooled		Members		Nonmembers		Test of means[b]
	Mean	SD	Mean	SD	Mean	SD	
Unmatched							
Conventional	0.64	0.15	0.69	0.15	0.63	0.13	4.34***
Sample selection	0.79	0.13	0.74	0.12	0.65	0.13	7.23***
TE Difference[a] (%)	23.43		7.25		3.20		
Matched							
Conventional	0.63	0.14	0.69	0.15	0.64	0.13	3.60***
Sample selection	0.71	0.12	0.74	0.12	0.66	0.12	6.69***
TE Difference (%)	12.69		7.25		3.13		

[a] Percentage difference in TE before and after accounting for sample selection
[b] *t* test of mean TE difference between group members and nonmembers
*** represents significance at 1% level

We also provide insights on the importance of correcting for selection bias by comparing TE scores across SPF models. The results in table 4.5 show higher TE scores associated with the use of sample selection SPF model, relative to the conventional SPF model. Specifically, the mean TE scores in the unmatched sample increase by about 23.4%, 7.25%, and 3.2% for the pooled sample, group members and nonmembers, respectively when sample selection SPF is used. We also record similar pattern of results in the matched sample. This means that in our context, accounting for selection bias has enabled us to obtain efficient parameter estimates, resulting in a larger share of farmers observed to be operating closer to the production frontier.

The distribution of TE scores of group members and nonmembers in Fig. 4.1 using unmatched conventional SPF model (without bias correction) and the matched sample selection SPF model (with bias correction) provides further insight on the importance of correcting for selection bias stemming from observed and unobserved attributes. We find that after controlling for these biases, the percentage of farmers who operate at TE level of between 71-80% increased from 22.1% to 28.3% for members, and from 28.8% to 30.9% for nonmembers. Moreover, only about 8.4% of the group members operate at TE levels of up to 50%, after correcting for the biases, suggesting that majority of this category of farmers have moved to operating at relatively higher TE levels. We also observe that none of the nonmembers in the unmatched sample (without bias correction) is found operating at the highest TE range (91-100%).

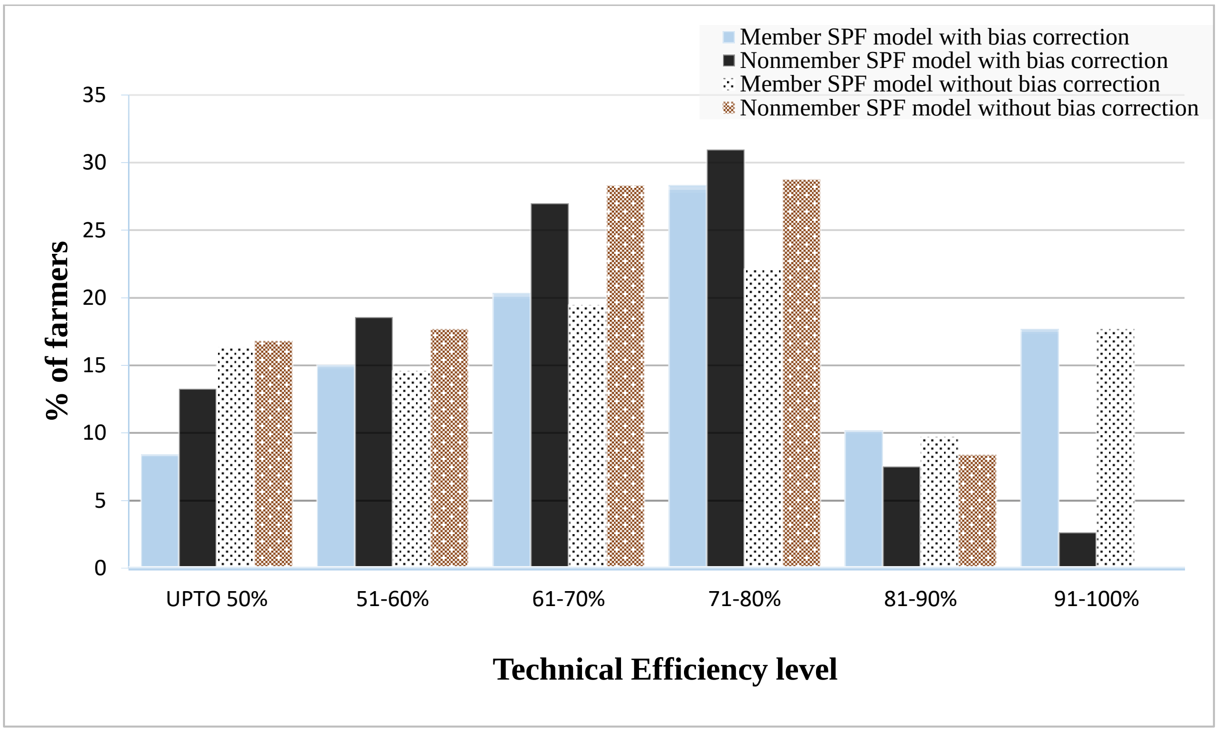


Fig. 4.1 Distribution of efficiency scores before and after selection bias correction.

Finally, we examine the differences in yield between group members and nonmembers with and without selection bias correction. This is done using the mean predicted frontier yield generated from the unmatched conventional SPF (without bias correction) and the matched sample selection SPF (with bias correction) models. The results are reported in Table 4.6 alongside the percentage yield differences and corresponding *t*-tests. We find that without correcting for selection bias, group members obtain higher yield than nonmembers, with percentage difference of about 36.2%. However, the difference in yield stands at 48.7% when selection bias due to both observed and unobserved attributes are taken into account, suggesting that participation in farmer groups contributes significantly to enhancing farm yield.

Table 4.6 Predicted frontier output before and after selection bias correction

SPF model	Pooled	Members	Nonmembers	% increase in predicted output	Test of means [c]
Conventional [a]					
Mean	845.49	974.74	715.91	36.15	4.57***
Minimum	185.05	197.96	156.47		
Maximum	6444.82	6565.94	2781.66		
Sample selection [b]					
Mean	991.50	989.92	665.87	48.67	5.51***
Minimum	196.39	194.71	138.82		
Maximum	6872.62	6639.12	2697.82		

[a] Before selection bias correction (unmatched sample)
[b] After selection bias correction (matched sample)
*** represents significance at 1% level.
[c] *t* test of predicted mean frontier output difference between members and non-members

4.6 Conclusions

This study analyzed the role of farmer groups in improving smallholder farm yield and technical efficiency, using recent survey data of 412 farmers from selected districts in northern Ghana. We used Propensity Score Matching (PSM) and Greene's (2010) sample selection Stochastic Production Frontier (SPF) approaches to account for potential selection bias associated with observed and unobserved attributes. These approaches allowed for the estimation of unbiased and consistent impact of farmer group participation on yield and technical efficiency. The estimates revealed the presence of selection bias, suggesting that unobserved attributes such as farmer motivation, innate skills and risk attitude influence farmers' decisions to participate in farmer groups. The empirical results revealed that farmer groups tend to enhance farm yield and technical efficiency. In particular, for both conventional and sample selection SPF model estimations, the results show that farmers who belong to farmer groups operate closer to their own production frontier than farmers who produce and market paddy on their own. Moreover, higher TE scores for group members and nonmembers are associated with the use of the sample selection SPF model. This means that in nonrandomized studies, it is important to account for selection bias when examining farmer welfare such as yield and technical efficiency. The empirical results show that farmer's age, access to credit and irrigation, extension visits, distance to markets are the important positive determinants of participation in farmer groups. Moreover, rice yield is positively and significantly influenced by land, fertilizer, chemicals, rice variety, soil quality and access to irrigation for both farmer group members and nonmembers. A number of policy implications can be drawn from the findings of this study. The important role of farmer groups in enhancing smallholder farm yield and technical efficiency, as evidenced in this study, calls for continuous and increased support from government, development agencies, and private agribusiness companies in farmer group formation when implementing agriculture and value chain development interventions. This could help address the multiple production and marketing challenges facing smallholder farmers. The evidence of selection bias in our study also calls for a broader consideration of farmer group dynamics in selecting beneficiaries for project implementation. Specifically, farmers' self-selection into project participation could as well be complemented with capacity building on group dynamics and technical capacity development. This is expected to enhance the skills and motivation of these farmers, as well as shape their attitudes towards risk for effective project participation and the achievement of project outcomes. Technical capacity development of farmer groups could also be complemented with effective extension services, especially on input application to increase yield and technical efficiency. Stakeholder collaborative efforts to establish and/or expand irrigation facilities in the study area would also enhance yield and efficiency. Incorporation of well-structured credit schemes into agricultural value chain interventions, coupled with the creation of sustainable business relationship between farmer groups and readily accessible financial institutions, could assist in addressing smallholder liquidity constraints for improved yield and technical efficiency gains.

References

Abate, G.T., Francesconi, G.N., Getnet, K., 2014. Impact of cooperatives on smallholders' technical efficiency: Evidence from Ethiopia. *Annals of Public and Cooperative Economics* 85(2), 11-21.

Abdulai, A-N., Abdulai A., 2017. Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. *Environment and Development Economics* 22, 77–2001.

Abebaw, D., Haile, M.G., 2013. The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy*, 38, 82-91.

Ainembabazi, J.H., van Asten, P., Vanlauwe, B., Ouma, E., Blomme, G., Birachi, E.A., Nguezet, P.M.D., Mignouna, D.B., Manyong, V.M., 2017. Improving the speed of adoption of agricultural technologies and farm performance through farmer groups: evidence from the Great Lakes region of Africa. *Agricultural Economics*, 48, 241-259.

Angelucci F., Asante-Poku A., Anaadumba P., 2013. Analysis of incentives and disincentives for rice in Ghana. *Technical note series*, MAFAP, FAO, Rome.

Barrett, C.B., Christian, P., Shiferaw, B.A., 2017. The structural transformation of African agriculture and rural spaces: introduction to a special section. *Agricultural Economics*, 40, 5-10.

Barrett, C.B., Bachke, M.E., Bellemare, M.F., Michelson, H.C., Narayanan, S., Walker, T.F., 2012. Smallholder participation in contract farming: comparative evidence from five countries. *World Development*, 40, 715-730.

Battese, G. E., 1997. A note on the estimation of Cobb-Douglas production functions when some explanatory variables have zero values. *Journal of Agricultural Economics*, 48(2), 250-252.

Bernard, T., Spielman, D., Taffesse, A. S., Gabre-Madhin, E., 2010. Cooperatives for stable crop marketing: Evidence from Ethiopia, Washington, DC: International Food Policy Research Institute (IFPRI) Research Report 166.

Bellemare, M. F., Novak, L., 2016. Contract farming and food security. *American Journal of Agricultural Economics*, 99(2), 357-378.

Bellemare, M. F., 2012. As you sow, so shall you reap: the welfare impacts of contract farming. *World Development*, 40 (7), 1418-1434.

Bravo-Ureta, B. E., Greene, W., Solis, D., 2012. Technical efficiency analysis correcting for biases from observed and unobserved variables: an application to a natural resource management project. *Empirical Economics*, 43, 55-72.

Bravo-Ureta, B. E., Solís, D., Moreira, V., Maripani, J., Thiam, A., Rivas, T., 2007. Technical efficiency in farming: a meta-regression analysis. *Journal of Productivity Analysis*, 27, 57–72.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22 (1), 31-72.

De los Santos-Montero, L. A., Bravo-Ureta, B. E., 2017. Productivity effects and natural resource management: econometric evidence from POSAF-II in Nicaragua. *Natural Resources Forum* 41, 220-233.

Francesconi, G. N., Wouterse, F., 2015. Promoting the role of farmer-based organizations for the value chain integration: the tension between a program's targeting and an organization's investment strategy. *Agricultural Economics*, 46, 527-536. 2.

Gedara, K.M., Wilson, C., Pascoe, S., and Robinson, T., 2012. Factors affecting technical efficiency of rice farmers in village reservoir irrigation systems of Sri Lanka. *Journal of Agricultural Economics*, 63(3), 11-21.

Gonzalez-Flores, M., Bravo-Ureta, B.E., Solis, D., Winters, P., 2014. The impact of high value markets on smallholder productivity in the Ecuadorean Sierra: A stochastic production frontier approach correcting for selectivity bias. *Food policy*, 44, 237-247.

Greene, W., 2010. A stochastic frontier model with correction for sample selection. *Journal of Productivity Analysis*, 34,15–24.

Greene, W. H., 2012. Econometric Analysis, Prentice Hall, Upper Saddle River, NJ.

Henderson, H., Isaac, A. G., 2017. Modern value chains and the organization of agrarian production. *American Journal of Agricultural Economics*, 99, 379-400.

Jappelli, T., 1990. Who is Credit Constrained in the U. S. Economy? *The Quarterly Journal of Economics*, 105 (1), 219-234.

Khandker, S.R., Koolwal, G.B., and Samad H.A., 2010. Hand book on impact evaluation: Quantitative Methods and Practices, Washington, DC: World Bank.

Kumbhakar, S., Tsionas, M., Sipilainen T., 2009. Joint estimation of technology choice and technical efficiency: an application to organic and conventional dairy farming. *Journal of Productivity Analysis* 31(3), 151–162.

Lai, H., Polachek, S., Wang, H., 2009. Estimation of a stochastic frontier model with a sample selection problem. Working Paper, Department of Economics, National Chung Cheng University, Taiwan.

Leuven, E., and Sianesi, B., 2003. PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing', Statistical software components, Boston College Department of Economics, Chestnut Hill, MA.

Ma, W., Abdulai, A., 2016. Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy*, 58, 94-102.

Ma, W., Abdulai, A., Goetz, R., 2018. Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. *American Journal of Agricultural Economics*, 100 (2), 502-520.

Markelova, H., Meinzen-Dick, R., Hellin, J., Dohrn, S., 2009. Collective action for smallholder market access. *Food Policy,* 34, 1-7.

Mayen, C.D., Balagtas, J.V., Alexander, C.E., 2010. Technology adoption and technical efficiency: organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics,* 92(1), 181-195.

MoFA., 2009. National Rice Development Strategy (NRDS). Coalition for African Rice Development, Accra.

Mojo, D., Fischer, C., Degefa, T., 2017. The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. *Journal of Rural Studies*, 50, 84-94.

Murphy, K., Topel, R., 2002. Estimation and inference in two stem econometric models. *Journal of Business and Economic Statistics*, 20,88–97.

Rahman, S., 2011. Resource use efficiency under self-selectivity: the case of Bangladeshi rice producers. *The Australian Journal of Agricultural and Resource Economics*, 55, 273-290.

Rahman, S., Wiboonpongse, A., Sriboonchitta, S., Chaovanapoonphol, Y., 2009. Production efficiency of jasmine rice producers in northern and north-eastern Thailand. *Journal of Agricultural Economics,* 60(2), 419–435.

Reardon, T., Barret, C.B., Berdegué, J.A., Swinnen, J.F.M., 2009. Agrifood industry transformation and small farmers in developing countries. *World Development*, 37, 1717-1727.

Salifu, A., Rebecca, L. F., Meagan, K., Shashidhara, K., 2012. Farmer Based Organizations in Ghana. IFPRI working Paper 31, *International Food Policy Research Institute (IFPRI),* Washington DC.

Seymour, G., 2017. Women's empowerment in agriculture: Implications for technical efficiency in rural Bangladesh. *Agricultural Economics*, 48, 513-522.

Smith, J. A., Todd, P. E., 2005. Does matching overcome LaLonde’s critique of nonexperimental estimators? *Journal of Econometrics*, 125(1), 305-353.

Spielman, D.J., Kelemwork, D., Alemu, D., 2011. Seed, fertilizer, and agricultural extension in Ethiopia. International Food Policy Research Institute (IFPRI): Ethiopia Strategic Support Program (ESSP), Working paper 020.

Terza, J. V., 2009. Parametric nonlinear regression with endogenous switching. *Econometric Reviews*, 28, 555-580.

Verhofstadt, E., Maertens, M., 2014. Smallholder cooperatives and agricultural performance in Rwanda: do organizational differences matter? *Agricultural Economics*, 45, 39-52.

Villano, R., Bravo-Ureta, B. E., Solis, D., Fleming, E., 2015. Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. *Journal of Agricultural Economics*, 66(1), 129-154.

Wang, H. H., Wang, Y., Delgado, S., 2014. The transition to modern agriculture: Contract farming in developing countries. *American Journal of Agricultural Economics* 96 (5), 1257-1271.

Wollni, M., Brümmer, B., 2012. Productive efficiency of specialty and conventional coffee farmers in Costa Rica: Accounting for technological heterogeneity and self-selection. *Food Policy*, 37, 67-76.

Wooldridge, J. M., 2015. Control functions methods in applied econometrics. *The Journal of Human Resources*, 50(2), 421-445.

Statistics, Research and Information Directorate (SRID)., 2016. Agriculture In Ghana: facts and figures (2015). Ministry of Food and Agriculture, October, 2016, Accra.

Appendix

Table 4.A1: Descriptive statistics of variables used in the analysis

Variable	Unmatched sample					Matched sample				
	Members		Nonmembers		Diff. (t-stat.)	Members		Nonmembers		Diff. (t-stat.)
	Mean	Std	Mean	Std		Mean	Std	Mean	Std	
Age	40.40	11.89	35.83	11.30	3.99***	40.40	11.89	40.69	11.39	-0.21
Education	1.97	4.03	2.11	4.05	-0.32	1.97	4.03	1.80	4.08	0.41
Gender	0.89	-	0.91	-	-0.63	0.89	-	0.90	-	- 0.53
Mobile phone	0.37	-	0.27	-	2.21**	0.37	-	0.44	-	-1.25
Distance to market	6.96	4.12	5.93	3.90	2.61***	6.96	4.12	6.88	3.89	0.20
Bicycle	0.68	-	0.74	-	-1.23	0.68	-	0.75	-	-1.58
Total Farm land	2.91	2.21	4.56	3.74	- 5.30***	2.91	2.21	2.93	2.46	-0.08
Access to credit	0.63	-	0.29	-	7.38***	0.63	-	0.61	-	0.63
Extension visits	2.13	2.87	1.08	2.55	3.92***	2.13	2.87	2.50	2.57	-1.03
Access to irrigation	0.28	-	0.16	-	2.86***	0.28	-	0.31	-	-0.75
Variety	0.79	-	0.61	-	3.90***	0.79	-	0.82	-	-0.82
Rice output	842.68	925.31	639.12	558.95	2.75***	842.68	925.31	763.67	562.94	0.85
Land	1.68	1.97	3.73	3.45	-7.20***	1.68	1.97	1.96	3.47	-1.32
seed	37.08	33.30	44.53	42.64	-1.94**	37.08	33.30	37.65	42.88	-0.30
Fertilizer	92.58	106.29	69.87	59.93	2.72***	92.58	106.29	91.33	59.01	0.13
Chemical	2.65	2.75	2.17	2.61	1.78*	2.65	2.75	2.55	2.62	0.37
labor	58.55	24.55	53.25	24.97	2.15**	58.55	24.55	62.70	25.06	-1.18
Soil quality	0.13	-	0.26	-	-3.05***	0.13	-	0.18	-	-1.12
Sagnarigu	0.29	-	0.17	-	8.57***	0.29	-	0.23	-	0.83
Tolon	0.26	-	0.22	-	1.01	0.26	-	0.29	-	-0.57
Kumbungu	0.22	-	0.29	-	-1.74*	0.22	-	0.23	-	-0.21
Savelugu Nanton	0.08	-	0.26	-	-4.88***	0.08	-	0.24	-	-4.50***
Sample size	**186**		**226**			**186**		**221**		

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 4.A2: First stage estimates for addressing potential endogeneity

Variables	Extension visits		Access to credit	
	Coefficient	Std. Err.	Coefficient	Std. err
Constant	-1.364***	0.409	-1.256***	0.405
Age	0.006	0.006	0.009	0.005
Education	0.008	0.017	0.003	0.016
Gender	-0.040	0.251	-0.134	0.250
Mobile phone	0.635***	0.159	-0.003	0.152
Distance to market	0.024	0.017	-0.003	0.016
Bicycle	-0.058	0.165	0.322**	0.159
Total farm land	-0.024	0.031	0.026	0.029
Access to irrigation	0.448**	0.189	0.264	0.168
Tolon	0.329	0.228	0.149	0.221
Sagnarigu	0.578**	0.261	1.131***	0.251
Kumbungu	-0.765***	0.237	0.194	0.217
Savelugu Nanton	-0.222	0.249	0.090	0.230
Access to credit	0.012	0.143		
Farm road status	0.738***	0.157		
Extension visits			-0.024	0.025
Distance(km) to credit institution			-0.056***	0.021
Log likelihood	-225.64		-261.21	
Number of observations	412		412	

Note: **, *** represent significance at 5%, and 1% levels, respectively.

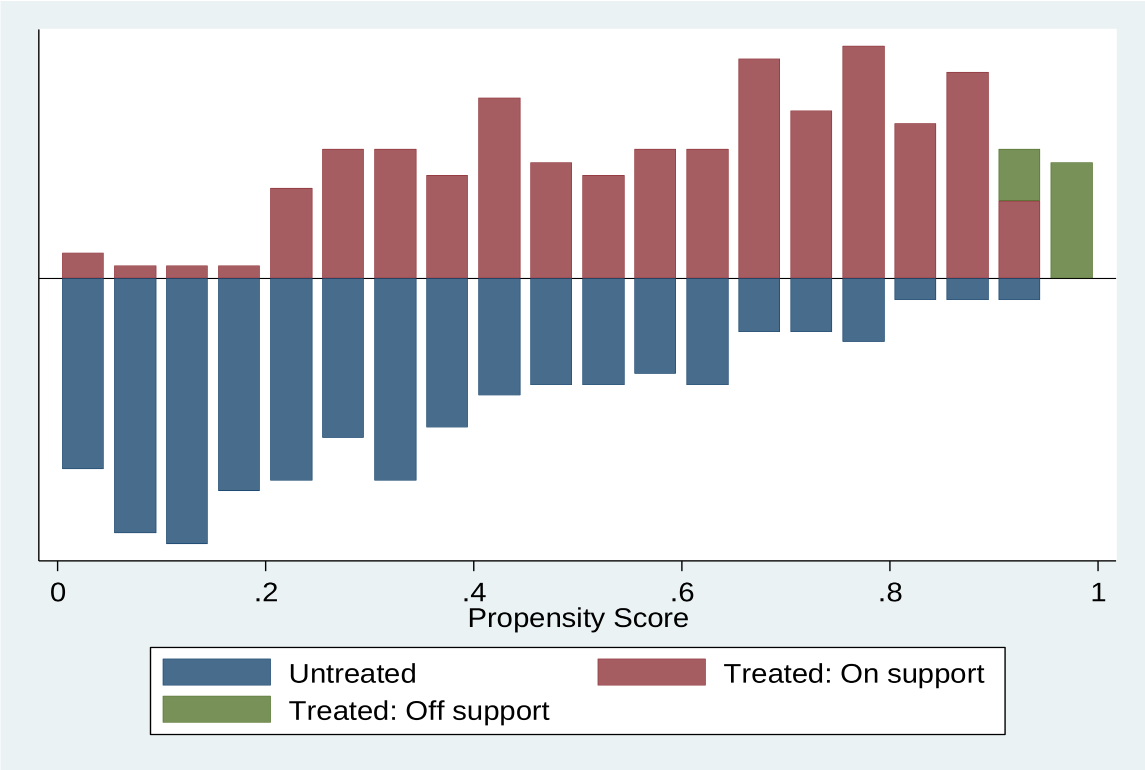


Fig 4.A1 Density of propensity scores for members and nonmembers of farmer groups.

Chapter 5

Social networks, value chain participation and market performance of smallholder farmers in Ghana

Awal Abdul-Rahaman and Awudu Abdulai

Department of Food Economics and Consumption Studies, University of Kiel, Germany

Submitted to *Applied Economics*

Abstract

This paper examines the impact of inclusive value chain participation and social networks on smallholder market performance outcomes such as paddy price, quantity of paddy traded, and net returns, using data from a recent survey of 458 smallholder farmers in northern Ghana. We employed treatment effects model in the estimations to account for potential selection bias associated with both observed and unobserved factors. The empirical results reveal that smallholder farmers' participation in rice value chain is associated with increased paddy price, quantity traded, and net returns. We also find that value chain participation decisions and market performance are positively and significantly influenced by social networks. The empirical results also suggest that gender, farm size, mobile phone ownership, and access to credit contribute positively and significantly to increased paddy prices, quantity traded, and net returns of smallholder rice farmers in the value chain.

Keywords: Rice value chain, social networks, treatment effects model, market performance.

5.1 Introduction

In the past 2-3 decades, the agricultural value chain system in developing countries has experienced dramatic structural transformation, driven by several factors such as population growth, rising urbanization, increasing consumer incomes, influx of both domestic and foreign direct investments, as well as varying consumer dietary requirements from food grains to high value and processed food products (Swinnen and Kuijpers, 2017; Henderson and Isaac, 2017; Reardon et al., 2009). While the value chain transformation is considered important in reducing rural poverty, improving food and nutrition security, and ensuring overall economic growth, smallholder farmers' inclusion in these chains still remains a major challenge in developing countries, largely due to lack of institutional and infrastructural support, inadequate resources for effective and efficient value chain coordination, high transaction costs associated with accessing inputs and markets, and other challenges related to accessing services such as extension, finance, and transportation, all of which impact farm production and market performance (Trienekens, 2011; Dillon and Dambro, 2017; Ecker, 2018).

Developing country governments, NGOs, and the private sector have increasingly recognized agricultural value chain development as an important area of donor interventions, and a centrepiece of agricultural development policies (World Bank, 2007; Humphrey and Navas-Alemàn, 2010; Ton et al. 2011). Motivated by concerns for agribusiness development, value chain development interventions do not only focus on strengthening the capacities of value chain actors (smallholder farmers, aggregators/traders, processors etc.), but also the institutions and enabling policy environment that ensure efficient coordination and competitiveness of these chains. They facilitate vertical linkages, and foster governance of relationships between smallholder farmers and agribusinesses through written or verbal contracts within value chains for improved welfare gains such as increased incomes, and access to new services for production and marketing (Poulton et al., 2010; Devaux et al., 2018).

Smallholder farmers have been typically recognized as important actors for the diffusion of value chain innovations such as information and technology (Ramirez et al. 2018). With the underlying assumption that the behavior of social network members influences farmers' decision-making with direct implications on welfare outcomes (Maertens and Barrett, 2012), the important role of farmers' social networks in improving value chain efficiency and rural economic transformation needs to be highlighted in the empirical literature. The concept of social networks emphasizes on the connections among individuals (e.g., farmers) through which goods and services, money, and information flow (Maertens and Barrett, 2013). Interestingly, local level initiatives in building social networks can lead to diverse forms of value chain inclusion with considerable welfare and market performance outcomes for smallholder farmers (Ramirez et al. 2018). Within the context of agrifood value chains, social networks focus on both the horizontal and vertical relationships that exist among value chain actors (Ruben et al., 2006; Trienekens, 2011). Horizontal social networks reflect cohesive social relationships that promote collective action for successful inclusion in value chains (Ramirez et al. 2018). They can draw upon their social capital to strengthen vertical relationships with buyers and other actors within the value chain (Bijman et al., 2006). More importantly, smallholder farmers organized into a strong social network can benefit from improved access to credit and extension services, increased bargaining power, exchange of input and output price information, as well as buyer quality requirements through participation in such formalized value chains.

This means that inclusive agrifood value chain development goes beyond vertically linking smallholder farmers to other actors in the value chain, but also organizing them into a strong cohesive social network for effective value chain participation (Poulton et al., 2010; Bijman et al., 2011; Kilelu et al., 2017). This argument is in line with the increasing calls for smallholder collective action (e.g., collective marketing) to improve farmers' bargaining power, while enhancing value chain efficiency (Bernardet al., 2010; Dillon and Dambro, 2017). Aside horizontal social networks, smallholder farmers often rely on their social connections and goodwill with other farmers in their communities to enjoy cost advantages associated with production and sales, as well as achieve optimum benefit from participating in agrifood value chains (Morgan, 2012). Such social connections are based on agreed-upon norms, and establish trust, as well as facilitate sharing of value chain information, skills, labor, and financial resources.

Some recent studies have examined the welfare gains associated with smallholder farmers' inclusion in agrifood value chains in developing countries (e.g., Bellemare, 2012; Michelson, 2013; Bellemare and Novak, 2016; Henderson and Isaac, 2017; Maertens and Vande Velde, 2017; Ma and Abdulai, 2017). Michelson (2013) found that inclusive value chain participation is associated with increased productive asset holdings among smallholder farming households in Nicaragua. Other studies also found that smallholder inclusion in agrifood value chains significantly improves prices received, farm profit, and gross income (e.g., Ma and Abdulai, 2017), farm yields, household income, and net farm income (e.g., Maertens and Vande Velde, 2017; Bellemare, 2012), and land and labour redistribution (e.g., Henderson and Isaac, 2017).

Meanwhile there is increasing interests in the role of social networks on the economic behavior and decision-making of smallholder farmers in developing countries. For example, the study by Bandiera and Rasul (2006) reveals that social networks influence smallholder farmers' sunflower and hybrid seed technology adoption decisions in northern Mozambique and India, respectively. Conley and Udry (2001) also find that social networks through social learning influence fertilizer adoption decisions by Ghanaian pineapple farmers. Moreover, the role of social networks in improving households' access to credit, income diversification, and non-farm employment decisions has also been revealed by past studies (e.g., Wydick et al., 2011; Johney et al., 2014; Mano et al., 2011). A recent study by Herforth et al. (2015) is limited to examining how social networks, and other farm and household characteristics affect modern supply chain participation among blackberry farmers in the Ecuadorian Andes.

This study explores the role of social networks in promoting smallholder inclusive value chain participation, as well as the impact of both social networks and inclusive value chain participation on smallholder market performance, using recent survey data from northern Ghana. Insights from this study could be relevant from development policy perspective, although lacking in the empirical literature. In particular, our study makes three contributions to the growing literature on social networks and inclusive value chains. First, we explore the role of social networks, and other farm and household characteristics in influencing smallholder farmers' participation in agrifood value chains. Second, we examine how social networks and value chain participation influence smallholder market performance outcomes: prices, quantity traded, and farm net returns. Finally, we examine whether value chain participation effects vary with farm size.

It is important to mention that examining the market performance outcomes associated with value chain participation poses unobserved heterogeneity and potential endogeneity challenges. For instance, we argue that value chain participation may result in improved market outcomes, likewise better market performance status of farmers may lead to inclusion in agrifood value chains. In this study, we acknowledge that the systematic differences in the outcomes between participants and non-participants could be attributed to potential unobserved heterogeneity, which needs to be addressed to obtain unbiased and consistent impact estimates associated with value chain participation. Therefore, the present study employs a treatment effects model to account for endogeneity of value chain participation decision due to unobserved characteristics of the farmers, as well as their farms.

The present study focuses on the rice sector, because of its potential of benefiting a large number of smallholder farmers in Ghana. In addition, agrifood value chain development efforts to revamp the cereal staples sector are already in progress in Ghana. The government together with donor agencies and the private sector have collaboratively rolled out a number of value chain development interventions[11] with the objective of ensuring smallholder market competitiveness, and rural economic transformation. These interventions promote inclusive value chain development by linking smallholder farmers with large agribusinesses[12] and other produce buyers for output market transactions. Findings from this study can inform policy on the design and implementation of inclusive value chain development programs for the benefit of smallholder farmers in northern Ghana.

The rest of this paper is organized as follows: section 2 describes the conceptual framework employed to guide the empirical analysis, followed by specification of the empirical models in section 3. Section 4 presents the data and descriptive statistics of the variables used in the analysis. Section 5 presents and discusses the empirical results, while conclusions and policy implications are presented in the final section.

5.2 Conceptual framework

5.2.1 Value chain participation decision and the role of social networks

In this section, we explore the effects of social networks and other farm and household characteristics on inclusive value chain participation by smallholder farmers. As stated earlier, the crucial role of social networks in influencing individual's economic behaviour, preferences, or decision-making cannot be overemphasized. This can be achieved through useful interactions

---

[11]Ongoing agricultural value chain development interventions in Ghana include the FtF-USAID-Ghana programme such as Agriculture Technology Transfer project (ATT), Resiliency in Northern Ghana (RING), Agricultural Development and Value Chain Enhancement (ADVANCE), Strengthening Partnerships, Results and Innovations in Nutrition Globally (SPRING) projects. The Ghanaian government is currently implementing some value chain development flagship programs including the Planting for Food and Jobs (PFJ) initiative and 1-village 1-dam project spanning from 2017-2020 (MoFA, 2017).

[12]Examples of agribusiness companies that transact with smallholder farmers in northern Ghana include premium foods limited, AMSIG Resources, SAVBAN limited, BUSAKA enterprise, Investment Protocol Services Limited (IPSL), Ofram supermarket, Avnash Industries Limited etc.

among network members, which may lead to sharing of valuable knowledge and information for improved innovative behavior and performance. Smallholder farmers' participation in inclusive agrifood value chains is an example of such innovative behavior and decision-making, capable of enhancing market performance and rural livelihoods. Different types of social network effects on such behavior and decision-making have been documented in the empirical literature. These include endogenous effects, exogenous (contextual) effects and correlated effects. The influence of a network member's behavior on the individual's decision-making, such as value chain participation, is termed an endogenous network effect, whilst the effect that network member's specific characteristics (e.g., age, education, gender etc.) may have on the individual's decision to participate in a value chain is referred to as an exogenous (contextual) network effect (Manski, 2000). According to Lee (2007), the exogenous (contextual) effects are measures of network members that are not affected by current behavior. Correlated network effects on the other hand stem from controlling for unobservable invariant characteristics between network points in a community or district that may influence farmer's value chain participation decision (Mekonnen et al, 2018). It is accounted for in an empirical analysis by including location dummies in the model.

To examine the effects of social networks, and other farm and household characteristics on inclusive agrifood value chain participation decision, we assume that farmers make binary decisions whether to participate or not to participate in agrifood value chain, depending on these characteristics. This decision is determined by comparing the expected utility from the participation, (U_i^P), and the expected utility from non-participation, (U_i^N). Intuitively, a farmer decides to participate in an agrifood value chain if the utility difference (VC_i^*) is positive, i.e. $VC_i^* = U_i^P - U_i^N > 0$, which implies that the utility the farmer derives from participating in the value chain outweighs the utility derived from non-participation. However, VC_i^* is a latent variable, and cannot be directly observed. In this context, what is observed is the actual decision by the farmer to participate in a value chain, VC. Therefore, we specify it as a function of observable farm, household and social network characteristics as:

$$VC_i^* = Z_i\delta + D_i\varphi + \eta_i, VC_i = \begin{cases} 1 & \text{if} VC_i^* > 0 \\ 0 & \text{if} VC_i^* \leq 0 \end{cases}, \quad (1)$$

where VC_i is a binary indicator variable that equals one if a farmer participates in an agrifood value chain, and zero otherwise; Z is a vector of farm and household characteristics believed to influence value chain participation decision. These include age, education, gender, farm size, distance to market, bicycle ownership, road status, mobile phone ownership, access to credit, and market perception; D_i denotes variables representing social networks; δ is a vector of parameters capturing the direct effects of exogenous observable characteristics in Z whilst φ measures the endogenous, contextual and correlated network effects on farmer's decision to participate in the value chain; and η_i is an error term, with zero mean and variance σ^2. The choice of the explanatory variables in this study is based on existing literature, as well as observations from our field survey.

Building on the existing literature on the effects of social networks on technology adoption (e.g., Bandiera and Rasul, 2006), and on modern supply chain participation (e.g., Herforth et al., 2015; Ramirez et al., 2018), we include in our analysis, variables representing farmer's horizontal social network relationship, which is assigned a value of one if a farmer belongs to such a network, and zero otherwise. As stated earlier, cohesive horizontal social network of farmers improves collective bargaining power, increases members' access to value chain services and ensures effective value chain participation. In addition, a variable that captures the number of value chain participants in a farmer's social network is included in the analysis. This variable was a self-reported response elicited from farmers on how many other farmers he/she knows in the community who participated in the rice value chain at the time of survey, and whether or not regular interactions about rice marketing exist between him/her and this category of value chain participants. These social network variables measure the existence of endogenous effects on value chain participation. However, measurement of these effects poses simultaneity issues, resulting from the fact that the behavior of an individual is influenced by the mean behavior of the group, who also in turn influences the group's behavior. Manski (1993) refers to this identification problem as reflection problem.

Moreover, smallholder farmers are normally organized horizontally into farmer groups, and taken through capacity building training to become strong and cohesive social network group for inclusion in agrifood value chains. Conversely, agribusiness companies and other produce buyers normally prefer to engage with smallholder farmers in the form of strong and cohesive groups to reduce transaction costs associated with having to aggregate paddy from individual farmers. Therefore, farmers may decide to be members of the horizontal social networks to be able to participate in a value chain, making both decisions jointly determined. With regards to the number of value chain participants in a farmer's social network, we argue that a farmer's network members who are already participants in a value chain can serve as sources of useful information, and potential avenues for sharing valuable experiences about the marketing opportunities in a value chain. The information and experience sharing between farmers and their network members are expected to influence the decisions of this category of farmers to participate in the value chain. On the other hand, produce buyers can also rely on participants for the information and recommendation of their network members for inclusion in the value chains. Similarly, access to credit variable in Z may also pose potential endogeneity problems in the value chain participation equation. In the study area, government and NGOs who facilitate smallholder inclusion in agrifood value chains, also facilitate farmers' access to credit through linkages with financial service providers. In that case, some farmers decide to participate in a value chain to be able to access credit to expand their farming operations, and to benefit from guaranteed market. This makes the decisions to participate in a value chain and to access credit jointly determined. These issues need to be addressed to ensure consistent estimation of these variables.

To address these issues, some approaches have been suggested in the literature. Manski (2000) suggests the introduction of dynamism to the model whereby an individual's behavior is influenced by the lagged behavior of his/her network instead of contemporaneous values of mean behavior of the group. Another approach is to use instruments to address these challenges (Manski, 2000). Due to data limitation, we use the latter approach in the present study, a two-stage approach clearly outlined in Wooldridge (2015). In the first-stage, we estimate the potential endogenous variables (access to credit, horizontal social network relationship and value chain participants in farmer's network) as functions of all other explanatory variables in the value chain participation equation, in addition to a set of respective instruments. These instruments should directly influence the potential endogenous variables, but do not directly affect farmers' value chain participation decisions. For the horizontal social network relationship variable, distance to meeting point of social network members was employed as instrument. Intuitively, farmers living farther away from the meeting point are less likely to be members of this network. For the number of value chain participants in a farmer's network, we used as instrument, a variable representing number of neighbors living 5km radius around farmer's home, which significantly influences number of value chain participants in a farmer's network, but not value chain participation decision. We argue that more neighbors are likely to be part of a farmer's network, and also double as value chain participants, if the number of neighbors living 5km radius around the farmer's home is higher. We also used distance to credit institution, measured in kilometres, as instrument in the access to credit equation. In this context, we argue that farmers residing farther away from credit institutions could be less likely to access credit from these institutions. In the second-stage, we estimate the value chain participation model, which includes both the observed potential endogenous variables and their respective residuals predicted from the first-stage. The *t*-test on the coefficients of the residuals is used as test for the endogeneity of the variables. Table 1A in the appendix presents the first-stage regression results. Following Mekonnen et al. (2018), we control for contextual network effects by averaging the values of observable exogenous characteristics of the farmers in the sample, based on the subsamples drawn from each study community. Based on our data, the exogenous characteristics used are the averages age, education, gender, and farm size. We also control for correlated network effects by including district dummies (location fixed effects) in our treatment effects model.

5.2.2 *Impact of social networks and value chain participation*

As indicated previously, we also examine the impact of social networks and inclusive value chain participation on smallholder farmers' market performance in northern Ghana. The market performance outcome measures considered in this study include paddy price received, quantity traded, and net returns. To link value chain participation decision to the market performance outcomes, we assume a linear function between a vector of the outcome variables and a vector of farm, household, and social network characteristics (X_i), and a dummy variable representing value chain participation (VC_i), specified as:

$$Y_i = X_i\theta + VC_i\beta + \mu_i, \tag{2}$$

where Y_i is a vector of outcome variables: paddy price, quantity traded, and net returns; θ and β are vectors of parameters to be estimated; and $\mu_i$is the error term. Farmers' decisions to participate in a value chain are not randomly assigned, but involves self-selection. In the decision making process, unobservable factors such as farmers' risk preferences, motivation, and innate skills influencing their decisions to participate in the value chain, may as well influence their market performance outcomes, resulting in correlation between the error term (η_i) in equation (1) and the error term (μ_i) in equation (2), such that corr $(\eta_i, \mu_i) \neq 0$. This leads to potential selection bias, which needs to be addressed to ensure unbiased and consistent value chain participation impact estimates. What this means is that, using standard regression methods such as ordinary least squares (OLS) would generate biased estimates. Some recent studies have employed propensity score matching (PSM) approach to address the selection bias (e.g., Faltermeier and Abdulai, 2009; Fischer and Qaim, 2012; Maertens and Vande Velde, 2017; Mojo et al., 2017; Mishra et al., 2018). However, the PSM accounts for selection bias stemming from only observed factors. In the present study, we use treatment effects model in the empirical analysis (Cong and Drukker, 2000).

5.3 Empirical specification

5.3.1 Treatment effects model

In this section, we estimate the factors influencing smallholder rice farmers' decisions to participate in a value chain, and their impacts on paddy price, quantity of paddy rice traded, and net returns, using treatment effects model. The treatment effects model accounts for selection bias due to both observed and unobserved factors, and provides direct marginal effect of value chain participation on the market performance outcomes. In the treatment effects model, the error terms in the selection equation (1) and the outcome equation (2) are assumed to follow a bivariate normal distribution with mean zero, and a covariance matrix $\begin{bmatrix} \sigma & \rho \\ \rho & 1 \end{bmatrix}$. Following Cong and Drukker (2000), we use the formula for the joint density of the bivariate normally distributed variables to specify respectively the expected market performance outcomes for farmer i conditional on value chain participation (equation.3: treatment), and non-participation (equ.4: control) as:

$$E(Y_i|VC = 1) = X_i\theta + \beta + E(\mu_i|VC = 1) = X_i\theta + \beta + \rho_{\eta\mu}\sigma_{\eta\mu}\frac{\phi(Z_i\delta)}{\Phi(Z_i\delta)} \quad (3)$$

$$E(Y_i|VC = 0) = X_i\theta + E(\mu_i|VC = 0) = X_i\theta - \rho_{\eta\mu}\sigma_{\eta\mu}\frac{\phi(Z_i\delta)}{1-\Phi(Z_i\delta)}, \quad (4)$$

where $\phi(.)$ is the standard normal density function, and $\Phi(.)$ denotes the standard normal cumulative distribution function. The ratio of $\phi(.)$ and $\Phi(.)$ is referred to as the inverse mills ratio. θ and β are vectors of parameters to be estimated; $\sigma_{\eta\mu}$ is the covariance between the two error terms, $\eta,\ \mu; \rho_{\eta\mu}$ is the correlation coefficient, and an indicator of selection bias on unobserved factors. In particular, a significant $\rho_{\eta\mu}$ indicates the presence of selection bias, and insignificant $\rho_{\eta\mu}$ means that selection bias due to unobserved factors is absent. The sign of $\rho_{\eta\mu}$ also has economic interpretation. For instance, a negative $\rho_{\eta\mu}$ implies a negative selection bias, which means that in our sample, farmers with lower than average paddy price, quantity traded, and net returns are more likely to participate in the rice value chain. Conversely, if $\rho_{\eta\mu}$ is positive, it means positive selection bias, suggesting that farmers with above average outcomes would be less likely to participate in the value chain. The average treatment effects (ATE) of value chain participation on the outcomes for sample N can be computed as the difference between the expected outcomes from participation (equ. 3), and the expected outcome from non-participation (equ. 4), specified as:

$$ATE = \frac{1}{N}\sum_{i=1}^{N}[E(Y_i|VC = 1) - E(Y_i|VC = 0)]. \tag{5}$$

It is important to properly identify the treatment effects model due to the fact that the variables in equations (1) and (2) are allowed to overlap. The identification requires that at least one variable known as instrument in Z should not appear in X during estimation. This instrument is required to significantly influence farmers' decisions to participate in a value chain, but does not directly affect the market performance outcomes. In this study, we use a variable representing farmers' perception of market demand for paddy in the previous year as an identifying instrument, measured as dummy, where farmer's perception of high market demand for paddy is assigned a value of one, and zero otherwise. We argue that farmers who perceive high market demand for paddy would be more likely to participate in a value chain to ensure guaranteed markets for their produce. An instrument validity test conducted shows that the market perception variable has a significant influence on value chain participation decision, but insignificant effect on output price, quantity of paddy traded, and net returns, suggesting that the instrument is valid. The test results are presented in table A2 in the appendix.

5.4 Data and descriptive statistics

The data used in this study were collected from a recent farm household survey, which spanned from June to August, 2016 in five selected districts of northern Ghana; Tolon, Kumbungu, Sagnarigu districts, Savelugu Nanton Municipal and Tamale metropolis. We employed multi-stage sampling approach in drawing our sample for the study. First, we used purposive sampling method to select the five study districts because of their geographic accessibility and the intensive rice production in these areas. In consultation with the agricultural extension agents (AEAs) of the Ministry of Food and Agriculture (MoFA) and other officials of ongoing donor funded projects (eg., Ghana-USAID/FtF), we randomly selected about two to three communities from each district based on the number of communities in each district. Finally, we used random matching within sample, whereby at least 20 households were randomly selected in each community. Each household were then matched with 5 farmers randomly drawn from the community sample.

In total, we sampled 458 smallholder rice farmers, comprising 206 value chain participants and 252 non-participants. In this context, value chain participants are smallholder farmers participating in the ongoing rice value chain development interventions in northern Ghana, received capacity building and input support, linked to agribusiness companies, and have successfully sold paddy to these companies for at least the past three years. However, non-participants are smallholder farmers who produce and market paddy rice on their own. Both categories of farmers were then engaged in face-to-face interviews, using structured questionnaire. The social network variables captured include horizontal social networks and number of value chain participants in a farmer's network. As indicated previously, a farmer with membership in a horizontal social network is assigned a value of one and zero otherwise. In addition, information was gathered from farmers on the number of farmers in their social networks who are also participants in agrifood value chains. This was based on whether resources such as credit, labor and/land, and farming and marketing information have ever been exchanged between the farmer and the network members. In addition, we considered whether they are relatives, friends, neighbors (farm-plots or residential), belong to the same religion, or ever visited each other. Other information gathered include farm and household characteristics, asset ownership, production and marketing activities related to the 2015 growing season. The field survey was conducted by the authors, with the help of trained research assistants. The outcome variables include average selling price of paddy per kilogram, quantity of paddy traded in kilograms, and net returns. We measured net returns as the difference between value of rice output and variable input costs per hectare.

The definition and summary statistics of variables used in the empirical analysis are presented in table 5.1. As shown in the table, 44% of farmers participate in the rice value chain. On average, a rice farmer in the sample is 37 years, with about 3 years of formal education, and cultivates about 1.14ha of farm size. Table 5.1 shows that on average, a rice farmer traded a quantity of 987.09 kg of paddy rice per hectare, received an average of GH¢1.21 for a kilogram of paddy rice, and generated GH¢ 725.26 of net returns per hectare. Table 5.2 presents the descriptive statistics and statistical significance tests on equality of means of variables for participants and non-participants. As shown in table 5.2, significant differences can be observed between participants and non-participants for some of the variables. On average, the value chain participants are older, and more educated than non-participants.

Table 5.1: Variable definition and summary statistics

Variable	**Definition**	**Mean (Std. Dev.)**
Value chain participation	1 if farmer participates in the rice value chain, 0 otherwise	0.44 (0.49)
Price	Average selling price of paddy rice (GH¢/kg)	1.21 (0.27)
Quantity traded	Quantity of paddy rice sold (kg/ha)	987.09 (766.50)
Net returns	Gross farm revenue from paddy rice production minus variable input cost (GH¢/ha)	725.26 (967.47)
Age	Age of respondent (years)	37.46 (11.65)
Education	Education of respondent (years)	2.71 (4.40)
Gender	1 if farmer is male, 0 otherwise	0.88 (0.32)
Farm size	Size of farm (hectares)	1.14 (1.26)
Distance to market	Distance to market (km)	6.57 (4.08)
Bicycle	1 if a farmer owns bicycle, 0 otherwise	0.70 (0.45)
Road status	1 if market road if motorable , 0 otherwise	0.73 (0.44)
Mobile phone	1 if farmer owns mobile phone, 0 otherwise	0.45 (0.49)
Access to credit	1 if farmer has access to enough credit and not credit constraint, 0 otherwise	0.40 (0.49)
Market perception	Farmer perception of market demand (1=high, 0=low)	0.35 (0.47)
Horiz. social network relationship	1 if farmer is member of HSN, 0 otherwise	0.42(0.49)
VCP in farmer's network	No. of value chain participants farmers in network	4.79 (10.49)
Sagnarigu	1 if farmer is located in Sagnarigu district, 0 otherwise	0.12 (0.33)
Tolon	1 if farmer is located in Tolon district, 0 otherwise	0.22 (0.41)
Kumbungu	1 if farmer is located in Kumbungu district, 0 otherwise	0.24 (0.42)
Savelugu Nanton	1 if farmer is located in Savelugunanton Municipal, 0 otherwise	0.20 (0.40)
Tamale	1 if farmer is located in Tamale metropolitan area, 0 otherwise	0.20 (0.40)
Sample size	Number of observations	458

Note: GH¢ is Ghanaian currency (US$1 = GH¢ 4.19), Std. Dev.: Standard Deviation

Table 5.2 also depicts that value chain participants travel longer distance to the nearest market and mostly own mobile phones. . With regards to social network variables, table 1 shows that participants are mostly (76%) members of horizontal social networks than non-participants (15%). Moreover, participants have higher number of network members who are also value chain participants than non-participants. Value chain participants constitute higher proportion of farmers with access to credit and are not credit constrained than non-participants. In this study, the dummy variable representing access to credit was constructed by gathering responses from a farmer on whether he/she needed credit to undertake production and marketing of rice for the 2015 growing season, and if so, whether he/she received the required amount applied for. Based on the responses, a farmer who did not need credit, or demanded credit, applied for it, and received the required amount is assigned a value of one, and zero otherwise. Similarly, the value chain participants sold higher quantities of paddy rice, received higher paddy price, and generated higher net returns from paddy production and marketing than non-participants. Table 5.2 also shows that both categories of participants also vary significantly in terms of the perception of paddy market demand in the previous season. In particular, participants constitute higher proportion of farmers with perception of high paddy market demand in the previous season than non-participants. In the next section, we verify whether these mean differences remain unchanged using rigorous analytical estimation model where all confounding factors are controlled for.

5.5 Empirical results and discussion

5.5.1 Social network and other factors influencing value chain participation decisions

The estimation results of the factors influencing farmers' decisions to participate in the rice value chain, and the impact of participation on paddy price, quantity of paddy traded, and net returns are presented in tables 5.3-5.5. The treatment effects model jointly estimates the value chain participation and the outcome models using maximum likelihood method. The results of the factors influencing value chain participation decisions are presented in the second column

Table 5.2: Differences in characteristics of farmers by value chain participation

Variable	Participants		Non-participants		Difference
	Mean	Std. Dev.	Mean	Std. Dev.	(t-stat.)
Age	39.29	11.94	35.97	11.22	3.05***
Education	3.09	4.60	2.40	4.20	1.66 *
Gender	0.89	0.30	0.87	0.33	0.83
Farm size	1.19	1.27	1.10	1.24	0.75
Distance to market	7.20	4.37	6.06	3.76	2.99***
Bicycle	0.69	0.46	0.71	0.45	-0.37
Road status	0.81	0.39	0.66	0.47	3.49***
Mobile phone	0.56	0.49	0.36	0.48	4.21***
Access to credit	0.53	0.50	0.30	0.45	5.17***
Market perception	0.50	0.50	0.22	0.41	6.47***
Horiz. social network relationship	0.76	0.42	0.15	0.35	16.85***
VCP in farmer's network	7.89	13.91	2.25	5.29	5.93***
Sagnarigu	0.22	0.42	0.04	0.20	6.13***
Tolon	0.24	0.43	0.20	0.40	1.05
Kumbungu	0.23	0.42	0.24	0.43	-0.32
Savelugu Nanton	0.12	0.32	0.26	0.44	-3.89***
Tamale	0.16	0.37	0.23	0.42	-1.79***
Price	1.33	0.35	1.11	0.12	9.22***
Quantity sold	1,191.27	800.63	820.17	695.69	5.305***
Net returns	1,057.95	1157.21	453.31	667.36	6.99***
Sample size	**206**		**252**		

Note: *, *** represent significance at 10% and 1% levels, respectively.

of tables 5.3-5.5. The results show that variables with the same name in these tables exert statistically similar effects on value chain participation decisions. We interpret and discuss these variables together as normal probit estimates. As shown in the tables, the coefficients of the residuals predicted from the first-stage regression for the potential endogenous variables such as access to credit, horizontal social network relationship, and number of value chain participants in a farmer's network are not significantly different from zero, suggesting that these variables have been consistently estimated (Wooldridge, 2015). As stated earlier, the treatment effects model is identified by excluding at least one variable in the value chain participation model from the outcome models. A variable representing farmer's perception of paddy market demand is employed as an identifying instrument, which significantly influences farmers' decisions to participate in a value chain but does not directly affect paddy price, quantity traded and net returns. As shown in tables 5.3-5.5, farmers with perception of high market paddy demand are more likely to participate in a value chain.

The empirical results reveal the important role of social networks in influencing farmers' decisions to participate in value chains. In particular, the coefficients of horizontal social network relationship and number of value chain participants in farmer's network are positive and significantly different from zero, suggesting farmers who are members of social network group, and those with higher number of value chain participants as network members are more likely to participate in a value chain. This finding presents a strong evidence of the role of social network externalities in inclusive value chain participation. Also, the coefficients of all the average exogenous characteristics of the farmer's peers except gender were not statistically different from zero, suggesting that contextual effects are absent. This means that farmer's value chain participation decision is not correlated with the exogenous characteristics of his network members in the sample. Similarly, we did not did find evidence of correlated network effects in our results, as revealed by the statistically insignificant effects of the district dummies

Table 5.3: Impact of value chain participation and social networks on paddy price

	Participation		Paddy price	
Variable	Coefficient	Std. err	Coefficient	Std. err
Constant	-11.624***	3.407	0.859***	0.124
VC participation	-	-	0.120***	0.021
Horiz. social network relationship	1.530***	0.220	0.011**	0.005
VCP in farmer's network	0.043***	0.012	0.007**	0.004
Av. age	0.036	0.043	0.003	0.002
Av. education	0.097	0.133	0.009	0.006
Av. gender	5.310***	2.040	0.032	0.087
Av. Farm size	0.222	0.229	0.000	0.011
Age	0.010	0.012	0.003	0.010
Education	0.016	0.020	0.001	0.001
Gender	0.138	0.314	0.004	0.017
Farm size	0.049	0.068	0.008**	0.003
Distance to market	0.051**	0.024	-0.001	0.001
Bicycle	-0.006	0.205	0.000	0.011
Road status	0.111	0.354	-0.014	0.010
Mobile phone	0.072**	0.022	0.009**	0.004
Access to credit	0.454***	0.164	0.008***	0.003
Tolon	0.243	0.415	0.028	0.017
Kumbungu	-0.386	0.333	0.039**	0.015
Savelugu Nanton	0.733	0.575	-0.004	0.017
Market perception	0.712***	0.170		
Residual (HSNR)	-3.298	2.995		
Residual (VCPN)	0.011	0.036		
Residual (Access to credit)	-0.736	2.061		
ath($\rho_{\varepsilon\mu}$)	-0.222***	0.012		
$\rho_{\varepsilon\mu}$	-0.218***	0.011		
ln (σ)	-2.340***	0.034		
Wald test ($\rho_{\varepsilon\mu} = 0$)	12.26***, with $\text{prob} > \text{Chi}^2 = 0.000$			
Sample size	458			

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

on value chain participation. Other important determinants of value chain participation decisions include distance to market, mobile phone ownership, and access to credit. As shown in the results, distance to market exhibits positive and statistically significant effect on value chain participation decision at least at 5% level, implying that farmers who travel longer distance to markets are more likely to participate in the rice value chain. This finding is in line with intuition because in the study area, paddy sales by value chain participants are usually carried out at farmgate, which can reduce farmers' transaction costs associated with transporting paddy to market centers. Value chain participation decisions are also positively and significantly influenced by mobile phone ownership. Farmers who own mobile phones are more likely to participate in value chains. Apart from the fact that farmers who own mobile phones can receive input and output price information, they are also able to effectively communicate with buyers to make arrangements for produce delivery (Zanello, 2012; Acker et al., 2016). Farmers with access to enough credit, and not credit constrained are more likely to participate in value chains, as revealed by the positive and significant effect of this variable on value chain participation. Farmers with access to credit from financial institutions participate in value chains to ensure guaranteed market for their paddy and probably timely credit repayment.

5.5.2 Impact of social networks and value chain participation on market performance

The estimation results of the impact of value chain participation and social networks on paddy price, quantity traded, and net returns are presented in the third column of tables 5.3-5.5. As can be observed, the correlation coefficient $\rho_{\varepsilon\mu}$is found to be negative and significant in all the model specifications, suggesting the presence of selection bias due to unobserved factors, and lending support to the use of treatment effects model for the estimation. Moreover, the negative $\rho_{\varepsilon\mu}$ indicates negative selection bias, which means that farmers with below average paddy price received, quantity of paddy traded, and net returns have a higher probability of participating in the rice value chain. This finding is consistent with other recent studies that participation in value chains tend to benefit smallholder farmers in developing countries (eg. Rao and Qaim, 2011; Michelson, 2013; Ma and Abdulai, 2017; Mishra et al., 2018). It can be observed from tables 5.3-5.5 that the Wald test is significant in the estimates, indicating a rejection of the null hypothesis of no correlation between the error terms in the value chain participation and outcome specifications.

With regards to the factors influencing the market performance outcomes of interest, we find a positive and significant marginal effect of the value chain participation dummy on paddy prices, quantity traded, and net returns by about 12.0%, 61.2%, and 86.3%, respectively. This finding further confirms the role of inclusive value chains in improving smallholder market performance. The results also reveal that social networks do not only influence farmers' decisions to participate in value chains, but also play significant role in enhancing the market performance outcomes for value chain participating farmers, relative to those who produce and market paddy rice on their own. In particular, the variable representing horizontal social network relationship is found to have positive and significant effect on paddy price, quantity traded, and net returns, suggesting that farmers who are members of such a social network tend to benefit from these outcomes. As stated previously, horizontal social networks promote sharing of information on input and output prices, which serve as guide for collective negotiations with buyers for increased bargaining power and prices. Moreover, horizontal social network can serve as conduit for the introduction and adoption of improved productivity-enhancing technologies and practices (Conley and Udry, 2001; Maertens and Barret, 2012), which tend to increase farm yields and consequently, quantities traded and net returns. The results also show that the social network variable representing number of value chain participants in farmer's network also exerts a positive and significant effect on paddy price, quantity traded, and net returns. This finding suggests that an increase in the number of value

Table 5.4: Impact of social network and value chain participation on paddy quantity traded

Variable	Participation		Quantity Traded	
	Coefficient	Std. err	Coefficient	Std. err
Constant	-5.070***	1.685	5.043***	0.754
VC participation	-	-	0.612***	0.181
Horiz. Social network relationship	1.565***	0.218	0.771***	0.113
VCP in farmer's network	0.042***	0.012	0.018***	0.006
Av. age	0.043	0.043	0.024*	0.013
Av. education	0.108	0.129	0.064*	0.037
Av. gender	4.057*	2.095	0.267	0.529
Av. Farm size	0.164	0.226	0.215***	0.071
Age	0.005	0.010	0.003	0.002
Education	0.024	0.020	0.009	0.006
Gender	0.216	0.312	0.319***	0.100
Farm size	0.039	0.073	0.228***	0.023
Distance to market	0.065**	0.025	-0.005	0.007
Bicycle	-0.032	0.203	-0.014	0.065
Road status	0.141	0.295	0.039	0.064
Mobile phone	0.078***	0.025	0.029 **	0.013
Access to credit	0.452***	0.160	0.013 *	0.060
Tolon	0.222	0.423	0.147 **	0.010
Kumbungu	-0.525	0.339	0.346***	0.092
Savelugu Nanton	0.253	0.609	0.151	0.104
Market perception	0.715***	0.205		
Residual (HSNR)	-1.672	2.065		
Residual (VCPN)	-0.002	0.034		
Residual (Access to credit)	-0.476	2.028		
ath($\rho_{\varepsilon\mu}$)	-0.359***	0.100		
$\rho_{\varepsilon\mu}$	-0.344***	0.106		
ln (σ)	-0.576***	0.022		
Wald test ($\rho_{\varepsilon\mu} = 0$)	15.06***, with $\text{prob} > \text{Chi}^2 = 0.000$			
Sample size	458			

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

chain participants who are members of farmer's network tend to enhance market performance. As argued earlier, network members doubling as value chain participants can share information on value chain opportunities, which encourages participation, and improvement in market performance outcomes. Similar to the effects on farmers' value chain participation decisions, the coefficients of the average characteristics of farmers' peers were found to be weakly significant on quantity traded, but insignificant on prices received and net returns, suggesting lack of evidence of contextual network effects on these outcomes. The coefficient of the location variables have positive and statistically significant effect on paddy prices, quantities traded and net returns.

Other factors influencing paddy prices received, quantity traded, and net returns, conditional on value chain participation include farmer's age, farm size, gender, mobile phone ownership, access to credit, and location variables. The results show that farmer's age exhibits positive and statistically significant effect on net returns but insignificant positive effect on prices received and quantity of paddy traded, suggesting that older farmers tend to generate higher net returns. Farm size is found to have a positive and significant effect on prices received, quantity traded, and net returns at least at the 5% level, indicating the important role it plays in improving smallholder market performance in agricultural value chains. This finding is consistent with other recent studies, which found that farm size positively and significantly increase market performance (e.g., Mishra et. al., 2018).

The results also reveal positive and significant effect of gender variable on quantities traded and net return, suggesting that male farmers tend to sell higher quantities of paddy, and net returns, suggesting that male farmers tend to sell higher quantities of paddy, and also generate higher net returns from rice production and marketing, relative to female farmers. Ownership of mobile phones increases paddy price received, quantities traded, and net returns, as revealed by its positive and significant impact on these performance outcomes. Ownership of mobile

Table 5.5: Impact of value chain participation and social networks on net returns

	Participation		Net returns	
Variable	Coefficient	Std. err	Coefficient	Std. err
Constant	-10.977***	3.464	5.222 ***	1.537
VC participation	-	-	0.863 **	0.408
Horiz. social network relationship	1.498***	0.223	0.260 **	0.140
VCP in farmer's network	0.043***	0.013	0.062***	0.006
Av. age	0.045	0.045	0.019	0.026
Av. education	0.101	0.135	0.013	0.076
Av. gender	4.964**	2.087	0.302	1.077
Av. Farm size	0.212	0.237	0.140	0.147
Age	0.004	0.012	0.004 **	0.002
Education	0.014	0.021	0.010	0.013
Gender	0.152	0.317	0.592***	0.201
Farm size	0.031	0.069	0.072 ***	0.026
Distance to market	0.061**	0.024	-0.012	0.015
Bicycle	-0.032	0.205	0.079	0.133
Road status	0.147	0.298	-0.039	0.131
Mobile phone	0.074***	0.022	0.071 **	0.029
Access to credit	0.457***	0.161	0.354***	0.122
Tolon	0.177	0.423	0.584***	0.217
Kumbungu	-0.527	0.340	1.168***	0.187
Savelugu Nanton	0.433	0.586	0.595***	0.215
Market perception	0.718***	0.207		
Residual (HSNR)	-2.397	2.057		
Residual (VCPN)	0.002	0.035		
Residual (Access to credit)	-0.872	2.100		
ath($\rho_{\varepsilon\mu}$)	-0.211***	0.024		
$\rho_{\varepsilon\mu}$	-0.208***	0.021		
ln(σ)	0.120***	0.037		
Wald test ($\rho_{\varepsilon\mu} = 0$)	25.82***, with $\text{prob} > \text{Chi}^2 = 0.000$			
Sample size	458			

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

phones can enhance net returns of smallholder farmers by lowering transaction costs associated with searching for input suppliers or produce buyers. Input and output price information can be received via mobile phone, which may serve as guide for negotiating satisfactory prices in both input and output markets (Aker et al., 2016). Moreover, farmers can also make informed decisions about the quantities traded based on the price information received via mobile phone. Access to credit exerts positive and significant impact on prices received, quantities traded, and net returns at least at the 10% level. This finding suggests that farmers who accessed credit, and not credit constrained tend to receive higher prices for paddy rice, trade in higher quantities, and also receive higher net returns. Depending on the measurement of smallholder market access, farmers with access to credit can negotiate for better prices for their produce to ensure timely credit repayment and satisfactory net returns. In addition, farmers who are not credit constrained are able to procure production inputs to increase output, as well as pay for expenses associated with hiring labor for production activities, thereby increasing quantity traded and net returns.

5.5.3 Average Treatment Effects (ATEs)

In this section, we compute the average treatment effects (ATEs), which measure the difference (causal impact) in the predicted market performances outcomes between value chain participants and non-participants as illustrated in equation (5). Note that selection bias stemming from both observed and unobserved factors are accounted for in estimating the ATEs. The results, which are presented in table 5.6, reveal significant positive impact of value chain participation on the market performance outcomes. In particular, smallholder participation in the rice value chain is associated with about 10%, 7%, and 6% increase in paddy price received, quantity of paddy traded, net returns, respectively. This finding is in line with intuition, and consistent with the notion that smallholder farmers benefit from inclusive value chain participation (Ragasa and Golan, 2014; Bellemare and Novak, 2016; Ma and Abdulai, 2016; Belemare and Lim, 2018).

Table 5.6: Average Treatment Effects (ATE) of value chain participation on market performance outcomes

Outcome Variables	Mean Outcome		ATE	t-value	Change (%)
	Participants	Non-participants			
Paddy price	0.830	0.753	0.077***	16.01	10.22
Quantity traded	7.540	7.031	0.509***	48.68	7.23
Net returns	6.614	6.229	0.385***	74.03	6.18
ATE of outcome variables disaggregated by farm size					
Paddy price					
Small (≤ 1.0 ha)	0.824	0.747	0.077***	12.68	10.30
Medium (1.1 - 1.5 ha)	0.838	0.760	0.078***	6.74	10.26
Large (> 1.5)	0.843	0.765	0.078***	9.70	10.19
Quantity traded					
Small (≤ 1.0 ha)	7.451	6.844	0.607***	38.72	8.86
Medium (1.1 - 1.5 ha)	7.614	7.202	0.412***	20.50	5.72
Large (> 1.5)	7.778	7.560	0.218***	21.70	2.88
Net returns					
Small (≤ 1.0 ha)	6.480	6.097	0.383***	58.96	6.28
Medium (1.1 - 1.5 ha)	6.841	6.451	0.389***	31.26	6.03
Large (> 1.5)	6.926	6.535	0.391***	32.85	5.98

Note: *** refers to significance at 1% level. The dependent variables are the log of outcome variables. ATE calculation is based on the log of the predictions.

It is important to point out that the estimation of the aggregate effect of farm size on market performance outcomes, as reported in table 3 and discussed in section 5.2 above, may not reveal actual farm size effects. Therefore, we estimate the causal impact of value chain participation on the market performance outcomes - paddy price, quantity traded, and net returns - for different farm sizes. We argue that this disaggregation provides further insights into differential impacts of value chain participation on the outcomes for various farm sizes. Based on our data, we classify farm size into three categories: small (≤ 1.0 ha), medium (1.1 - 1.5 ha), and large (> 1.5). As shown in table 4, value chain participation significantly increases paddy prices, quantity traded, and net returns for all the farm size categories, relative to non-participation. However, differential increments of these outcomes have been recorded for the different farm sizes, although not statistically significant. In particular, relative to non-participants, value chain participating farmers with small rice farm sizes receive the highest paddy price (10.30%), followed by farmers with medium farm sizes (10.26%). The lowest paddy prices are received by value chain participating farmers with larger farm sizes (10.19%). This finding suggests that farmers with small farm sizes tend to benefit the most from paddy prices when participating in agrifood value chains in the study area. Similar pattern of results can be observed for quantities traded and net returns. In particular, relative to non-participation, value chain participation is associated with significantly higher quantity traded by 8.86%, 5.72%, and 2.88% for farmers with small, medium, and large farm sizes, respectively. Similarly, rice farmers with small farm sizes who are value chain participants generate the highest (6.28%) net returns from rice production and marketing, followed by farmers with medium farm sizes (6.03%), and the lowest net returns is obtained by farmers with large farm sizes (5.98%). These findings are contrary to the assertion by Swinnen et al. (2010), but consistent with the study by Mishra et al. (2018) that smallholder farmers tend to benefit significantly from inclusive agrifood value chain participation for low-value crops such as rice in developing countries like Ghana.

5.6 Conclusions

In this study, we examined the role of inclusive value chains and social networks in improving smallholder market performance outcomes such as paddy price, quantity of paddy traded, and net returns, using data from a recent survey of 458 smallholder rice farmers from five districts in northern Ghana. We employed treatments effects model in the empirical estimations to account for potential selection bias associated with both observed and unobserved factors. The estimation results revealed the presence of negative selection bias, implying that rice farmers with below average paddy price, quantity traded, and net returns are more likely to participate in a value chain. The empirical results showed that participation in a value chain contributes significantly to increased paddy prices, quantity traded, and net returns by 10%, 7%, and 6%, respectively. Relative to non-participants, value chain participating farmers with small farm sizes tend to benefit the most from these market performance outcomes, compared to those with medium and large farm sizes. This implies that inclusive value chain participation for low-value crops like rice improves smallholder market performance in developing countries such as Ghana.

The empirical results also show that social networks significantly influence smallholder farmers' inclusion in agricultural value chains, and improve market performance. Smallholder farmers who are members of horizontal social networks, and those with network members who are already value chain participants, are more likely to also participate in a value chain. This category of farmers also tend to benefit from increased paddy prices, quantity traded, and net returns. Similarly, value chain participation decisions are positively and significantly influenced by distance to market, mobile phone ownership and access to credit. The empirical results also revealed that mobile phone ownership, and access to credit exert positive and significant effects on paddy prices, quantity traded, and net returns of smallholder rice farmers in the value chain.

Important policy implications can be drawn from the findings of this study. The significance of inclusive value chain participation in improving smallholder market performance calls for all stakeholder collaboration towards continuous promotion of agricultural value chain development for smallholder farmers. Agricultural value chain development interventions could focus on setting incentives capable of promoting agribusiness transformation. This could include, but not limited to, investment in market infrastructure (e.g., grain dryers, warehouses), technology transfer and economic stimulus policies, as well as processing facilities to enhance value chain efficiency and smallholder market access. Government policies that promote credit access by facilitating smallholder linkages with financial service providers in value chain interventions could ease smallholder credit constraints for improved production and market performance. With effective coordination and implementation, value chain development programs have the potential to not only benefit smallholder production and market performance, but also create rural and off-farm jobs in agro-processing, as well as accelerate rural structural change. The promotion of social networks within the context of inclusive value chain development can contribute to upgrading developing country value chains in the cereal staple sector. It remains important that in value chain development interventions, smallholder farmers are organized into groups, and their capacities built to become strong and cohesive social network groups for effective and efficient participation in value chains. The capacity building can strengthen the connectedness of network members, and promote sharing of diversity of knowledge and resources for improved power balance and bargaining position in the value chain.

References

Akar, J. C., Ghosh, I., and Burrell, J. (2016). The promise (and pitfalls) of ICT for agriculture initiatives. *Agricultural Economics*, 47(2016): 35-48.

Bandiera, O., Rasul I., 2006. Social networks and technology adoption in northern Mozambique. *Economic Journal*, 116, 869-902.

Bellemare, M.F., 2012. As you sow, so shall you reap: The welfare impacts of contract farming. *World Development*, 40, 1418-1434.

Bellemare, M.F., Novak, L. (2016). Contract farming and food security. *American Journal of Agricultural Economics*, 99 (2), 357-378.

Bellemare, M.F., Lim, S., 2018. In all shapes and colors: varieties of contract farming. *Applied Economic Perspectives and Policy,* 40 (3), 379-401.

Bernard, T., Spielman, D. J., Taffesse, A. S., Gabre-Madhin, E. Z., 2010. Cooperatives for staple crop marketing: evidence from Ethiopia. *IFPRI Research Monograph* 164. Washington DC, USA.

Bijman, J., Omta, S.W.F., Trienekens, J. H., Wijnands, J.H.M., and Wubben, E.M.F. (2006). Management and organization in international agri-food chains and networks. In *International agri-food chains and networks, Management and organization*. *Wageningen Academic Publishers* 15-28.

Bijman, J., Muradian, R., Cechin, A., 2011. Agricultural cooperatives and value chain coordination. In *Value Chains, Inclusion, and Endogenous Development: Contrasting Theories and Realities,* 82-101 (Eds B. Helmsing and S. Vellema). New York: Routledge.

Conley, T., Udry, C., 2001. Social learning through networks: The adoption of new agricultural technologies in Ghana. *American Journal of Agricultural Economics,* 83 (3), 668-673.

Cong, R., Drukker, D. M., 2000. sg141-Treatment effects model. *Stata Technical Bulletin*, May

2000 STB-55.

Devaux, A., Torero, M., Donovan, J., Horton, D., 2018. Agricultural innovation and inclusive value-chain development: a review. *Journal of Agribusiness in Developing and Emerging Economies*, 8(1), 99-123.

Dillon, B., Dambro, C., 2017. How competitive are crop markets in sub-Saharan African? *American Journal of Agricultural Economics*, 99(5), 1344-1361.

Ecker, O., 2018. Agricultural transformation and food and nutrition security in Ghana: Does farm production diversity (still) matter for household dietary diversity? *Food policy*, 79, 271-282.

Faltermeier, L., Abdulai, A., 2009. The impact of conservation and intensification technologies: empirical evidence for rice farmers in Ghana. *Agricultural Economics*, 40, 365-379.

Fischer, E. and Qaim, M. (2012). Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya, *World Development*, 40 (6): 1255–1268.

Henderson, H., Isaac, A. G., 2017. Modern value chains and the organization of agrarian production. *American Journal of Agricultural Economics*, 99, 379-400.

Herforth, N., Theuvsen, L., Vasquez, W., Wollni, M., 2015. Understanding participation in modern supply chains under a social network perspective –evidence from blackberry farmers in the Ecuadorian Andes. *Global Food Discussion Paper* No. 54.

Humphrey, J., Navas-Aleman, L., 2010. Value chain, donor interventions and poverty reduction: a review of donor practice, IDS Research Report 63, Institute of Development Studies, Brighton, UK.

Kilelu, C. W., Klerkx, L., Leeuwis, C., 2017. Supporting smallholder commercialization by enhancing integrated coordination in agrifood value chains: experiences with dairy hubs in Kenya. *Experimental Agriculture*, 53(2), 269-287.

Ma, W., Abdulai, A., 2016. Does cooperative membership improve household welfare? Evidence from apple farmers in China. *Food Policy, 58*, 94–102.

Ma, W., Abdulai, A., 2017. The economic impacts of agricultural cooperatives on smallholder farmers in rural China. *Agribusiness: an International Journal,* 33, 537-551.

Maertens, M., &Vande Velde, K., 2017. Contract farming in staple food chains: The case of rice in Benin. *World Development*, 95, 73–89.

Maertens, A. & Barrett, C., 2012. Measuring social networks' effect on agricultural technology adoption. *American Journal of Agricultural Economics,* 95 (2), 353-359.

Mano, Y., Yamano, T., Suzuki, A. & Matsumoto, T. (2011). Local and Personal Networks in Employment and the Development of Labor Markets: Evidence from the Cut Flower Industry in Ethiopia. *World Development*, 39 (10), 1760-1770.

Manski, C.F. (2000). Economic analysis of social interactions. National bureau of economic research.

Manski, C.F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies*, 60, 531–542.

Mekonnen, D. A., Gerber, N., Matz, J. A. (2018). Gendered social networks, agricultural innovations, and farm productivity in Ethiopia. *World Development*, 105, 321-335.

Michelson, H. C. (2013). Small farmers, NGOs, and a walmart world: welfare effects of supermarkets operating in Nicaragua. *American Journal of AgriculturalEconomics*,95, 628-649.

Mishra, A. K., Kumar, A., Joshi, P. K., D'souza, A., 2018. Cooperatives, contract farming, and Farmsize: The case of tomato producers in Nepal. *Agribusiness: an International Journal*, 2018, 1–22.

Mishra, A. K., Kumar, A., Joshi, P. K., D'souza, A., 2018. Impact of contract farming on yield, costs and profitability in low-value crop: evidence from a low-income country. *Australian Journal of Agricultural and Resource Economics,* 00, 1-19.

MoFA (Ghana Ministry of Food and Agriculture), 2017. Planting for food and Jobs: strategic plan for implementation (2017-2020). Ministry of Food and Agriculture, Accra, Ghana.

Morgan, M., 2012. Social networks and value chain development. *Technical note*. The Seep Network. Arlington, Virginia, USA.

Mojo, D., Fischer, C., and Degefa, T. (2017). The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. *Journal of Rural Studies*, 50 (2017): 84-94.

Poulton, C., Dorward, A., Kydd, J., 2010. The future of small firms: New directions for services, institutions, and intermediation. *World Development*, 38(10), 1413-1428.

Ragasa, C., & Golan, J. (2014). The role of rural producer organizations for agricultural service provision in fragile states. *Agricultural Economics*, 45, 537-553.

Ramirez, M., Bernal, P., Clarke, I., Hernandez, I., 2018. The role of social networks in the inclusion of small-scale producers in agri-food developing clusters. *Food Policy* (2018), https://doi.org/10.1016/j.foodpol.2018.04.005.

Rao, E.J.O., &Qaim, M. (2011). Supermarkets, farm household income, and poverty: insights from Kenya. *World Development*, 39, 784-796.

Reardon, T., Barret, C.B., Berdegué, J.A., &Swinnen, J.F.M. (2009). Agrifood industry transformation and small farmers in developing countries. *World Development*,37, 1717-1727.

Ruben, R., Slingerland, M, Nijhoff, H., 2006. Agro-food chains and networks for development: Issues, approaches and strategies. In *The Agro-food chains and networks for development*, 1-25 (Eds R. Ruben, M. Slingerland and H. Nijhoff). Netherland: Springer.

Swinnen, J., Kuijpers, R., 2017. Value chain innovations for technology transfer in developing and emerging economies: Conceptual issues, typology, and policy implications. Food Policy (2017), http://dx.doi.org/10.1016/j.foodpol.2017.07.013.

Swinnen, J., Vandeplas, A. and Maertens, M. (2010). Governance and Surplus Distribution in Commodity Value Chains in Africa, in Sarris, A. and Morrison, J. (eds*) Food Security in Africa: Market and Trade Policy for Staple Foods in Eastern and Southern Africa*. Edwards Elgar, Cheltenham, UK, pp. 77–88.

Trienekens, J. H., 2011. Agricultural value chains in developing countries. A framework for analysis. *International Food and Agribusiness Management Review*, 14(2), 51-82.

Ton, G., Vellema, S., de wildt, M. R., 2011. Development impacts of value chain interventions: how to collect credible evidence and draw valid conclusions in impact evaluations? *Journal on Chain and Network Science*, 11(1), 69-84.

World Bank, 2007. World development report 2008: agriculture for development, World Bank, Washington DC, USA.

Wooldridge, J.M. (2015). Control function methods in applied econometrics. *The Journal of Human Resources*. 50(2): 421-445.

Wydick, B., Hayes, H. &Kempf, S. (2011). Social networks, neighborhood effects, and credit access: evidence from rural Guatemala. *World Development*, 39 (6), 974–982.

Appendix

Table 5.A1: First-stage regression results for addressing potentially endogenous variables

Variable	Access to credit		Horiz. Social network		VCP in farmer's network	
	Coefficient	S. E	Coefficient	S. E	Coefficient	S. E
Constant	-1.660***	0.370	-1.489***	0.404	4.930***	0.638
Age	0.005	0.005	0.020***	0.005	-0.014***	0.002
Education	0.003	0.014	0.007	0.016	0.038***	0.004
Gender	0.196	0.229	0.159	0.250	-0.187***	0.071
Farm size	0.003	0.053	0.030	0.056	-0.367***	0.043
Distance to market	0.003	0.016	0.045**	0.021	0.024***	0.005
Bicycle	0.081	0.148	-0.122	0.160	-0.213***	0.050
Road status	0.168	0.148	0.541***	0.159	-0.013	0.054
Mobile phone	0.250 **	0.139	0.074	0.141	0.473***	0.047
Tolon	-0.114	0.240	-0.435	0.274	-0.686***	0.077
Kumbungu	0.006	0.203	-0.492 **	0.221	-0.247***	0.070
Savelugu Nanton	0.023	0.235	-0.986***	0.290	-0.497***	0.088
Market perception	0.288**	0.142	0.784***	0.148	0.325***	0.049
Av. Age	0.009	0.029	0.051	0.031	-0.035***	0.011
Av. Education	-0.114	0.085	0.097	0.090	-0.325***	0.032
Av. Gender	0.389	1.197	-2.620**	1.324	-1.029**	0.416
Av. Farm size	0.230	0.158	0.035	0.166	-0.087	0.067
Access to credit	-	-	0.258 *	0.137	0.010	0.045
Distance to credit instit.	-0.034 **	0.013	-	-	-	-
Horiz. social network relationship	0.248 *	0.142	-	-	0.410***	0.053
Distance to NMs meeting ground	-	-	-0.062**	0.030	-	-
VCP in farmer's network	0.001	0.006	0.011 *	0.006	-	-
Neighbors 5km around farmer's home	-	-	-	-	0.008***	0.004
Log likelihood	-287.98		-240.22		-2771.13	
Number of observations	458		458		458	

Note: *, **, *** represent significance at 10%, 5%, and 1% levels, respectively.

Table 5.A2: Instrument variable test for the Treatment Effects model (market perception)

Treatment effects model	Chi-square (X^2)	$p - value$
Value chain participation decision	7.28	0.005
Paddy price	0.76	0.384
Value chain participation decision	8.08	0.001
Quantity traded	1.28	0.258
Value chain participation decision	10.39	0.000
Net returns	0.57	0.448

Chapter 6

Conclusions and Policy Implications

The rapid transformation of agrifood value chains in developing countries, driven by factors such as urbanization, increasing consumer incomes, changes in consumer dietary requirements, among others has presented valuable opportunities for smallholder farmers' integration into these chains. This study has contributed to the growing literature on smallholder farm and market performance impacts associated with participation in agrifood value chains in developing countries including Ghana. First, the study has examined the vertical coordination mechanisms- written contracts, verbal contracts and spot market- used for output market transactions in farmer-buyer relationships in agrifood value chains, and the impact of these mechanisms on farm performance including net farm income, total farm income, total household income, labor productivity and price margins. Second, due to the renewed interests of governments, donor agencies and the private sector in farmer groups' role in enhancing effective value chain participation by smallholder farmers, this study has drawn a link between farmer group membership and collective marketing, and their implications on improving smallholder farmers' livelihoods in northern Ghana.

Third, the study has also explored the important role farmer groups play in improving smallholder farm performance such as farm yield and technical efficiency. Finally, the study examined the contribution of inclusive value chain participation and social networks to enhancing smallholder farmers' market performance outcomes such as prices received, quantity traded, and net returns. In the following sections, the analytical methods employed in the empirical estimations are summarized and presented, followed by summary of the main results of the study. Suggested policy implications based on the findings from the study are presented in the last section.

6.1 Summary of empirical methods

The empirical methods employed in this study include multinomial BFG model, bivariate probit model, endogenous switching regression (ESR), propensity score matching method, sample selection stochastic production frontier model, and treatment effects model. Given the fact that farmers self-select into participating in agrifood value chains, horizontal coordination (farmer groups, collective marketing), and vertical coordination (written contracts, verbal contracts and spot markets) mechanisms, some of the factors (observed and unobserved) influencing farmers' participation decisions in these mechanisms may also influence their farm and market performance outcomes. This leads to potential selection bias stemming from both observed and unobserved factors, which needs to be addressed in the empirical estimations to obtain unbiased and consistent outcome impact estimates.

In chapter two, the multinomial BFG model was employed to examine the factors influencing smallholder rice farmers' decisions to participate in vertical coordination mechanisms such as written contracts, verbal contracts, and spot market, and the impact of these factors on farm performance outcomes including net farm income, total farm income, total household income, labor productivity and price margins. The multinomial BFG model is a two-stage impact assessment procedure involving the estimation of a multinomial logit model in the first-stage to examine the determinants of vertical coordination mechanism participation, and the computation of selectivity correction terms, which are included in the second-stage to estimate the farm performance outcomes consistently. The causal impacts of vertical coordination mechanisms: written contracts and verbal contracts on farm performance, relative to spot market transactions are also evaluated using the model. The multinomial BFG model accounts for selection bias due to both observed and unobserved factors.

Chapter three employed the bivariate probit and endogenous switching regression models to assess the factors influencing farmer group and collective market participation decisions, and the impact of these decisions on farm net revenues among smallholder rice farmers in northern Ghana. First, the joint determination of group membership and collective marketing decisions, and the related drivers of both decisions are estimated using a bivariate probit regression model. In the bivariate probit regression model estimation, if farmers' decisions to join farmer groups and also to participate in collective marketing are interrelated, which is indicated by a significant ρ, then employing the traditional univariate probit model would generate biased and inconsistent estimates. The model is estimated using maximum likelihood method. Second, due to farmers' self-selection into farmer groups and collective marketing, an endogenous switching regression model is also employed to examine the factors influencing farmer group and collective market participation decisions (binary endogenous treatment variables) and the impact of these factors on farm net revenues (continuous outcome variable). Full information maximum likelihood method is used to estimate the ESR model. Selection bias arising from both observed and unobserved factors are accounted for in the empirical estimations. Moreover, the ESR model also allows for the computation of average treatment effects (ATT) of farmer group and collective market participation on farm net revenues.

In chapter four, the impact of farmer groups on farm yield and technical efficiency among smallholder rice farmers is examined using propensity score matching and sample selection stochastic production frontier approaches. Using the PSM method, a counterfactual group of farmers with similar time-invariant characteristics as farmer group members is constructed for the analysis. The method involves fitting a binary (in our case probit) model to generate propensity scores, which are then used to match group members and non-members with similar observed time-invariant characteristics. The PSM method accounts for farmers' self-selection into farmer group participation arising from observed farmer attributes. After the matching procedure, the sample selection stochastic production frontier model is estimated, and compared with the estimates from conventional stochastic production frontier model in the analysis for both matched and unmatched samples. The sample selection stochastic production frontier model accounts for farmers' self-selection into farmer group participation due to unobserved farmer attributes. It is important to mention that accounting for the self-selection allows for the estimation of unbiased and consistent farmer group impact estimates.

The treatment effects model is employed in the empirical estimations in chapter five to examine the role of inclusive value chain participation and social networks in improving market performance among smallholder rice farmers in northern Ghana. The market performance outcomes considered in this chapter are paddy prices received by farmers, quantity of paddy traded, and net returns. With the treatment effects method, the factors influencing inclusive value chain participation and their related effects on the market performance outcomes can be examined. It also allows for the estimation of the marginal effects and average treatment effects of inclusive value chain participation on the market performance outcomes, and as well accounts for selection bias arising from both observed and unobserved farmer attributes.

6.2 Summary of results

In chapter two, the results showed that participation in written and verbal contracts in smallholder output transactions tend to improve farm performance outcomes such as net farm income, total farm income, total household income, labor productivity and price margins, relative to farmers who supply paddy in spot market. Farmers who participate in written contracts tend to perform better than their counterparts who engage buyers through verbal contracts. The results further showed that participation in vertical coordination is significantly influenced by access to credit, mobile phone ownership, labor, membership in farmers' associations, sales to institutional buyers, market perception, and importance attached to legal contracts. Education, farm size, mobile phone and farm vehicle ownership are found to be the important determinants of farm performance.

The results in chapter three revealed that farmers that were members of farmer groups and participated in collective marketing obtained higher prices, and also incurred lower input costs. In addition, farmers' decisions on farmer group and collective market participation are shown to be jointly determined, indicating that most farmers with group membership also participate in collective marketing. The empirical results support the notion that farmer group membership and collective market participation decisions in smallholder agriculture essentially enhance farmers' livelihoods through improvement in farm net revenues. Farmer's age, access to credit, mobile phone ownership, distance to market and road status are found to be the main drivers of farmer group and collective market participation decisions. The empirical results also showed that both group membership and participation in collective marketing exerted positive and statistically significant impacts on farm net revenues.

In chapter four, the findings indicate that unobserved attributes such as farmer motivation, innate skills, and risk attitude influence farmer group participation decisions. The empirical results revealed that members of farmer groups benefit significantly from improved yield and technical efficiency. In particular, farmer group members operate closer to their own production frontier than nonmembers. Moreover, the yield and efficiency gaps between group members and nonmembers increase significantly when self-selection is taken into account in the analysis. This means that in nonrandomized studies, it is important to account for self-selection when examining farmer welfare gains. The empirical results further showed that farmer's age, access to credit and irrigation, extension visits, distance to markets positively influence participation in farmer groups. Moreover, rice yield is positively and significantly influenced by land, fertilizer, chemicals, rice variety, soil quality and access to irrigation for both farmer group members and nonmembers.

The empirical results in chapter five showed that participation in rice value chain is associated with increased paddy prices received, quantity traded, and net returns, relative to non-participation. Moreover, participating farmers with small farm sizes tend to benefit the most from improved market performance outcomes, relative to those with medium and large farm sizes. Social networks have also been found to promote inclusive value chain participation. In particular, smallholder farmers who are members of horizontal social networks, and those with network members who are already value chain participants, are more likely to also participate in a value chain. Such category of farmers also tend to benefit from increased paddy prices, quantity traded, and net returns. Distance to market, mobile phone ownership, and access to credit positively and significantly influence farmers' value chain participation decisions. In addition, gender, farm size, mobile phone ownership, and access to credit tend to influence smallholder market performance positively.

6.3 Policy implications

Several important policy implications can be drawn from the findings of this study, which suggest that written and verbal contracts are effective vertical coordination mechanisms that benefit smallholder farmers in output market transactions. This calls for promotion of contracts in smallholder output transactions, especially with the renewed interests of government, donor agencies, and the private sector in transforming the domestic rice value chain in Ghana. These stakeholders should as well intensify their engagement with smallholder farmers on the importance and use of legal contracts in output transactions, which could be an important contributor to improved and effective participation in agrifood value chains.

The important role of farmer groups in improving smallholder farm performance, as evidenced in this study, calls for increased support from government, development agencies, and private agribusiness companies in farmer group formation when implementing agriculture and value chain development interventions. Moreover, these interventions should as well incorporate strategies to facilitate smallholder collective marketing. Such development efforts could help address the multiple production and marketing challenges facing smallholder farmers in northern Ghana. The findings also suggest that social networks within the context of inclusive value chain development should be promoted since it can contribute to upgrading developing country value chains especially in the cereal staple sector. Capacity building of smallholder farmer groups to become strong and cohesive social network groups can strengthen the connectedness of network members, and promote sharing of diversity of knowledge and resources for improved power balance and bargaining position in agricultural value chains. Finally, policy initiatives to expand irrigation facilities, improve smallholder access to credit, extension services, and education could ease smallholder constraints, promote pro-poor agricultural growth and smallholder farmers' welfare in northern Ghana.

Appendices

Appendix 1: Questionnaire

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

Coordination and Impact of Value Chain Approach, Evidence from Rice Value Chain in Northern Ghana

Questionnaire for smallholder rice farmers

This questionnaire is purposely for field survey on rice value chain in Northern Ghana. Please note that all information provided is for research purposes only and shall be kept strictly confidential. Thank you in advance for participating in this interview.

Survey Identification

Questionnaire number ---

District& Community ---

Name of enumerator ---

Code of enumerator ---

Date of interview ---

Time started ---

Section A: Socio-demographic features of respondents

Please provide the following basic information about the respondent

A.1 Name of respondent…………………………………………………………………

A.2 Contact and house no. of respondent…………………………………………………..

A.3 Age of respondent…………(years) A.4 Number of years in school……………………

A.5 please complete the table below on other information about the respondent (table 1)

Characteristics	**Information**		**Characteristics**	**Information**
Gender	1=Male 2=female		**Family kind**	1=Monogamous 2=Polygamous
Marital status	1=Married 2=Unmarried 3=widowed 4=Divorced 5=separated		**Religion**	1=Islam 2=Christianity 3=traditional 4=None
Relationship with Household head	1=Head 2=Spouse 3=Child 4=Parent 5=other (specify)…….. ………………		**Ethnicity (Tribe)**	1=Dagomba 2=Mamprusi 3=Gonja 4=Moshi 5=other (specify)…………………… …..
Gender of HH	1=Male 2=Female		**Number of children**	....
Status in community	1=chief 2=Imam/pastor/traditi onalist 3=Member 4=”Magazia” 5=Other(specify) …………………		**Educational Level**	1=Primary 2=JHS 3=SHS 4=Tertiary 5=Other(specify)…………… ……….
Family System	1=Nuclear 2=Extended		**Household Size**	…………………………… …….
Experience of HH (years)	-------------------		**HH years of schooling**	----------------------------------- ------

A.6 When did you start farming on your own? ……………………..(years)

A.7 When did you start cultivating rice? …………………………….(years)

A.8 What is your major occupation? ……………………………………………….

A.9 What is your secondary occupation? …………………………………………..

A.10 Please complete the table below on the age composition of the household members

Children (less than 18 years)		Youths (18 - 30 years)		Adult 30 - 60 years)		Aged (above 60 years)		Male family farm workers		Female family farm workers	
Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female

Rice Production Information for 2015 Growing Season

B Land Utilization and Land Preparation Information

B.1 What is the total size of your farm land? ---------------- (Ha)

B.2 What size of your land did you use for rice farming in 2015? ---------------------------------

B.3What is the mode of acquisition of the farm land? (1) inherited (2) bought (3) tenancy (4) borrowed (5) other(specify)………………..

B.4 If tenant, what type of tenancy arrangement did you operate? (1) fixed rent (2) sharecropping

B.5 If fixed rent: duration of tenure? -------------------- (years)

B.6 How much do you pay for tenancy per year? ---------- (GhC)

B.7 If share cropping, what arrangement or percentage of the crop do you give the land owner? ----

B.8 If land owner; what size of your land is currently under lease/rented out? --------- (Ha)

B.9 Kindly provide information on land use for crop cultivation (in different locations) in 2015 growing season (table 2)

Item	**Plot 1**	**Plot 2**	**Plot 3**	**Plot 4**
Size (Ha)				
Rice (Ha)				
Other crops planted(*Include Ha of each crop*)	1= 2= 3=	1= 2= 3=	1= 2= 3=	1= 2= 3=

Distance from home (km)				

B.10 Do you keep some part of your land under fallow? (1) yes (2) no

B.11 If yes for how long has the land been under fallow? .... (years)

B.12 What is the total farm land under sole rice cultivation? (Ha) --------------------------------

B.13 What is the total farm land under rice intercropped with other crops? (Ha) ---------------

B.14 What is the total farm land under cultivation of other crops? (Ha) --------------------------

B.15 What is the overall type of the soil on your farm? (1) clayey (2) loamy (3) sandy

B.16 Have you ever carried out soil test on your farm? (1) yes (2) no

B.17 Do you practice crop rotation on the piece of land rice is cultivated? (1) yes (2) no

B.18 Do you plant land enriching cover crops and legumes purposely to improve soil quality? (1) yes (2) no

B.19 How will you describe the main soil on which rice is planted ----------- (1) fertile (2) better than average (3) Average (4) below average

B.20 How long have you used this land for rice cultivation since you acquired it? ....(years)

B.21 Has the land ever been under fallow after acquisition? (1) yes (2) no

B.22 If yes, for how long? .... (years)

B.23 How many planting season did you plant rice in 2015? (1) major season (2) Irrigation

B.24 Which tools did you use for rice cultivation in 2015 season? [ ] [ ] [ ] [ ]

1=cutlass, 2= hoes, 3= tractor, 4=plough, 5=ridger, 6=harrow, 7=other facility (specify),

B.25 Which land preparation method did you employ in 2015 growing season (1) Manual (2) Tractor

B.26 If tractor, please complete the table below on the cost of land preparation per hectare of rice in 2015 growing season (table 3)

Item	**Plot 1 (GHc)**	**Plot 2(GHc)**	**Plot 3(GHc)**	**Plot 4(GHc)**
Size				
Land clearing (slashing)				
1st ploughing				
2nd Ploughing				
Harrowing				
Ridging				

transplanting				
others				

Value Chain Activities/Services

C. Formal Value Chain Participation

C.1 Are you currently benefiting or have you ever benefited from a rice value chain development project? (1) Yes (2) No

C.2 If yes to C1 above, please provide information on your value chain project participation in the table below

Name of VC project	Year began	Year ended	Satisfactory? 1=yes 2=no 3=don't know

C.3 which of the following services did you benefit from the project **(*tick the ones applicable*)**

(i) Capacity building services (production techniques, Business development and marketing, group dynamics)

(ii) Attending business networking events

(iii) Crop insurance services

(iv) Quality assurance services and quality improvement standards

(v) Market linkage services (contract design, negotiation meetings/platforms)

(vii) Market information services (prices, product demand, and quality specification)

(viii) Microfinance services (credit acquisition)

C.4 Are you willing to pay for these value chain services? (1) Yes (2) No

C.5 If no, please state reasons for your inability to pay for these services

C.6 If yes in C.5, which of the services are you willing to pay for? (*use the roman numerals*)

C.7 Before participating in formal rice value chains, what were your expectations? Multiple response is allowed ………(1) Yield increase (2) increased revenue (3) reduced cost (4) labour savings (5) food security, (6) input subsidy (7) other (specify)…………………………

C.8 Were your expectations met? (1) yes (2) No

C.9 if no to C.8, why?---

C.10 if yes to C.8, how?--

C.11 Please provide information on your participation in rice value chain project

Item	**Before participation**		**During participation**	
	Participants	**Non-participants**	**Participants**	**Non-participants**
Land size (Ha)				
Cost of rice production per hectare (GhC)				
Quantity of rice harvested in 2015 (kg)				
Quantity of rice sold in a year (kg)				
Price per kg of paddy (GhC)				

D. Planting Information

D.1 Please provide information on planting activities for 2015 growing season in table 4 below

Item	**Plot 1**	**Plot 2**	**Plot 3**	**Plot 4**
Size (Ha)				
Varieties of rice planted				
Reasons for planting the varieties				
Duration of crop planted (months)				
List the other crops planted on the plot	**1=** **2=** **3=**	**1=** **2=** **3=**	**1=** **2=** **3=**	**1=** **2=** **3=**
Quantity of seeds planted (kg)				

How much did you buy 1kg of the seed?				
How many times did you plant rice on this plot in 2015 planting seasons?				

D.2 What is the source of the rice seed you used for planting in 2015 growing season? -------------------

1=Mofa, 2= family member, 3=own seeds kept from last harvest, 4= farmer friend, 5=NGO 6=village seed merchant 7=other (specify)

D.3 What is the source of knowledge of the rice varieties you planted in 2015 growing season? ----------***1=farmer from the village, 2= farmer from another village, 3= private seed company, 4=MoFA/Extension Services 5=NGO (specify name), 6=local market, 7 = Agro-input dealer 8=other (specify)***

D.4 If not MoFA in D.3, is the source a member of formal value chain? (1) Yes (2) No

E Fertilizer Application, Pest, disease and Weed Management

E.1 Did you apply fertilizer on your rice field? (1) Yes (2) No

E.2 If yes to E.1, please provide detailed information on fertilizer use in 2015 growing season in the table below.

Name of fertilizer	Price/ kg (GhC)	Round of application (1st or 2nd)	Quantity of fertilizer applied (kg)					
			Plot 1	Plot 2	Plot 3	Plot 4	Total qty (kg)	Total cost (GhC)
NPK								
Urea								
Ammonia								
Manure								
Other (specify) …………… …..								

E.3 How did you decide on the type of the fertilizer applied -------- (1) result from soil test (2) input dealer's recommendation (3) extension service recommendation (4) any other please specify ---

E.4 Was there any pest infestation on your farm(s) during 2015 season? (1) yes (2) no.

E.5 if yes which pest ---

E.6 Was there any disease infestation on your farm(s) during 2015 season? (1) yes (2) no.

E.7 If yes which disease --

E.8 What is the value of your crop lost to pest and diseases? -------------------------------------

E.9 Did you use any pesticide for pest control? (1) yes (2) no.

E.10 If yes, what is the name and how many of it did you use? ---------------------------------

E.11 Did you use any other chemical for disease control? If yes what is the name and how many of it did you use --

E.12 Kindly provide information on chemical used for disease and pest control for 2015 growing season.

Name of pesticide	Price per litre (GhC)	**Volume of pesticide used**					
		Plot 1	Plot 2	Plot 3	Plot	Total Volume (Litre)	Total Cost (GhC)

E.13 What method did you use for weed control? (1) Chemical (2) Manual (3) both (4) others (specify) --

E.14 If manual which tools do you use? (1) Cutlass (2) Hoes (3) both, others specify -----------

E.15 Are the sources of the agro-chemicals members of formal value chains? (1) Yes (2) No

E.16 If chemical, kindly provide detailed information on weed control on your farm in 2015 growing season.

Name of chemical	**Volume of chemical used (Litres)**				Total volume (litres)	Price per litre (GhC)	Total cost (GhC)
Herbicides	Plot 1	Plot 2	Plot 3	Plot 4			
Pre-emergence							
Post-emergence							
Total							

F. Technical Support/Extension services

F.1 Have you ever visited any agricultural extension office? (1) yes (2) no.

F.2 If yes specify number of visits in 2015 farming season--

F.3 Has an extension officer ever visited you? ---

F.4 If yes, how many visits in 2015 production season? ---

F.5 Kindly provide detailed information about extension visits in the table below

Item	Public	Private	NGO
extension visit (yes or no)			
frequency of visit*			
where do you meet**			
distance to extension office from meeting point (km)			

**(1) weekly (2) monthly (3) once in 6 months (4) once in a year (5) Never ** (1) my farm (2) my house (3) farmers field school (4) others, specify*

F.6 which of the following is the major source of useful information for your farming operations? (1) TV (2) Radio (3) newspaper (4) extension agents (5) fellow farmers (6) farmers' organisation (7) others; please specify ---

F.7 Rank your level of confidence is the government extension system (1-5), 5 is very confident ……

F.8 Rank the level of qualification of the government extension officers (1-5), 5 is very qualified …

F.9Have you received farming or business training before (1) yes (2) no

F.10 If yes, please provide specific training and technical support services in the table below

When	Topic?	How was it done	By whom?	How relevant was it? 1=irrelevant …..5=very relevant

G. Harvest Information for 2015 growing season

G.1 Did you carry out timely harvesting? (1) Yes (2) No

G.2 If No, please state reason(s)---

G.3 Which method did you use to harvest your rice? (1) Mechanical (combine harvester) (2) manual (3) others (please specify) ---

G.4 Please provide detailed information on rice harvesting in 2015 season in the table below

Item	**Plot 1**	**Plot 2**	**Plot 3**	**Plot 4**	**Total quantity of rice**
Quantity of rice paddy harvested (rain-fed) (kg)					
Quantity of rice harvested (irrigation season) (kg)					
Varieties planted					
Yield (kg)					
Quantity sold before processing					
Quantity sold after processing					
Quantity stored and sold later					
Total					

H. Marketing, Coordination Mechanisms and Transaction costs

H.1 Do you apply agro-inputs on your farm(s)? 1. Yes 2. No (if No, skip to H 25)

H.2 If yes to H.1, where do you normally buy the inputs from? (1) farmer's community (2) District capital (3) regional capital (4) other (specify)---

H.3 which mechanism do you employ in buying your inputs? (1) Contracts (2) open market (pricing mechanism) (3) through trust and relationship with buyers (Relational coordination mechanism). (***Tick the applicable ones***)

H.4 If you use all mechanisms in H.3, which of them do you think is the most effective and why? --

H.5 If contracting mechanism is used in H.3, is it written or Oral contract? -------------------

H.6 What was the contract duration? ---(months)

H.7 Did you meet the contract terms and conditions? 1. Yes 2. No

H.8 If no to H.7, please state reasons--

H.9 If yes to H.7, How?---

H.10 Did your Agro-input dealer(s) meet the contract terms and conditions? 1. Yes 2. No

H.11 If no to H.10, please state reasons---

H.12 If yes to H.10, How?---

H.13 If contract was used as in H.3, was the contract arrangement facilitated under a value chain project? 1. Yes 2. No

H.14 If yes to H.13, please provide details---

H.15 If no to H.13, How was the contract arrangement initiated? ------------------------------------

----

H.16 Do your Agro-input dealer(s) support you in any way? 1. Yes 2. No

H.17 If yes to H.16, state how they support you.--

H.18 Do the agro-input dealer(s) sometimes supply you with inputs and you pay them later? 1. Yes 2. No

H.19 If yes to H.18, what is the value of inputs in a year?----------------------------(Ghc)

H.20 Did you pay back on time? 1. Yes 2. No

H.21 If no to H.20, state reasons--

H.22 If yes to H.20, how?---

H.23 What other support do you get from your agro-input dealers? --------------------------------

----

H.24 Are your agro-input dealers members of formal value chains? (1) Yes (2) No (3) Both formal and Informal value chains.

H.25 How do you sell your rice produce after harvest? (1) Group sale (2) individual sales (3) both

H.26 What is your percentage distribution of your rice output after harvest?

Family use………..sales………..gifts…………………other (specify)………………..(%)

H.27 Do you sell your paddy to particular/regular customers? (1) yes (2) No

H.28 if yes to H.27, who are these customers? (*Tick the ones applicable*) (1) Aggregators (2) small scale processors (3) large scale processors (4) Institutional Buyers (5) Other(specify)----

H.29 Where are these customers located?--

H.30 How do you supply/deliver your rice to customers? (1) Community level (2) Farmgate (3) Market center

H.31 If delivery is done at market center, indicate the distance from home to market------(Km)

H.32 Are your buyers members of formal value chains? (1) Yes (2) No (3) Both formal and Informal value chains

H.33 which mechanism do you employ in selling your rice produce after harvest? (1) Contracts (2) open market (pricing mechanism) (3) through trust and relationship with buyers (Relational coordination mechanism). (Tick the applicable ones)

H.34 If you use all mechanisms in I.8, which of them do you think is the most effective and why?---

H.35 If contracting mechanism was used in H.33, was it written or Oral contract? -------------

H.36 What was the contract duration? --- (months)

H.37 Did you meet the contract provisions? 1.Yes 2. No

H.38 If no to H.37, please state reasons--

H.39 If yes to H.37, How?---

H.40 How important are these contracts to your business transactions? (1) Very important (2) Partly important (3) not important.

H.41 How does the buyer support you? (1) Provision of training (3) provision of credit service in kind or cash (4) any other please specify ---------------------------

H.42 If you received trainings, which topics were you trained on? --------------------------------
----

H.43 What value of credit did you receive from them in 2015 season? -------------------------

H.44 How did you repay the credit? (1) Deduction from farm proceed (2) cash payment (3) other please specify ---

H.45 What other support do you get from your buyers? ---

H.46 kindly provide information on rice marketing for 2015 season in the table below

Item	Community level	market	processed	Large scale processor	small scale processor
Quantity of rice paddy sold in kg					
Selling price/kg					
Distance (km)					
Frequency of sales*					
Travel time (hours)					
Transportation cost (aggregator)GhC					
Transportation cost per bag of paddy Ghc					
Price of empty jute sack					
Cost of twines (Ghc)					
Cost of sowing a bag of paddy					
Cost of loading a bag of paddy (Ghc)					
Cost of offloading a bag of paddy (Ghc)					
Communication cost per transaction					
Storage cost per bag(GhC)					
Cost of chemicals for fumigation (Ghc)					

1=weeky 2=monthly 3=quarterly 4=every six months 5=annually

H.47 Which of the following best describes your advance knowledge of rice prices in the market? (1) Full knowledge (2) Partial Knowledge (3) no Knowledge

H.48 Where do you obtain knowledge of advance prices? (1) Fellow farmers (2) traders and buyers (3) Government institution (4) mass media………………………….(4) through negotiation other(specify)---

H.49 How available are your buyers of rice? (1) Readily available (2) somehow available (3) difficulty getting buyers

H.50 Please indicate the distance from farm to main road of your community----------(km)

H.51 Do you use mobile phone in your farm business? (1) Yes (2) No

H.52 If yes to H.51, what do you specifically use it for in the farm business? (*Tick the applicable ones*)(1) Searching for buyers (2) searching for input prices (3) sourcing price information (4) others (specify)--

H.53 On average, how much worth of air time do you spend in a season for the activities in H52?-----------(GHc)

H.54 Are you normally successful in the choices in I.26? (1) Yes (2) No

H.55 if no, kindly state reason(s)--

H.56 If yes to H.54, how?---

I. Labour Information/Activities

I.1 What was the wage rate per day during 2015 season? ---

I.2 Was the wage rate same for male and female? -------------------------------- (1) yes (2) no

I.3 If no, what was the wage rate for a female worker during 2015growing season? -------------

I.4 Please provide detailed information on labour use in 2015growing season

Activity/Task	Unit	**Male>14 years**			**Female>14 years**			**Child (10-14 years)**		
		No. of meals	Cash pay-GhC	In-kind (Value)-GhC	No. of meals	Cash pay(GhC)	In-kind (Value)-GhC	No. of meals	Cash pay(GhC)	In-kind (Value)-GhC
Land Preparation										
Planting										
Chemical spraying										
Manual weeding 2										

Manual weeding 2										
Fertilizer application 1										
Fertilizer application 2										
Manure application										
Disease/pest control-spraying										
Harvesting										
Threshing										
Bagging/packaging										
Loading and offloading										

Codes for units-1=day, 2=Acre, 3=Task, 4=hours, 5=other(specify)

J. Household Information

J.1 Please complete the table below on the asset owned by your household

which of the assets below do you have?	availability		if yes, please state the number available	year of purchase	cost of purchase	Please indicate source of income for the purchase
	Yes	No				
Cutlass						
Hoe						
Knapsack						
Radio						
Television						
Bicycle						
Motorcycle						
Car/minitruck						
Mobile phone						

Bullock						
Paddy weeder						
Tractor						
Tractor accessories						
Mechanized ripper						
Combine harvester						
Weighing scale						
House						
Warehouse						

J.2 Please provide information on sources and amount of your household income the last 3 years in table below.

Revenue from Agriculture	code	2013-GhC	2014- GhC	2015- GhC
Rice income				
Income derived from other produce				
Non-agricultural income				
First non-agricultural income source				
Second non-agricultural income source				
Third non-agricultural income source				

Codes for non-agricultural income: 1=handicraft, 2=rearing, 3=processing, 4=commerce, 5=extraction (salt, honey, gravel, sand, mine), 6=salary (fixed, temporary, contracts, etc.), 7=other(specify)

J.3 please provide information on ownership of livestock in the table below

1	What types of animals do you own? (tick)	Cattle	Sheep	Goat	pigs	chicken	guinea fowls	Others
2	How many did you have at the beginning of 2015?							
3	On average how many do you acquire in a year							

4	On average how many do you sell/kill in a year							
5	How many did you have at the end of 2015?							
6	How many more have you acquired this year?							
7	How many did you sell in 2015?							
8	Do you seek for veterinary services for them ? (1=yes, 2=no)							

J.4 Please provide detailed information on your household size and educational profile

Members	***Level of education**	**Members**	***Level of education**	**Members**	***Level of education**
Respondent		Female 1		Male child 3	
Head		Female 2		Male child 4	
Male 1		Female 3		Female child 1	
Male 2		Female 4		Female child 2	
Male 3		Male child 1		Female child 3	
Male 4		Male child 2		Female child 4	

*1=Illiterate, 2=1-5 years of schooling, 3=6-10 years of schooling, 4=Above 10 years of schooling, 5=tertiary education

J.5 Please provide detailed information on expenditure of your household in the last year

Items	**Expenditure/year (Ghc)**	**Items**	**Expenditure/year (Ghc)**
Housing (rent/repair)		Medical	
Food items		Education	
Clothing and footwear		Recreation	

Tobacco		Water charges	
Fuel, lighting		Durable goods	
Electricity		Social expenses (marriages, gifts, funerals etc.)	
Transport		Miscellaneous	
Livestock		Personal	
Poultry		Other (specify)	

K. Financial support/Access to Credit Information

K.1 Did you access credit for the purchase of inputs during 2015 growing season? (1) Yes (2) No

K.2 If no to K.1, please state the reasons for not using credit in the season? ----------------------

----

K.3 If yes to K.1, from which source did you get the credit? (1) Rural Bank (2) microfinance company (3) financial NGO (4) Lead firm (5) Other (specify)--------------------------------------

K.4 Do you have information about all credit sources? (1) yes (2) No

K.5 Did you buy any input on credit during the 2015 season? (1) yes (2) no.

K.6 If yes, provide detailed information ---

K.7 If you suddenly need money where do you turn to?.--

K.8 What is the average amount of money you can get from this source?-------------------------

K.9 What are your other sources of finance for your farm operations?.----------------------------

K.10 Do you know of other farming credit sources in your locality? ----- (1) yes (2) no

K.11 if yes please name them.---

K.12 Have you sourced credit from them before?.........(1) Yes (2) No

K.13 If yes to K.12, do you still source credit from them and why?--------------------------------

K.14 If yes to K.13, was the credit enough for farming business? (1) yes (2) no

K15 If no to K.13, did you apply for more credit? (1) yes (2) no

K.16 If yes to K.15, was your application granted? (1) yes (2) no

K.17 Has your loan application ever been rejected? -------- (1) yes (2) no

K.18 If yes, for what reason?---

K.19 Did you buy any input on credit during the 2015 season? -------- (1) yes (2) no.

K.20 If yes list the inputs ---

K.21 If yes, what were the terms of the credit?--------(1) repay in cash (2) repay with farm produce (3) repay with cash and farm produce (4) other (specify) ---------------------------------

K.22 Did you repay with interest............(1) yes (2) no

K.23 If yes what was the interest rate ....(% p.a.)

K.24 What was the average repayment period ....months

K.25 please indicate the distance to credit source for your farm business------------(km)

K.26 Kindly provide detailed information about your credit history in the table below

Source of credit	Year	Amount (GhC)	Interest rate	Purpose	Duration	Installment Amount(GhC)

L. Community Level Information

L.1 What type of access road is in your community? [ ] [ ] [ ]

1 = Asphalt 2=track in good shape all year round 3= track hardly usable 4= track unusable in certain periods of the year, 5=use of a ferryboat, 6=use of a canoe, 7=path, 8=other specify)

L.2 if road is untarred (asphalted), show distance from the nearest tarred road: ----------- Km

L.3 Where road is tarred, since when? ---

L.4 Does your community have Market (s)? ----------------- 1=yes 2=no market

L.5 If there is no market show distance to the nearest market: ------------------------- km

L.6 if people go to market by car/bus, how much does it cost---------------------- GhC

L.7 if there is a market, how many communities are involved? ------------------------

Code: 1=less than 5 2=5 to 10 3= 11 to 20 4= more than 20.

L.8 other institutions present in the community [ ] [ ] [ ]

Code: 1=rural credit, 3=NGO, 4=other institutions (specify)

L.9 Has the community benefited from development projects? (1)Yes (2) No

L.10 If yes, please indicate which of these development projects your community benefited from.

***1=Irrigation development project, 2=acquisition of community-based infrastructures, 3=acquisition of agricultural equipment, 4=extension, 5=training courses/awareness, 5=other (specify)*------------------------**

L.11 Are there stores where production inputs are traded in your village? --- (1) yes (2) no

L.12 If yes which of the following inputs are traded in the stores? [ ] [ ] [ ] [ ] [ ] [ ]

1= rice seeds for planting, 2=chemical fertilizer, 3=herbicides for weed control, 4=pesticides for disease control 5=tillage equipment 6= knapsack sprayer 7=other (specify)

L.13 If no, please list inputs not available ---

L.14 If no, what is the distance to the nearest input store? ----------------- (km)

L.15 Which of the following water point(s) exists in your community? [ ] [ ] [ ] [ ]

1=waterworks 2=borehole 3= developed source 4=improved wells 5=traditional wells 6= river/dam and others

L.16 Existing but non-operational water points [ ] [ ] (***use codes in L.15***)

L.17 Which of the following school infrastructure and vocational training exists in your community? [ ] [ ] [ ]

1=pry. sch. 2=junior high sch. 3=senior high sch. 4=Arabic sch. 5=vocational school 6=Tertiary institution

L.18 Where there is a primary school, since when: ---

L.19 Where there is no primary school, show distance to the nearest primary school-------km.

L.20 Which of the following health care infrastructures exists in your community? [ ] [ ]

1= CHIPS compound 2= health center, 4=hospital, 5=others (specify)--------------------------

L.21 Is there a medicine store in the village: [ ] 1=yes 2=no

L.22 Where there is no medicine stores, show how far to the nearest medicine store: [ ] km

L.23 Is there electricity in the village? [ ] 1= yes 2=no

L.24 If there is electricity, since when? [ ]

L.25 Existence of irrigation facility (1) yes (2) No

L26 What is the estimated population in your community? ---------------------

M. Social Capital and Network Information

M.1 Social capital from participation in farmer group activities

No.	Description	Farmer	Spouse
1	Are you a member of a farmer group? (1=yes, 2=no)		
2	If yes to 1, when did you join the group?		
3	Was the group formed because of a particular project?(1) yes (2) no		
4	If yes to 3, what is the name of the project?		
3	What benefits do you derive from the farmer group (1) training (2) marketing assistance (3) input support (4) lead farmer training services (5) bulk input purchase (6) social network within the group (7) others (specify)---------------------		
4	Name of farmer group you belong		
5	What is the size of your group: Male------- Female------------		
6	How often do you meet? (1) once a week (2) twice in a month (3) once in a month (4) once every quarter		
7	How often do you attend meetings? (1= very often …..5=not at all		
8	Indicate the distance to your meeting venue ----------------km		
9	Current relationship with this farmer group…(1) member (2) not a member (3) old member		
10	Status in farmer group …(1) executive member (2) non-executive member (3) old executive (4) ordinary member (5) other (specify)		
11	Do you discuss production and marketing issues during meetings? (1) Yes (2) No		
12	If yes to 9, do you learn and implement the ideas generated from these discussions in your farming business? (1) Yes (2) No		

13	Do your group members influence your produce selling strategies? (1) Yes (2) No		
14	if Yes to 11, please provide details		
15	Do you have other farming groups in your community? (1) Yes (2) No		
16	If yes to 13, do you tap ideas from these groups on production and marketing techniques? (1) Yes (2) No.		
17	if yes to 14, kindly provide details		
18	Do you trust your group and implement their ideas on production and marketing strategies? (1) Yes (2) No		
19	If yes to16, kindly indicate the level (%) of trust for these peers		
20	If no to 16, kindly state reasons for the mistrust:		

G/2 Social Networks

No.	**(A) Informal Social Networks**	**Farmer**	**Spouse**
1	Do you have friends apart from your relatives? (1=yes, 2=no)		
2	If yes to 1, how many times do you visit these friends (in a month)		
3	How many farmers live in a radius of 5km around your home (and your farm)		
4	How many of them do you discuss business with?		
5	How often do you have these discussions (in a month)?		
(B) Networks for specific purposes			
1	Do you have someone who assists you practically in your farming activities (1= yes, 2=no)		
2	If yes to 1, who is he/she (1=field officer, 2=farmer coordinator, 3=other (specify)		
3	If yes to 1, how many times does he/she visit you (in a month)		
4	If yes to 1, how many of you does he/she help?		
5	Is there someone who assists you with money in case of need? 1= yes, 2=no		
6	If yes to 5, how many would help you? Differentiate between 1=relatives, 2= friends and neighbours, 3=others (specify) (use the code and state number of individuals for each) How much will they help you with?------------------------------- (GhC)		
7	Name the religious network you belong (if any)		
8	Do you have close relation in government?		
9	If yes to 8, indicate exact relationship (1=member of the nuclear family, 2=extended family member, 3=friends and neighbours, 4=other (specify)		
10	Indicate the position		

(C) Information and Networks			
	Community Level		
1	On the average, when you decide to participate in Formal Value Chains (FVC) how many formal value chain participants were in your community/village?		
2	On the average, how many do you think are in your community/village now?		
3	How many of them participated in FVC through you?		
4	How many of them are your family members?		
5	How many of them are your friends and neighbours?		
6	How many of them belong to your religious faith (if any)?		
7	How many of your religious faith participate in FVC?		
8	What is the experience of your friends and or neighbours in FVC participation? 1=very bad, 2=bad, 3=average, 4=good, 5=very good		
9	Do you discuss value chain activities with some of them? (1=yes, 2=no)		
10	If yes to 9, how many of them do you discuss with?		
11	If yes 9 applies, how many times in a year?		
12	Do members of your group/locality seek your advice on FVC participation? (1=yes, 2=no)		
13	If yes to 12, how many of them do you seek advice from?		
14	How many of them seek your advice on FVC participation?		
15	If so, how many times in a year?		
16	Do you seek advice on FVC from other members of your community? (1=yes, 2=no)		
17	If yes to 16, from how many of them?		
18	If so, how many times in a year?		
19	Do you experience new FVC participants in your community often? (1=yes, 2=no)		
20	If yes, on the average how many people in a year?		
21	Do you anticipate a time that there will no longer be new participants? (1=yes, 2=no)		
22	If yes, how many years from now and why?		
23	Are you aware the government is promotion rice value chains in your community? (1=yes, 2=no)		

N. Challenges Faced by Rice Producers

N.1 kindly provide information on the challenges you face in rice farming

	Yes/No	If yes, please rank	Additional Information
Land			
Small land size			

Poor property rights (ownership) on land			
Difficulty in getting land to rent			
Difficulty in getting land to buy			
Land Preparation			
Difficulty in getting tractor services			
Seed			
Poor quality seed			
Unavailablity of certified seed			
Seed Price variability			
Fertilizer			
High cost			
Not available throughout the year			
Available late in the season			
Long distance to the fertilizer market			
Labor			
Not enough labour			
Labour cost too high			
Seasonal shortage			
Equipment & Infrastructure			
Difficult to acquire rice production equipment			
Difficult to acquire rice harvesting equipment			
Difficult to acquire planters			
Difficult to maintain equipment			
Poor access to the road			
Water management at plot level			
Difficult to access water			
Difficult to manage water			
High cost of water fees			
Credit Aquicision			
Non- availability of credit			
High interest rate charges on credit			
Delays in acquiring credit			
Difficult to repay credit			
Post-harvest grain losses due to			
Threshing			
Winnowing			
Storage			

Transport			
Decorticating (removing husks)			
Product market			
Long distance to market for rice			
Low prices for rice			
High transport cost			
Lack of market/demand for rice			
Extension services			
Unavailability of extension services			
Lack of effectiveness			
Long distance to the extension workers			
Others			

Code: 1=High; 2= Medium; 3= Low; 0= Not exist

NB: Use code 99 where farmer(s) knows nothing on the characteristic referred to (99= don't know)

Thank you for your time, patients and responses. Is there any other information you will like us to know about your business? Please feel free to discuss it.

Time ended ---

Appendix 2: Curriculum Vitae

Abdul-Rahaman, Awal, born on November 6, 1981, Tamale, Ghana.

Citizenship: Ghanaian

Award: DAAD-Government of Ghana (MoE) Scholarship for Doctoral Studies at the University of Kiel, Germany.

Professional Experience

04/2012 – Date: Lecturer, Department of Agribusiness Management and Finance, University for Development Studies, Nyankpala Campus, Tamale, Ghana.

05/2008 – 03/2012: Programme Coordinator, Center for Sustainable Local Development (CSLD), Tamale, Ghana.

10/2006 – 08/2007: National Service Personnel, Ghana Commercial Bank, Kete-Krachi, Ghana.

Academic Qualifications

10/2015 – 01/2019 PhD Candidate, University of Kiel, Germany.

Thesis title: The coordination and Impact of Value chain Approach: evidence from smallholder rice farmers in Northern Ghana.

08/2007-12/2009 Mphil Agribusiness, University of Ghana, Legon, Ghana.

Thesis title: The Prospects of the Cotton Industry in the Northern Region of Ghana.

08/2002-05/2006 BSc. Agriculture (Agribusiness), University of Ghana, Legon, Ghana.

Thesis title: Evaluation of the Organization and Performance of the Sheanut Marketing System in the Northern Region of Ghana.

02/1999-07/2001 Senior Secondary School Certificate, Ghana Secondary School, Tamale, Ghana.