The Institute for Food Economics and Consumption Studies

of the Christian-Albrechts-Universität Kiel

Impacts of social networks, technology adoption and market participation on smallholder household welfare 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. Yazeed Abdul Mumin

born in Ghana

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werden.

Dedication

I dedicate this dissertation to my parents, Alhaji Abdul Mumin Siraj and Hajia Alimatu Fuseini, my wife, children and my siblings for their support and prayers throughout the study

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Kiel, November, 2020 — Yazeed Abdul Mumin

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Abstract

Food insecurity remains a major challenge in many parts of sub-Saharan Africa, despite the increased access to improved agricultural technologies and markets in the past few decades. Several attempts have been made to understand the factors accounting for the low uptake of improved agricultural technologies and smallholder market engagement, and their implications on household income, food security and nutrition in the sub-region. Social networks have been recognized as playing important roles in influencing household production decisions in many developing countries. However, not much has been done, in the empirical literature, on how heterogeneities in social learning about both benefits and production techniques of improved technologies, social networks structures and smallholder market orientation affect smallholder production decisions and welfare. This study, therefore, contributes to these strands of literature by examining the role of social networks on smallholder adoption of improved soybean varieties, and the impacts of smallholder adoption and market orientation on household welfare in Northern Ghana. Specifically, the study first examines the impacts of peer adoption of two improved and competing soybean varieties on smallholders' adoption decisions of these varieties using spatial autoregressive multinomial probit model to account for interdependence across varieties. Second, random-effects complementary log-log hazard model was used to investigate the role of social learning, network *transitivity*, *centrality* and *modularity* on the diffusion of these improved varieties. Third, the study examines the effects of own and peer adoption of the improved varieties on household soybean yield, food security and nutrition using the marginal treatment effects. It also explores the effects of policies that either increase affordability or access to improved seeds on adoption and the outcomes using the policy relevant treatment effects. Finally, the study employed an ordered probit selection model to examine the impacts of smallholder market-orientation on household food security and nutrition. The results show that a farmer's adoption decision of a given improved variety is positively influenced by the adopting peers of this variety, but negatively by the adopting peers of the competing improved variety. Furthermore, when the relative share of adopting peers are equal, farmers are more likely to wait and not to switch from the old variety. In addition, the results show that both learning about benefits and production process are important in accelerating adoption, although the effects of learning about production process are higher when sufficient peers adopt the improved varieties. Also, the role of *transitivity* in the learning and diffusion processes is stronger, compared to *centrality*, although *modularity* tends to slow down the diffusion process, and also constrains the effects of both *transitivity* and *centrality*. The results further show that own and peer adoption of the improved varieties significantly increase smallholder yield and food consumption, and that adoption tend to make less endowed households to catchup with more endowed households. Similarly, policies that increase either affordability or accessibility significantly increase adoption, yield and consumption, but increasing accessibility appears to deliver somewhat higher food consumption than the affordability-oriented policies. The estimates also reveal substantial heterogeneity in consumption gains across market orientations and suggest the need for transition targeted and sensitive policies in promoting smallholder food security and nutrition through crop commercialization. Similarly, the findings on adoption suggest the need for policymakers to focus promotion efforts on demonstrating the relative benefits and production process of improved varieties to farmers. Also, interventions, such as self-help groups, farmer field-days and training workshops aimed at promoting smallholder interactions, and enhancing exchange can increase the effectiveness of social networks in promoting adoption and household welfare.

Zusammenfassung

Trotz des vermehrten Zugangs zu verbesserten Agrartechnologien und Märkten in den letzten Jahrzenten, stellt Ernährungssicherung nach wie vor eine große Herausforderung in vielen Teilen Sub-Sahara Afrikas dar. Viele Versuche wurden unternommen, die Hintergründe der geringen Aufnahme verbesserter Agrartechnologien und Marktteilnahme von Kleinbauern zu verstehen und die Implikationen für Haushaltseinkommen, Ernährungssicherung und Ernährungsweise in der Subregion zu determinieren. Obwohl die Bedeutung Sozialer Netzwerke für die Haushaltsproduktionsentscheidung in Entwicklungsländern bekannt ist, wurde der Einfluss von Heterogenität in Sozialem Lernen in Bezug auf Nutzen, Produktionsmethoden verbesserter Technologien, Sozialer Netzwerkstrukturen und Marktorientierung, auf Produktionsentscheidung und Wohlfahrt der Kleinbauern in der empirischen Literatur bisher weitestgehend vernachlässigt. Um diese Lücke schließen, wird in dieser Studie der Einfluss Sozialer Netzwerken auf die Adoption verbesserter Sojabohnensorten untersucht und die Auswirkungen von Adoption und Marktorientierung auf die Wohlfahrt kleinbäuerlicher Haushalte in Nord-Ghana analysiert. Am Beispiel von zwei verbesserten und miteinander konkurrierenden Sojabohnensorten wird zunächst untersucht, wie sich die Adoptionsentscheidung der Peer-Gruppe auf die eigene Entscheidung auswirkt. Um Interdependenzen zwischen den Sorten zu berücksichtigen wird hierfür ein räumlich-autoregressiven Multinomial-Probit Modell verwendet. Anschließend wird anhand eines Random-Effects Complementary Log-Log Hazard Modells der Einfluss Sozialen Lernens und der Netzwerkcharkteristika *Transitivität*, *Zentralität* und *Modularität* auf die Verbreitung verbesserter Sorten untersucht. Schließlich werden anhand marginaler Behandlungseffekte die Auswirkung der Adoption verbesserter Sojasorten auf Ertrag, Ernährungssicherung und Ernährungweise der Haushalte untersucht. Darüber hinaus werden mittels politikrelevanter Behandlungseffekte die

Auswirkungen von Politikmaßnahmen auf Adoption und deren Folgen untersucht, die entweder die Erschwinglichkeit oder den Zugang zu verbessertem Saatgut erhöhen. Schließlich werden anhand eines Ordered-Probit Selection Modells die Auswirkungen der Marktorientierung von Kleinbauern auf deren Ernährungssicherheit und Ernährungsweise untersucht. Die Ergebnisse zeigen, dass die Entscheidung der Adoption einer bestimmte verbesserte Sorte durch die Adoption ebenjener Sorte durch die Peer Gruppe positiv beeinflusst wird, wohingegen die Aufnahme der konkurrierenden Sorte einen negativen Effekt hat. Sind die relativen Gruppengrößen der Peers gleich, so warten die Bauern eher ab und werden die ursprünglich angebaute Sorte nicht wechseln. Sowohl Lerneffekte bezüglich Gewinn als auch in Bezug auf Produktionsprozesse beschleunigen die Adoption, obgleich letztere höher ausfallen, wenn genügend Peers die verbesserten Sorten übernommen haben. Die Rolle von *Transitivität* in den Lern- und Diffusionsprozessen ist stärker im Vergleich zu *Zentralität*, wobei *Modularität* den Diffusionsprozess abschwächen und die Effekte von *Transitivität* und *Zentralität* mindern kann. Darüber hinaus kann die eigene wie die Adoption durch Peers den Ertrag und Nahrungsmittelverbrauch der Kleinbauern signifikant erhöhen und dazu führen, dass weniger gut ausgestattete Haushalte zu besser ausgestatteten Haushalten aufschließen können. Gleichermaßen führen Politiken, die entweder die Erschwinglichkeit oder den Zugang fördern, zu einem signifikanten Anstieg von Adoption, Ertrag und Konsum führen, wobei verbesserter Zugang einen scheinbar höheren Nahrungsmittelkonsum begünstig als kostenreduzierende Politiken. Die Schätzungen zeigen eine beträchtliche Heterogenität in dem Konsumzuwachs über die Marktausrichtung hinweg und verdeutlichen die Notwendigkeit von auf Transition abgezielten, sensiblen Politiken, die durch die Kommerzialisierung der Anbauprodukte Ernährungssicherheit und Ernährungsweise fördern. In ähnlicher Weise legen die Ergebnisse der Adoption nahe, dass die politischen Entscheidungsträger ihre Werbemaßnahmen darauf konzentrieren müssen, den Landwirten den relativen Nutzen und den Produktionsprozess verbesserter Sorten aufzuzeigen. Interventionen, wie Selbsthilfegruppen, Landwirtschaftstage und Workshops, die Interaktion und Austausch der Kleinbauern fördern, können die adoptions- und wohlfahrtsfördernden Effekte Sozialer Netzwerke zusätzlich verbessern.

Chapter One

General Introduction

1.1 Background

The role of agriculture in the economic development of countries in sub-Saharan Africa (SSA) has been widely proclaimed. The sector has been estimated to account for about 61% of aggregate employment, 25% of the gross domestic products (GDP), and 9.2% and 13.4% of total exports and imports respectively, between 2001 and 2016 (Tralac, 2017). These suggest that agricultural transformation and development would constitute a bedrock for the growth and development of developing countries particularly in SSA. For instance, it has been argued that the realization of the United Nations' Sustainable Development goal of eradicating extreme poverty, hunger and all forms of malnutrition depends on raising the productivity of agriculture, particularly in developing countries (United Nation, 2016).

Despite the important role of agriculture in developing countries, agriculture in sub-Saharan Africa is faced with several challenges. The most prominent among these is the lack of access to, and efficient use of improved technologies and inputs by farmers due to infrastructure limitations and decline in state-funding of agriculture following the implementation of structural adjustment programs (Markelova et al., 2009). Agriculture in SSA has been characterized by low and inefficient use of improved technologies despite the increasing availability and access to improved agricultural technologies in Africa (Suri, 2011). In fact, whereas there has been an expansion in the use of improved agricultural inputs and technologies in Asian and Latin America, which has resulted in increased agricultural productivity and reduced poverty, SSA has lagged behind in the use of improved and modern technologies and has, therefore, not been able to reap the productivity and welfare benefits of the so-called Green Revolution (Sheahan & Barrett, 2017).

The lack of innovation in Africa has been intensified by high cost of dissemination and inadequate effective demand for improved technologies (Wiggins & Leturque, 2010). Several propositions, including promotion of farmer market engagement and commercialization, and the use of social and collective actions have been made in order to enhance smallholder incomes; effective demand for and dissemination of information about improved technologies in Africa (Conley & Udry, 2010; Ecker, 2018). Agriculture marketing and commercialization have been recognized by development practitioners and researchers as important mechanisms of addressing smallholder production and consumption challenges because of its potential in promoting greater specialization, economies of scope, higher productivity and increased income (Bernard et al., 2008).

The literature has generally categorized agricultural commercialization into output sales and input purchases (Wiggins et al., 2011). In terms of output sales, commercialization of farm output can lead to increase smallholder income, which may lead to increased smallholder spending on consumer goods and production inputs (Ecker, 2018). At the input side, commercialization leads to increased access to purchased inputs and use of improved inputs by smallholders (Govereh & Jayne, 2003; Ecker, 2018). In spite of the importance of commercialization and agricultural marketing, smallholders in Africa face high costs of marketing (i.e., either in buying farm inputs or selling of output) due to poor infrastructure, high maintenance costs as well as government and markets failures (Govereh & Jayne, 2003; Wiggins et al., 2011).

These challenges and following the recent increase in food insecurity and malnutrition in the sub-Saharan countries, where agriculture is the mainstay of most economies, motivated key policy priorities such as the Comprehensive Africa Agricultural Development Programmme (CAADP) and the Africa Regional Nutrition Strategy (ARNS) to call for a rethinking and multidimensional approach to agriculture development in Africa (Sheahan & Barrett, 2017; FAO, ECA & AUC, 2020). Several propositions for promoting the use of improved technologies and agricultural marketing have been advanced to include trade and macroeconomic policy reforms, development and liberalization of rural financial and capital markets, investment in and development of infrastructure and market as well as development of support services (Ariga & Jayne, 2009). In addition to conventional view of transformation and marketization of agriculture, contemporary thinking also emphasizes the role smallholder social capital, collective action and cooperation for agricultural innovations and marketing (Bernard et al., 2008). This thinking is premised on the assertion that social capital and networks create and strengthen relationships, which drive actors and actions to be interdependent and enhance exchange of information and resources (Smith & Christakis, 2008).

Studies have underscored the relevance of social networks in innovation, product and technology diffusion (Munshi, 2004; Conley & Udry, 2010), insurance, labor and risk sharing (Fafchamps, 2011) as well as in marketing of crops (Bernard et al., 2008). This study attempts to provide a comprehensive insight into the role of social networks in smallholders' adoption and diffusion of improved technologies, and the implications of adoption of improved technologies and smallholder market-orientation on household welfare in northern Ghana.

1.2 Problem setting and motivation

In developing countries, where the reliance on agriculture is high, enhancement of agricultural productivity and income growth through adoption of new and improved innovations, and transformation of the sector from subsistence to more productive commercialize sector remains a major developmental concern (Diao et al., 2010). While studies have shown that improved crop varieties are responsible for about 50 to 90% of increase in global crop yield (Muange, 2014), smallholders in SSA appear constrained in the availability and access to new technologies due to lack of physical infrastructure, failure of markets, high cost of dissemination and lack of effective demand (Sheahan & Barrett, 2017). In addition, whereas the contribution of agricultural marketing to smallholder productivity, incomes, and poverty reduction, has been recognized and documented by policies and researchers (Bernard et al., 2008; FAO, ECA & AUC, 2020), its impacts on food and nutrition security appear to be inconclusive, especially in SSA (Ogutu et al., 2019).

Several attempts have been made to understand how social networks and groups can be leveraged as mechanisms by which smallholder adoption of new technologies can be promoted in order to circumvent some of the challenges imposed by information asymmetries and the high cost of technology dissemination in developing countries (Bandiera & Rasul, 2006; Conley & Udry, 2010). Many studies have shown that social networks can promote technology diffusion by allowing farmers either to imitate the adoption choices of their network members or to consciously learn about the production techniques and the expected benefits of the new technologies from their social network members (Bandiera & Rasul, 2006; Conley & Udry, 2010).

However, there is lack of empirical evidence on the role of adoption of competing technologies by smallholders' social network members on their adoption decisions, and the relative dominance of these technologies in terms of adoption in smallholders' social networks. Previous studies have mainly been theoretical, focusing on the use of economic theory to derive normative results and predictions of adoption (Arthur, 1989; Kornish, 2006). Yet, smallholders are often faced with the adoption decision of several competing technologies, where the decision to adopt a given technology depends not only on the adoption rates of that particular technology by the network members but also on the past and future adoption-rates of each of the competing technologies (e.g., Katz & Shapiro, 1986; Kornish, 2006). There is therefore the need to empirically examine the impacts of social networks on smallholder adoption of multiple and competing improved technologies.

The literature also provides a number of explanations on how cropping conditions and benefits influence social learning in technology adoption, although the results have been mixed, with some authors finding positive impacts of social learning on adoption (Munshi, 2004; Magnan et al., 2015), while a few find no effects (e.g., Duflo et a., 2011). One possibility of enhancing the understanding of adoption in social interaction settings and, perhaps, resolving these seemingly contrasting results is to move beyond the implicit assumption that farmers observe the field trials of their social network contacts with little friction in the flow of information (BenYishay & Mobarak, 2018) to examine the roles of heterogeneities of network structures in social learning since these shape the learning process (Jackson et al., 2017).

Social network structures play important roles in shaping the nature of interaction within networks, and have been shown to exert overarching effects on many behavioral patterns and other economic outcomes (Jackson et al., 2017). Many studies have argued that network structures, such as *transitivity*[1] and *modularity*[2], play important roles in social interactions and influence patterns of

[1] *Transitivity* or local cohesiveness/clustering coefficient measures how close the neighborhood of a farmer is to being a complete network.

[2] *Modularity* measures the proportion of links that lie within communities (i.e., components or segments) of a network minus the expected value of the same quantity in a network where links were randomly generated. It shows the extent of partition of the entire social network into latent groups and such partitioning can condition the flow of information within and across groups (Jackson et al., 2017).

behavior (Karlan et al., 2009). For instance, higher *transitivity* of a farmer's neighborhood[3], and low *modularity* of a network will mean more opportunities for the farmer to learn from peers and from different neighborhoods in the network. Such opportunities can lead to reduced cost of learning and increase the possibility of diffusion across the network (Jackson et al., 2017). However, less is known about the role of these network structures in the social learning process and technology adoption. It is therefore significant to understand whether learning about both production techniques and benefits, and these network structures influence smallholders timing of adoption of improved technologies.

Several studies have evaluated the impact of improved technologies on household welfare (Shiferaw et al., 2014; Verkaart et al., 2017). However, not much consideration has been given to the impact of improved crop varietal adoption by households and their peers on household food and nutrients consumption. In particular, studies that examined the impact of technology adoption on performance outcomes tend to focus on crop yield and income related measures (e.g., Verkaart et al., 2017; Wossen et al., 2019). Even though a better understanding of the link between adoption of improved technology and consumption of food and nutrients is key in helping policy-makers design policies to promote food and nutrition security, this has received less attention in the literature.

Moreover, the large literature on social interactions has virtually not provided evidence on the potential benefits of peer adoption of agricultural technologies on household food and nutrients consumption. For instance, in addition to the social learning effects on own productivity, income and consumption, peer adoption that leads to increased peer productivity, income and changes in

[3] A farmers neighborhood is defined as the individuals the farmer has contacts with in a social network.

peer consumption, can also affect household consumption either due to endogenous peer effect, or through private cash transfers (De Giorgi et al., 2019). With the exception of a few such as De Giorgi et al. (2019) who examined endogenous consumption peer effects, and Charles et al. (2009) who analyzed the effects of race on consumption, this has not been done on peer adoption effects. Thus, we examine the impact of smallholders' own and peer adoption of improved technologies on yield, food security and nutrition.

Furthermore, in spite of the widespread agreement on the role of commercialization in improving food security and nutrition, the empirical evidence on this issue remain scanty, with mixed findings (Ogutu et al., 2019; Ochieng et al., 2019). Whereas some argue that income from commercialization that leads to substitution of purchased food for own produced food can result in increased food consumption, but not nutrients intake (Ogutu et al., 2019), others argue that these income gains may lead to preference for higher quality and cost foods and no change in food intake (Skoufias et al., 2011).

Moreover, most of these studies have often failed to consider the possible market-orientation of smallholders' crop sales, which may mask the extent and pattern of gains from crop sales, given that smallholders' crop sales are driven by profit and non-profit motives (Pingali & Rosegrant, 1995; Jacoby & Minten, 2009). In particular, production and marketing decisions of smallholders in Africa are often fragmented and characterized by a blend of subsistence, surplus, commercial and distress motives, which may have varying implications on the gains from commercialization across farmers (Pingali & Rosegrant, 1995). Hence, it is therefore important to evaluate the impact of smallholder market-orientation on household food and nutrients consumption.

This dissertation attempts to contribute to the literature by filling these research gaps using recent data from a survey of 500 farm households in Northern Ghana. The choice of Northern Ghana was because agriculture is the main economic activity in the area with about 88% of households relying on agriculture in this area (GSS, 2014). In addition, whereas social networks have been identified to facilitate exchange of information, credit, labor and land in Ghana (Udry & Conley, 2004) and could facilitate technology diffusion and agricultural productivity, the northern regions appear to have the highest incidences of poverty, food insecurity and malnutrition. These make the choice of the region appropriate in examining the role of social networks, technology adoption and crop marketing on household welfare.

1.3 Objectives of the study

The main objective of this study is to examine the impacts of social networks, improved technology adoption and crop commercialization on household welfare of smallholders in the Northern region of Ghana. The specific objectives are:

1. To analyze the impacts of social networks on smallholder adoption of competing improved technologies;
2. To examine the role of social learning and social network structures in the diffusion of improved technology among smallholders;
3. To evaluate the impacts of smallholders’ own and peer adoption of improved technologies on household welfare;
4. To conduct a review of food security and nutrition strategies in sub-Saharan African countries, and an empirical analysis of the impact of smallholder market participation on household welfare.

1.4 Significance of the study

First, examining the role of social networks in the adoption and diffusion process could provide an efficient means of dealing with information asymmetry about the availability, access and uncertainties of improved technologies. Such information asymmetry has often limited farmers response to improved technologies and contributed to significant heterogeneities in the cost of adopting improved technologies in many sub-Saharan countries (Wiggins & Leturque, 2010; Suri, 2011). Also, information about the influence of social networks in adoption decisions in the context of competing technologies will inform policymakers when to promote single or multiple improved technologies in a given social setting. This will show the relative adoption of these improved varieties in networks (i.e., villages), and whether a full-scale introduction and promotion of all improved varieties, as often done by policymakers and stakeholders in Africa, is meritorious.

Second, examining the influence of social networks structures in the adoption and diffusion process will inform policymakers about when to leverage social networks in promoting diffusion. Information about the role of the density of farmers' neighborhoods in a network and the overall structure of the network will inform policymakers when, and when not, to rely on the use of central nodes and extension agents in the diffusion process. For instance, information about the extent of partition of farmers' networks will show whether targeting an influential farmer (as suggested by many studies) or promoting extension contacts with few farmers will be effective in facilitating diffusion since the extent of information flow will depend on the how dense and segregate the social network is (i.e., the village).

This study extends the current frontiers of the analyses of impacts of technology adoption on household welfare by considering the impacts of exogenous social interactions on household welfare. Give the sustainability challenges and problems of lack of exit mechanisms of public transfer schemes (Holden et al., 2006), understanding the effects of peer adoption on own consumption will provide an alternative to policy and other stakeholders in their attempt to promote food and nutrition security through food or cash transfer schemes. The study also provides insights into the impacts of commercialization by examining such impacts along the lines of farmer motivation for commercialization in order to disentangle impacts due to commercialization from those due to other sales such as “distress” (Jacoby & Minten, 2009). This will inform policymakers on the type of commercialization that matters, in order to develop more informed policies in promoting food security, nutrition and agriculture transformation in Africa (Pingali & Rosegrant, 1995).

1.5 Agriculture in Ghana

The agriculture sector remains the major source of living for majority of Ghanaians and accounted for about 22.2% of Ghana’s GDP in 2017 (GSS, 2018). The sector provides employment for over 50% of employed people and for about 82.5% of rural households (GSS, 2014) in Ghana. Agriculture is predominantly on smallholder basis with about 90% of land holdings being less than 2 hectares (ha) and accounting for about 80% of the total agricultural output in Ghana (MoFA, 2017). Also, almost all economic activities and livelihoods of smallholder farmers depend on agriculture and related businesses. For instance, over 65% of non-oil manufacturing uses raw materials from agriculture in the country, and the sector also accounts for more than 25% of the country’s total foreign exchange earnings (World Bank, 2017).

In Ghana, the food crops subsector, which include rice, maize, yams, groundnuts, soybean, cassava and plantains, tend to dominate, and accounts for about 70% of the agriculture GDP (MoFA, 2017).

Despite the importance of the sector and reported increment in area under farming, the contribution of the sector to national GDP has consistently decline to 22.2 in 2017, down from 31.2% in 2005. At the same time, the incidence of poverty increased from 39.2% in 2012/13 to 42.7% in 2016/17 among households engaged in the agricultural sector (GSS, 2018). Low yields of both staple and cash crops has partly contributed to the declining performance of agriculture in the country. Existing evidence show that Ghana's yields of cereals are estimated at 1.7 metric tons (MT)/ha, which is lower than the regional average of 2.0MT/ha and far less than the national potential yields of more than 5.0MT/ha (World Bank, 2017). Also, postharvest losses due to market failures and challenges have been estimated at 20 to 30% for cereals and legumes (MoFA, 2007).

Several factors including climate change, market constraints, poor soils, pests and diseases and lack of access to, and application of improved inputs have contributed to the low agricultural productivity in Ghana (MoFA, 2017). For instance, Ghana has been reported as one of the lowest countries in terms of the appropriateness and precision of inputs and fertilizer (e.g., 12kg/ha) application, particularly in all of SSA (World Bank, 2017). Furthermore, the low yields and declining contribution of the sector to GDP have also been attributed to lack of extension services, lack of availability and access to markets and the limited use of information and communication technology (ICT) in the sector (MoFA, 2017).

Given these challenges of the agricultural sector, successive governments have sought to promote the sector in many ways in order to circumvent the declining productivity and to make the sector an engine of growth through increased farm incomes and job creation in the country (World Bank, 2017). The Food and Agriculture Sector Plans (FASDEP I and II) focused on promoting the efficiency of the sector through commodity markets and value chains, application of appropriate technologies and improved environmental sustainability (MoFA 2007). This was followed by the Medium-Term Agriculture Sector Investment Plan (METASIP 2011-2015) which aimed at increasing the role of agriculture in the transformation of the Ghanaian economy. This emphasized the need to increase agricultural productivity and food security, creation of decent job and increase agricultural competitiveness through mechanization, innovation and technology application; promotion of seed and planting material development and promotion of domestic and international marketing of commodities (MoFA, 2017).

More recently, the Government of Ghana launched a new program for the agriculture sector under the name Planting for Food and Jobs (PFJ) with focuses of the promotion of maize, rice, sorghum, soybean and vegetables (MoFA, 2017). The PFJ also seeks to engender structural transformation of the country through agriculture by increasing availability of food crops, job creation and agricultural productivity. Among the major interventions earmarked to achieve this goal are increased access to, and adoption of improved inputs and promotion of marketing of both crop inputs and outputs through farmer-based organizations and private sector led networks (MoFA, 2017). The above discussion shows the relevance of improved input adoption and agricultural marketing to the sector in Ghana, and the keen consideration given to these two issues by successive governments. These, therefore, justifies the need to examine how adoption of improved technologies and agricultural marketing can be promoted in order to stimulate national agricultural productivity and to enhance household welfare.

1.6 Agricultural commercialization defined

Most definitions consider commercialization as the production of goods and services for sale as opposed to subsistence farming. Strasberg et al. (1999) defined commercialization as the ratio of gross value of all crop sales to gross value of all crop produced multiplied by 100. An obvious limitation of this definition is that it narrows commercialization to output market participation (see Wiggins et al., 2011). With this definition, there is also the likelihood of treating "distress" sales (i.e., sale of crops immediately after harvest due to immediate cash needs) of a farmer as commercialization (Leavy & Poulton, 2007). Other authors have indicated that mainly focusing on the crop output market may not be an appropriate indicator of commercialization, and therefore advocated for the consideration of input market participation (Leavy & Poulton, 2007; Wiggins et al., 2011). For instance, Leavy and Poulton (2007) defined input commercialization index as the value of inputs acquired from markets divided by agricultural production value. A broader definition is the Integration into the Cash Economy (ICE), which measures the ratio of value of goods and services acquired through cash transaction and total income (von Braun & Kennedy, 1994).

However, the concept of agricultural commercialization mean more than just involvement in market transactions but also takes into consideration the motive of the farmer (Leavy & Poulton, 2007). Pingale and Rosegrant (1995) categorized farmer commercialization into three namely: subsistence motive which is characterized by the use of own inputs and produces principally with the objective of food self-sufficiency; semi-commercial motive which is also characterized by the use of own and purchased inputs and produces with an objective of selling some surplus. The final category is the commercial motive, which is characterized by the use of mainly purchased inputs and with the objective of producing for profit. Finally, FAO (1989) defines agricultural commercialization by also categorizing farmers into subsistence-oriented if the farmer sells less than 25% of the harvest; surplus-oriented if the farmer sells between 25 and 50% of the harvest, and commercial-oriented if the farmer sells at least 50% of the harvest. Given the lack of unified definition, Wiggins et al. (2011) suggest that the choice of definition should depend on the objective of the study.

1.7 Agricultural commercialization in Ghana

Commercialization of agriculture is considered as an important strategy in Ghana's current agricultural policy frameworks and national development plans as these emphasize the relevance of moving from a subsistence-based small-holder system to a market-oriented production (MoFA, 2015; MoFA, 2017). Despite the importance of agricultural commercialization, the average marketed surplus of crops is considered low in Ghana. For instance, IFAD-IFPRI (2011) estimated the average marketed surplus ratio as 33% in Ghana. However, the extent of agricultural commercialization varies depending on the crop or livestock type and agroecological zone. GSS (2014) reported that cocoa was the crop with highest value sold in the forest and coastal zones accounting for 45% and 24% respectively, whereas yam and maize, representing 59% of sales, were the most important in terms of value of crop sales in the savannah zone. The low national average marketed surplus and the variations across crops has also been attributed to low crop productivity and poor market conditions (IFAD-IFPRI, 2011).

These have led to the pursuit of specific programs and interventions by government with the aim of increasing farmers' market engagements. The Commercial Development for Farmer-Based Organization (CDFO) aspect of the Millennium Challenge Account (MCA), and the Ghana Commercial Agriculture Project (GCAP) are specific cases in point, which encouraged smallholder market-orientation and also trained and provided them with credit to enhance their production and sales of farm produce. In particular, the Ghana Commercial Agriculture Project (GCAP) was initiated by the Government of Ghana to promote integrated commercialization along selected value chains of rice, maize, fruits and vegetables, and soybean (MoFA, 2015). Following this and other recent policy interventions such as the PFJ, soybean has become an integral crop in northern Ghana being promoted by most governmental and non-governmental parties [such as the USAID Feed the Future program, Alliance for Green Revolution in Africa (AGRA), the Agricultural Development and Value Chain Enhancement project (Advance I and II) and Ghana Greenfield Investment Program among others] (Gage et al., 2012).

1.8 Soybean in Ghana

Soybean (*Glycine max, L*) is a commercial crop that has the potential of primarily increasing farm incomes and also improving nutritional status of farmers and other consumers in Ghana. The crop also provides feed to support livestock rearing and fish, and raw materials for agribusinesses in the country (CSIR-SARI, 2013). Production and promotion of soybean in Ghana witnessed significant increase in the past two decades. Figure 1.1 show that annual domestic production of soybean increased over four folds from 39,000MT in 2005 to a peak of 170,000MT in 2017, an increase that is mainly due to increased intervention in the subsector by the government of Ghana and other development partners (such as USAID ADVANCE[4]) and expansion in the amount of area cultivated.

For instance, the area of land cultivated to the crop witnessed a sustained increase from as low as 45,000 hectares (ha) in 2005 to about 101,000ha in 2017. In addition, the soybean market in Ghana is rapidly growing with an estimated annual demand of about 150,000 MT, which is mainly driven by the local poultry industry. The increasing demand has led to an increase in national annual

[4] ADVANCE refers to the Feed the Future Ghana Agricultural Development and Value Chain Enhancement Project funded by the United States Agency for International Development (USAID).

wholesale price of soybean from about 0.36 USD/Kg in 2008 to over 0.6 USD/Kg in 2015 (MoFA-SRID, 2015).

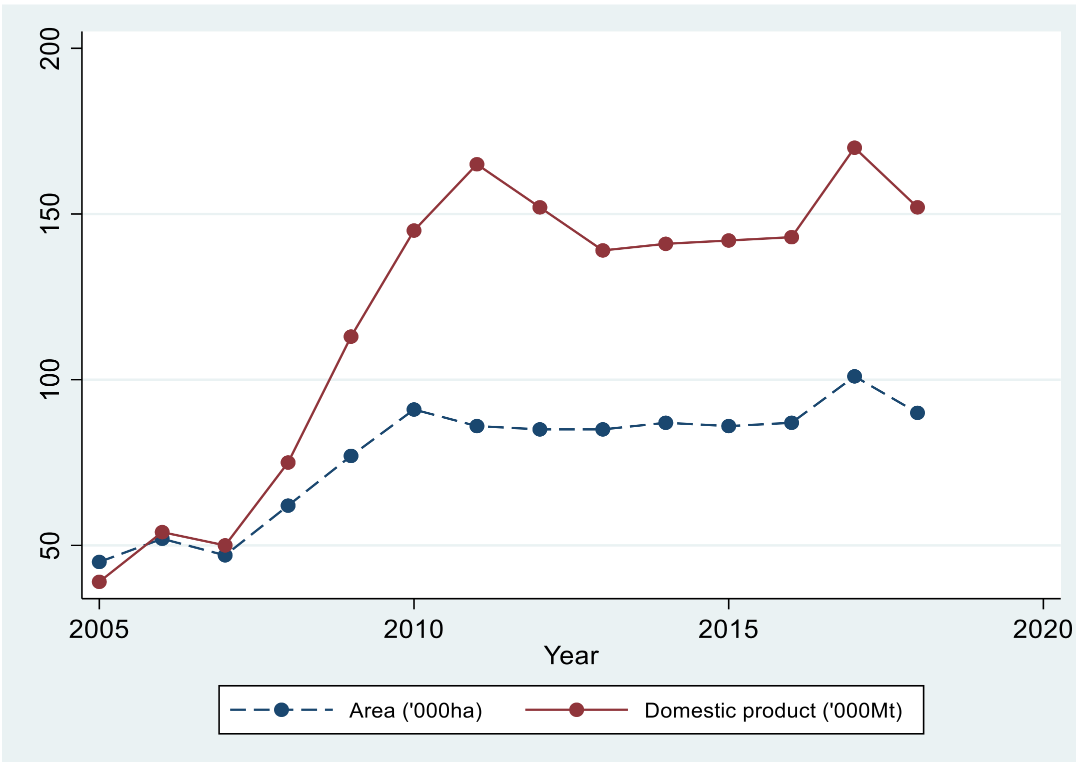

Figure 1.1 Area cultivated and domestic production of soybean

Source: FAOSTAT, 2019.

In relation to other legumes (i.e., groundnut and cowpea), soybean appear to have lower susceptibility to pests and diseases, better shelf life and larger leaf biomass that is important for soil fertility (CSIR-SARI, 2013). Climatic conditions in Ghana and in particular, northern Ghana, are considered suitable for its cultivation because of the mean temperature requirement of 20^{o}C to 30^{o}C by the crop for successful cultivation (CSIR-SARI ,2013). Despite the advantages of soybean over the other grain legumes, the crop still lags behind these other legumes in terms of area cultivated and domestic production nationally. Whereas the area cultivated to groundnut and cowpea were estimated at 394,000ha and 159,000ha, respectively, the area cultivated to soybean was estimated at 90,000ha in 2018. Similarly, the national production of groundnut and cowpea were estimated at 521,000Mt and 215,000Mt, while the production of soybean was estimated at 152,000Mt in 2018 (FOASTAT, 2019).

Also, soybean output in Ghana has been argued as being low with about 46.7% of its attainable output produced annually. In addition, the average yield of soybean yield has been estimated at 1.68MT/ha which is far less than the potential yields of 3.10MT/ha (MoFA-SRID, 2015). This has been attributed to a number of production constraints, including lack of extension and training to ensure good handling, care and storage of soybean seeds; inadequate breeder and foundation seed supply; reliance on rain-fed, manual and rudimentary production systems and lack of awareness and use of improved seed varieties (CSIR-SARI, 2013). For instance, access to improved seeds and other inputs has been estimated at 23% and 9% respectively (SIL, 2015).

Given this low access and use of improved varieties, the Council for Scientific and Industrial Research (CSIR) and Savannah Agricultural Research Institute (SARI) have over the years developed and introduced a number of improved seed varieties and other innovations such as inoculant to promote the cultivation and output of the crop. Initially, two varieties, *Anidaso* and *Bengbie* were released in 1992, but were not well received by farmers. Consequently, seven other varieties were introduced from 2003 and only two of these (namely *Jenguma* and *Afayak*) are still in cultivation today, in addition to the traditional variety (*Salintuya*). These improved varieties have been reported to have higher yield potential of over 2.0 MT/ha, resistant to pod-shattering, mature in about 35 days earlier compared to the traditional variety and resistant to other agricultural stress such as pests, diseases, low phosphorous soil and climatic variabilities (CSIR-SARI, 2013).

However, the use of these improved varieties and other technologies are still described as being far from desired. For instance, studies on the rate of soybean adoption in Ghana have shown that, despite the high penetration of soybean production, the use of improved seeds has been low and estimated as ranging between 16% and 33% of soybean farmers (SIL, 2015). Moreover, available evidence shows that 35% of soybean producers use inoculum, 32% apply phosphorous and 4% use mechanical planters (SIL, 2015). The low adoption of improved technologies in the midst of increased availability of improved soybean planting technologies, and the high yield and market potential of the crop present an interesting and suitable context to investigate the drivers and impacts of adoption of improved soybean technologies on household welfare in the area.

1.9 Farmer social networks in Ghana

Farmer-based associations and social networks have been integral parts of socio-economic arrangements and policies to promote smallholder technology adoption and agricultural marketing in developing countries (Conley & Udry, 2010). This is because social capital has been shown to have several effects on production, investment and marketing decisions (Udry & Conley, 2004; Karlan et al., 2009). In Ghana, Udry and Conley (2004) identified four main types of social networks, namely information, credit, labor and land networks, that tend to influence smallholder production decisions. Information networks present opportunity for smallholders to learn about new innovations and technologies from peers. Credit networks involve the exchange of financial resources between peers, and enable smallholders mitigate or overcome the constraints of credit in the production process. The third network effect is labor transactions networks where smallholder in a network tend to exchanged labor during farm operations and finally, land transaction network which presents an opportunity to redistribute and increase access to land by land constraint farmers. These aspects were taken into consideration in this study in defining social network links given their influence on learning opportunities and on various productive resources.

1.10 Study area and data collection

Soybean is mainly produced in Northern, Upper West, Volta and Upper East regions of Ghana with the Northern region, which is the study area, accounting for more than half of the total area cultivated to the crop (65.72%) and the national output (72%) of the crop (Gage et al., 2012). The Northern region is the largest region in terms of land mass in Ghana and occupies about 70,384 square kilometers of land. Geographically, it is bounded by Upper West and Upper East regions to the north, Brong Ahafo and Volta regions to the south (see Figure 1.2), Togo to the east and Côte d'Ivoire to the west. The region has a total population of 2,479,461 with 69.7% being rural. The total number of households in the region is 318,119 and the average household size in the region of 7.7 persons is higher than the national average of 4.4 persons. The literacy level in the region is very low with only 37.5% of persons who are 11 years and older can read and write a simple statement with understanding in at least English or a Ghanaian language (GSS, 2013). Administratively, the region has 26 districts.

Agriculture is the mainstay of the region, engaging about 74% of employed persons and 93% of rural households in the area (GSS, 2013; GSS, 2018). The main crops cultivated include yam, maize, millet, guinea corn, rice, groundnuts, beans, soybean and cowpea (GSS, 2013). Unfortunately, the incidence of poverty and extreme poverty are not only high in the region but have increase from 50.4% and 22.8% to 61.1% and 30.7%, respectively, between 2012/13 and 2016/17 (GSS, 2018).

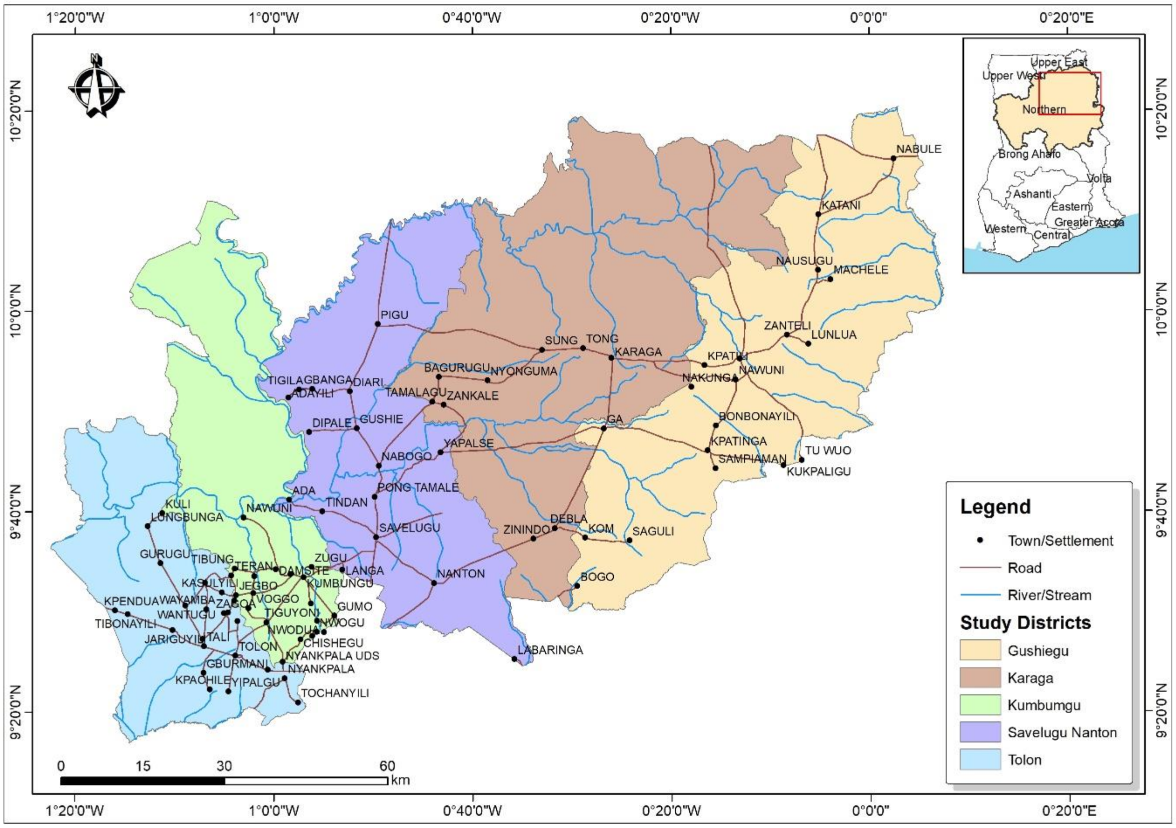

Figure 1.2 Map of study area

Source: Regional and district map of Ghana, 2017.

Food insecurity and malnutrition have also been the highest in the area compared to the rest of the country, with an average of 18% of households being severely food insecure. The prominent causes of food insecurity and malnutrition in this area include inadequate rains, poor soils, structural constraints and lack of improved inputs, which have often led to low agricultural outputs, fluctuation in food prices and seasonal constraints in accessing food (WFP & GSS, 2012).

In order to investigate smallholder adoption of improved soybean variety and crop commercialization as well as their impact of household welfare, cross-sectional household survey was conducted in five districts in the Northern region between June and September 2017. A random sample of 500 farm households was drawn in three stages. In the first step, five (5) soybean producing districts was purposively selected based on their intensity of soybean production. Next, a list of soybean producing villages in each district was obtained from MoFA district offices, and used to randomly sample 8 villages in Savelugu-Nanton, 6 in Gushegu, 5 in Tolon, 4 in Karaga and 2 in Kumbungu districts, in proportion to the number of households engaged in agriculture in each district (GSS, 2014). In the third stage, listing of households in each village was conducted and a randomly sample of 20 households was selected for interview in each village using a structured questionnaire. In order to obtain village level information, focus group discussion with 4 to 6 village and farmer group leaders was conducted in each village. (see Appendix for the questionnaire and the discussion guide).

1.11 Structure of thesis

The dissertation is organized into six chapters including chapter one as the general introduction. Chapters two to five consist of journal articles. Specifically, chapter two examines the impacts of social network members' adoption of competing improved soybean varieties on smallholder adoption decisions of these varieties and the relative dominance of these varieties in the social networks. Chapter three explores the influence of social learning about production techniques and benefits of new technologies, as well as the effects of social network structures: *transitivity* and *modularity* on diffusion of the improved soybean varieties. Chapter four evaluates the impact of smallholders' own and peer adoption of the improved varieties on soybean yields, food security and nutrition. An analysis of the impact of smallholder market-orientation is presented in Chapter five. Chapter six presents summary, conclusions and policy implications of the study.

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Chapter Two

The Role of Social Networks in the Adoption of Competing New Technologies in Ghana

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Abstract

In this study, we use a unique and detailed dataset to examine the impact of social networks, conditional on contextual and individual confounders, on farmers' adoption of competing improved soybean varieties in Ghana. Based on the contagion conceptual framework, we employ a spatial autoregressive multinomial probit model to examine how neighbors' varietal and cross varietal adoption of improved varieties, affect a farmer's adoption decision in the social network. Our results show that adoption decisions in a network tend to converge on one variety, such that beyond a threshold of adopting neighbors of that improved variety, the cross-varietal effects tend to lose significance in the network. We also find evidence that farmers are not more likely to adopt either of the improved variety compared to farmers with no neighbors who have adopted the improved varieties, if the shares of adopting neighbors of the improved varieties are equal. The findings demonstrate the significance of neighborhood effects in the adoption of competing technologies.

Keywords: Social network; Technology adoption; Cross-varietal effect; Threshold; Spatial model

JEL codes: C21; D83; O13; O33

2.1 Introduction

In developing countries where the reliance on agriculture is high, enhancement of agricultural productivity and income growth through the adoption of new and improved innovations are widely accepted as quite significant. Studies have shown that improved crop varieties are responsible for about 50% to 90% of increase in world crop yield per ha (Muange, 2014). Unfortunately, adoption of improved varieties and other forms of new technologies remain quite low, especially among smallholders in sub-Saharan Africa (Muange, 2014). Walker et al. (2014) argue that out of 20 main crops grown by farmers in Africa, improved varieties account for only about 35% of the area cultivated to these crops, which underscores the significance of understanding the determinants of technology adoption for research and policy.

Modern technologies have often been introduced with the normative anticipation that such technologies will do well, as they allow peers to learn from each other, thereby displaying increasing returns as more people adopt (Arthur, 1989). Beyond this, many empirical studies have shown the importance of social networks in the adoption and diffusion of new agricultural technologies (e.g., Foster and Rosenzweig, 2010; Bandiera and Rasul, 2006; Conley and Udry, 2010; Beaman and Dillon, 2018; BenYishay and Mobarak, 2018). Unfortunately, there is lack of empirical evidence on the role of adoption of competing technologies by agents' neighbors on their adoption decisions, and the relative dominance of these technologies in terms of adoption in agents' social networks. Previous studies on this front have mainly been theoretical, focusing on the use of economic theory to derive normative results, predicting adoption and characterizing equilibrium conditions of adoption (Arthur, 1989; Kornish, 2006; Acemoglu et al., 2011).

In this article, we investigate the case where farmers are faced with the adoption decision of three technologies. The farmer's adoption of a given technology depends not only on the adoption-rate of this particular technology, but also on the adoption-rate of competing technologies available in the farmer's network (see, e.g., Katz and Shapiro, 1986). This study, to the best of our knowledge, provides the first empirical assessment of farmers' adoption decisions in a multiple competing technology setting, where a farmer's adoption behavior is influenced by that of adopting neighbors of all available improved technologies. This type of investigation is important for the following reasons: First, this analysis reflects the situation farmers face in contemporary economic, socio-political and technological environment, where similar and/or different technologies for the same purpose are developed (Dorfman, 1996). Second, and perhaps more important in the context of social network externalities, is that a farmers' decision about a given technology depends on the past and future adoption-rates of each of the competing technologies (e.g., Katz and Shapiro, 1986; Kornish, 2006). The higher the adoption-rate of a particular technology, the higher are the complementary network externalities for this technology. For instance, a technology incompatible with other available technologies may become dominant, i.e., in the sense of a standard, so that previous investments in any other technology may become completely obsolete and their future net benefits tend to zero.

To guide our empirical analysis, we develop a simple contagion model to show that farmers' adoption decisions of a given variety depend on the adoption decisions of network neighbors who are adopters of that variety and neighbors who are adopters of the other varieties. Our model setup is related to other works on technology adoption and consumer market shares (Arthur, 1989; Kornish, 2006; Acemoglu et al., 2011). However, as an extension of these previous frameworks, we allow the status quo technology to affect farmers' adoption decisions rather than assuming it is an obsolete option with its value normalized to zero. This makes the adoption of the traditional variety in a farmer's neighborhood an argument in the value function of farmers' adoption decisions in our framework. We then employ spatial econometric techniques similar to Lee (2007), Lin (2010) and Bramoullé et al. (2009) to examine the impacts of social networks on farmers' adoption decisions of two improved soybean varieties in Ghana, using unique and detailed observational data.

Our results show that a farmer's likelihood of adopting an improved variety is lower than the proportion of adopting neighbors of that variety when the proportion is below a given threshold. However, the likelihood of adoption becomes higher than the proportion of adopting neighbors when the share of neighbors adopting that variety is above this threshold. We also find that a farmer's adoption decision of a given improved variety is positively influenced by the adopting neighbors of this variety, but negatively by the adopting neighbors of the competing improved variety. This is consistent with contagion effects, where the behaviors of one's peers change the likelihood that one engages in those behaviors. We also observe that when the relative share of adopting neighbors are equal, farmers are not more likely to adopt any of the improved varieties compared to farmers without adopting neighbors of the improved varieties. This finding offers additional explanation of the differences in adoption rates of competing technologies and why some technologies may become dominant, while others end up as subordinates, or even nonexistent in some circumstances.

Our analysis is novel in the following respects. First, by incorporating endogenous effects, contextual effects and unobserved correlated fixed effects, we are able to delineate the effects due to behavioral decisions, average neighbors' characteristics and those due to unobserved common characteristics. The consideration of all three effects is highly important, as their unbundling helps in teasing out the effects of behavioral decisions, which is the most important aspect of these network effects in designing and targeting innovation policies more effectively (Manski, 1993 p.533). Second, we examine cross-variety dependence in the mean part of the model to show how farmers' adoption of the improved varieties are related to their neighbors' adoption decisions. With this, we are able to circumvent the interpretation problem of the estimated parameters that is usually associated with the approach of capturing interdependence among alternatives in the variance-covariance structure[5] (Autant-Bernard et al., 2008; LeSage and Pace, 2009; Wang et al., 2014).

The rest of the paper is structured as follows. The next section describes the context and data. In Section 2.3, we present the theoretical framework that we use to guide the empirical analysis. We present the empirical framework and estimation in Section 2.4. In Section 2.5, we report and discuss the results, and then conclude in Section 2.6.

2.2 Context and data

2.2.1 Context

Soybean is a crop that is mainly cultivated in the northern part of Ghana (Northern, Upper East and Upper West regions), with the Northern region accounting for 65.72% of the total area cultivated to the crop in Ghana. It is a commercial crop that has the potential to raise farmers' incomes and improve their nutritional status. It is also a versatile crop that supports livestock

[5] Typically, in order to identify the multinomial probit model, the first diagonal element of the covariance matrix is set to unity, which makes the interpretation of the dependence among alternatives problematic when captured in the variance-covariance structure (Autant-Bernard et al., 2008; Chakir and Parent, 2009).

rearing, fisheries and provides raw materials for local industries. However, it has not yet been fully accepted by farmers, because of the perceived cropping and handling difficulties (Plahar, 2006). Also, available evidence suggests that average yields are as low as 0.8MT/ha, even though there is the potential to achieve yields as high as 2.5MT/ha, with improved varieties of seeds and proper agronomic practices (Gage et al., 2012).

In lieu of this, the Council for Scientific and Industrial Research (CSIR) and Savannah Agricultural Research Institute (SARI) have over the years developed and introduced a number of innovations including improved seed varieties and inoculant to promote the cultivation and output of the crop. Two of the improved varieties (namely *Jenguma* and *Afayak*) are currently in cultivation, in addition to the traditional variety (*Salintuya*). These improved varieties were first introduced to farmers at demonstration sites in the various districts by SARI, and following adoption of some farmers, seeds were subsequently made available to these farmers and to extension offices of the Ministry of Food and Agriculture (MoFA) to promote farmers' access to the seeds and information about planting (CSIR-SARI, 2013). These avenues remain the main sources of information about the cultivation and yield potentials of these varieties.

The improved varieties have higher yield potential of over 2.0 MT/ha, resistant to pod-shattering, earliness in maturity (i.e., about 35 days less compared to the traditional variety) and resistant to other agricultural stress such as pests, diseases, low phosphorous soil and climatic variabilities (CSIR-SARI, 2013). In addition, planting the improved varieties does not require any special complementary inputs that are different from the inputs required by the traditional variety. These notwithstanding, studies show that the use of improved soy seed is quite low, with estimates ranging between 16% and 33% (SIL, 2015) of soybean farmers. The indigenous, late maturing and shattering variety is still in wide use, and CGIAR (2009) reported that this variety constituted more than 50% of all soybean varieties under cultivation in Ghana.

Table 2.1 provides information on farmers' awareness and subjective perception of the costs and expected benefits of adopting the improved varieties. Panel A shows that whereas about 64% and 60% of farmers know about *Jenguma* and *Afayak* respectively, the proportion of adopters are 42% and 26%, respectively. The potential setbacks to adoption identified in the literature are lack of information about the production techniques and benefits of new technologies, credit constraints and market[6] constraints (Zeller et al., 1998; Croppenstedt et al., 2003; Beaman et al., 2020). Panel A of Table 2.1 further reports the reasons why farmers adopted the improved varieties. The most frequent reason given in each case is agronomic and climate resistance of *Jenguma* and high yielding advantage of *Afayak*. The second most frequent reason indicated is the perceived high yielding potential of *Jenguma* and agronomic and climatic resistance of *Afayak.* For non-adopters, the top reasons for not adopting the improved varieties are due to inadequate information about the production and agronomic requirements of the improved varieties, and that these improved varieties are not high yielding compared to the traditional varieties[7].

In order to assess the extent to which non-adopters are informed about the yields of the improved varieties, panel B shows the estimated change in yields between each of the improved varieties

[6] The high and excess demand for soybean over its supply, especially by the poultry sector, in Ghana (Plahar, 2006), and the high integration of the soybean market into the international market (Goldsmith, 2017), suggest that the degree of marketability of soybean may not be the main barrier to adoption given that all three varieties face similar market conditions. In addition, Table 2.A1 in the appendix shows no systematic difference in market access across farmers' adoption status.

[7] Discussions with MoFA officials and village level key informants revealed that some farmers hold the perception that the traditional variety grows well and will provide good yield with good management and timely harvest (see also SIL, 2015).

and the traditional variety based on computation from the sample and estimates of non-adopting farmers.

Table 2.1 Awareness and main reasons for adoption or non-adoption of the improved varieties

	%
Panel A	
Know about *Jenguma*	64.4
Know about *Afayak*	59.8
Why adopted Jenguma	
Agronomic and climatic advantages	74.6
High yielding	66.8
High marketability	42.1
Less labor demanding	38.6
Easy to cultivate	8.4
Why adopted Afayak	
High yielding	67.2
Agronomic and climatic advantages	62.4
High marketability	44.0
Less labor demanding	36.8
Easy to cultivate	11.2
Why non-adopters did not adopt	
Do not know the production and agronomic requirements	76.0
I feel it is not high yielding	34.0
Credit constraints	21.0
Poor prices and market	21.0
Need for other food crops	4.0
Panel B	
Estimated yield difference between:	
Jenguma and *Salintuya* from average yields of the sample[$]	67.1
Afayak and *Salintuya* from average yields of the sample	58.8
Jenguma and *Salintuya* estimated by non-adopters	4.9
Afayak and *Salintuya* estimated by non-adopters	4.2

Notes: The table consist of two panels. Panel A presents descriptive statistics of farmers' awareness and farmers' reasons for adoption and non-adoption. Panel B presents descriptive statistics of estimated yield difference between each of the improved varieties and the traditional variety by official sources, computation using average yield of the sampled farmers and by non-adopters. The official estimates suggest much higher yield potentials of *Jenguma* and *Afayak* of 2.8Mt/ha and 2.4Mt/ha, respectively, compared to the yield potential of the traditional variety is 1.0Mt/ha (CSIR-SARI, 2013).

There are substantial differences between the change in yields (on average) obtained by adopters and the estimates (5%) reported by non-adopters. The reported differences suggest that despite the existence of the improved varieties for some time, and the promotion of the improved variety by SARI and MoFA through the existing extension system, non-adopters seem to have different information and perceptions about the production processes and expected benefits of the improved varieties compared to adopters. This differential access to information among adopters and non-adopters, and failure of several improved varieties to be accepted by farmers suggest the need to understand what could possibly explain farmers' adoption of a particular variety in a context of multiple improved varieties. This will be useful in the formulation of hypotheses that explain the underlying drivers of varieties emerging as dominant or marginal in the farmers' villages (social networks).

2.2.2 Data

Social networks

The data used in this study were collected from 483 farm households across 5 districts in 25 villages in the Northern region of Ghana, between July and September 2017. The survey design employed a multistage random sampling technique to first purposively select soybean growing districts, based on intensity of soybean production[8] and then randomly selecting villages and households, proportionate to the number of households in each district. Finally, random matching within sample was used, whereby in each village (i.e., a village represents a social network or group), 20 farm households were randomly selected and each household was matched with 5 other farm households also randomly drawn from the village sample. For each match, conditioned on

[8] This was done in consultation with the Ministry of Food and Agriculture (MoFA) Regional and Districts Offices and Resilience in Northern Ghana (RING)

knowing the matched household, detailed information about the relationship between them were elicited. For determining existing links in the network, we used both social and locational indicators in the definition of a farmer's neighbors (Banerjee et al., 2013). Table 2.2 presents these social and locational dimensions of social network contacts. The farmer knows on average 3.13 of the 5 farmers randomly matched to him[9]. Also, the average farmer has 1.77 agricultural information contacts, 2.17 relatives, 1.18 friends, and exchanged labor with 1.73 of the known matched farmers. The farmer, on average, has ever visited 2.18 of the contacts, and has 0.87 or 0.67 of the contacts as farm or residential neighbors, respectively.

Table 2.2 Social network information

Network connections and information	Mean	S.D.	Min	Max
Number of random matched known	3.13	1.15	0	5
Conditional on knowing the matched:				
Social dimension of contact				
Number of agricultural information contacts	1.77	1.79	0	5
Number of neighbors who are relatives	2.17	1.67	0	5
Number of neighbors who are friends	1.18	1.56	0	5
Number of neighbors with same religion	0.64	1.07	0	5
Number of neighbors ever exchanged labour	1.73	1.86	0	5
Number of neighbors ever exchanged credit	0.69	1.35	0	5
Number of neighbors ever exchanged land	0.33	0.95	0	5
Locational dimension of contact				
Number ever visited	2.18	1.64	0	5
Number of farm neighbors	0.87	1.20	0	5
Number of residential neighbors	0.67	0.96	0	5
Social links (Social ties)				
Number of social contacts	3.12	1.25	0	5
Degree*	3.73	1.51	1	8
Network transitivity	0.46	0.09	0.18	0.60
Proportion of *Jenguma* adopters in neighborhood (unconditional)**	0.42	0.36	0	1
Proportion of *Afayak* adopters in neighborhood (unconditional)**	0.29	0.31	0	1

Notes: SD denotes standard deviation and Min and Max are minimum and maximum values respectively.
*The farmer *i*'s average degree is higher than the number of his/her social ties due to the fact that the number of social ties took into consideration only directed contacts (from farmer *i* to farmer *j*) based on the social and locational dimensions of contacts. The degree on the other hand is based on undirected relationships where the existence of a link between farmer *i* and farmer *j* was defined as either by *i*, or by *j*, or both mentioned having any of these contacts with the other farmer.
** The unconditional implies that the proportion of adopting neighbors (j's) of each variety does not condition on the variety adopted by the farmer (i).

[9] We use the masculine gender because majority (60%) of the farmers in the sample are males.

We define the farmer's neighbors as those among the 5 farmers randomly assigned to him/her, that he/she shares any of these social and locational contacts with (i.e. the union of these contacts). When we take the union of these social and locational contact dimensions, an average farmer has 3.12 social ties (Table 2.2). We use the social and locational contacts to construct our social network matrix with entries, w_{ij}, being equal to one if the respondent i had any of these relationships with a matched farmer j (i.e., i and j are neighbors), and zero otherwise (i.e., i and j are not neighbors). The resulting social network matrix, W, is a 483 x 483 block-diagonal matrix, along villages networks. Based on the matrix, W, the average farmer has 3.73 neighbors in the social network and a maximum of 8 neighbors as indicative by the term degree in Table 2.2 (see Figure A.1 for networks). The table also shows that an average farmer has 42% and 29% adopting network members of *Jenguma* and *Afayak* varieties, respectively.

Descriptive statistics

We also elicited detailed information on the household and farm level characteristics. Table 2.3 shows definition, measurement and descriptive statistics of variables for the surveyed households and of their neighbors. Majority of farmers in the sample are males. The average education attained by the surveyed farmers is low, about 1.11 years, but with an average experience of about 12.7 years of farming. In addition, the majority (55%) of the farmers and (56%) of their neighbors ever had contact with extension agents, while only 28% of farmers and 30% of their neighbors ever had contact with research and non-governmental organization.

Table 2.3, further shows that majority of the farmers and their neighbors, 55%, are credit-constrained. The proportion of credit constrained farmers are significantly lower for *Jenguma* producers (Table 2.A1, panel B), and as noted in Section 2.2.1, suggest that access to credit could affect farmers decisions to adopt this variety. In our analysis such differences in access to credit are controlled for by using household credit constraints (Table 2.3). Households were classified as credit-constrained, if they obtained credit, but expressed interest in borrowing more at pertaining interest rates, and if there was no credit available to them through formal and informal lenders.

Furthermore, about 42% and 26% of the households were adopters of *Jenguma* and *Afayak*, respectively, whereas 32% cultivated *Salintuya.* Table 2.3 also shows a strong association between a farmer's adoption of an improved variety and the proportion of farmers' neighbors who adopted that variety. In particular, farmers who adopted *Jenguma* have up to 88% of their neighbors also adopting *Jenguma*. At the same time, about 82% of neighbors of *Afayak* adopters are themselves adopters of *Afayak*, while farmers who are cultivating the traditional variety have about 85% of their neighbors also producing the traditional variety. This indicates the possibility of farmers exchanging information about soybean, and/or imitation by copying their neighbors' cultivation choices.

2.3 Theoretical framework

In order to motivate our discussion on how local correlations in social networks affect adoption decisions in our context of multiple and competing technologies, we present a theory of contagion, which is based on the linear threshold model (Granovetter, 1978; Morris, 2000; Acemoglu et al., 2011)[10]. In our study, the technology under consideration is soybean varieties, where two (i.e., *Jenguma* and *Afayak*) of these are improved and *Salintuya* is the traditional variety. Thus, we model adoption as the outcome of optimizing behavior of agents, based on the frameworks presented in Arthur (1989) and Kornish (2006).

[10] The reader is referred to Beaman et al. (2020) for a discussion on the merits of the linear threshold model.

Table 2.3 Variable description, measurement and descriptive statistics

Variable	Definition	Own (*X*) Characteristics		Neighbors (*WX*) Characteristics	
		Mean	SD	Mean	SD
Independent variables					
Age	Age of farmer (years)	44.002	12.007	43.929	7.151
Gender	1 if male; 0 otherwise	0.596	0.491	0.581	0.333
Education	No. of years in school	1.112	3.077	1.105	1.810
Experience	No. of years in farming	12.677	2.718	12.708	2.006
Household	Household size (No. of members)	5.725	2.090	5.722	1.477
Landholding	Total land size of household (in hectares)	2.597	1.556	2.626	1.120
Credit	1 if farmer indicated did not obtain sufficient credit or not successful in applying for credit; 0 otherwise	0.554	0.497	0.554	0.344
Risk	Risk of food insecurity (No. of months household was food inadequate)	0.948	1.387	0.925	0.942
Extension	1 if ever had extension contact; 0 otherwise	0.546	0.924	0.563	0.687
NGO/Res.	1 if ever had contact with non-governmental/research organization; 0 otherwise	0.284	0.451	0.295	0.332
Association	No. of village-based associations a farmer is a member	1.091	1.285	1.081	0.898
Electronic	1 if own phone, radio and/or television; 0 otherwise	0.817	0.386	0.821	0.264
Soil quality	4=fertile; 3=moderately fertile; 2=less fertile; and 1=infertile	2.962	0.972	2.965	0.688
Price	Soybean price in GHS/kg	1.055	0.188	1.062	0.135
Dependent variable					
Jenguma	Adopters of *Jenguma* variety (1 if adopted *Jenguma*; 0 otherwise)	0.418	0.494	0.878^{+}	0.214
Afayak	Adopters of *Afayak* variety (1 if adopted *Afayak*; 0 otherwise)	0.258	0.438	0.815^{+}	0.238
Salintuya	Adopters of *Salintuya* variety (1 if adopted *Salintuya*; 0 otherwise)	0.322	0.468	0.849^{+}	0.263
Instruments					
Village born	1 if farmer was born in village	0.696	0.461		
Authority	1 if any parent of the farmer had an authority in village	0.130	0.337		
ExtDistance	Distance to the extension office (in kilometers)	9.890	9.140		
RNDistance	Distance to the nearest agric. research or non-governmental organization (in Kilometers)	14.561	11.797		
FinDistance	Distance to the nearest financial institution (in kilometers)	9.256	6.884		

Notes: SD denotes standard deviation. "+" implies that the proportion of adopting neighbors (j's) of each variety is conditional on the farmer (i) adopting that variety. That is why the proportion of adopting neighbors of each variety in this table is higher than the unconditional proportions in Table 2.2.

The main insights in these frameworks are that agents are confronted with the situation of having to choose among competing technologies, of which one is a status quo (default) technology. Also, adoption decisions are based on the relative and absolute number of adopting and non-adopting neighbors and the expected net benefits from adopting these technologies. We define a set of farmers $m = (1, \ldots, M)$ in a network represented by an undirected graph $g(m, E)$, where E is a set of edges (i, j) that represent the connectivity between farmers i and j. We also define the neighborhood of a farmer $i \in m$ as $N_i(g) = [i \mid (i, j) \in E]$. That is, $N_i(g)$ consists of the set of the neighbors of farmer i and $d_i = |N_i(g)|$ denotes the number of farmers that form part of the neighborhood.

Farmer i sets out using a traditional variety, 0, and has the choice of adopting any of the two new improved varieties, denoted as 1 and 2, from the set $V = \{1, 2\}$ or retaining the traditional variety. These new varieties compete for adoption and are assumed not to be sponsored or strategically manipulated (Arthur, 1989). We further assume that farmer i faces one-time cost of adopting variety 1 or 2, denoted by $C_i^1 > 0$ and $C_i^2 > 0$, respectively. The farmer's infinite horizon net benefit function is given by $\pi(d_i, d_i^1, d_i^2) \geq 0$, where $d_i - d_i^1 - d_i^2$ indicates the number of neighbors that have adopted none of the improved varieties, with d_i^1 representing the number of neighbors that have adopted variety 1 and d_i^2 the number of neighbors that have adopted variety 2. The farmer's decision problem is to maximize the expected net benefit from adoption, by selecting the strategy that offers the highest payoffs. The alternative strategies are characterized by payoff from (i) adopting variety 1, (ii) adopting 2 and (iii) from maintaining the traditional variety 0. Let us denote the one-period discount factor by λ.

We define the probability that the next potential adopter has preference for variety 1 as $h\left(d_i^1/d_i\right)$ and for variety 2 as $h\left(d_i^2/d_i\right)$. Both of these functions are increasing with the shares, d_i^1/d_i and d_i^2/d_i, of 1 and 2 adopting neighbors, respectively. Moreover, the conditional probability $p\left(d_i^1\right)$ that a farmer adopts variety 1, given that he/she has preference for variety 1, is an increasing function of the number of adopting neighbors of variety 1 $\left(d_i^1\right)$. The complement of $p\left(d_i^1\right)$, given by $1-p\left(d_i^1\right)$, indicates the probability that the farmer does not adopt variety 1. Similarly, the conditional probability of adopting variety 2 for a potential user is $p\left(d_i^2\right)$, given that he/she has preference for variety 2. Thus, as an example, the term $p\left(d_i^1\right)h\left(d_i^1/d_i\right)$ indicates the conditional probability of adopting variety 1, given the preference for variety 1 multiplied by the probability of having these preferences for variety 1. Likewise, one can formulate the probabilities for adopting variety 2 and for non-adopting variety 1 or 2. Based on these formulations, the farmer's decision problem can be formulated as

$$(1)\ \hat{\pi}\left(d_i,d_i^1,d_i^2\right)=\max\begin{cases}\pi^1\left(d_i,d_i^1,d_i^2\right)-C_i^1,\\ \pi^2\left(d_i,d_i^1,d_i^2\right)-C_i^2,\\ \lambda\left[\left[h\left(\frac{d_i^1}{d_i}\right)\left(1-p\left(d_i^1\right)\right)+\left(1-h\left(\frac{d_i^1}{d_i}\right)\right)\left(1-p\left(d_i^2\right)\right)\right]\pi\left(d_i,d_i^1,d_i^2\right)\right.\\ \left.+h\left(\frac{d_i^1}{d_i}\right)p\left(d_i^1\right)\pi\left(d_i-1,d_i^1+1,d_i^2\right)+\left(1-h\left(\frac{d_i^1}{d_i}\right)\right)p\left(d_i^2\right)\pi\left(d_i-1,d_i^1,d_i^2+1\right)\right]\end{cases}.$$

Following equation (1), we express the expected net benefits from adopting variety 1, when there are d_i^1 adopters of variety 1 and d_i^2 adopters of variety 2 as

$$(2)\quad \bar{\pi}^1\left(d_i,d_i^1,d_i^2\right)=q^1\left(d_i^1\right)+\lambda\left\{\left[h\left(\frac{d_i^1}{d_i}\right)\left(1-p\left(d_i^1\right)\right)+\left(1-h\left(\frac{d_i^1}{d_i}\right)\right)\left(1-p\left(d_i^2\right)\right)\right]\pi^1\left(d_i,d_i^1,d_i^2\right)\right.$$

$$\left.+h\left(\frac{d_i^1}{d_i}\right)p\left(d_i^1\right)\pi^1\left(d_i-1,d_i^1+1,d_i^2\right)+\left(1-h\left(\frac{d_i^1}{d_i}\right)\right)p\left(d_i^2\right)\pi^1\left(d_i-1,d_i^1,d_i^2+1\right)\right\},$$

where $q^1\left(d_i^1\right)$ is the periodic benefit of adopting 1, which is a function of the neighbors that have already adopted variety 1. The term $\bar{\pi}^1\left(d_i,d_i^1,d_i^2\right)$ accounts for the immediate and discounted future stream of payoffs, if the farmer does not adopt, and of the discounted stream of future payoffs, if the farmer adopts variety 1 or variety 2. Similarly, we express the expected net benefit from adopting variety 2, when there are d_i^1 adopters of variety 1 and d_i^2 adopters of variety 2 as,

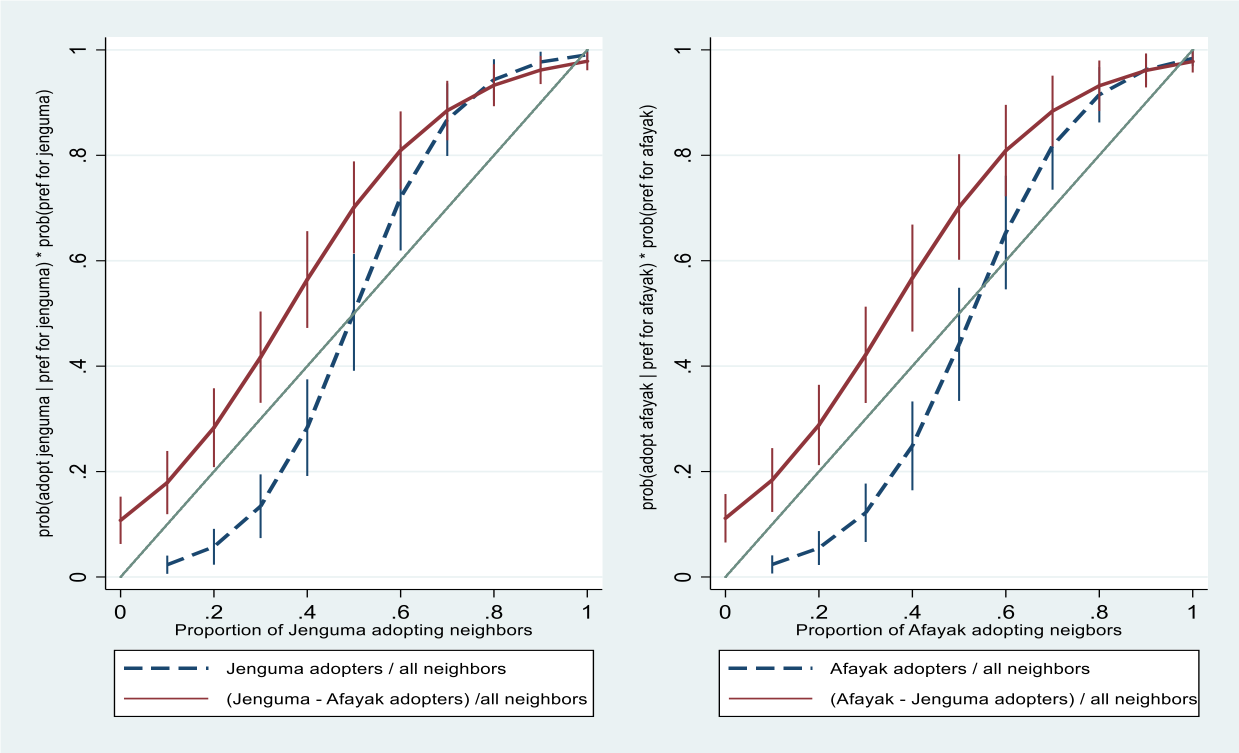
$$(3)\quad \bar{\pi}^2\left(d_i,d_i^1,d_i^2\right)=q^2\left(d_i^2\right)+\lambda\left\{\left[h\left(\frac{d_i^1}{d_i}\right)\left(1-p\left(d_i^1\right)\right)+\left(1-h\left(\frac{d_i^1}{d_i}\right)\right)\left(1-p\left(d_i^2\right)\right)\right]\pi^2\left(d_i,d_i^1,d_i^2\right)\right.$$

$$\left.+h\left(\frac{d_i^1}{d_i}\right)p\left(d_i^1\right)\pi^2\left(d_i-1,d_i^1+1,d_i^2\right)+\left(1-h\left(\frac{d_i^1}{d_i}\right)\right)p\left(d_i^2\right)\pi^2\left(d_i-1,d_i^1,d_i^2+1\right)\right\}.$$

The functions $q^1(.), q^2(.)$ may contain network-dependent and network-independent elements. In order to express network dependence, it can be seen that the agent's expected net benefits from adopting a particular variety are increasing with the number of adopting neighbors of that variety.

Based on observational data, we next explore the nature of $p(.)$ $h(.)$ for both varieties, which are shown in Figures 2.1A and 2.1B. We observe that both the proportions of adopting neighbors of each improved variety relative to the neighborhood (i.e., $d_i^1/d_i, d_i^2/d_i$, indicated by the dashed line), and the difference in the share of adopting neighbors of the two improved varieties (i.e., $(d_i^1-d_i^2)/d_i$, indicated by the solid line), are important for influencing a farmer's adoption decision (Figure 2.1). This distinction is important because the first measure takes into account the number of non-adopting farmers of the two improved varieties, while the second measure focuses exclusively on the difference in adoption of the two improved varieties. In respect of the proportions of adopters of the improved varieties in the neighborhood, the curve exhibits an S-shaped function for the conditional probability of adoption $p(.)$, given the probability of the preference $h(.)$ for a variety, as a function of the share of neighbors that have adopted this variety. Thus, when the proportion of adopting neighbors of an improved variety is low, the probability of a farmer adopting this variety is lower than the proportion of the neighbors who have already adopted it. However, the likelihood of adopting an improved variety is higher than the proportion of adopting neighbors of this variety, when the proportion of adopting neighbors of this variety is high.

Moreover, the solid line, which is based on the difference in the share of adopters of the two improved varieties, shows stronger effect on adoption than the share of adopters of these varieties in relation to the whole neighborhood (dashed line). It lies above the dashed line for most part, and is consistently higher than the 45-degree line in both figures. This suggests that farmers give significant consideration to the difference in the share of adopting neighbors of the improved varieties when making adoption decisions. The S-shaped function and the importance of the difference in relative adoption of the improved varieties by farmer's neighbors implies that the adoption process will result in one of the varieties becoming "dominant", while the other varieties become "subordinates" in the network. Thus, the neighborhood becomes increasingly 'locked-in' on the dominant variety, where a farmer's likelihood of adopting that variety is higher, if adoption pushes that variety ahead of the other improved variety in relative and absolute numbers and in expected net benefits. Thus, we deduce the following hypotheses;



A. Adoption of *Jenguma (v=1)* **B. Adoption of *Afayak (v=2)***

Figure 2.1 Association between own and neighbors' adoption of *Jenguma* and *Afayak*

Notes: The dashed line represents the probability of adoption given the probability of the preference for *Jenguma* or *Afayak* (in Fig. 2.1A or 2.1B respectively). In Figures 2.1A and 2.1B, it represents the mapping of the proportion of adopting neighbors of *Jenguma* and *Afayak* (i.e., the horizontal axis) to the probability of adopting *Jenguma* and *Afayak*, respectively (i.e., the vertical axis). The point of intersection of this line and the identity function (i.e., the 45-degree line) shows the threshold. The solid line, on the other hand, focuses exclusively on the difference in share of adopting neighbors of the two improved varieties. In Figure 2.1A, it represents the mapping of the difference in the share of adopting neighbors of *Jenguma* and *Afayak* [i.e., (*Jenguma* minus *Afayak*) / all neighbors] to the probability of adopting *Jenguma*. In Figure 2.1B, it shows the mapping of the difference in the share of adopting neighbors of *Afayak* and *Jenguma* [i.e., (*Afayak* minus *Jenguma*) / all neighbors] to the probability of adopting. The short vertical lines on the two curves denote 95 percent confidence intervals.

Hypothesis 1. *For a given neighborhood $N_i(g)$ of farmer i, adoption will not occur as long as the number of adopters d_i^1 or d_i^2 relative to all neighbors $|N_i(g)|$ remains below an absolute threshold denoted by $\tilde{d}_i^{1,2} / |N_i(g)|$.*

Hypothesis 2. *For a given neighborhood $N_i(g)$ of farmer i, there exist a relative threshold $\hat{d}_i^{1,2} / |N_i(g)|$ where the probability of adoption of variety 1 or 2 is equal to the share of adopters*

$d_i^{1,2} / |N_i(g)|$. *If this share of adopters is below the relative threshold, the farmer is less likely to adopt, and if it is above the threshold the farmer is more likely to adopt.*

Hypothesis 3. *Adoption in a given neighborhood* $N_i(g)$ *of farmer* i *will converge towards a single dominant variety (1 or 2) if the proportion of adopters of this particular variety leads to a higher adoption probability than the proportion of the non-adopting neighbors of the variety. If the relative shares of adopters of the improved varieties are equal, the farmers are not more likely to adopt either the improved variety*.

2.4. Empirical framework

In 2.4.1, we first present the base model and then discuss the identification concerns and strategies we use in the empirical analysis. We next discuss the empirical estimation in 2.4.2, and then the computation of marginal effects for the control variables in 2.4.3.

2.4.1 The model and identification

The studies of social interaction models have generally focused on the delineation of the effects of individual or group interactions on individual or group behavior and socio-economic outcomes (Blume et al., 2010; Lee et al., 2010). Three types of behavioral effects have been identified in the literature that can arise from social interactions. These are the endogenous effects, exogenous/contextual effects and correlated effects (Manski, 1993; Moffitt, 2001). To motivate our discussion on these effects, consider the following linear regression

$$(4) \qquad Y_{ig} = \rho_0 E\left(Y_{d_i} | g\right) + \beta_1 X_{ig} + \beta_2 E\left(X_{d_i} | g\right) + \mu_{ig},$$

where Y_{ig} is the outcome of individual i in group g, X_{ig} is a vector of characteristics of i from group g, with β_1 as the associated parameter estimates, and μ_{ig} are innovations. The neighborhood mean outcome and characteristics are captured by the terms $E\left(Y_{d_i}|g\right)$ and $E\left(X_{d_i}|g\right)$, respectively. The parameter ρ_0 denotes the endogenous network effect, whereas β_2 defines the contextual effects. Manski (1993) showed that specification (4), called the linear-in-means model, suffers from the "reflection problem", which is the difficulty in differentiating between endogenous (behavioral) and exogenous (contextual) factors, since expressing the endogenous effects $E\left(Y_{d_i}|g\right)$ as the average behavior or outcome of the group makes it a linear function of the mean characteristic of the group $E\left(X_{d_i}|g\right)$ in model (4). This shrouds what each of the two effects are, and the inherent implications associated with each becomes misleading, as they have been identified to have effects different in nature and in policy conclusions (Manski, 1993; Lin, 2010).

Another important confounder of the behavioural effects is the argument by Moffitt (2001) that unobserved factors in μ_{ig}, noted earlier as correlated effects, may also be a source of correlation among individuals in a given group (see also Manski, 1993; Calvo-Armengol et al., 2009; Lee et al., 2010). Moffitt (2001) distinguished between correlations due to similarities or preferences that drive a group of individuals to group together, and those that are attributable to similar environmental characteristics, suggesting that any social impact could be a reflection of omitted variables, or spurious effect. Accordingly, we use a spatial autoregressive (SAR) model, where the disturbance in equation (4) is decomposed into network-fixed effects, α_g, (which defines unobserved characteristics that are similar for all network members) and innovations, ε_{ig}, to account for endogenous, contextual and group fixed effects in the group interaction setting as follows

$$(5) \qquad Y_{kg} = \rho_0 W_{kg} Y_{kg} + X_{kg}\beta_1 + W_{kg} X_{kg}\beta_2 + l_{mg}\alpha_{g0} + \varepsilon_{kg},$$

where $g = 1, \ldots, G$ and G is the number of groups (villages) in the sample, m_g is the number of members in the g th group and $k = \sum_{g=1}^{G} m_g$ is the total number of observations. The term Y_{kg} is a vector of adoption decisions, X_{kg} is a matrix of characteristics for the m_g individuals in group g , W_{kg} is a non-stochastic $k \times k$ network weights matrix with zero diagonal elements, which also captures the group network structure, l_{m_g} is an m_g vector of ones, with the coefficients α_{g0} capturing group fixed effects and ε_{kg} 's are assumed to be i.i.d, with Var(ε_{kg}) $= \sigma_0^2 I_{m_g}$.

Studies by Bramoullé et al., (2009), Calvo-Armengol et al., (2009) and Lee et al., (2010) demonstrate that the SAR model in our setting is identified by accounting for group fixed-effects, because W_{kg} could have any arbitrary structure, thereby making the interaction patterns sufficiently different across networks, due to the different structure of each network's weight matrix. Given that we define networks at the village level, we account for group fixed-effects by controlling for village dummies of all the 25 sampled villages. The intuition is that farmers in the same village face similar environmental and institutional conditions and thus, the inclusion of these village fixed-effects is expected to account for any unobserved conditions that may affect the behavior and outcomes of farmers in the same village/network (Lee, 2007).

Whereas the network fixed-effects can account for correlated unobservables at the group level, these do not account for the issue of endogenous network formation or correlated unobservables between individuals in the same group, which may result in endogeneity problems (Moffitt, 2001). To account for this, we use the control function approach suggested by Brock and Durlauf (2001) to control for the potential endogeneity of neighbors' adoption, using farmers' birth status (i.e., whether the farmer was born in the village) and the authority of farmers' parents (i.e., whether any of the farmer's parents ever had an authority in the traditional chieftaincy structure in the village) as instruments (see Table 2.2).

The reasoning behind the use of farmers' birth status as an instrument is that farmers who are born in the village are expected to have deeply rooted and well-connected social ties with other members of the village because of the social bond that have evolved overtime. Also, the remote nature of these villages tends to reduce the incentive of non-natives to move and settle in these village, making the issue of out-migration more likely than in-migration in these settings. Thus, farmers who were born in the village are expected to have more social connections and links with other village members than those who were not born in the village. However, we do not expect a farmers' birth status in the village to directly affect his decision to adopt any of the improved varieties except through his interactions with the farmers that he has social ties with, suggesting the instrument is fairly exogenous to the farmers adoption decisions.

The second instrument is the authority of farmers' parents in the traditional chieftaincy structure in the village. We believe this is a relevant instrument because the traditional authority of the parents affects the farmer by increasing the farmer's contact with people who contact the parents through him, and may increase the popularity of the farmer in the village. These are expected to increase the social connections of the farmer compared to a farmer without such royal privileges. However, the traditional authority of the parents does not directly affect the farmers adoption, since this is not directly related to adoption decisions, and that authorities in the traditional system are mostly predetermined by lineage in these areas. One issue that might threaten the use of this as an instrument is when privileges due to parents' authority lead to increase access to production opportunities and resources which affect adoption through access to land, other resources and information. For this reason, we control for household landholding, credit, and other information sources on farming in all specifications.

We then use these instruments together with a set of other control variables to estimate a first-stage conditional edge independence model of network formation (Fafchmaps and Gubert, 2007), retrieve the predicted residuals and insert them into our adoption equations (5) as control functions to account for endogeneity of neighbors' adoption. The inclusion of the residuals controls for the endogeneity of peer adoption by accounting for the correlation between the endogenous peer effects and the unobservables that affect farmers' adoption decisions (Wooldridge 2015). The first-stage network formation model and the estimates are shown in Appendix B.

2.4.2 Empirical Estimation: Spatial Autoregressive Multinomial Probit

Our theoretical framework shows how a farmer's decision to adopt a given variety is based on the expected net benefit from adopting that variety, the proportion of adopters of each of the varieties in the neighborhood, as well as the expected benefits from adopting other varieties in equations (2) and (3). Based on equations (2) and (3), and the motivation for identification of network effects in subsection 2.4.1, as well as the fact that the empirical analysis aims at examining the adoption of two improved soybean varieties (*Jenguma and Afayak*) in relation to a conventional variety (*Salintuya*), we specify farmers' adoption decisions in a spatial autoregressive multinomial probit model.

The spatial autoregressive multinomial probit (SAR MNP) model is based on the random utility framework, which is expressed as a system of seemingly unrelated regression models, with each latent choice considered as an equation (LeSage and Pace, 2009; Wang et al., 2014). Thus, we denote the model as $kV \times 1$ vector of outcomes $Y^{*} = \left(Y_{i,1}^{*}, \ldots, Y_{i,V}^{*}\right)'$, where each of the

$Y_i^{*'} = \left(Y_1^{*'}, Y_2^{*'}, \ldots, Y_n^{*'}\right)$ elements is expressed as a continuous SAR model. Given this formulation and following equations (2) and (3), we express our estimation model as:

$$(6) \qquad Y_{kg,V}^{*} = \rho_1 W_{kg} Y_{kg,1}^{*} + \rho_2 W_{kg} Y_{kg,2}^{*} + X_{kg}\beta_{1,V} + W_{kg} X_{kg}\beta_{2,V} + l_{m_g}\alpha_{g0,V} + \varepsilon_{kg,V}\,,$$

where $V = \{1,2\}$ represents the varieties, ρ_1 and ρ_2 are the endogenous effects of variety 1 and 2, respectively, on the adoption of all varieties. For example, in the equation of variety 2, ρ_1 is the cross effect of variety 1 and ρ_2 is the own effect of variety 2. The vector X, like the $kV \times 1$ matrix, is stacked based on the respective observed choices V, where X represents a $1 \times r$ vector of explanatory variables associated with each choice.

The observed response values of Y are such that $Y_i = V$, if $Y_{i,V}^{*} = \max\left(Y_{i,1}^{*}, \ldots, Y_{i,V}^{*}\right) > 0$, and 0 if $Y_{i,V}^{*} \leq 0$, $\forall V = 1, 2$. The stacked V observations also require the network weight matrix to be re-casted in order to generate the interaction lags of $Y_{i,V}^{*}$ and to ensure conformability. This involves repeating each row of the $k \times k$ weight matrix V times to yield a matrix expressed as; $I_V \otimes W = \tilde{W}$, where I_V is a $V \times V$ identity matrix. Typically, the error terms $\varepsilon = \left(\varepsilon_{1i}, \ldots, \varepsilon_{Vi}\right)'$ and $\varepsilon_i' = (\varepsilon_1', \varepsilon_2', \ldots, \varepsilon_n')$ has a covariance matrix as $I_k \otimes \Sigma$, with $\Sigma = \sigma_1^2$, $\sigma_{12} = \sigma_{21}$, σ_2^2. This is the cross-variety covariance which is assumed to be identical and independent across individuals, but not varieties. However, modeling the cross-variety dependence in the mean part of the model implies restricting $\Sigma = I_V$, as suggested by LeSage and Pace (2009).

The challenges to the estimation of equation (6) are the issues of the multidimensional integrals, correlations in the error terms and the complexity of the spatial dependence (Kelejian and Prucha, 1999; Fleming, 2004). We use the Markov Chain Monte Carlo (MCMC) sampling, as it is mostly applied in such settings, where the higher dimensional integrals are re-specified into sequence of draws with sometimes known conditional distribution (Wang et al., 2014). If $Y_{i,V}^{*}$ were observable, the likelihood function of the model could be expressed as $p(\tilde{Y}^{*} \mid \rho, \beta, \Sigma) \propto \left| I_{k,V} - \rho \otimes \tilde{W} \right|^{1/2} \exp\left\{ -\frac{1}{2}\left(\tilde{H}\tilde{Y}^{*} - \tilde{X}\beta \right)^{'} \cdot \left(\tilde{H}\tilde{Y}^{*} - \tilde{X}\beta \right) \right\}$, with the posterior distribution given as $p\left(\rho, \beta, \Sigma \mid \tilde{Y}^{*}\right) \propto p\left(\tilde{Y}^{*} \mid \rho, \beta, \Sigma\right) \cdot \pi\left(\rho\right) \cdot \pi\left(\beta\right) \cdot \pi\left(\Sigma\right)$, where $\tilde{H} = (I_{k,V} - \rho \otimes \tilde{W})$. However, since $Y_{i,V}^{*}$ is not observable, we apply Bayesian estimation approach to elicit the conditional posterior distributions $p\left(\rho \mid \tilde{Y}^{*}, \beta, \Sigma\right)$ and $p(\beta \mid \tilde{Y}^{*}, R, \Sigma)$. The entire Bayesian estimation approach is presented in the Appendix C.

2.4.3 Marginal effects

Given the estimates of the SAR equation (6), the marginal effect of a variable x on a given variety v can be calculated as a series of $\left((V+1) \times X\right)$ $k \times k$ matrices, where $V+1$ is the total number of varieties, which is 3 in our case; X is the total number of variables and k is the sample size (483). The direct effects, representing the effect of a given covariate x on the probability of farmer i adopting this variety, is evaluated as the mean of the diagonal elements of the sociomatrix. The total effect is computed as the mean of this entire matrix and then the direct effect subtracted to obtain the indirect effect of this covariate. The indirect effects show the spillover effects and represent the effect(s) of an individual's (i's) covariate x on the probability of i's neighbors adopting a given variety (see Wang et al., 2014). The difference in the probability of adoption among varieties is the change from the original probabilities at the initial value of the covariates to the new probabilities, given a standard deviation change in the variables.

2.5 Empirical results

We present the empirical results in this section, where subsection 5.1 shows the aggregate effects of adopting neighbors of each improved variety on adoption. In 5.2, we discuss the distribution effect of adopting neighbors of each improved variety, whereas in 5.3, we consider network effects in terms of the difference in the shares of adopting neighbors of each improved variety. Finally, we discuss the effects of other controls and robustness in subsections 5.4 and 5.5, respectively.

2.5.1 Effects of absolute number of adopting neighbors

The Bayesian estimates of the parameters and diagnostics of the spatial autoregressive multinomial probit model for adoption of improved soybean varieties are reported in Tables 2.4 to 2.7. As shown by the Geweke diagnostics in Table 2.4, all the variables have test statistics lower than the critical value of 2.71. This suggests that these parameters meet the convergence test criterion and the Markov chain of the Gibbs sampler draws attained an equilibrium state. Comparing estimates in Table 2.5 with those in columns (1) and (2) of Table 2.A2 in the Appendix, obtained without accounting for group fixed effects, show marked differences. The higher deviance information criteria (DIC[11]) and the lower Log-likelihoods for the model without group fixed effects (DIC of 1,212 and -1,009 in Table 2.A2) suggest the models with group fixed effects are best fit, and thus we account for group fixed effects in all specifications. The estimates of the residuals of the network formation model are generally not statistically significant in all specifications (see e.g., Tables 2.4 and 2.5), suggesting that the results are not driven by endogenous network formation or other correlated unobservables between individuals in the same group.

[11] The DIC is a goodness-of-fit measure proposed by Spiegelhalter et al. (2002) for Bayesian models comparison and is given as the sum of the effective number of parameters and the expectation of the deviance. Models with smaller DIC are preferred to models with larger DIC.

Table 2.4 SAR MNP estimates based on the absolute number of adopters (influence of non-adopting neighbors is not taken into account)

Variables	*Jenguma*		*Afayak*	
	Estimates	SD	Estimates	SD
Endogenous effects				
No. Neighbadopt_*Jenguma*	0.095 [0.095]***	0.013	-0.028 [0.028]***	0.010
No. Neighbadopt_*Afayak*	-0.019 [0.019]**	0.009	0.147 [0.146]***	0.007
Own characteristics:				
Age	3.40E-04 [0.345]	0.001	0.001 [0.399]	0.001
Gender	-0.028 [0.001]	0.024	0.023 [0.001]	0.027
Education	0.004 [0.028]*	0.002	0.014 [0.023]***	0.005
Experience	-0.011 [0.004]***	0.004	-0.015 [0.014]***	0.003
Household	0.003 [0.011]	0.005	-0.011 [0.015]**	0.005
Landholding	0.066 [0.004]***	0.006	0.022 [0.011]***	0.008
Credit	-0.190 [0.066]**	0.089	0.017 [0.022]	0.032
Risk	0.004 [0.191]	0.008	-0.003 [0.017]	0.008
Extension	0.061 [0.004]**	0.024	0.114 [0.003]***	0.021
NGO/Res	0.002 [0.061]	0.067	0.061 [0.114]**	0.033
Association	-0.050 [0.002]***	0.011	0.020 [0.062]**	0.010
Electronic	0.013 [0.051]	0.025	-0.028 [0.020]	0.027
Soil quality	0.068 [0.014]***	0.012	-0.010 [0.029]	0.011
Price	-0.163 [0.068]**	0.081	-0.103 [0.010]	0.084
Contextual effects:				
Age	0.061 [0.167]	0.064	0.088 [0.102]*	0.063
Gender	3.40E-04 [0.063]	0.001	0.001 [0.089]**	0.001
Education	0.011 [0.001]	0.011	0.002 [0.001]	0.014
Experience	-0.002 [0.011]	0.002	-0.006 [0.002]**	0.003
Household	-0.002 [0.002]	0.002	-0.001 [0.006]	0.002
Landholding	0.001 [0.002]	0.002	0.007 [0.001]**	0.003
Credit	-0.013 [0.001]***	0.003	0.003 [0.008]	0.004
Risk	0.066 [0.013]***	0.017	0.029 [0.003]*	0.017
Extension	0.001 [0.067]	0.004	0.001 [0.029]	0.004
NGO/Res	0.005 [0.002]	0.009	0.011 [0.001]	0.009
Association	-0.049 [0.005]***	0.014	-0.037 [0.011]**	0.019
Electronic	-0.010 [0.049]**	0.005	0.003 [0.037]	0.005
Soil quality	0.026 [0.011]*	0.016	-0.019 [0.003]	0.015
Price	-0.007 [0.026]	0.006	-0.001 [0.019]	0.005
Residliquid	-0.069 [0.007]*	0.040	-0.055 [0.001]	0.046
Residextens	0.044 [0.070]	0.054	0.017 [0.055]	0.017
ResidNGO	0.003 [0.045]	0.016	-0.009 [0.017]	0.015
Link formation residual	0.019 [0.003]	0.042	-0.015 [0.009]	0.021
Constant	0.341 [0.038]**	0.182	0.399 [0.048]***	0.136
Network Fes	Yes		Yes	

Notes: Pseudo-R^2 = 0.8207; DIC = 2,794.90; Mean Log-likelihood = -2,329.10; n = 483; # of draws = 5000 and burnin = 2000. Figures in square brackets are Geweke diagnostics test of convergence and it is a Z-test of the null of equality between means of the first 20% and last 50% of the sample draws. The chi-squared statistics are reported and large values of the statistic imply rejection of the null of convergence (i.e., equal means). SD denotes standard deviation. In this case, the endogenous and cross variety effects indicate the effects of an increase in the number of adopters of each variety on the probability of adoption. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Tables 2.4 and 2.5 present estimates of endogenous own and cross varietal effects on adoption of *Jenguma* and *Afayak*, using the absolute numbers of adopting neighbors and the proportion of adopting neighbors as measures of endogenous effects, respectively as in equations (2) and (3) in the theoretical framework, and equation (6) in the empirical framework. The endogenous own varietal effects examine the effects of having *Jenguma* or *Afayak* adopting neighbors on adoption of *Jenguma* or *Afayak*, respectively, while the endogenous cross varietal effects consider the effects of having *Afayak* or *Jenguma* adopting neighbors on the adoption of *Jenguma* or *Afayak*, respectively. In terms of absolute numbers in own effects, respondents with adopting neighbors of *Jenguma* or *Afayak* are 9.5 or 14.7 percentage points more likely to adopt *Jenguma* or *Afayak*, respectively, compared to farmers with no adopting neighbors of the improved varieties. Also, having neighbors adopting cross variety (i.e., *Afayak* or *Jenguma*) are 1.9 or 2.8 percentage points less likely to adopt *Jenguma* or *Afayak*, respectively, compared to farmers without adopting neighbors of any of the improved varieties. These effects are all statistically significant at least at the 5% level.

Given that farmers could be more concerned with the proportion and not the absolute number of adopters in their network, as it gives an indication of the skewness of the neighborhood in terms of adoption, we present in Table 2.5 the estimates of these endogenous effects in terms of proportion of neighbors adopting a particular variety in the farmer's neighborhood. The effects are similar to the effects in Table 2.4 in terms of direction and significance levels of these effects, but differ in the magnitude of the coefficient. In particular, a farmer with higher proportion of his neighbors in the network adopting *Jenguma* or *Afayak* is 23.1 or 34 percentage points more likely to adopt *Jenguma* or *Afayak* than those with no adopting neighbors of *Jenguma* or *Afayak*, respectively.

Table 2.5 SAR MNP estimates based on the proportion of adopters in farmer's neighborhood (influence of non-adopting neighbors is taken into account)

Variables	*Jenguma*		*Afayak*	
	Estimates	SD	Estimates	SD
Endogenous effects				
Prop. Neighbadopt_*Jenguma*	0.231***	0.024	-0.053***	0.017
Prop. Neighbadopt_*Afayak*	-0.052***	0.018	0.340***	0.016
Own characteristics:				
Age	7.6E-5	0.001	0.001	0.001
Gender	-0.029	0.022	0.016	0.024
Education	0.002	0.002	0.014***	0.004
Experience	-0.011***	0.004	-0.013***	0.003
Household	0.003	0.004	-0.009**	0.005
Landholding	0.057***	0.006	0.022***	0.007
Credit	-0.142*	0.084	0.013	0.028
Risk	0.001	0.008	-0.003	0.007
Extension	0.050**	0.022	0.100***	0.019
NGO/Res	0.039	0.063	0.057**	0.031
Association	-0.043***	0.011	0.017**	0.010
Electronic	0.015	0.023	-0.019	0.025
Soil quality	0.062***	0.011	-0.011	0.010
Price	-0.155**	0.075	-0.083	0.075
Contextual effects:				
Age	0.138	0.118	0.118	0.110
Gender	0.001	0.001	0.002**	0.001
Education	0.017	0.021	0.004	0.027
Experience	-0.001	0.003	-0.012**	0.005
Household	-0.002	0.003	2.0E-4	0.003
Landholding	0.001	0.005	0.013**	0.005
Credit	-0.020***	0.006	0.001	0.007
Risk	0.138***	0.031	0.040*	0.030
Extension	0.005	0.008	0.003	0.008
NGO/Res	0.014	0.016	0.024*	0.018
Association	-0.077***	0.027	-0.069**	0.032
Electronic	-0.018**	0.009	0.012	0.010
Soil quality	0.063**	0.026	-0.012	0.026
Price	-0.019**	0.011	-0.001	0.010
Residliquid	0.021	0.051	0.021*	0.016
Residextens	0.006	0.014	-0.010	0.013
ResidNGO	0.001	0.039	-0.020	0.018
Constant	0.356**	0.171	0.319**	0.127
Link formation residual	0.029	0.052	-0.051	0.059
Network Fes	Yes		Yes	

Notes: Pseudo-R^2 = 0.8390; DIC = 1,171.30; Mean Log-likelihood = −976.07; n = 483; # of draws = 5000 and burnin = 2000. SD denotes standard deviation. The estimates were obtained from the standardized social weight matrix. Thus, the endogenous and cross variety effects indicate the effects of an increase in the proportion of adopters of each variety on the probability of adoption. The Prop. Neighbadopt_*Jenguma* is the own effect of Jenguma under the *Jenguma* equation but shows the cross-variety effect of *Jenguma* in the *Afayak* equation. Likewise, the Prop. Neighbadopt_*Afayak,* is the own effect of *Afayak* under the *Afayak* equation but also shows the cross-variety effect of *Afayak* in the *Jenguma* equation. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

The cross-varietal effects are also negative, suggesting that the likelihood of adopting a given variety, say *Jenguma*, by a farmer declines by 5.2 percentage points when a proportion of his neighbors adopts the other variety, i.e., A*fayak*, in the neighborhood, compared to a farmer without adopting neighbors of the improved variety. These findings generally suggest contagion effects, where farmers adopt the behavior of their neighbors in the network. The endogenous own and cross variety effects taken together imply substitutability between the new varieties. This corroborates the argument by Niehaus (2011) that an agent's marginal valuation of the knowledge obtained from different neighbors is evaluated in relative terms if different kinds of knowledge is substitutable in the social learning process.

2.5.2 Effects of the relative number of adopting neighbors

In our theoretical model, the choice of agents between these new varieties depends on meeting a lower limit $\tilde{d}_i$ and a threshold in terms of adopting neighbors of each variety $\hat{d}_i$, as formulated in hypothesis (1) and (2). However, the number of adopters that needs to be attained before a significant relationship between the share of adopters of one variety versus the other and the likelihood of adoption is not quite obvious. To shed some light on this, we consider three ranges of adopting neighbors of each variety. The results are presented in Table 2.6, where we report estimates of specifications that include quartiles of *Jenguma* adopting neighbors only in columns (1-3), *Afayak* adopting neighbors only in columns (4-6) and both *Jenguma* and *Afayak* adopting neighbors in columns (7-9).

When we compare the estimates in columns (1-6) to those in columns (7-9), we see the estimates are relatively similar in direction and even in magnitudes in most of the cases. The results show that the likelihood of switching from the traditional variety (*Salintuya*) is higher when a proportion of a farmer's neighbors adopt any of the new varieties. Specifically, a farmer is more likely to switch from *Salintuya* by at least about 12 or 5 percentage points to *Jenguma* or *Afayak* when at most a quarter of the neighbors adopts either *Jenguma* or *Afayak*, respectively, compared to those with no neighbor adopting either of these new varieties (i.e., the reference case), *albeit* not statistically significant for Afayak adopting neighbors (col. 7). Also, the likelihood is even higher when the share of adopters of *Jenguma* (*Afayak*) consists of the second and third quartiles of adopters in the farmer's neighborhood, with probabilities of switching from *Salintuya* being at least 24.1(7.7) and 34.1(19.9) percentage points more than those with no adopting neighbors of these varieties, respectively. This inclination of switching from *Salintuya*, is expected in cases where the traditional variety is relatively inferior, given the growing and environmental conditions[12].

We now turn to the adoption of *Jenguma* and *Afayak* (Table 2.6). The likelihood of adopting *Jenguma* or *Afayak* when only a quarter of a farmer's neighbors adopt *Jenguma* or *Afayak*, respectively, declines with the coefficient of *Afayak* being statistically significant at 5 percent significance level. Thus, having at most a quarter of neighbors adopting *Jenguma* or *Afayak* is not sufficient to persuade the farmer to adopt that variety, and in fact this significantly reduces the likelihood of adopting *Afayak* by 11 percentage points (cols. 6 and 9). However, in terms of cross varietal effects, a farmer with only a quarter of the neighbors adopting *Afayak* (in cols. 5 and 8) is about 10-13 percentage points more likely than those with no adopting neighbors of *Afayak* to adopt *Jenguma*.

[12] This is also the case in our study setting because of the high susceptibility of the traditional variety to environmental stress, which is quite unfavorable for this variety.

Table 2.6 SAR MNP estimates of distribution in proportion of adopter in farmer's neighborhood

Prop. of adopting neighbors	(1) *Salintuya*	(2) *Jenguma*	(3) *Afayak*	(4) *Salintuya*	(5) *Jenguma*	(6) *Afayak*	(7) *Salintuya*	(8) *Jenguma*	(9) *Afayak*
	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
3rd Quartile_*Jenguma*	-0.341***	0.314 ***	-0.062**				-0.527***	0.321 ***	-0.002
	(0.016)	(0.059)	(0.029)				(0.056)	(0.063)	(0.028)
2nd Quartile_*Jenguma*	-0.241***	0.153***	-0.045*				-0.290***	0.144***	0.012
	(0.042)	(0.041)	(0.031)				(0.043)	(0.045)	(0.032)
1st Quartile_*Jenguma*	-0.134***	-0.032	0.107**				-0.119***	-0.032	0.139***
	(0.037)	(0.036)	(0.039)				(0.042)	(0.038)	(0.038)
3rd Quartile *Afayak*				-0.199***	-0.066**	0.533***	-0.521***	-0.048*	0.536***
				(0.043)	(0.031)	(0.062)	(0.056)	(0.031)	(0.061)
2nd Quartile *Afayak*				-0.077**	-0.037	0.252***	-0.235***	-0.013	0.231***
				(0.037)	(0.031)	(0.044)	(0.045)	(0.032)	(0.047)
1st Quartile *Afayak*				0.021	0.100**	-0.110**	-0.050	0.126***	-0.114**
				(0.047)	(0.042)	(0.043)	(0.046)	(0.039)	(0.043)
Own characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Network Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Link formation residual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.307***	0.318**	0.387***	0.249**	0.442***	0.218**	0.452***	0.258***	0.294***
	(0.131)	(0.157)	(0.118)	(0.132)	(0.159)	(0.111)	(0.131)	(0.167)	(0.114)
Pseudo R^2	0.8660			0.8363			0.8712		
DIC	1,269.3			999.3			1,125.8		
Mean Log-likelihood	-1,057.7			-832.7			-938.2		

Notes: n = 483; # of draws = 5000 and burnin = 2000. SD denotes standard deviation. The estimates in this table were also obtained from the standardized social weight matrix. The quartiles denote the distribution of adopting neighbors of each improved variety. Columns (1-3) present estimates of specification where we include only the quartiles of adopting neighbors of *Jenguma* in the model, while columns (4-6) present estimates where we include only the quartiles of adopting neighbors of *Afayak*. Columns (7-9) report estimates of specification that include both quartiles of *Jenguma* and *Afayak* adopting neighbors. The 1st, 2nd and 3rd quartiles were defined as having a proportion of adopting neighbors of an improved variety falling in 0.0 to 0.25, 0.26 to 0.75 and 0.76 to 1.0, respectively. The estimates show that having adopting neighbors of an improved variety (e.g., *Jenguma*) in the 1st quartile reduces the likelihood of adopting the traditional (*Salintuya*) and that improved variety (i.e., *Jenguma*), but increases the likelihood of adopting the other improved variety (i.e., *Afayak*). However, having adopting neighbors of *Jenguma* in the 2nd and 3rd quartiles increases the likelihood of adopting *Jenguma* but reduces the likelihood of adopting the other improved (i.e., *Afayak*) and the traditional varieties. The values in the parenthesis are standard deviations. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Similarly, a farmer with only a quarter of the neighbors adopting *Jenguma* (in cols. 3 and 9) is about 11-14 percentage points more likely than those with no adopting neighbors of *Jenguma* to adopt *Afayak*. These effects are statistically significant, but the difference in their magnitudes across varieties is not significantly different from zero ($p>0.3$). We also observe that the probability of adopting a variety increases as the share of adopting neighbors increases and enters the 2nd and 3rd quartiles. Still in Table 2.6, a farmer is about 15 and 31 percentage points more likely to adopt *Jenguma*, when the proportion of his neighbors adopting *Jenguma* is within the 2nd and 3rd quartiles, respectively, compared to a farmer without *Jenguma* adopting neighbor (cols. 2 and 8).

For *Afayak*, a farmer with 2nd or 3rd quartile of *Afayak* adopting neighbors is at least 23 and 53 percentage points more likely than a farmer without *Afayak* adopting neighbors, to adopt *Afayak* (cols. 6 and 9). These effects are statistically significantly different from zero ($p<0.01$). Also, the effects of the 3rd quartile are significantly higher than the 2nd quartile effects for each of the two varieties ($p<0.01$). Finally, we also find that the cross-variety effects lose their significance or become negative as more neighbors adopt a particular improved variety. For instance, in the case of *Jenguma* or *Afayak*, the cross-variety effects are generally negative for the 2nd and 3rd quartiles of adopting neighbors of *Afayak* or *Jenguma*, respectively, (cols. 8 and 9).

These estimates suggest self-reinforcement in the adoption process, as shown in the theoretical model and in Figures 2.1A and 2.1B, where a farmer is less likely to adopt a given variety when the proportion of adopting neighbors of that variety is low (i.e., less than an absolute threshold) and more likely, as the proportion of adopting neighbors increases (see also Kornish 2006). The figures further reveal that for a low share of adopting neighbors, the mapping of the share of adopters into probability is below the identity function, but above the threshold, the probability lies above the identity function. The observation in the first quartile of the share of adopters in a farmer's neighborhood is consistent with our first hypothesis of the need to exceed an absolute threshold and to meet the relative threshold in terms of adoption shares of the improved varieties. This is clearly seen in Figures 2.1A and 2.1B, where this relative threshold is marked by the points of intersection between the dashed line and the 45-degree line, and thus confirming our second hypothesis formulated previously.

Finally, this also confirms the third hypothesis that adoption behavior in respect of the two improved varieties, converges towards the variety that leads in meeting the lower limit and persists in its lead, if the proportion of adopting neighbors of this variety translates to a higher adoption probability than the proportion of the adopting neighbors of the competing variety[13]. Such skewed conditions could lead to a "lock-in" on the lead variety in the neighborhood and in the network. This result is consistent with the argument of Arthur (1989) that customers' choice of technologies among competing technologies, in a market, will lock-in on the technology that by chance and historical events leads in terms of adoption by neighbors, and that this could continue to the extent that reversal of such pattern of adoption will be impossible even with policy intervention.

2.5.3 Relative share of adopting neighbors of varieties

Our theoretical model suggests that the expected net benefits (reduction in costs and increase in potential gains) from adopting the improved variety with more adopting neighbors will be higher than the improved variety with lower adopting neighbors, because of the reduced risk and uncertainty that comes with higher rates of adoption among neighbors. In this section, we estimate the effects of the difference in the share of neighbors adopting *Jenguma* and *Afayak*

[13] Our interpretation of the convergence process need to be taken with caution as this is a snap shot of adoption behavior in these social networks (villages) and not overtime. This is a potential area of future empirical research to examine dynamics and the equilibria state of adoption in these networks overtime.

on the likelihood of adopting these two varieties, and present the results in Table 2.7. This analysis is also significant because it allows us to show the likelihood of adoption when a farmer has equal proportion of adopting neighbors of each improved variety in the neighborhood.

Table 2.7 SAR MNP estimates of differences in proportion of adopters of improved varieties in farmer's neighborhood

Difference in adopting Neighbors	(1) *Salintuya*	(2) *Jenguma*	(3) *Afayak*	(4) *Salintuya*	(5) *Jenguma*	(6) *Afayak*
	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Very High Jenguma	-0.275***	0.271 ***	-0.058**	-0.258***	0.265***	-0.061**
	(0.035)	(0.043)	(0.025)	(0.038)	(0.046)	(0.027)
Moderately High Jenguma	-0.005	0.047*	-0.057**	-0.006	0.048*	-0.058**
	(0.036)	(0.033)	(0.032)	(0.035)	(0.033)	(0.031)
Very High Afayak	-0.293***	-0.055**	0.451***	-0.278***	-0.056**	0.450***
	(0.039)	(0.028)	(0.044)	(0.040)	(0.029)	(0.047)
Moderately High Afayak	-0.085**	-0.021	0.142***	-0.085**	-0.015**	0.141***
	(0.041)	(0.035)	(0.039)	(0.040)	(0.035)	(0.039)
Equal	0.063	-0.019	-0.041			
	(0.064)	(0.056)	(0.057)			
Both > 0.25				0.047	-0.024	-0.003
				(0.044)	(0.039)	(0.041)
Both < 0.25				0.057	0.023	-0.042
				(0.050)	(0.045)	(0.047)
Own characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes	Yes	Yes
Network Fes	Yes	Yes	Yes	Yes	Yes	Yes
Link formation residual	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.412***	0247*	0.188**	0.391***	0.239*	0.191*
	(0.128)	(0.160)	(0.111)	(0.128)	(0.164)	(0.109)
Pseudo R^2	0.8647			0.8648		
DIC	1,048.1			1,035.0		
Mean Log-likelihood	-873.45			-862.47		

Notes: n = 483; # of draws = 5000 and burnin = 2000. SD denotes standard deviation. The estimates in this table were also obtained from the standardized social weight matrix. The *very high Jenguma* or *Afayak* denotes when the difference between the proportions of *Jenguma* and *Afayak* adopters is greater than 0.5 for *Jenguma* or *Afayak*, respectively. Also, the *moderately high Jenguma* or *Afayak* denotes when the difference between the proportions of *Jenguma* and *Afayak* adopting neighbors is greater than 0 but less than or equal to 0.5 for *Jenguma* or *Afayak*, respectively. Equal means the proportion of adopting neighbors of *Jenguma* and *Afayak* are equal. Both > 0.25 and both < 0.25 denote both the proportion of *Jenguma* and *Afayak* adopting neighbors are greater and less than 0.25, respectively. The base category is those without any adopting neighbors of the improved varieties and consist of 18.6% of the sample. The values in the parenthesis are standard deviations. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

We find that the likelihood of adopting improved variety 1 (*Jenguma*) is higher when the difference in the share of adopting neighbors between the two improved varieties, 1 and 2 (*Afayak*), is higher for variety 1 than variety 2. This becomes negative for variety 1 when the difference in the share of adopting neighbors is lower for variety 1 than variety 2. Specifically, relative to farmers with no adopting neighbors of any of the improved varieties, a farmer's adoption of *Jenguma* is 5 percentage points more likely, if the share of neighbors adopting *Jenguma* is moderately higher (i.e., $0<$ difference ≤ 0.5) than the share of neighbors adopting the other (i.e., *Afayak*), in the neighborhood (cols. 2 and 5).

Similarly, a farmer's adoption of *Afayak* is 14 percentage points more likely, if the share of neighbors adopting *Afayak* is moderately higher than the share of neighbors adopting *Jenguma*, compared to a farmer without adopting neighbors of the improved varieties in the neighborhood (cols. 3 and 6). The difference in magnitudes of the coefficients across varieties are statistically (weakly) different from zero (p=0.07). We observe similar pattern, and even stronger effects in adoption, when the difference in the share of adopters of each variety is very high (i.e., difference > 0.5). In particular, a farmer with a very high relative share of neighbors adopting *Jenguma* (*Afayak*) is 27 (45) percentage points more likely to adopt *Jenguma* (*Afayak*) than farmers with no adopting neighbors of these new varieties. The effect of *Afayak* is significantly higher than that of *Jenguma* (p=0.005).

Table 2.7 also shows that, adoption of either of the two improved variety is less likely when the share of adopting neighbors of these varieties are equal, although the effects are not statistically significant (cols. 1-3). In order to shed more light on what happens when the share of adopters of the improved varieties in a farmer's neighborhood are equal, we examined the effects of having both shares of adopting neighbors of the improved varieties being higher than 0.25 and the effects of having both shares being lower than 0.25. Interestingly, the results (cols. 4-6) further show a farmer is less likely to adopt any of the improved varieties (and *Jenguma*), if both the shares of adopting neighbors of the improved varieties are higher than 0.25 (lower than 0.25), relative to a farmer without adopting neighbors of the improved varieties, *albeit* not statistically significant in all cases.

Conversely, a farmer is more likely to continue planting the traditional variety (*Salintuya*) if the share of adopters of both improved varieties are higher or lower than 0.25, relative to a farmer with no adopting neighbors of any of the improved varieties, although the effects are also not statistically significant. These further confirm our hypothesis 3 that farmers are not more likely to adopt any of the improved varieties compared to farmers without adopting neighbors, if the share of adopters of these improved varieties are equal. However, the likelihood of using the traditional variety (*Salintya*) declines when the difference in share of adopting neighbors between the improved varieties becomes higher in favor of any of the improved varieties. We also see that the magnitudes of the effects of *Afayak* adopting neighbors is mostly higher than the effects of *Jenguma* adopting neighbors, although these differences are not statistically different ($p > 0.1$) in all cases.

2.5.4 Effects of other controls

Following the above discussion on differential impact of social network effects and in the interest of brevity, we discuss the effects of covariates by focusing on the comparison of the significant variables across the two varieties. Table 2.8 documents the marginal effects of these controls for all the three varieties. For each variety, the table presents the direct and indirect (spillover) effects of each variable. We find that a standard deviation (SD) increase in education covariate of all soybean adopters is estimated to increase *Jenguma* and *Afayak* adoption probabilities by 0.2 and 1.7 percentage points, while decreasing the probability of using *Salintuya* by 1.2 percentage points. The spillover effects of education of a farmer is estimated to increase the probabilities of his neighbors adopting *Jenguma* and *Afayak* by 0.1 and 0.4 percentage points, respectively. The effect of education is higher on the adoption of *Afayak* compared to *Jenguma*, and generally emphasizes the importance of human capital in learning about new technologies (Foster and Rosenzweig, 2010).

Table 2.8 SAR MNP Marginal effects

Variables	*Salintuya*		*Jenguma*		*Afayak*	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
Own characteristics:						
Age	-0.001	-1.60E-04	8.1E-05	1.70E-05	0.001	1.8E-04
Gender	-0.029	-0.006	-0.031	-0.006	0.019	0.004
Education	-0.012	-0.003	0.002	0.001	**0.017**	**0.004**
Experience	0.032	0.007	**-0.012**	**-0.003**	**-0.017**	**-0.004**
Household	0.005	0.001	0.003	0.001	**-0.011**	**-0.002**
Landholding	-0.019	-0.004	**0.061**	**0.013**	**0.027**	**0.006**
Credit	0.024	0.005	**-0.152**	**-0.032**	0.017	0.004
Risk	-0.003	-0.001	0.001	2.60E-04	-0.004	-0.001
Extension	-0.085	-0.019	**0.054**	**0.011**	**0.123**	**0.029**
NGO/Res	-0.090	-0.020	0.041	0.009	**0.070**	**0.016**
Association	0.049	0.011	**-0.046**	**-0.009**	**0.021**	**0.005**
Electronic	-0.017	-0.004	0.017	0.003	-0.024	-0.005
Soil quality	-0.067	-0.015	**0.067**	**0.014**	-0.014	-0.003
Price	0.280	0.063	**-0.166**	**-0.035**	-0.102	-0.024
Contextual effects						
Age	-0.658	-0.149	0.147	0.031	0.144	0.034
Gender	0.001	1.60E-04	4.70E-04	1.00E-04	**0.003**	**0.001**
Education	-0.035	-0.007	0.018	0.003	0.005	0.001
Experience	0.011	0.003	-0.002	-4.40E-04	**-0.015**	**-0.004**
Household	0.008	0.002	-0.003	-0.001	2.40E-04	5.90E-05
Landholding	-0.010	-0.002	0.002	4.40E-04	**0.016**	**0.004**
Credit	0.021	0.004	**-0.022**	**-0.005**	0.001	1.20E-04
Risk	-0.168	-0.038	**0.148**	**0.031**	**0.049**	**0.011**
Extension	-0.002	-0.001	0.006	0.001	0.004	0.001
NGO/Res	-0.071	-0.016	0.015	0.003	**0.030**	**0.007**
Association	0.072	0.016	**-0.083**	**-0.017**	**-0.084**	**-0.020**
Electronic	0.027	0.006	**-0.019**	**-0.004**	0.015	0.003
Soil quality	0.053	0.012	**0.067**	**0.014**	-0.015	-0.003
Price	0.001	3.90E-04	**-0.021**	**-0.004**	-0.002	-3.90E-04

Notes: Values in bold denote variables that are significant. These are the marginal effects of the other covariates and the direct effects of own characteristics indicate the effect of the farmer's characteristics on his adoption decision whereas indirect effects show the effects of the farmer's characteristics on the neighbors. Likewise, the direct contextual effects show the effects of the neighbors on the farmer's adoption decision and the indirect contextual effects are the effects of the neighbors' covariates on their own adoption decisions.

The results further show that the magnitudes of own effects of extension, NGO and research agents, and association are significantly different from zero across these varieties and are generally in favor of *Afayak* adoption. Specifically, a SD increase in extension contact increases the direct [spillover] effects of adopting *Jenguma* and *Afayak* by a likelihood of 5.4[1.1] and 12.3[2.9] percentage points, respectively, and decreases the use of *Salintuya* by 8.5[1.9] percentage points. These results are qualitatively similar to the effects of NGO/Research agents on adopting *Afayak* and could be due to the recent field demonstrations and farmer field-days carried out by the Ministry of Food and Agriculture, Council for Scientific and Industrial Research, and Savannah Agricultural Research Institute.

These results suggest that exposure to external and other sources of information (see also Beaman et al. 2020), and also to public learning are very important in the adoption of new technologies, particularly in cases where there is the need to induce adoption beyond a threshold required to trigger adoption in the neighborhood. In addition, access to credit and soybean seed price appear to significantly reduce the likelihood of adopting *Jenguma*. For instance, a credit constrained farmer is significantly less likely to adopt *Jenguma* by 15.2[3.2] percentage points. At the same time, a cedi increase in soybean seed price reduces a farmer's likelihood of adopting *Jenguma* by 16.6[3.5] percentage points, but does not significantly affect *Afayak* adoption. Similar effects are observed in the contextual effects where a farmer's probability of adopting *Jenguma* decreases with increased proportion of credit constrained neighbors or in average soybean seed price reported by neighbors.

These suggest that whereas credit constrained and cost of production play important roles in affecting adoption of *Jenguma* these are not significant in the case of influencing the adoption of *Afayak*. This can possibly be due to differences in locational advantages between *Afayak* and *Jenguma* adopters since *Afayak* adopters are relatively closer to the district capitals, where most financial and credit institutions are located, and also obtain higher selling price from soybean sales (Table 2.A1). The other variables of significant difference in the magnitudes of adoption are landholding and soil quality, where the effects on *Jenguma* adoption are higher than that on *Afayak*.

5.5.5 Robustness

Given the importance of contextual effects and correlated fixed effects in confounding the network effects and the fact that we captured the cross-variety effects in the mean and not in the variance-covariance of the equations, we perform robustness to ascertain the sensitivity of our estimates to different specifications of our empirical model. We first check to see whether it is important to account for contextual effects in order to obtain best model fit and estimates, and columns (3-4) in Table 2.A2 in the appendix present estimates of our model without these effects. The DIC and the loglikelihood are 1,224 and -1,020. These values are, respectively, higher and lower than the DIC and loglikelihhood values obtained for the model which account for contextual effects in Table 2.5. We next present estimates where we control for proxies of farmer access to markets. This is to assess whether differential market conditions and constraints (as shown in panel A of Table 2.A1) faced by farmers could be driving the differences in adoption of the improved varieties, which may then confound the observed peer adoption effects. The results of this specification are reported in columns (5-6) in Table 2.A2. Interestingly, none of these are statistically significant and the peer adoption effects are much closer to those observed in Table 2.5.

We further present estimates in columns (7-8) of Table 2.A2, where the cross-varietal effects are captured by the variance-covariance structure, instead of the mean part of the model (LeSage and Pace 2009). The cross-variety correlations are also negative and statistically significant, suggesting that the likelihood of adopting *Jenguma* (*Afayak*) is negatively correlated with the share of adopting neighbors of *Afayak* (*Jenguma*). However, these correlations are difficult to interpret because of the identification restriction imposed on the first element of the variance-covariance matrix (Chakir and Parent 2009). The diagnostics (i.e., higher DIC of 2,868 and lower log-likelihood of -2,390) also tend to favor the specification that captures the cross-varietal effects in the mean part of the equations as in Tables 2.4 to 2.7. In addition, all the endogenous estimates have similar patterns as in Tables 2.4 and 2.5 suggesting that our results are robust to these alternative specifications.

Finally, we present estimates of alternative specification of the network weight matrix in columns (9-10) in Table 2.A2 as additional robustness check. This is meant to check whether the random matching within sample of the 5 households to each farm household, which truncates the number of links, could severely impact the estimates. As such, farmers who knew all 5 matched farmers, and/or were neighbors to all 5, who were randomly matched to them were dropped in this estimation. The estimates still show evidence of social network effects, and without substantial qualitative differences in most of the estimated endogenous effects compared with Table 2.5, *albeit* with attenuation bias in the magnitudes. This suggests that the social network effects are quite robust to the altered sociomatrix. This is not surprising, because the truncation at 5 matches is not binding in our sample, since only 4.5% of farmers in the sample mentioned they knew and/or were neighbors to all randomly matched 5 households (see also Liu et al. 2017).

2.6 Conclusions

We examine the impacts of social networks on the adoption of two improved soybean varieties in northern Ghana, using observational data, and find that a farmer's adoption decision of a given improved variety depends on the status of neighbor's adoption of all varieties in the social network. In aggregate terms, a farmer's adoption decision of a given improved variety is positively influenced by the decisions of adopting neighbors of the same variety, but negatively by the adopting neighbors of the competing variety. However, the interesting aspects of our findings are: For a given new variety, say *Jenguma*, the effect of the neighbors' adoption of that variety (i.e., *Jenguma*) is negative and only becomes positive after at least a quarter of the neighbors have adopted this variety. When this limit is passed, the effects of cross varietal adoption by neighbors loses its importance, irrespective of the level of adopting neighbors of the cross variety in the network. This is suggestive of the existence of thresholds for each, even in the adoption of multiple and competing improved technologies, such that when a particular variety leads in meeting the threshold in terms of adopting neighbors, there is a higher chance that the variety will dominate in the neighborhood or network (i.e., village).

The second aspect is that, when the relative proportion of adopting neighbors of each of the new varieties are equal, the farmer is not more likely to adopt either of the improved variety compared to farmers without adopting neighbors of the improved varieties. This could be due to the fact that, at this stage, farmers are most likely not certain about the expected benefits of these new varieties and will therefore less likely to switch. This observation is significant because it gives an insight into why traditional varieties still dominate in some villages, as well as the persistent use of these traditional varieties, as shown in the literature (CGIAR 2009), even though the new varieties are significantly superior in terms of yields and resistance to agro-climatic stress. These findings also suggest the importance of social effects, even under conditions of multiple and competing improved technology setting. This is further reinforced by the effects of education, contact with extension and NGO/Research agents, as well as associations, which normally facilitate individual and public learning in adoption of new technologies.

Our findings have some implications for policy. First, the result can help explain the differential adoption rates of competing technologies and why some technologies become dominant in a particular village, while others end up as subordinate or cease to exist in some circumstances.

The findings also suggest the need to do a stepwise introduction of improved varieties before a full-scale promotion in the villages. This will require first exposing some farmers in the network to the improved varieties, observing the extent of adoption and then following-up with a wide-scale introduction and promotion of the variety that leads in adoption in the network. This will reduce cost associated with the multiple introduction and promotion of competing technologies, where only one or some will gain acceptance by farmers, despite promotion efforts and expenditure. Moreover, there is the need for policymakers to focus promotion efforts on demonstrating the relative benefits of improved varieties introduced to farmers, since this would be a motivation for farmers to adopt. Finally, the findings suggest that interventions to promote soybean farming should also consider measures that improve access to financial resources and enhance the human capital of farmers to reduce challenges of adoption.

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Appendix

Appendix A

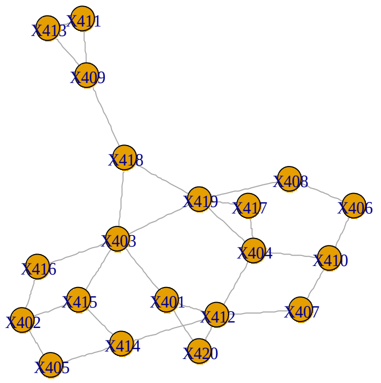

Fig. 2.A1 Network with minimum transitivity of 0.182

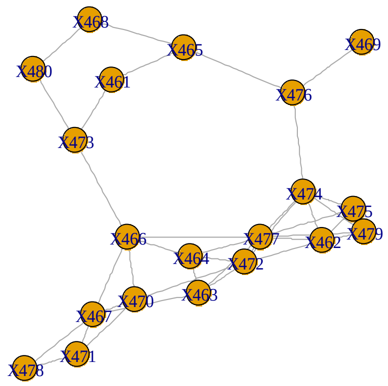

Fig. 2.A2 Network with the mean transitivity of 0.470

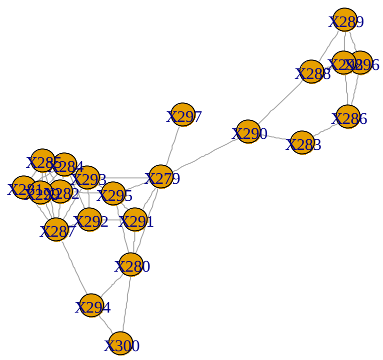

Fig. 2.A3 Network with the 75th transitivity of 0.534

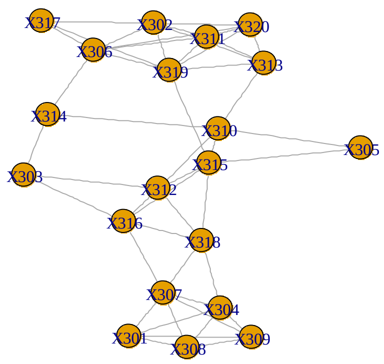

Fig. 2.A4 Network with the highest transitivity of 0.603

Figure 2.A Networks by distribution of transitivity

Notes: Figures 2.A1 - 2.A2 show representations of graphs by the distribution of the transitivity values in the sample networks. Fig. 2.A1 shows the network with the lowest transitivity value, Fig. 2.A2 shows a network with the average transitivity of all the networks while Figs. 2.A3 – 2.A4 present the networks with the 75th percentile and with the highest transitivity, respectively.

Table 2.A1 Mean differences in market access and production cost of adopters of respective varieties

	Salintuya	Jenguma	Mean difference	Afayak	Mean difference	Mean difference
	(1)	(2)	(3) = (2-1)	(4)	(5) = (4-1)	(6) = (4-2)
Panel A: Marketing						
Sold in market in the village (0,1)	36.5	33.7	-2.8	29.6	-6.9	-4.1
	(3.8)	(3.3)	(5.1)	(4.1)	(5.7)	(5.3)
Sold in market outside village (0,1)	53.2	62.4	9.2*	65.6	12.4**	-3.2
	(4.0)	(3.4)	(5.2)	(4.3)	(5.9)	(5.4)
Sold to market traders (0,1)	80.1	79.7	-0.4	81.6	1.5	1.9
	(3.2)	(2.8)	(4.3)	(3.4)	(4.7)	(4.5)
Sold to buying organization (0,1)	12.8	15.8	3.0	14.4	1.6	-1.4
	(2.6)	(2.5)	(3.7)	(3.2)	(4.1)	(4.1)
Selling price in GHS/kg	1.27	1.25	-0.02	1.37	0.10**	0.12**
	(0.03)	(0.02)	(0.04)	(0.04)	(0.05)	(0.04)
Distance to district centre in kilometres	18.4	15.1	-3.3**	12.9	-5.4***	-2.2*
	(1.1)	(0.8)	(1.4)	(0.7)	(1.4)	(1.2)
Panel B: Seed price and other production cost						
Price in GHS/kg	1.06	1.07	0.01	1.04	-0.02	-0.03
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Farm size in acres	1.82	2.01	0.19	1.85	0.03	-0.16
	(0.08)	(0.08)	(0.12)	(0.08)	(0.11)	(0.12)
Expenditure on seeds in GHS per acre	7.11	6.57	-0.54	6.95	-0.15	0.39
	(0.43)	(0.33)	(0.53)	(0.48)	(0.64)	(0.56)
Exp. on fertilizer in GHS per acre	0.99	3.85	2.86**	2.18	1.19	-1.68
	(0.65)	(1.13)	(1.40)	(0.82)	(1.03)	(1.57)
Exp. on pesticide in GHS per acre	0.90	1.48	0.58	1.33	0.42	-0.16
	(0.29)	(0.38)	(0.51)	(0.33)	(0.45)	(0.55)
Exp. on weedicides in GHS per acre	15.0	22.5	7.5***	23.7	8.7**	1.2
	(0.7)	(2.1)	(2.5)	(3.4)	(3.2)	(3.8)
Labor use in man-days per acre	14.5	15.0	0.6	15.4	0.9	0.4
	(0.8)	(0.8)	(1.1)	(0.9)	(1.2)	(1.2)
Soil quality	2.73	3.47	0.74***	2.87	0.14	-0.60***
	(0.08)	(0.04)	(0.09)	(0.09)	(0.12)	(0.09)
Credit constraint (0,1)	0.69	0.42	-0.27***	0.68	-0.01	0.26***
	(0.04)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)
Extension	0.21	0.37	0.14***	0.24	0.03	-0.12**
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Risk	1.04	1.02	-0.02	1.04	0.00	0.02
	(0.11)	(0.10)	(0.15)	(0.13)	(0.17)	(0.16)

Notes: the table reports comparison of the mean differences in proxies of market access in panel A, and production cost components across the three varieties. Exp. denotes expenditure. The values in the parenthesis are standard errors. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.A2 Sensitivity of estimates to alternative specifications, network links truncation and additional market factors

	No Network FEs		No contextual effects		With additional market access controls		Cross-choice influence in variance-covariance		Excludes those who were neighbors to all 5 matches	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Jenguma	*Afayak*	*Jenguma*	*Afayak*	*Jenguma*	*Afayak*	*Jenguma*	*Afayak*	*Jenguma*	*Afayak*
	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates	Estimates
Prop. Neighbadopt_ *Jenguma*	0.315***	-0.039***	0.283***	-0.058***	0.228***	-0.054***	0.140***		0.133***	-0.027**
	(0.017)	(0.014)	(0.016)	(0.015)	(0.025)	(0.017)	(0.008)		(0.011)	(0.010)
Prop. Neighbadopt_*Afayak*	-0.040**	0.361***	-0.076***	0.355***	-0.053***	0.336***		0.158***	-0.007	0.153***
	(0.015)	(0.014)	(0.016)	(0.013)	(0.018)	(0.016)		(0.005)	(0.010)	(0.007)
Cov [σ_{12}] of *Jenguma* and *Afayak*							-1.472**			
							(0.634)			
Cov [σ_{21}] of *Afayak* and *Jenguma*								-1.472**		
								(0.634)		
Market in village					0.045	-0.047				
					(0.052)	(0.057)				
Market outside village					0.021	0.032				
					(0.047)	(0.052)				
Traders					-0.007	-0.036				
					(0.043)	(0.046)				
Organization					0.016	-0.055				
					(0.052)	(0.055)				
Distance to town					-0.003	0.001				
					(0.025)	(0.002)				
Selling price					-0.026	0.019				
					(0.025)	(0.028)				
Own characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Network Fes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Link formation residual	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.189	0.276**	0.221*	0.326***	0.412**	0.349**			0.615***	0.394***
	(0.156)	(0.116)	(0.169)	(0.118)	(0.184)	(0.149)			(0.132)	(0.130)
Pseudo R^2	0.718		0.793		0.841		0.639		0.671	
DIC	1,211.70		1,224.10		1,279.90		2,868.00		2,340.00	
Mean Log-likelihood	-1,009.80		-1,020.10		-1,066.60		-2,390.10		-1,950.40	

Notes: n = 483; # of draws = 5000 and burnin = 2000. The Cov [σ_{12}] and Cov [σ_{21}] denote the covariance of the two improved variety equations and show the cross variety effects. The estimates in this table were also obtained from the standardized social weight matrix and thus these estimates represent the effects of these covariates on adoption in terms of proportions. The values in the parenthesis are standard deviations. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 2.A3 Estimates of Group Fixed-Effects (Table 2.4 continued)

	Jenguma		*Afayak*	
	Estimates	SD	Estimates	SD
Village 2	0.014	0.057	-0.047	0.066
Village 3	-0.073	0.065	-0.139**	0.069
Village 4	-0.064	0.065	0.008	0.069
Village 5	-0.022	0.070	-0.109*	0.071
Village 6	-0.045	0.066	0.013	0.072
Village 7	0.064	0.065	-0.034	0.069
Village 8	-0.053	0.071	-0.044	0.071
Village 9	-0.115**	0.062	-0.131**	0.072
Village 10	0.082	0.073	-0.129*	0.081
Village 11	0.058	0.066	-0.040	0.070
Village 12	0.024	0.072	0.045	0.082
Village 13	0.181**	0.066	-0.071	0.073
Village 14	0.232***	0.067	-0.020	0.080
Village 15	0.262***	0.062	-0.135**	0.072
Village 16	0.283***	0.065	-0.012	0.080
Village 17	-0.150**	0.068	0.010	0.074
Village 18	-0.045	0.064	0.018	0.071
Village 19	-0.025	0.064	-0.031	0.065
Village 20	-0.086	0.070	-0.083	0.072
Village 21	-0.136**	0.064	-0.154**	0.069
Village 22	-0.091*	0.065	-0.148**	0.073
Village 23	0.014	0.061	-0.084	0.070
Village 24	0.059	0.064	0.051	0.070
Village 25	0.017	0.070	0.043	0.071

Notes: the table is a continuation of the estimates reported in table 2.4 and shows the group/network fixed-effects estimates. The base category is village 1. SD denotes standard deviation. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Appendix B: Network formation and endogeneity

2.B1. Network formation and endogeneity of neighbors' adoption

The section describes the network formation model estimated and discussed under subsection 2.4.1. We estimated a conditional edge independence model, which assumes links form independently, conditional on node- and link- level covariates (Fafchamps and Gubert 2007) as follows;

$$L_{ij,g} = \delta_0 + \delta_1 |c_{ig} - c_{jg}| + \delta_2 (c_{ig} + c_{jg}) + \delta_3 |\mathcal{L}_{ijg}| + \epsilon_{ijg}$$

where L_{ijg} is an $m_g \times (m_g - 1)$ matrix indicating whether there is a link between individuals i and j in group/village g (g =1,…, G, and G is the number of groups/villages in the sample), c_{ig} and c_{jg} are characteristics of individual i and j in group g. δ_1 measures the influence of differences in their attributes, and δ_2 measures the effect of combined level of their attributes. $\mathcal{L}_{ijg}$ captures attributes of the link between i and j such as geographical or social distance between them, and δ_3 is the associated parameter estimate. The estimates of this model are reported in Table 2.B1. We next use the average of the predicted residuals of this link formation model as control functions in our adoption equation to account for the endogeneity of peer effects due to unobserved factors that determine link formation.

Table 2.B1 First-stage dyadic regression of network formation by village

	Vill._1	Vill. 2	Vill. 3	Vill. 4	Vill. 5	Vill. 6	Vill. 7	Vill. 8	Vill. 9
Distance between peers in kilometres	-0.066	-0.000	0.114**	-0.007	0.031	-0.009	0.056	-0.035	-0.012
	(0.065)	(0.046)	(0.051)	(0.043)	(0.055)	(0.046)	(0.045)	(0.044)	(0.047)
Difference in distance to road between peers in kilometres	0.024	0.191*	-0.070	0.097	0.048**	0.085*	0.054*	-0.124**	0.051*
	(0.033)	(0.103)	(0.056)	(0.063)	(0.022)	(0.047)	(0.030)	(0.058)	(0.030)
Relatives = 1	0.261	-0.026	0.144	-0.190	-0.383	0.382	0.479	-0.509	-0.741**
	(0.382)	(0.362)	(0.606)	(0.522)	(0.286)	(0.657)	(0.368)	(0.330)	(0.351)
Same religion = 1	n.a.	n.a.	-0.175	-0.437	-0.363	-0.017	0.501	-0.418	-0.346
	n.a.	n.a.	(0.224)	(0.328)	(0.303)	(0.483)	(0.516)	(0.484)	(0.328)
Difference: Sex (= 1 if male)	1.135***	0.808***	7.435***	-0.318	0.425	0.045	0.782**	0.607*	0.260
	(0.354)	(0.241)	(0.387)	(0.255)	(0.329)	(0.255)	(0.367)	(0.345)	(0.531)
Difference: Age	-0.003	-0.026*	0.035**	-0.015	-0.050***	-0.041***	0.036***	0.132***	0.040***
	(0.009)	(0.015)	(0.014)	(0.012)	(0.018)	(0.012)	(0.011)	(0.036)	(0.013)
Difference: Years of schooling	0.090*	-0.006	0.056	0.061	3.078***	-0.148***	-0.054*	2.854***	0.030
	(0.047)	(0.039)	(0.054)	(0.064)	(0.189)	(0.046)	(0.028)	(0.498)	(0.070)
Difference: Household size	-0.214**	-0.103	-0.070	0.096	-0.224**	0.156**	-0.138	0.021	0.099
	(0.102)	(0.093)	(0.090)	(0.083)	(0.091)	(0.077)	(0.103)	(0.075)	(0.068)
Difference: Household landholding in hectares	-0.202	-0.164	0.060	0.460***	0.158	0.439**	-0.159	0.005	-0.097
	(0.238)	(0.103)	(0.172)	(0.111)	(0.169)	(0.219)	(0.110)	(0.112)	(0.135)
Difference: Village born = 1 if farmer was born in village	1.109**	0.163	-0.607**	0.824***	-0.258	-0.054	-0.885***	6.091***	-0.691**
	(0.509)	(0.347)	(0.307)	(0.277)	(0.237)	(0.340)	(0.262)	(0.437)	(0.297)
Difference: Household wealth (predicted) in GHS	1.359	-0.953	0.346	-0.075	0.933	-0.553	-1.959***	1.209	0.148
	(1.142)	(0.641)	(1.046)	(0.889)	(1.284)	(0.879)	(0.721)	(1.197)	(0.927)
Difference: Authority = 1 if any parent of the farmer had an authority in village	6.788***	0.636*	0.924***	-0.145	-13.271***	7.636***	-0.017	0.498	7.011***
	(0.420)	(0.370)	(0.327)	(0.309)	(1.385)	(0.821)	(0.310)	(0.472)	(0.405)
Sum: Sex (= 1 if male)	-0.407	0.630***	7.241***	0.054	0.959***	0.387*	0.478*	0.464	0.256
	(0.279)	(0.213)	(0.362)	(0.235)	(0.302)	(0.232)	(0.249)	(0.291)	(0.341)
Sum: Age	0.003	0.010	-0.019	-0.021***	0.011	0.003	-0.041***	-0.072***	-0.013
	(0.007)	(0.010)	(0.013)	(0.008)	(0.014)	(0.009)	(0.008)	(0.027)	(0.011)
Sum: Years of schooling	-0.045	0.041**	0.012	-0.085	-3.041***	0.101***	-0.026	-3.946***	-0.055
	(0.041)	(0.020)	(0.036)	(0.059)	(0.175)	(0.035)	(0.032)	(0.564)	(0.065)
Sum: Household size	-0.076	0.122**	0.145**	-0.044	0.069	-0.043	0.018	-0.086	0.106**
	(0.049)	(0.056)	(0.071)	(0.053)	(0.047)	(0.035)	(0.059)	(0.062)	(0.052)
Sum: Household landholding in hectares	-0.120	0.028	-0.051	-0.076	-0.282**	-0.334**	0.252**	0.154**	0.142
	(0.120)	(0.060)	(0.160)	(0.108)	(0.132)	(0.166)	(0.115)	(0.072)	(0.121)
Sum: Village born = 1 if farmer was born in village	1.118***	0.049	0.186	0.338	-0.027	0.237	0.035	7.209***	-0.874***
	(0.337)	(0.328)	(0.348)	(0.217)	(0.256)	(0.254)	(0.213)	(0.394)	(0.223)
Sum: Authority = 1 if any parent of the farmer had an authority in village	-7.669***	0.292	-0.822**	1.182***	12.932***	-7.503***	0.508***	1.451***	-6.989***
	(0.381)	(0.394)	(0.379)	(0.354)	(1.255)	(0.910)	(0.162)	(0.518)	(0.450)
Constant	-3.496*	-4.083**	-16.801***	-0.384	-3.759**	-0.987	1.351	-12.817***	-1.143
	(1.803)	(1.634)	(2.016)	(1.505)	(1.619)	(2.075)	(1.395)	(2.078)	(1.752)
Observation	400	400	400	400	400	400	400	400	400
Pseudo R^2	0.133	0.090	0.108	0.099	0.097	0.087	0.120	0.169	0.093

Notes: Standard errors in parenthesis. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 2.B1 (continued)

	Vill._10	Vill._11	Vill. 12	Vill. 13	Vill. 14	Vill. 15	Vill. 16	Vill. 17	Vill. 18
Distance between peers in kilometres	-0.021	-0.085	-0.048	-0.008	-0.017	-0.073	-0.030	0.002	-0.012
	(0.059)	(0.064)	(0.037)	(0.044)	(0.080)	(0.062)	(0.047)	(0.047)	(0.030)
Difference in distance to road between peers in kilometres	0.070	8.799***	-0.044	-0.018	-0.027	-0.170***	0.018	0.025	0.075
	(0.069)	(2.821)	(0.050)	(0.025)	(0.030)	(0.029)	(0.017)	(0.019)	(0.047)
Relatives = 1	-0.024	-0.062	0.241	0.115	0.293	0.413	-0.079	0.884	0.115
	(0.552)	(0.390)	(0.354)	(0.242)	(0.387)	(0.302)	(0.496)	(0.659)	(0.497)
Same religion = 1	0.105	0.062	0.372	0.267	-0.661*	-0.622*	0.006	-0.137	-0.217
	(0.321)	(0.350)	(0.313)	(0.390)	(0.385)	(0.327)	(0.400)	(0.420)	(0.301)
Difference: Sex (= 1 if male)	-0.122	0.310	0.546	-0.404	0.442	0.337	0.970***	0.369	0.965***
	(0.343)	(0.316)	(0.462)	(0.273)	(0.332)	(0.329)	(0.296)	(0.359)	(0.306)
Difference: Age	0.022**	-0.032**	0.009	0.011	-0.011	-0.044	-0.004	0.019	0.002
	(0.011)	(0.015)	(0.012)	(0.011)	(0.016)	(0.031)	(0.018)	(0.022)	(0.022)
Difference: Years of schooling	1.440***	-0.058	0.083	1.308***	-0.043	-0.181***	6.607***	0.862***	-0.158***
	(0.103)	(0.051)	(0.053)	(0.075)	(0.046)	(0.043)	(0.609)	(0.061)	(0.048)
Difference: Household size	0.150	0.119*	-0.029	-0.178**	0.046	0.042	-0.183***	-0.003	-0.024
	(0.126)	(0.070)	(0.114)	(0.076)	(0.096)	(0.098)	(0.055)	(0.094)	(0.135)
Difference: Household landholding in hectares	0.585***	-0.052	-0.067	0.075	-0.197	0.371***	0.022	0.321***	-0.157
	(0.150)	(0.084)	(0.137)	(0.166)	(0.211)	(0.130)	(0.086)	(0.088)	(0.155)
Difference: Village born = 1 if farmer was born in village	-0.598*	-0.492	1.038**	0.289	0.406	0.576**	0.205	-1.484***	-0.011
	(0.354)	(0.357)	(0.454)	(0.281)	(0.361)	(0.257)	(0.456)	(0.424)	(0.249)
Difference: Household wealth (predicted) in GHS	-0.101	-1.171	0.993	0.038	-0.088	-0.633	-1.175	-2.981***	-1.232*
	(0.772)	(1.159)	(0.933)	(1.032)	(1.148)	(0.649)	(1.815)	(0.908)	(0.726)
Difference: Authority = 1 if any parent of the farmer had an authority in village	7.301***	0.422	-0.398	8.514***	7.684***	5.605***	-0.331	6.989***	0.346
	(0.381)	(0.631)	(0.363)	(0.450)	(0.392)	(0.641)	(0.331)	(0.572)	(0.399)
Sum: Sex (= 1 if male)	0.928***	-0.492*	0.687**	0.208	0.193	-1.030***	0.649*	-0.040	-0.096
	(0.244)	(0.279)	(0.307)	(0.229)	(0.347)	(0.232)	(0.334)	(0.356)	(0.240)
Sum: Age	-0.013	-0.002	-0.000	0.004	-0.008	-0.004	0.017*	0.029	-0.017*
	(0.009)	(0.010)	(0.009)	(0.009)	(0.013)	(0.017)	(0.009)	(0.021)	(0.010)
Sum: Years of schooling	-1.530***	-0.075**	0.001	-1.198***	0.006	0.020	-5.548***	-0.774***	0.041
	(0.081)	(0.033)	(0.046)	(0.085)	(0.040)	(0.037)	(0.658)	(0.055)	(0.025)
Sum: Household size	-0.162*	0.252***	0.142**	0.020	0.086	0.147***	0.141**	0.205***	0.095
	(0.092)	(0.054)	(0.070)	(0.078)	(0.055)	(0.045)	(0.057)	(0.058)	(0.077)
Sum: Household landholding in hectares	-0.547***	0.238***	-0.108	-0.082	0.178	0.129	0.079	-0.073	0.104
	(0.144)	(0.081)	(0.110)	(0.140)	(0.131)	(0.099)	(0.081)	(0.080)	(0.093)
Sum: Village born = 1 if farmer was born in village	0.423	1.021***	0.697*	0.508*	0.903***	0.756***	0.976**	0.343	0.160
	(0.331)	(0.323)	(0.390)	(0.274)	(0.347)	(0.273)	(0.393)	(0.396)	(0.198)
Sum: Authority = 1 if any parent of the farmer had an authority in village	-7.146***	0.984*	-0.327	-7.003***	-7.211***	-5.772***	0.870**	-7.568***	1.121***
	(0.418)	(0.581)	(0.261)	(0.463)	(0.445)	(0.721)	(0.340)	(0.883)	(0.289)
Constant	0.921	-3.133	-6.525***	-2.981***	-3.922**	-3.085	-4.933	-2.307	0.173
	(1.952)	(2.655)	(2.180)	(1.109)	(1.943)	(1.941)	(4.367)	(2.875)	(2.125)
Observation	400	400	400	400	400	400	400	400	400
Pseudo R^2	0.131	0.075	0.059	0.098	0.088	0.146	0.089	0.162	0.114

Notes: Standard errors in parenthesis. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 2.B1 (continued)

	Vill._19	Vill._20	Vill._21	Vill._22	Vill._23	Vill._24	Vill._25
Distance between peers in kilometres	-0.006	0.018	-0.009	0.060	0.014	-0.047	0.044
	(0.061)	(0.030)	(0.039)	(0.067)	(0.046)	(0.048)	(0.050)
Difference in distance to road between peers in kilometres	0.012	1.274	0.686	0.059**	0.686	-1.425	0.024
	(0.008)	(2.839)	(0.659)	(0.024)	(3.460)	(3.339)	(0.016)
Relatives = 1	-0.471*	0.358	0.090	1.345	-0.492	0.262	-0.523
	(0.268)	(0.223)	(0.272)	(1.195)	(0.459)	(0.320)	(0.538)
Same religion = 1	-0.304	n.a.	0.180	0.107	0.714	n.a.	0.152
	(0.383)	n.a.	(0.479)	(0.578)	(0.517)	n.a.	(0.423)
Difference: Sex (= 1 if male)	-0.385	0.862*	-0.352	8.166***	-0.932***	-0.539*	0.744*
	(0.275)	(0.478)	(0.423)	(0.404)	(0.205)	(0.285)	(0.392)
Difference: Age	0.003	-0.007	-0.040**	-0.000	0.011	0.016	0.029
	(0.019)	(0.020)	(0.020)	(0.014)	(0.009)	(0.013)	(0.025)
Difference: Years of schooling	0.009	-0.052	0.043	n.a.	0.119	0.373***	0.142***
	(0.045)	(0.033)	(0.065)	n.a.	(0.079)	(0.062)	(0.050)
Difference: Household size	0.049	0.145*	0.086	0.076	-0.032	0.254***	0.229***
	(0.063)	(0.088)	(0.088)	(0.097)	(0.089)	(0.092)	(0.081)
Difference: Household landholding in hectares	-0.066	-0.085	-0.077	0.126	0.359**	0.600**	-0.263
	(0.088)	(0.103)	(0.100)	(0.163)	(0.168)	(0.233)	(0.218)
Difference: Village born = 1 if farmer was born in village	6.526***	-0.247	8.173***	0.638	-0.122	0.216	-0.235
	(0.422)	(0.325)	(0.403)	(0.490)	(0.309)	(0.323)	(0.412)
Difference: Household wealth (predicted) in GHS	1.450	-1.346	-0.100	2.782***	2.355***	-1.985**	-0.522
	(1.150)	(0.987)	(0.639)	(0.976)	(0.868)	(0.851)	(1.269)
Difference: Authority = 1 if any parent of the farmer had an authority in village	n.a.	-1.108***	n.a.	n.a.	-0.205	-0.898***	n.a.
	n.a.	(0.291)	n.a.	n.a.	(0.290)	(0.289)	n.a.
Sum: Sex (= 1 if male)	0.504*	0.850*	-0.293	8.878***	0.734***	0.112	0.161
	(0.284)	(0.436)	(0.245)	(0.510)	(0.215)	(0.187)	(0.278)
Sum: Age	-0.012	-0.006	0.010	0.017	0.005	0.036**	-0.002
	(0.011)	(0.019)	(0.011)	(0.015)	(0.009)	(0.014)	(0.021)
Sum: Years of schooling	0.033	0.075***	0.210***	n.a.	0.097	-0.427***	0.019
	(0.024)	(0.021)	(0.037)	n.a.	(0.067)	(0.048)	(0.059)
Sum: Household size	-0.000	-0.054	-0.072	0.028	0.160***	0.056	-0.284***
	(0.048)	(0.061)	(0.062)	(0.062)	(0.056)	(0.090)	(0.056)
Sum: Household landholding in hectares	0.123	-0.081	0.270***	-0.382*	-0.344***	-0.237	0.248
	(0.092)	(0.084)	(0.082)	(0.198)	(0.126)	(0.217)	(0.169)
Sum: Village born = 1 if farmer was born in village	6.413***	-0.400*	7.525***	1.116**	0.078	0.658***	-0.821***
	(0.380)	(0.239)	(0.431)	(0.435)	(0.193)	(0.244)	(0.278)
Sum: Authority = 1 if any parent of the farmer had an authority in village	n.a.	0.828**	n.a.	n.a.	-0.822***	-0.404	n.a.
	n.a.	(0.331)	n.a.	n.a.	(0.268)	(0.336)	n.a.
Constant	-17.238***	0.065	-18.598***	-26.287***	-5.388***	-3.241*	0.730
	(2.569)	(2.076)	(1.453)	(2.379)	(1.821)	(1.969)	(2.514)
Observation	400	400	400	400	400	400	400
Pseudo R^2	0.075	0.093	0.160	0.155	0.094	0.098	0.201

Notes: Standard errors in parenthesis. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 2.B2 Instrumenting regression for Wealth in Dyadic model

	Difference of wealth			Sum of wealth		
	Coefficient	Robust S. E.	Dyadic S. E.	Coefficient	Robust S. E.	Dyadic S. E.
	All regressors as difference			All regressors as sums		
Sex = 1 if male	0.080	0.036	0.086	−0.237*	0.034	0.154
Years of education of farmer	−0.026**	0.004	0.010	−0.040**	0.004	0.017
Born = 1 if born in village	−0.106*	0.036	0.069	0.200*	0.034	0.144
Value of inherited land in GHS	0.277***	0.040	0.089	0.925***	0.048	0.142
District dummies						
1 if farmer resides in district 1	−0.322	0.052	0.262	−0.552*	0.066	0.397
1 if farmer resides in district 2	−0.493**	0.051	0.257	−0.757**	0.066	0.405
1 if farmer resides in district 3	0.298	0.068	0.327	0.429	0.090	0.539
1 if farmer resides in district 4	−0.150	0.082	0.426	−0.369	0.097	0.560
Intercept	1.488***	0.056	0.214	2.614***	0.088	0.429
Observations	9500			9500		

Notes: the table presents first-stage estimates for instrumenting wealth in the dyadic link formation model. Columns 1, 2 and 3 present results for the difference of wealth between neighbors. Columns 4, 5 and 6 show results of the sum of wealth estimates. The table also show both the conventional robust standard errors (in columns 2 and 5) and the Fafchamps and Gubert (2007) group dyadic standard errors (columns 3 and 6). The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

2.B2. Endogeneity of other covariates

The variables credit-constrained, extension contact and non-governmental/research organization (NGO/Res) are potentially endogenous in the specification. In particular, credit-constrained could be endogenous because adopters of the improved varieties could be farmers with higher yields and incomes, which provide them an urge in acquiring collaterals and in meeting minimum savings requirements for accessing credit. Endogeneity of extension and NGO/Res contacts could result from the fact that extension and NGO/Res officers visit farmers because they adopted the improved varieties. These potential endogeneity concerns were addressed through a two-stage generalized residual inclusion estimation procedure suggested by Wooldridge (2015). We first estimate a probit model for each of the endogenous variables with a set of explanatory variables and at least an instrument that highly explains these endogenous variables, but indirectly affects adoption.

The generalized residuals for the first-stage probit estimates are then plugged into the second-stage adoption equation to account for potential endogeneity of these variables. This approach provides an optimal test of the null hypothesis that the potential endogenous variable is exogenous and also makes it possible to consistently estimate the average structural model by averaging out the generalized errors (Wooldridge, 2015). The first-stage estimates are reported in Table 2.B3. In the credit constraint equation, distance to the nearest financial institution was used as an instrument, which affects access to credit, but not the decision to adopt the technology. With regard to the extension and NGO/Research contacts equations, we employed distance to the nearest extension office and distance to the nearest NGO/Research station, respectively, as instruments, which affect extension and NGO/Research contacts but not adoption of the technology directly. These instruments were excluded from the second-stage estimation to ensure identification in the estimation of the adoption (structural) equation.

Table 2.B3 First-stage probit estimates for liquidity constraint, extension and NGO/Research equations

Variable	Model (1)		Model (2)		Model (3)	
	Credit constraint		Extension contact		NGO/Res contact	
	Coefficient	Std Error	Coefficient	Std Error	Coefficient	Std Error
Constant	4.752***	1.015	−4.132***	1.147	−3.759***	1.218
Own characteristics						
Age	−0.001	0.006	0.014**	0.006	0.005	0.007
Gender	−0.363**	0.157	0.165	0.185	0.040	0.196
Education	−0.061	0.044	0.042	0.031	0.046	0.035
Experience	−0.084***	0.030	0.005	0.026	0.098***	0.029
Household	0.046	0.036	−0.023	0.042	−0.066	0.047
Landholding	−0.045	0.062	0.037	0.064	0.117	0.075
Risk	0.117**	0.055	−0.023	0.064	−0.032	0.071
Association	−0.238***	0.067	−0.005	0.078	−0.277***	0.094
Electronic	0.001	0.209	−0.049	0.217	0.006	0.263
Soil quality	−0.178**	0.084	−0.031	0.094	0.068	0.101
Price	−1.199*	0.634	1.865***	0.636	0.132	0.672
Credit	−	−	−0.699***	0.192	0.027	0.226
Extension	−0.382	0.409	−	−	0.364**	0.152
NGO/Res	−0.055	0.214	0.546***	0.197	−	−
Contextual effects						
Age	−0.003	0.003	0.004*	0.002	0.003	0.003
Gender	−0.048	0.069	0.024	0.074	0.124	0.092
Education	−0.006	0.016	0.010	0.013	0.012	0.017
Experience	−0.001	0.013	−0.002	0.015	0.011	0.015
Household	0.019	0.017	0.013	0.022	−0.044*	0.023
Landholding	−0.019	0.026	0.018	0.028	0.085***	0.028
Risk	0.011	0.028	−0.035	0.036	−0.184***	0.046
Association	−0.005	0.028	−0.010	0.028	−0.035	0.033
Electronic	−0.096	0.111	−0.025	0.151	0.056	0.128
Soil quality	−0.074**	0.035	−0.022	0.042	0.022	0.043
Price	−0.831	0.802	0.621	0.782	2.014**	0.893
Credit	−	−	−0.255***	0.082	0.043	0.097
Extension	−0.318	0.494	−	−	0.132**	0.059
NGO/Res	0.046	0.086	−0.025	0.089	−	−
Instruments						
FinDistance	−0.037***	0.012	−	−	−	−
ExtDistance	−	−	−0.032***	0.011	−	−
RNDistance	−	−	−	−	−0.090***	0.013
Pseudo R^2	0.378		0.391		0.425	
Loglikelihood	−205.0		−170.2		−145.3	
LR X^2	249.1		218.2		215.3	
Prob X^2	0.000		0.000		0.000	

Notes: table reports first-stage instrumenting probit estimates of household credit constraints in model (1), extension contact in model (2) and NGO/Research agent contact in model (3). The predicted generalized residuals of these models were used to account for the potential endogeneity of household credit constrains (Residliquid), extension contact (Residextens) and NGO/Research agent contact (ResidNGO). Std Error denotes standard error. The asterisks ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Appendix C

Bayesian Estimation Procedure

Conditional distribution of β and ρ

Let's assume an independent normal-Wishart prior for the β and Σ parameters, a uniform prior for ρ and consequently given that the conditional and prior distributions of β come from the same distribution type with updated parameters (Wang et al. 2014), the normal prior of β can be set as $\beta \sim MVN(b, B)$. This allows the conditional posterior distribution of β to be expressed as:

$$
\begin{aligned}
p(\beta \mid Y^{*},\ \rho,\ \Sigma) &\propto p\left(Y^{*}|\rho,\beta,\Sigma\right)\pi(\beta) \\
&\propto MVN\left[\tilde{H}^{-1}X\beta,\ (\tilde{H}^{-1}\tilde{H})^{-T}\right]MVN(b,B) \qquad \text{(C1)} \\
&\propto MVN\left[\beta, \Sigma_{\beta}\right]
\end{aligned}
$$

where $\hat{\beta} = \Sigma_{\beta}\left[B^{-1}b + X'\tilde{H}'Y^{*}\right]$; $\tilde{H} = \left(I_{kV} - \rho \otimes \tilde{W}\right)$; $\Sigma_{\beta} = \left[X'X + B^{-1}\right]^{-1}$ and X is a vector representing all other controls in equation (6).

Uninformative prior mean distribution $(b = 0)$ and a diffuse prior variance $(B = 1e+12)$ for β were used to avoid biasing estimates and inferences by assuming high prior information. LeSage and Pace (2009) also show that assuming non-informative and diffuse priors in sufficiently large samples produce estimates comparable to those obtained from maximum likelihood. The sampling of the posterior conditional distribution of ρ can be done either by Metropolis-Hasting (M-H) or by integration and draw by inversion approach (see LeSage and Pace 2009, chapter 5). The use of these procedures are necessitated by the fact that conditional posterior distribution of ρ doesn't lend itself to a known standard distribution like β and Σ

(Autant-Bernard et al., 2008). Given that the posterior distribution of ρ_{ij} relies on its Beta prior function of $p(\rho)$, the posterior distribution of ρ is expressed as;

$$\text{(C2)} \qquad p(\rho_{ij} \mid \rho_{-ij}, \beta, \Sigma, Y^{*}) \propto \left|\tilde{H}\right|^{\frac{1}{2}} exp\left(-\frac{1}{2}\left[\tilde{H}Y^{*} - X\beta\right]^{'} \tilde{H}^{'}\tilde{H}\left[\tilde{H}Y^{*} - X\beta\right]\right) p(\rho),$$

where ρ_{-ij} is a matrix ρ except the ij th element. For the M-H sampling, we require a *proposal distribution* from which a potential value for the parameter ρ is to be obtained. This potential parameter is labeled as ρ^{*}. An *acceptable probability* for drawing ρ based on a random walk from a standard normal distribution is computed in equation (C2) using the ρ^{*}, a current value of ρ defined as ρ^{P} and a *tuning parameter* T suggested by Holloway et al (2002). The *proposal distribution* is expressed as;

$$\text{(C3)} \qquad \rho^{*} = \rho^{P} + T \sim N(0,1).$$

The tuning of the proposal distribution from the normal distribution is to enable the M-H sampling process goes through the whole conditional distribution in order for the proposal distribution to yield draws that are within the dense part of the distribution (LeSage and Pace, 2009). This process is done on each pass of the MCMC sampling steps. Following, Autant-Bernard et al. (2008), the log-determinant of $\tilde{H}$ was computed with the lattice of values for ρ, in the feasible range of – 1 and 1, and with the direct sparse matrix LU decomposition procedure.

Conditional distribution of Σ *and* Y^{*}

In this study, Σ is restricted to equal I_V following LeSage and Pace (2009) because the cross-choice dependence is being captured in the mean part instead of in the covariance structure of the model reducing the number of parameters to be estimated. Hence, the variance-covariance matrix also becomes $\Omega = \left(\tilde{H}'\tilde{H}\right)^{-1}$ which is used in the n-steps of the Gibbs sampling procedure. The latent Y^* is the terminal draw to be done and each Y^* can be drawn distinctly given that the observations are considered independent (Autant-Bernard et al. 2008; Wang et al., 2014). The Y^* variable has a conditional distribution which is multivariate normal truncated[14] (Geweke 1991). This takes the form as follows with a mean of μ and variance-covariance matrix of ω. as;

$$\text{(A4)}\quad Y^* \sim TMVN\left[\tilde{H}^{-1}X\beta, \left(\tilde{H}'\tilde{H}\right)^{-1}\right],$$

$$Y^* \sim TMVN\left[\mu,\omega\right]$$

subject to the constraint $a < dY^* < b$ where d is the diagonal of an $kJ \times kJ$ block diagonal matrix limiting Y_{ji} to assume the largest value of Y^* if $Y_{ji} = j$ or assumes negative if max($Y_{ji}) = 0$, $\mu = \tilde{H}^{-1}X\beta$, $\omega = \left(\tilde{H}'\tilde{H}\right)^{-1}$ and a and b are the truncation bounds which depends on the observed 0,1 values of y. Autant-Bernard et al. (2008) and LeSage and Pace (2009) modified the Geweke (1991)[15] n-step Gibbs sampler for a multinomial setting to generate draws of kJ variate truncated normal distribution. The procedure uses a *precision* matrix $\eta = d^{-T}\tilde{H}'\tilde{H}d^{-1}$ with dimensions $kJ \times kJ$ to sequentially generate draws from the transformed normal distribution $u \sim N\left(0,\eta\right)$ subject to the constraint $\underline{b} \le z^* \le \overline{b}$, where $\underline{b} = a - d\mu; \overline{b} = b - d\mu$ and the z^* samples are used to produce $Y^* = \mu + d^{-1}z^*$. Following

[14] Note the observed response values are such that $Y_i = j$ if $Y^*_{i,V} = \max\left(Y^*_{i,1},\ldots,Y^*_{i,V}\right) > 0$ and 0 if $Y^*_{i,0} \le 0$.

[15] Geweke (1991) shows that drawing from $Y^* \sim TMVN\left[\mu,\omega\right]$ subject to $a \le \tilde{Y}^* \le b$ is equivalent to generating draws from n-variate normal distribution $z^* \sim N\left[\mu,\omega\right]$ subject to the linear restriction $\underline{b} \le z^* \le \overline{b}$.

Wang et al. (2014), z_i^* is expressed as a weighted average of the other elements (z_{-i}^*) plus a noise tem as;

(A5) $z_i^* = \sum_{-i}^{kV} \gamma_{-i} z_{-i}^* + V_i u_i$,

subject to the constraint $\left(\underline{b}_i - \sum_{-i}^{nV} - \gamma_{-i} z_{-i}^* \right) / V_i < u_i < \overline{b}_i - \sum_{-i}^{nV} - \gamma_{-i} z_{-i}^*) / V_i$, where $\gamma_{-i} = -\eta_i^{-1} \eta_{-i}$, and $V_i^2 = \left(\eta_i \right)^{-1}$. Each pass of the entire n passes samples one element of z_i^* which is conditional on the rest of the z_{-i}^* 's and this continues until all the kV z_i^* 's are sampled with the last pass of z_i^* used to impute the Y^* using the $Y^* = \mu + d^{-1} z^*$ equality. A value of n = 10 was used because Geweke (1991) indicated that even relatively small values of n can produce fairly desirable estimate.

Chapter Three

Social Learning and the Acquisition of Information and Knowledge - A Network Approach for the Case of Technology Adoption

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Abstract

The complexity of agricultural innovations and heterogeneity of circumstances of technology application, outcomes and social network structures have often led to obstacles in social learning and sub-optimal adoption. This paper examines technology diffusion in the context of heterogeneous peer benefits, know-how and network structures, using survey data of 500 farm households in Northern Ghana and random matching within sampling to generate social network contacts. We identify network effects and the impact of social learning on adoption, using a selectivity control function in a discrete survival model. Our results reveal that social learning favors adoption, if past adopters with increased yields, or even more with profound knowledge of the cultivation techniques form part of the social network. We also find that social learning and the likelihood of adoption is higher when peers are central nodes, and particularly, when they belong to cohesive subgroups, but lower in highly segregated networks. The results shed a new light on the role of central agents, since highly cohesive neighborhoods seem to promote diffusion more in high modularity networks than central nodes.

JEL codes: C31, C35, C41, D83, O13, O33

Keywords: Benefits, Know-how, Social learning, Social network structures, Technology diffusion

3.1 Introduction

Adoption of agricultural technologies is comparatively low in developing countries, with sub-optimal adoption of these technologies by farmers, despite their potential benefits in improving productivity and agricultural performance (Magnan et al. 2015). Available evidence shows that improved crop varieties and other inputs have contributed between 40% to 100% increase in farm yields and profits, food security and poverty gains in sub-Saharan Africa. In spite of these noteworthy benefits, adoption levels of improved crop varieties in this region are comparatively low compared to the rest of the world (Suri 2011; Walker et al. 2011). Walker et al. (2014) estimate the mean level of adoption across 20 improved crop varieties at 35%, with two-thirds of these crops falling below this mean level. Understanding the way and rationale behind farmers' adoption of these technologies is, therefore, important for economic policies meant to promote agricultural productivity and household welfare through improved technologies.

Numerous studies have shown the significance of social interaction and learning in the agricultural technology adoption literature, although the results have been mixed, with some authors finding positive impacts of social learning on adoption (Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010; Beaman et al. 2018), while a few find no effects (e.g., Duflo, Kremer and Robinson 2011). One possibility of enhancing the understanding of adoption in social interaction settings and, perhaps, resolving these contrasting results is to move beyond the implicit assumption that farmers observe the field trials of their neighbors with little friction in the flow of information (BenYishay and Mobarak 2018) to examine the roles of both benefits and know-how as well as network structures in social learning, as these shape the learning process (Jackson et al. 2017; Nourani 2019).

The literature provides a number of explanations on how adoption decisions of neighbors, heterogeneities cropping conditions and benefits (Foster and Rosenzweig 1995; Munshi 2004;

Conley and Udry 2010) influence social learning in technology adoption. More recently, BenYishay and Mobarak (2018) and Beaman et al. (2018) considered the performance of targeting strategies within networks. Specifically, BenYishay and Mobarak (2018) showed that performance incentives and social identity of experimenting farmers are important, whereas Beaman et al. (2018) found that it is the targeting strategy that matters in social learning. Less is, however, known about the role of know-how (i.e., production process) of the technology[16] in the social learning process and whether both benefits and/or know-how[17] could play important roles in the learning process, given the technological context.

Our study first explores the impact of know-how (i.e., knowledge on cultivating the crop) on adoption of agricultural technologies, and whether given the technology and the social and agronomic context, both benefits and knowledge among social network members matter in social learning. Examining the roles of benefits and know-how are important in learning because farmers decisions to invest in learning about a new technology, and whether to adopt or not to, depend on the expected benefits, and the associated learning and investment costs of the technology. When the learning and investment costs are higher than the expected benefits, farmers may not be inclined to learn and/or adopt the new technology (Beaman et al. 2018; Nourani, 2019). Thus, learning about benefits (i.e., expected profitability) and know-how are important in understanding the diffusion process of new technologies[18].

[16] A notable exception is Beaman and Dillon (2018) who traced how knowledge is aggregated in a network based on the social distance of a node to a central node, but did not examine how differences in the knowledge accumulated by network members influences the decision of farmers in the adoption process.

[17] Existing studies have either found learning about benefits for ease-to-use (Magnan et al. 2015) or know-how for hard-to-use (Oster and Thornton 2012) technologies.

[18] We conceptualize learning about the expected profitability as farmers' beliefs about the benefits of the improved variety which is based on the shares of past adopters among their peers. That is, farmers' beliefs about profitability vary with the share of adopting peers such that more adopting peers will stimulate beliefs that the expected benefit of the improved variety is high and vice versa. Know-how is about farmers' efforts to acquire knowledge about the production process, which involves cost in time and commitment that decrease with increased learning opportunities from peers and own experimentation. That is, learning opportunities (costs) about know-how increase (decrease) with increasing peer experience.

Furthermore, examining both benefits and know-how has context relevance for two reasons. First, the technology (improved soybean variety) we consider has been introduced mainly to enhance farmers' incomes (MoFA 2017), but awareness and knowledge of farmers about the returns are limited (AGRA-SSTP 2017). Second, many farmers are not aware of the standard agronomic practices[19] required for this variety in order to achieve the desired yields, which has usually resulted in sub-optimal productivity, profitability and weak diffusion of the technology (Goldsmith 2017). Existing evidence shows that the use of improved soybean seed is quite low, and ranges between 16% and 33% of soybean farmers in Ghana (Dogbe et al. 2013). In such setting, it is significant to highlight the differences in benefits and know-how regarding the application of the innovation by network contacts and their relative roles in the diffusion of the technology.

Our discussion so far assumes homogenous network structures and hence similar conditions of learning across networks. However, social network structures play important roles in shaping the nature of interaction within networks and neighborhoods, and have been shown to exert overarching effects on many behavioral patterns and other economic outcomes (Jackson et al. 2017). Many studies have argued that network structures, such as *transitivity*[20] and *modularity*, play important roles in social interactions and influence patterns of behavior used as social collateral (Karlan et al. 2009; Jackson et al. 2012), risk sharing (Ambrus et al. 2014; Alatas et al. 2016), and diffusion processes (Bollobas 2001; Centola 2010; Jackson et al. 2017). *Transitivity* or local cohesiveness/clustering coefficient measures how close the neighborhood of a farmer is to being a complete network. *Modularity* measures the proportion of links that

[19] These agronomic rules and regulations were spelt out by the inspectorate division of the Ministry of Food and Agriculture (MoFA), Council for Scientific and Industrial Research (CSIR) and the Savannah Agricultural Research Institute (SARI).

[20] Assortativity is a related structure which refers to the level of interconnectivity between agents with similar individual or micro-scale network characteristics. We do not examine it in this study as it has been shown that high transitive networks display high assortativity and thus are quite correlated (Foster et al. 2011).

lie within communities (i.e., components or segments) of a network minus the expected value of the same quantity in a network where links were randomly generated (Jackson 2008). Higher transitivity of a farmer's neighborhood, and low modularity of a network will mean more opportunities for the farmer to learn from peers and from different neighborhoods in the network. Such opportunities can lead to reduced cost of learning and increase the possibility of diffusion across the network. These two network characteristics are also very important for the understanding of, and in policy design to support learning in social networks (Girvan and Newman 2002).

This implies that the diffusion rate of a new technology will be different across communities, if *transitivity* and *modularity* of the networks, which condition information externalities, vary across these communities. For instance, if network structures exhibit the tendency to be *less transitive* or *highly modular*, then there may be friction in the diffusion of information about benefits and know-how of the technology through the social network, thereby reinforcing differences in farmers' response rates to the technology, even under uniform cultivation conditions and benefits. Hence, higher *transitivity* (lower *modularity*) implies the possibility of effective and efficient spread of information due to the increased number of alternative routes information can take through the network.

In spite of the significance of these network structures, the empirical literature on social learning and technology diffusion has focused on the role of central agents, with very few studies providing evidence on the significance of *transitivity* and *modularity*. (Karlan et al. 2009; Beaman et al. 2018). In particular, Karlan et al. (2009) show that multiplicity of routes associated with higher transitivity enhance the credibility of agents in a network, while Beaman et al. (2018) demonstrate that understanding of aspects of an innovation that are particularly difficult to learn requires several interactions among agents.

Our study relates to the existing literature on network characteristics, influence of central agents[21], technology conditions and adoption (Jackson et al. 2012; Beaman and Dillon 2018; BenYishay and Mobarak 2018; Beaman, et al. 2018). However, the current study differs from these previous studies because it examines the impact of transitivity and network modularity, and how modularity influences the performance of other network characteristics such as centrality and transitivity in the diffusion process. This is particularly significant, because the effectiveness and efficiency of *centrality* in technology processes depend on the extent to which *modularity* and cohesiveness of the neighborhood (*transitivity*) will allow for it.

Specifically, we use observational data from a recent survey of soybean farmers conducted in Ghana to show how learning about benefits, know-how and network structures drive adoption in a dynamic theoretical framework. We estimate the model with a two-step selectivity approach of network formation and survival analysis to account for correlated unobservables at the link formation level (Brock and Durlauf 2001), and to investigate the threats of measurement errors due to missing network data issues (Chandrasekhar and Lewis 2016). The estimation results suggest that both learning about benefits and know-how are important in accelerating adoption, although the effects of know-how are higher when sufficient peers adopt the improved variety in all specifications. We find the role of *transitivity* in the learning and diffusion processes to be stronger, compared to *centrality*, but *modularity* tends to slow down the diffusion process, and also limits the significance of both *transitivity* and *centrality*.

These results have the following policy implications. First, it will inform policymakers about when to focus on promoting adoption, directly, through extension services, public learning and/or training workshops – especially when the share of adopters is low –, and when to focus

[21] Few other studies such as Krishnan and Sciubba (2009) considered network architecture among village labor-sharing networks in explaining farm returns in Ethiopia, and Banerjee et al. (2013) focused on network centrality in microfinance.

on module bridging measure that indirectly promote adoption through increased interactions between adopters and non-adopters, as well as across segments of the village. Second, our findings on the relative importance of *transitivity* and *centrality* will help policymakers to identify when to leverage influential nodes (*centrality*) or the cohesiveness of the neighborhood (*transitivity*) in encouraging adoption under different complexities of the technology (Beaman et al. 2018) and in socially structured settings. Finally, an analysis of *modularity* will show whether specific biases and/or patterns exist in these villages in terms of social interactions and structures (Jackson 2008; Jackson et al. 2017), which will be relevant in informing policy intervention options. For example, the existence of such structures or biases in these villages, when failed to be considered in policy intervention, could result in policy impacts focusing on specific segments of the villages instead of the whole village.

The rest of this paper is organized as follows. Section 3.2 describes the context and the data. Section 3.3 discusses the theoretical framework, showing the role of learning about expected profitability, know-how and network structures on speed of adoption. The empirical model and estimations are described in section 3.4. Section 3.5 presents the empirical results, whereas section 3.6 concludes.

3.2 Context and data

3.2.1 Context

We now describe the context of the technology in question and the data used. Soybean is primarily a commercial crop mainly cultivated in the Northern, Upper East, Upper West and Volta regions of Ghana, by smallholder farmers and under rain-fed conditions, with Northern region alone producing 72% of the national output. The crop has very high local demand and potential of increasing farmers' incomes in Ghana (MoFA 2017). The compounded annual growth in demand for the crop was recorded as 39% from 2008 to 2010, compared to 10.5%

and 6.3% for the other two legumes (cowpea and groundnut), respectively over the same period (AGRA-SSTP 2017). However, the average yield of 1.68MT/ha has been described as below the national achievable yields of 2.50 – 3.10MT/ha (CSIR-SARI 2013).

Realizing this, the Council for Scientific and Industrial Research (CSIR) and the Savanna Agricultural Research Institute (SARI) developed and introduced the Jenguma variety, in 2003, for adoption by farmers in order to circumvent the problems associated with the existing traditional variety[22]. This improved variety has higher yield potential of over 2.0 MT/ha, resistant to pod-shattering, matures about 35 days earlier, and is resistant to other agricultural stress such as pests, diseases, low phosphorous soil and climatic variabilities (CSIR-SARI 2013). Although the crop was introduced primarily as a commercial crop meant to increase smallholder farm profitability and incomes (MoFA 2017), there is lack of awareness and certainty among farmers about the expected yields, market outlets and returns on investments of this improved variety. This is due to limited investment in promotion events and lack of continued campaign to demonstrate returns and profitability of this variety (AGRA-SSTP 2017).

Added to this is that cultivation of the improved variety requires adherence to the rules and regulations of the inspectorate division of the Ministry of Food and Agriculture (MoFA) in order to achieve potential high yields of 2MT/ha, and to reduce labor cost by about 20% of total production cost. These requirements include planting depths, row-spacing, quantity of seeds and timing of sowing, inoculant and phosphorus application, as well as timing of harvesting and plant growth for effectiveness of other inputs and varietal suitability (Heatherly and Elmore 2004). The discussion suggests that both knowledge of benefits and of the

[22] The traditional variety, Salintuya, has been described as low yielding (about 1.0 MT/ha), early shattering of pods and susceptible to disease and pests which sometimes lead to complete loss of the crop (Ampadu-Ameyaw et al. 2016).

production process are important, and therefore important for the analysis of their impact on the diffusion of the variety.

3.2.2 Data

We describe our data, before moving to a formal discussion of the theoretical and econometric aspects of social learning and social network structures. We conducted a survey of 500 farm households in Northern Ghana between July and September 2017. Five districts were purposively selected based on their intensity of soybean production[23], and then 25 villages were randomly selected across these districts, with the allocation of villages done in proportion to the total households in each district. These villages are remote and small with less than 150 households in each. Given this, we randomly selected 20 household heads in each village, and then used structured questionnaires to interview the primary decision makers in the households. In addition, a detailed discussion using an interview guide was administered in each village to a group of village leaders and/or representatives to obtain information on village characteristics. The study combines modules of household characteristics, social networks and agricultural production to construct pseudo-panel data for the analysis of timing of adoption of the improved soybean variety.

Improved soybean adoption and household characteristics

In order to collect data on the year of adoption of the improved soybean variety by households, we use a question that asked farmers to recall the year they adopted the improved variety. Responses to this recall question was used to construct the time to adoption variable, A_{it}, of a household. Table 3.1, panel A shows the summary statistics of adoption of the improved variety by selected years, and depicts an increased adoption overtime since its introduction in 2003. Only 4% of farmers had adopted the improved variety among the sampled farmers in the

[23] This was done in consultation with the Ministry of Food and Agriculture and Resilience in Northern Ghana (RING).

year of its introduction. By 2007, 28% of farmers had adopted. Adoption continued to increase from 2007, and by 2012 and 2016, 56% and 67% of farmers had adopted the improved variety, respectively. Whereas the percentage of adoption in 2012 is more than double that of the rate in 2007, the percentage of adoption in 2016 suggests a slowdown in uptake of the improved variety.

Table 3.1. Variable definition, measurement and descriptive statistics

Variables	Definition and measurement	Mean	S.D.
Panel A			
Dependent variable			
Adopted by			
2003	1 if the farmer adopted the improved variety in 2003; 0 censored	0.04	0.19
2007	1 if the farmer adopted the improved variety by 2007; 0 censored	0.28	0.45
2012	1 if the farmer adopted the improved variety by 2012; 0 censored	0.56	0.49
2016	1 if the farmer adopted the improved variety by 2016; 0 censored	0.67	0.47
Panel B: *Control variables*			
Time-varying			
Age in			
2003	Age of farmer in 2003 (years)	30.03	12.04
2007	Age of farmer in 2007 (years)	35.03	12.04
2012	Age of farmer in 2012 (years)	40.03	12.04
2016	Age of farmer in 2016 (years)	43.03	12.04
Time-invariant			
Gender	1 if male; 0 otherwise	0.59	0.49
Education	Number of years in school	1.27	3.27
Experience	Number of years in farming	13.06	4.02
Household	Household size (No. of members)	5.64	2.14
Landholding	Total land size of household (in hectares)	2.56	1.56
Credit	1 if farmer was credit constrained and/or not successful in applying for credit; 0 otherwise	0.55	0.49
Risk	Risk of food insecurity (No. of months household was food inadequate)	0.93	1.37
Extension	1 if ever had extension contact; 0 otherwise	0.34	0.47
Association	No. of associations a farmer is a member	1.07	1.27
Price	Soybean price in GHS/kg	1.06	0.19
Soil quality	4=fertile; 3=moderately fertile; 2=less fertile; and 1=infertile	2.97	0.97
Panel C			
Instruments			
G^2Credit	Proportion of peers of peers who are credit constrained	0.55	0.28
G^2Extension	Proportion of peers of peers who ever had extension contact	0.35	0.28

Notes: the table depicts the definition, measurement and descriptive statistics of farmers and households. Panel A shows the proportion of adopting farmers across selected year. Panel B shows that of time-varying and time-invariant characteristics of the sampled households whereas the descriptive statistics of instruments for the first-stage liquidity constraints and extensions regressions are in panel C. S. D. denotes Standard deviation. G denotes the network.

The analysis controls for a number of individual and household level variables that may affect a farmer's decision to adopt the improved variety. Panel B of table 3.1 shows the definition, measurement and descriptive statistics of these observable characteristics of farmers. Age is the only time-varying characteristic of individual farmers, the summary statistics of which has been presented for selected years. The average farmer is 43 years in 2016, has 1.3 years of schooling, 13 years of farming experience and has an average household size and landholding of 6 members and 2.56 hectares, respectively. Majority of these farmers are males (59%) and are credit constrained (55%).

Social networks

We used random matching within sample, following Conley and Udry (2010), to generate the potential social network contacts. For each of the 20 household heads selected in a village, we randomly selected and assigned to him 5 household heads from the remaining 19 sampled households heads, as his[24] potential social network contacts. Each farm household was asked whether they know any of the 5 households randomly assigned to them. On average, the respondents knew 3.14 of the households randomly assigned to them, and with an average standard deviation of 1.22 (Table 3.2). Conditional on knowing the assigned households, we elicited detailed information on their relationships, interactions and knowledge with the known randomly assigned households.

Table 3.2. Network links by years known

Number of network links	Mean (%)	SD	5-Pctile	Median	95-pctile	N
Known for <1-5 years	0.10 (0.03)	0.49	0	0	1	500
Known for 5-10 years	0.16 (0.05)	0.60	0	0	1	500
Known for 10-14 years	0.42 (13.4)	0.97	0	0	3	500
Known for 14+ years	2.46 (78.3)	1.56	0	4	5	500
Total	3.14	1.22	0.5	4	5	500

Notes: The table depicts the number of links by the number of years the relationship was formed. Known for <1-5 years represents links that were formed within 1 to 5 years (i.e., nodes indicated they know their randomly assigned matches for 1 to 5 years). Known for 5-10 years represents links that were formed between 5 to 10 years, known for 10-14 is for relationship formed between 10 to 14 years and known for 14+ years represents relationships that were formed for at least 14 years since 2016.

[24] We use the masculine gender because majority (59%) of the farmers in the sample are males.

In order to create time variation in the social network, we asked each responding household "How long have you known this person?". Table 3.2 also shows the distribution of links across selected number of years respondents stated to have known their randomly assigned households. Of the 3.14 assigned households a farm household knows, 78% have been known by the farm household before 2003 (i.e., 14+ years, from 2002 to 2016), 13% have been known for 10 to 14 years and less than 1% have been known for less than 10 years. Given that the improved variety was introduced in 2003, this distribution of links across years suggests that most of these households knew each other prior to the introduction of the improved variety.

We then construct farmers' social network as a sociomatrix of each of the 25 village samples. We refer to each village as a group, G. Thus, the entries of this sociomatrix g_{ij} is one, if the farmer i has stated he knows farmer j, and zero if otherwise. We define links as undirected such that i is said to have a link with j and vice versa, if any of them stated knowing the other. This yields a symmetric sociomatrix of the group G. We then use answers to the question of how long i knows j to construct time varying social networks from 2002 to 2015/16 (i.e., yearly sociomatrix for 14+ years to 1 or less year-old relationships), thus, making it possible for us to index the sociomatrix with a time subscript. Using the sociomatrix, vectors of yearly binary adoption decisions, and the other control variables, we construct peer characteristics by multiplying the yearly vectors of adoption and other control variables by the sociomatrix of the respective years to obtain time-varying peer adoption, average peer experience and other contextual (peer) characteristics required for the analysis.

Table 3.3 shows the summary statistics by selected years of peer adoption, average peer experience in farming the improved variety, and other peer characteristics. With only 3% of peers adopting the improved variety in 2003, the proportion of adopting peers of a farm household increased to 28% in 2007. By 2012, the proportion of adopting peers of a farm household increased to 57%, and subsequently increased to 68% by 2016. Similarly, the average peer experience witnessed an increasing trend over time.

Table 3.3. Contextual (peer) characteristics

Time-varying variables	**Characteristics by year of network**			
	2003	**2007**	**2012**	**2016**
A. Learning mechanism				
Average adopting peers	0.03	0.28	0.57	0.68
	(0.11)	(0.33)	(0.39)	(0.40)
Average peer experience	0.17	0.99	2.30	2.79
	(0.45)	(1.41)	(1.84)	(1.87)
B. Other peer characteristics				
Average peer age	29.86	34.86	39.86	43.86
	(7.16)	(7.16)	(7.16)	(7.16)
Average peer education	1.59	1.59	1.58	1.58
	(2.47)	(2.34)	(2.29)	(2.24)
Average peer household size	5.74	5.72	5.73	5.74
	(1.50)	(1.42)	(1.39)	(1.38)
Average peer landholding	2.67	2.66	2.66	2.66
	(1.10)	(1.04)	(1.02)	(1.01)
Average peer risk of food insecurity	0.78	0.76	0.81	0.76
	(0.85)	(0.79)	(0.91)	(0.78)
Average peer group associations	1.18	1.19	1.20	1.21
	(0.91)	(0.85)	(0.84)	(0.83)
Average peer soil quality	2.97	2.99	2.99	2.99
	(0.68)	(0.65)	(0.65)	(0.65)
Proportion of male peers	0.66	0.65	0.65	0.64
	(0.33)	(0.32)	(0.31)	(0.30)
Proportion of liquidity constraint peers	0.49	0.49	0.49	0.49
	(0.35)	(0.33)	(0.32)	(0.32
Proportion of peers with extension contact	0.41	0.41	0.42	0.42
	(0.35)	(0.32)	(0.32)	(0.32)

Notes: the table presents descriptive statistics of time-varying household variables in panel A, and that for peer characteristics constructed based on the networks defined using the number of years the agent indicated to have known the peer, in panel B. Columns 2003 to 2016 represent characteristics of households and peers as at the years 2003, 2007, 2012 and 2016 (for the peer characteristics, these are based on the relationships that existed prior to 2003, i.e., J known for 14+ years; 2007 – J known for 10-14 years; 2012 – J known for 5-10 years; and 2016 – J known for <1-5 years. Each of the contextual (peer) characteristic value was obtained by multiplying the respective variable by the D to obtain the value of an agents' peer characteristics in respect of each of these variables. Values in parenthesis are standard deviations.

We also constructed social network statistics at the individual level (i.e., degree, transitivity and eigenvector centrality)[25] as the effects of these statistics on time-to-adoption are important in this study. Panel A of table 3.4 presents the descriptive statistics of these across selected years. The average number of connections (degree) an individual has increases from 3, for the

[25] See Appendix A for the calculation of these statistics.

14+ year length network, to about 4 persons, for the <1 to 5-year length network. Similarly, the average transitivity and eigenvector centrality both increase marginally, from 0.12 and 0.44, for the 14+ year network to 0.18 and 0.47, for the <1 to 5-year network, respectively.

Table 3.4. Social network information

	Mean	SD	Min	Max	N
Panel A					
Degree					
J known <1-5 years	3.708	1.868	1	12	500
J known 5-10 years	3.594	1.837	1	12	500
J known 10-14 years	3.437	1.804	1	12	500
J known 14+ years	3.118	1.755	1	11	500
Local transitivity					
J known <1-5 years	0.176	0.246	0	1	500
J known 5-10 years	0.178	0.251	0	1	500
J known 10-14 years	0.153	0.235	0	1	500
J known 14+ years	0.123	0.223	0	1	500
Eigenvector centrality					
J known <1-5 years	0.472	0.261	0	1	500
J known 5-10 years	0.473	0.267	0	1	500
J known 10-14 years	0.473	0.264	0	1	500
J known 14+ years	0.441	0.280	0	1	500
Panel B					
Network modularity					
J known <1-5 years	0.284	0.073	0.143	0.414	500
J known 5-10 years	0.293	0.079	0.173	0.424	500
J known 10-14 years	0.294	0.108	0	0.521	500
J known 14+ years	0.352	0.113	0.175	0.678	500

Notes: the table presents descriptive statistics by the number of years a farm household (i.e., node) knows the respondent who was randomly matched to and known to him. Panel A presents the descriptive statistics of the 5 respondents randomly assigned to, and known to the farm household, and the degree distribution for 4 networks which were constructed based on the number of years the farmer indicated to have known the contact. Specifically, J known <1-5 years implies i indicated knowing J for at least from 2012; J known 5-10 years implies i knows J since 2007 but not later than 2012; J known for 10-14 years represents i mentioned knowing J since 2003 but not late than 2007, and J known for 14+ years implies i mentioned knowing J since 2002 and earlier. Panel B shows the descriptive statistics of two node level characteristics (i.e., local transitivity and eigenvector centrality), and one network level statistic (i.e., network modularity) by these 4 networks. S.D. is standard deviation. Min is minimum and Max is maximum. N is observation.

Of particular interest, in this study, is modularity which enables us measure the extent to which village networks are segregated into latent segments or communities. Suppose a given network is divided into two groups with $P_i = 1$ if node i belongs to group 1 and $P_i = -1$ if the node belongs to group 2. Let g_{ij} be the number of links between nodes i and j, and denote the expected number of links between nodes i and j if links were generated at random as $d_i\, d_j/2m$, then the modularity of the network is calculated following (Newman 2006) as

$$(1) \qquad M = \frac{1}{4m}\sum_{ij}\left(g_{ij} - \frac{d_i d_j}{2m}\right)P_i P_j$$

where d_i and d_j are the degrees of the nodes and $m = \frac{1}{2}\sum_i d_i$ is the total number of links in the network. The statistic ranges from -1 to 1, where a measure of negative values mean segments are not isolated from others (i.e., integrated components). Positive values of modularity statistic mean strong segments (i.e., segmented components) and 0 means the components of the network are not capturing anything.

Panel B of table 3.4 presents modularity statistic of the networks, also across selected years. For the 14+ year length network, the network (average) modularity is 0.35 and this consistently declines overtime to 0.28, for the <1 to 5-year network. These values suggest the presence of latent network structures in these networks, which appears to gradually weaken overtime. This is unsurprising because of the possibility of social structures to weaken overtime due to changes in demographics and development. The modularity of a network can condition the rate of diffusion of the improved technology, such that if the village network is highly segregated into components (i.e., high modularity), it can slow down diffusion at the village level.

To show such a possibility, we present the summary statistics of the time-taken-to-adopt (i.e., adoption spell) and adoption decisions (i.e., failure or adopted) across terciles of modularity, for the network based on links known for 14+ years and <1 to 5 years, in table 3.5. The average time-taken-to-adopt increases from about 7 years for the bottom tercile to an average of about 12 years for the top tercile of modularity, with the difference in average time-to-adoption being significantly higher for the middle and top terciles ($p<0.05$). Conversely, the proportion of adopters significantly decreases from 81% in the bottom tercile, for both networks, to about 49% and 47% for the top terciles for the <1 to 5 and 14+ years networks, respectively. These changes show the possible role of network structures in affecting diffusion of the improved variety in these networks. Please refer to table 3.B2 in Appendix B for the sampled networks (column 1) across quintiles of modularity.

Table 3.5. Adoption spell and adoption by modularity distribution

	By tercile of modularity distribution				
	(1)	(2)	(3) = (2) - (1)	(4)	(5) = (4) – (2)
	1st	2nd	Difference	3rd	Difference
Adoption spell					
J known <1-5 years	7.31	8.71	1.39**	11.51	2.81***
	(0.35)	(0.35)	(0.49)	(0.35)	(0.43)
J known 14+ years	7.25	8.78	1.53***	11.51	2.73***
	(0.34)	(0.35)	(0.49)	(0.27)	(0.44)
Failure (adopted)					
J known <1-5 years	0.81	0.70	0.11**	0.49	0.21***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)
J known 14+ years	0.81	0.70	0.11**	0.47	0.23***
	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)
N	180	160		160	

Notes: Table shows the adoption spell (i.e., the time taken to adopt) and failure (i.e., whether adopted) by tercile of modularity distribution. These were reported for networks that were defined based on relationships formed before the introduction of the improved variety (i.e., the node indicated to have known the match, $j \in J$, for 14+ years) and the network of relationships that were formed within the past 5 years to 2016 (i.e., the node indicated to have known the match, , $j \in J$, for <1-5 years). Column (1) reports these for the first tercile of modularity, column (2) reports for the second tercile and column (4) reports that of the third tercile. Columns (3) and (5) shows the differences between the first and second terciles and the second and third terciles, respectively. Values in parenthesis are standard errors. *, ** and *** are significant at the 10%, 5% and 1% respectively

3.3 Theoretical framework

Using the target input model outlined in Foster and Rosenzweig (1995) and Bandiera and Rasul (2006), we develop a model of how farmers learn about new technologies from their social network members. Our model extends this framework by taking account of the drivers of social learning in the form of benefits, know-how, and the topological characteristics of the social network structure. For the theoretical as well as the empirical models, we do not only consider that farmers learn from those they have direct social links with (i.e., neighbors), but also the cohesiveness of their neighborhood, the level of segregation of the community and the farmer's importance within the social network.

3.3.1 Updating profitability belief

The model assumes each farmer i knows the yield Q_i^{TV} of the traditional variety cultivated on an acre of his land. The average yield of the improved variety Q_i^{IV} is not known. Thus, farmer i forms beliefs about the profitability of the improved variety $Q_i^{IV}(\mathscr{b})$ to guide his decision to learn or not. Farmers' beliefs are within the range of $\mathscr{b} \in [\underline{\mathscr{b}}, \overline{\mathscr{b}}]$, with 0< $Q_i^{IV}(\underline{\mathscr{b}}) < Q_i^{IV} < Q_i^{IV}(\overline{\mathscr{b}})$.

We delineate social learning process in two stages (Nourani 2019).[26] In the first-stage, farmers are interested in knowing whether the expected yield potential of the improved variety is higher than the expected yield of the traditional variety cultivated on his land. We specify the first-stage of the social learning process as a DeGroot updating process (DeGroot 1974), where we assume that the beliefs of the yield are based on the yield potential, i.e., the yields obtained with excellent production know-how. Since the formation of beliefs about the average yield of the improved variety is seen as a filter before realizing more intensive social learning based on Bayesian updating, it is desirable that this stage of the learning process is computationally simple and immediate. Moreover, DeGroot-updating allows for agents' beliefs not converging to the same belief. Instead, groups of agents may reach different consensuses. The occurrence of different consensuses seem plausible in the case of farmers, since groups of farmers have context specific conditions, such as agronomic or farmer specific characteristics like, soil quality, exposition of the land, microclimate, agronomic experience or education.

Communication with other farmers provides farmer i information about other farmers' beliefs. Farmer i weights this information according to the reliability or trust he puts on farmer j. Let

[26] Nourani (2019) links each stage of the two-stage learning process with a different type of agents. In our theoretical model each stage is based on all social ties of each agent. However, in the first-stage agents learn about the yield potential and in the second-stage about the know-how.

B be an $N \times N$ interaction matrix between agents, where entries b_{ij} indicate the relative weight or trust farmer i puts on farmer j in comparison with all other farmers $k, k \neq j$, he relates to. As the weight is relative, the entries of each row of the matrix, B sum up to one when normalized. The farmers' initial beliefs at time 0 are exogenous and denoted by $\mathscr{b}_{i0}$ for farmer i. DeGroot updating from time period $t-1$ to period t is given by the following rule $\mathscr{b}_{it} = \sum_{j=1}^{N} b_{ij}\, \mathscr{b}_{jt-1}$. Based on the updated value of $\mathscr{b}_{it}$, farmer i decides to learn about the cultivation technique, once his beliefs $\mathscr{b}_{it}$ are higher than a given threshold. It can be given, for instance by the yield of the traditional variety, i.e., $Q_i^{IV}(\mathscr{b}) > Q_i^{TV}$.

3.3.2 Learning about the production process

Farmers can improve their initially rudimentary knowledge about the cultivation of the improved variety by learning from farmers that have adopted in the past and by their own experience once they have adopted. We assume that farmers use Bayesian updating to improve their knowledge about the cultivation technique. To keep the model simple, we do not consider institutional or public learning and focus on the effect of social learning. Furthermore, we assume that the price of output is normalized to one, inputs are costless and all farmers own the same size of land that is entirely cultivated to either the traditional or the improved variety. The agricultural production of farmer i at time t is a function of the applied input I_{it}. Farmers know the underlying production function of the improved variety up to a random optimal or "target" use of the applied input I. The yield of the improved variety $\hat{Q}_{it}^{IV}$, declines in the square of the deviation of actual applied input I_{it} and the uncertain target $\hat{\theta}_{it}$. By observing the obtained yields of the improved variety and the applied input, the farmer learns about optimal target by his own and other farmers' experiences. The observed yield of the improved variety $\hat{Q}_{it}^{IV}$ is expressed as

(2) $\hat{Q}_{it}^{IV} = Q_{it}^{IV} - \left[I_{it} - \hat{\theta}_{it}\right]^2$,

where $\hat{\theta}_{it} = \theta^* + u_{it}$. The term θ^* represents the mean optimal effective input and u_{it} is the transitory random shocks that are i.i.d. with $N\left(0, \sigma_u^2\right)$. At time t, farmers are assumed to be informed about σ_u^2 and to have prior beliefs about θ^* that are distributed as $N\left(\theta_{it}^*, \sigma_{\theta it}^2\right)$. In each period, farmers learn about the systematic part of the target by observing input and yield from their own trial and/or from their social network members. This information allows farmers to update their prior θ_t^*, and infer the systematic component of $\hat{\theta}$. This results in a posterior belief about the variance over θ^* as

(3) $\sigma_{\theta_{it}}^2 = \frac{1}{\pi_0 + \pi_p p_{it-1} + \pi_p H\ (C_{it-1}, \lambda_i, \tau_i, M)}$,

where $\pi_0 = 1/\sigma_{\theta_{i0}}^2$ is the precision of the farmer's initial priors about the true value of θ^*, $\pi_p = 1/\sigma_u^2$, is the precision of the information produced by farmer i's own trial or by his peers' trials, p_{it-1} is an indicator of i's cumulative information of his own trial up to time $t-1$, and $H(\cdot)$ represents the cumulative information farmer i´s has obtained from his peers in the past up to time $t-1$. The information gathered in the term $C_{i,t-1}$ is based on the share of peer adopters in farmer i´s neighborhood, A_{jt-1}, farmer i´s neighbors' input I_{jt-1} and the yields Q_{jt-1}^{IV} of the improved variety of farmer i´s neighbors at time t. Thus, it is given by the function $C_{it-1}\left(A_{jt-1}, I_{jt-1} Q_{jt-1}^{IV}\right) \geq 0$.

The term λ_i denotes the centrality of farmers, which accounts for farmer i's immediate learning possibilities from farmers who are directly connected to him, as well as learning from well-connected neighbors (walks of length one). A high score means that a farmer is connected to many farmers or to farmers who themselves have high scores. If the number of walks tend to infinity, λ_i stands for eigenvector centrality.[27] Farmers learn from others as they receive information about input and yield. However, farmers may give more or less credibility to the information, depending on the strength of the social ties between farmer i and farmer j. Although the strength of social ties cannot be measured directly, it can be assumed to be stronger if the neighborhood is tied together by mutual friendships, or shared responsibilities. As a proxy for the strength of social ties, we consider the cohesiveness of the neighborhood (i.e., farmer i's neighbors are also connected among each other). Thus, the more cohesive farmer i´s neighborhood is, the more credible is the information that flows to farmer i. The local cohesiveness of farmer i's neighborhood is denoted by τ_i, with $\tau_i \in [0,1]$ in equation (3), see Appendix A for a precise definition of these network statistics and their corresponding metrics.

Another influential factor for social learning, and central to this study, is the strength of segregation of a network into modules (modularity) that is denoted by M. In a highly segregated community, farmers obtain information from their neighbors, but there is no or only weak flow of information between the segregated modules. Thus, farmers are more likely to learn only from others if adopters form part of their module, while their chances of learning are slim if adopters do not form part of their module. Also, the strength of modularity affects the structure of the neighborhood of all agents, such that the centrality and cohesiveness are lower for agents who are not located in the central parts of the module relative to that of agents at the center of the module. The unbalanced distribution of these topological characteristics due to modularity can shape the nature of information diffusion and social learning. Thus, the overall quantity and quality of information gathered from other farmers, together with the effect

[27] Paths are possible connections between agents of any length where no agent is visited more than once. Walks are also connections but agents and links can be visited/traversed multiple times.

of local cohesiveness, eigenvector centrality and modularity are given by the function $H\left(C_{it-1}, \lambda_i, \tau_i, M\right) \geq 0$. The function H recognizes that the social network related variables $A_{jt-1}, \lambda_i, \tau_i, M$ are interdependent. For instance, an increase in the degree or modularity changes the strength of local cohesiveness, the eigenvector centrality and the share of adopters. For this reason, one should think of H as a composite function where the inner function reflects the interdependencies between the social network variables in a form of a system of equations, and the outer function as the quantity and quality of the information the social network variables together with $I_{jt-1}$and Q_{jt-1}^{IV} provide.

To maximize expected output, farmer i applies inputs at the expected optimal level, such that $I_{it} = E_t(\hat{\theta}_{it}) = \theta_t^*$, given $E_t(u_{it}) = 0$. Following equations (2) and (3), and the expected optimal level of input application, we express the conditional expected output function as

$$(4) \qquad E_t\hat{Q}_{it}^{IV}[\,H(C_{it-1}, \lambda_i, \tau_i, M)] = Q_{it}^{IV} - \frac{1}{\pi_0 + \pi_p p_{it-1} + \pi_p H\,(C_{it-1}, \lambda_i, \tau_i, M)} - \sigma_u^2$$

which implies that the expected output increases as the uncertainty of the farmer's beliefs on the optimal target and the variance of the transitory random shocks decreases.

3.3.3 Adoption decision

We assume farmers have access to improved variety and a riskless traditional variety with output Q_i^{TV}, such that adoption, $A_{it} = 1$, if a farmer adopts the new crop variety at time t, and $A_{it} = 0$ otherwise. Following equation (4), we express the value of output flow to farmer i from time t to $t+1$ as

$$V_t[p_{it-1}, H(C_{it-1}, \lambda_i, \tau_i, M)]$$

$$(5) \qquad = \max_{A_{it}\in\{0,1\}} (1 - A_{it})Q_{it}^{TY} + A_{it}E_t\hat{Q}_{it}^{IV}[p_{it-1}, H(C_{it-1}, \lambda_i, \tau_i, M)]$$

$$+ rV_{t+1}[\{(1 - A_{it})p_{it-1}, A_{it}p_{it}\}, H(C_{it-1}, \lambda_i, \tau_i, M)]$$

where r is the farmer's discount rate.[28] The farmer adopts the new crop variety at time t, if

$$(6)\qquad E_t\{\hat{Q}_{it}^{IV}[p_{it-1}, H(C_{it-1}, \lambda_i, \tau_i, M)] + rV_{t+1}[p_{it}, H(C_{it-1}, \lambda_i, \tau_i, M)]\}$$
$$\geq E_t\{Q_i^{TY} + rV_{t+1}[p_{it-1}, H(C_{it-1}, \lambda_i, \tau_i, M)]\} \quad .$$

Thus, farmer i's adoption decision at time t depends on the information obtained from his neighbors and the change in net value of output from adopting at time t with respect to his neighbors experiences, C_{it-1}, and other social network related information A_{jt-1}, λ_i, τ_i and M. Let these five variables form a set denoted by S, with each element denoted by S_v, where $v = 1,2,\ldots,5$. With respect to an increase in a farmer- or social network-related variable S_v, the derivative of expected stream of net benefits at time t is given by:

$$\left[\frac{\partial E_t \hat{Q}_{it}^{IV}[p_{it-1}, H(C_{it-1}, \lambda_i, \tau_i, M)]}{\partial H} + r\frac{\partial E_t\{V_{t+1}[p_{it}, H(C_{it-1}, \lambda_i, \tau_i, M)] - V_{t+1}[p_{it-1}, H(C_{it-1}, \lambda_i, \tau_i, M)]\}}{\partial H}\right]\frac{\partial H}{\partial S_v}$$

$$(7)\qquad = \left[\frac{1}{[\pi_0 + \pi_p p_{it} + \pi_p H\,(C_{it-1}, \lambda_i, \tau_i, M)]^2} \right.$$
$$\left. + r\sum_{u=1}^{T} r^u \left\{\frac{1}{[\pi_0 + \pi_p p_{it} + \pi_p H\,(C_{it-1}, \lambda_i, \tau_i, M)]^2} - \frac{1}{[\pi_0 + \pi_p p_{it-1} + \pi_p H\,(C_{it-1}, \lambda_i, \tau_i, M)]^2}\right\}\right]\frac{\partial H}{\partial S_v} \lesseqgtr 0$$

where the first terms on both sides of the equation indicate the increase in current benefits resulting from more information, $\partial E_t \hat{Q}_{it}^{IV}[\cdot]/\partial H > 0$, conditional on adoption of the improved variety.[29] This indicates the learning externality, as farmer i obtains more and better information about cultivating the improved variety. The sign of the learning externality is positive and favors adoption. The second term, enclosed in curly brackets, represents the difference in the future stream of discounted benefits, between adoption and non-adoption at

[28] For instance, if we consider the initial moment of time where $t = 0$, the values of p_{t-1} and p_t are given by 0 and 1, respectively.

[29] If the improved variety were not adopted the current benefits would not change as a result of more information.

time t. Given that $\sum_{u=1}^{T} p_u > \sum_{u=1}^{T} p_{u-1}$, the sign of the sum is negative, suggesting that additional information from farmer i´s own trials is less valuable than the additional information obtained from the farmer's neighbors. Thus, farmer i may strategically delay adoption to make use of the additional and more precise information obtained from his peer adopters. Thus, the sign of strategic delay is negative and tends to delay adoption. The overall effect of more and better information about the cultivation of the improved variety depends on the magnitude of these two effects and the sign of $\partial H/\partial S_v$. The latter derivative indicates the marginal effect of farmer-related and social network-related variables on the quantity and quality of information received by farmer i from neighbor j.

It is expected that decrease in modularity, and an increase in local cohesiveness τ_i, the centrality of farmer i in the social network, λ_i, the share of past adopting peers, A_{jt-1}, and the peers' experiences about their input and output lead to more and better information about the improved variety, i.e., $\partial H/\partial S_v > 0$. Since the learning externality is always positive and strategic delay is always negative, the change in the magnitude of these two effects as a result of more and better information tends to determine whether the farmer adopts or delays adoption. Although strategic delay is always negative, the difference between the terms in curly brackets decreases, if the value of H increases and becomes dominant in both denominators. Thus, the sum of all terms in equation (7) tends to change sign from negative to positive as H increases and adoption takes place. However, if $\partial H/\partial S_v < 0$, the opposite result is obtained, whereby adoption is delayed.

Hypothesis 1: *When the belief about expected profitability of the improved variety is lower than a given threshold, higher learning opportunities from experienced peers do not significantly increase the likelihood of adopting the improved variety*.

Hypothesis 2: *The likelihood of adoption is low with increased modularity of the social network, but the influence of modularity on learning from peers for adoption is weaker, if social learning is among direct peers or within modules*.

Hypothesis 3: *When increased local cohesiveness and centrality lead to more opportunities for learning and adoption, lower modularity is more likely to increase the likelihood of adoption than higher modularity*.

The theoretical model describes the signs of the effects of the driving forces on adoption, but does not offer insights about the strength of the effects. In the next section, we employ observational data to examine the magnitude of the influence of these unknowns.

3.4. Empirical specification and estimation

3.4.1 Empirical specification

Our theoretical framework shows that the time at which a farmer adopts the new technology relates to the past adoption decisions of peers, information from past peer experiences, and the structure and characteristics of the social network. Based on the notation used in the theoretical framework, we specify our empirical model, by assuming a lag transmission of social network effects (Manski 1993) as:

(8) $$Pr[T = t | T \geq t, G, A_0 \ldots A_t, C_0 \ldots C_t, X_t]$$
$$= \rho G_t A_{t-1} + \alpha G_t C_t + \beta_1 M_t + \beta_2 D_t + \beta_3 G_t D_t + X_t' \gamma_1 + X_t' G_t \gamma_2 + \iota_{tG} + \varepsilon_t,$$

where T is a random variable that denotes the time of adoption of the improved variety, G_t is a normalized social network matrix, and $G_t A_{t-1}$ is the share of past adopting peers. Given that adoption decisions are based on the net expected returns from adoption, as discussed in the theoretical framework, it follows that changes in peer adoption decisions will inform the farmer about the profitability of the improved variety. Thus, ρ shows the effect of the association between share of past peer adoption decisions, which indicates profitability signal, and the conditional probability of adoption at any given time. C_t is farmers' experience in cultivating the improved variety, $G_t C_t$ is the average peer experience in the cultivation of the variety and α is the association between peer experience (i.e., learning about production process) and the conditional probability of adoption at time t. D_t is a vector of farmer level network statistics [i.e., transitivity (τ_t) and centrality measures (λ_t)], $G_t D_t$ is the farmer's average peer network statistics, M_t is the modularity of the network, and β_1, β_2 and β_3 are vectors of parameters to be estimated, while ε_t is the error term.

Our specification of the effects of peer adoption decisions differs from the "traditional" endogenous peer effect as in Manski (1993). Specifically, we define this effect based on previous peer adoptions, and not contemporaneous adoptions. This simplifies the econometric framework because of the reflection problem. It also enhances identification, since farmers react to their peers' adoption decisions only when observed (i.e., timing between own decision and peer decisions). However, two critical concerns that arise are the contextual and correlated effects. Contextual effects refer to similarities in exogenous characteristics among peers, which can cause behaviors to correlate through such peer exogenous characteristics, and not due to peer behavior. We control for contextual effects with individual and peer characteristics (i.e., X_t' and $X_t' G_t$, respectively), and the associated parameters to be estimated as γ_1 and γ_2 in equation (8).

Next is the possibility of unobservables at the network and individual levels to drive correlations in individual adoption decisions (i.e., correlated effects) and cause identification problems by confounding the peer effects estimates (Manski 1993; Moffitt 2001; Blume et al. 2011). These are represented with the vector ι_{tG} in equation (8), which consists of time, village and environmental factors (i.e., correlated effects) that affect adoption. Available approaches for accounting for these unobservables in the literature, given our setting, include, the use of a (i) standard instrumental variable approach, (ii) network fixed-effects to account for potential network-specific unobserved factors (Lee 2007; Liu and Lee 2010),[30] and (iii) the control function for accounting for self-selection within social interactions (Goldsmith-Pinkham and Imbens 2013; Hsieh and Lee 2016).

Our approach to accounting for correlated unobservable basically involve the last two: First, we decompose ι_{tG} into time, δ_t, and network, υ_G, effects and control for both in our specifications. The second approach (i.e., (iii) above) involves a first-stage model of network formation, given that link formation is a phenomenon of choice, determined by observed and unobserved agents' characteristics. The estimated unobserved determinants of link formation, defined as $\hat{r}_t$, at the first-stage, are retrieved and inserted into a second-stage adoption decision model to account for endogeneity of the network effect. This is similar in spirit to the Heckman (1979) sample selection approach and the Brock and Durlauf (2001; 2006) generalized multinomial control function for self-selection corrections with social interactions. Another merit of the use of this approach is that it allows us account for concerns of measurement errors due to the use of sampled networks (Chandrasekhar and Lewis 2016), as well as provides a natural source of instruments for identifying the social interaction effects (Brock and Durlauf 2001) in order to obtain consistent estimates.

[30] See Horrace et al. (2016) and Hsieh and Lee (2016) for discussion of these approaches.

3.4.2 Empirical estimation

Our interest is in examining the network effects on the conditional probability of adopting improved soybean variety at time t given that the farmer has not adopted until this time. Given that adoption of the technology in question were observed on annual basis, where observed durations are clustered at mass points, we model our duration to adoption in a discrete-time method to account for the banded nature of the survival time. Also, discrete-time methods do not impose functional form restriction on the time effects (allowing for specific time fixed effects to be captured) compared to the continuous time proportional hazard models, and make it possible to account for time-varying covariates (Jenkins 2005).

If we define n as the total number of farmers ($i = 1,2,3, \ldots$) observed until time t_i, at which point the farmer either adopts the improved variety (i.e., uncensored) or do not adopt (i.e., censored). In this study, the entrance date is 2003 which is the year in which the improved variety was introduced (i.e., $t = 1$). The exit date of the spell for the farmers who adopt the improved variety is the year of adoption, and farmers who have not adopted at the 2016 farming season are right-censored, because the data was collected on farmers' agricultural production in the 2016 farming season. If we define $\boldsymbol{X}_{it}$ as a vector of explanatory variables and $\boldsymbol{\mathcal{B}}$ as the associated vector of parameters in equation (8), we express the discrete-time hazard rate as

$$(9) \qquad A_{it} = Pr[T_i = t | T_i \geq t, \boldsymbol{X}_{it}]$$

where T is the discrete random variable representing the adoption time of the farmer[31]. In order to express the dependence of the hazard rate on time and the explanatory variables, we use the complementary log-log link function which is not sensitive to the length of the time intervals, compared to the logistic regression function (Allison 1982). The complementary log-log

[31] This also represents the conditional probability of adoption at time t, given that the farmer has not adopted until this time.

function assumes the data generating process is based on the continuous-time proportional hazard model and is express as

$$(10) \quad A_{it} = 1 - \exp[-\exp(\boldsymbol{\mathcal{B}}'\boldsymbol{X}_{it})].$$

Equation (10) represents the discrete-time proportional hazard model. We estimate the hazard model by maximizing the likelihood of the function. Given that some of the observations are censored, we express the likelihood function of the data generation process as

$$(11) \quad L = \prod_{i=1}^{n}[\Pr(T_i = t_i)]^{a_i}[\Pr(T_i > t_i)]^{1-a_i}$$

where L is the likelihood of function, and a_i is set equal to 1 if i is uncensored and zero otherwise. Expressing each of the probabilities in equation (11) as a function of the hazard rate and taking the logarithm of this deliver the log-likelihood function as

$$(12) \quad \log L = \sum_{i=1}^{n}\sum_{s=1}^{t_i} y_{it}\log[A_{is}/(1 - A_{is})] + \sum_{i=1}^{n}\sum_{s=1}^{t_i}\log(1 - A_{is})$$

where y_{it} is a dummy variable equal to 1 if farmer i adopted the improved variety at time t, and zero otherwise[32]. Each discrete-time unit for a farmer is treated as a separate observation, and the dependent variable is coded 1 if the farmer adopted the improved variety in that time unit and zero otherwise. The farmer contributes to the computation of A_{is}, if he adopts the improved variety at time t_i, and $(1 - A_{is})$ for the period before t_i. If the farmer does not adopt (i.e., censored) by the 2016 cropping season, he only takes part in the computation of the term second term of the right-hand size**.**

Following the discussion of the identification of the peer effects and the hazard model, equation (8) can now be specified as:

$$\begin{aligned} A_{it} = {} & \rho G_t A_{it-1} + \alpha G_t C_{it} + \beta_1 M_t + \beta_2 D_{it} + \beta_3 G_t D_{it} \\ (13) \qquad & + \rho_\alpha G_t A_{it-1} \times G_t C_{it} + \rho_M G_t A_{it-1} \times M_t + \alpha_M G_t C_{it} \times M_t + \beta_M G_t D_{it} \times M_t \\ & + X_{it}'\gamma_1 + X_{it}' G_t \gamma_2 + \delta_t + \upsilon_G + \widehat{r}_{it} + \epsilon_{it}, \end{aligned}$$

[32] See Allison (1982) for the steps required to arrive at the log-likelihood function.

where ρ and α represent the effects of learning about profitability and know-how, respectively; β_1, β_2 and β_3 show the effects of network characteristics; γ_1 and γ_2 represent contextual effects; δ_t, $\mathcal{v}_G$ and $\hat{\mathcal{r}}_{it}$ account for correlated effects. The parameter δ_t is a flexible baseline hazard which indicates the pattern of duration dependence in the diffusion process over time, and is used to account for time fixed effects. The parameter $\mathcal{v}_G$ accounts for network level effects that might drive peers' behavior to be correlated. $\hat{\mathcal{r}}_{it}$ is a vector of predicted residuals of the link formation model used to account for unobserved factors that affect network formation at the farmer level (refer to Appendix B for discussion and estimation of the network-formation model).

To examine the relationship between learning about profitability, know-how, and network statistics, the second row of equation (13) shows the interactions among these variables. In particular ρ_α denotes the interaction effects of past adopting, G_tA_{it-1}, and experienced peers, G_tC_{it}. ρ_M and α_M show the effects of past adopting, G_tA_{it-1}, and experienced peers, G_tC_{it}, conditioned on modularity of the network, M_t, respectively. β_M represents the effect of farmer level network statistics, G_tD_{it}, (i.e., local transitivity, degree and eigenvector centrality), conditioned on modularity of the network, M_t, and the rest are as defined in equation (8).

3.5 Empirical results and discussions

This section presents and discusses the results of our empirical estimates. Table 3.6 presents the unconditional hazard ratio estimates of peer adoption, peer experience and network statistics on adoption, whereas table 3.7 presents the hazard ratio estimates of these conditioned on modularity of the social network.

We first consider the unconditional hazard ratios of past peer adoption of the improved variety on adoption in columns (1, 3, 5 and 7) with degree centrality, and in columns (2, 4, 6 and 8) with eigenvector centrality, in table 3.6. Columns (1-4), present a restricted specification, which does not control for contextual peer effects. Columns (5-8) control for peer contextual effects, γ_2, (refer to Appendix C table 3.C1 for estimates of the controls). There is little difference in the hazard ratios of peer adoption, peer experience and network statistics in any given year, when we estimate with and without the contextual peer effects. This suggests that adoption of the improved variety is unlikely to be due to the observable contextual peer characteristics. Columns (5-8) of table 3.C1 in the appendix show that the residuals, $\hat{r}_t$, of the network formation model are jointly statistically significant at the 5% level, indicating the significance of controlling for the unobservable factors that affect link formation at the farm household level. The baseline hazard[33] estimates reveal that the rates of adoption increase overtime and peak in years 9 and 10 bin, and then begins to slowdown afterwards (see Appendix C, tables 3.C1 and 3.C2). The coefficients of the time effect dummies together show increasing and positive duration dependence in the adoption process. This is not surprising, because one will expect the adoption conditions to improve overtime, as the aggregate experience with the improved variety at the village level makes learning from others more effective.

3.5.1 Peer adoption decisions, experiences and diffusion

We now focus on the unrestricted model in columns (5-8) in table 3.6 in discussing social network effects on the speed of adoption. The estimates reveal a positive and significant effect of past share of adopting peers on the conditional probability of adoption across all specifications. In fact, a percentage increase in adopting peers is associated with about 135 percent higher hazard rate. Similarly, the coefficient estimates of peer experience indicate that those with more experienced peers with the improved variety have higher hazard rates.

[33] A challenge with the time dummies in our application is that some of the year bins have very few incidences of adoption, which drops out during estimation. This means that using year specific time effects can lead to loss of important information required to estimate the network effects. To circumvent this situation, we select same-length of time bins (i.e., two-year-long periods) which allows for at least enough incidence of adoption for each of the time bins.

Specifically, a year increase in average peer experience with the improved variety is associated with about 84 percent higher hazard rate. Thus, signals from increased peer adoption decisions and experienced peers tend to increase learning opportunities and decrease learning costs, which consequently can speed up adoption of the improved variety (Beaman et al. 2018).

We also present the distribution of marginal effects of estimates of the main specification in column (5) in Figure 3.1. These estimates reveal that a 20 percent standard deviation increase in adopting peers is associated with a 10 percentage points increase in the conditional probability of adoption in any given year. Similarly, a 20 percent (which translated into 1.4 years) standard deviation increase in average peer experience is associated with about 9 percentage points increase in the probability of adoption in any given year.

The effects of peer experience with the improved variety on the conditional probability of adoption is lower than the effects of share of adopting peers, when the share of past adopting peers is below 25 percent. However, the effects of peer experience become higher and remains so with increasing peer experience in the cultivation of the improved variety, when more than 30 percent of peers have adopted the improved variety. This is expected because the higher efforts required in learning about the production process will make farmers expect a certain level of peer adoption in order to increase learning opportunities, as indicated in the theoretical framework. Past studies found evidence of either learning about hard-to-use (Oster and Thornton 2012), or easy-to-use technologies in conditions of visible benefits (Magnan et al. 2015). A possible implication of our finding is that network effects could drive both learning about benefits and application (use) of a technology that is relatively hard-to-apply, and with visible expected benefits that can be inferred from peer decisions, *albeit* the precise mechanisms cannot be determined with the data.

Table 3.6. Estimates of Social learning and farmers' adoption

		No Contextual Effects				Contextual Effects			
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Share of peer adopters	ρ	2.350**	2.319**	1.424	1.417	2.374**	2.348**	1.513	1.503
		(0.761)	(0.746)	(0.542)	(0.541)	(0.762)	(0.746)	(0.569)	(0.567)
Peer experience	α	1.840***	1.885***	1.770***	1.818***	1.834***	1.883***	1.771***	1.821***
		(0.232)	(0.224)	(0.226)	(0.220)	(0.224)	(0.216)	(0.216)	(0.209)
Peer experience × Share of peer adopters	ρ_α			1.523	1.512			1.459	1.453
				(0.414)	(0.419)			(0.382)	(0.391)
Modularity	β_1	0.182**	0.139**	0.166**	0.127**	0.186**	0.126**	0.169**	0.115**
		(0.146)	(0.118)	(0.129)	(0.103)	(0.139)	(0.103)	(0.121)	(0.088)
Transitivity	β_2	3.146**	3.186**	3.155**	3.191**	3.301**	3.328**	3.303**	3.322**
		(1.340)	(1.435)	(1.331)	(1.424)	(1.449)	(1.534)	(1.438)	(1.521)
Degree	β_2	1.088		1.090		1.099*		1.102*	
		(0.058)		(0.058)		(0.056)		(0.057)	
Average peer degree	β_3	1.124*		1.127*		1.160**		1.163**	
		(0.074)		(0.073)		(0.080)		(0.081)	
Eigenvector	β_2		1.092		1.119		1.211*		1.243
			(0.389)		(0.397)		(0.409)		(0.419)
Average peer eigenvector	β_3		2.170**		2.208**		2.464**		2.509**
			(0.793)		(0.799)		(1.049)		(1.066)
Controls	γ_1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual effects	γ_2	No	No	No	No	Yes	Yes	Yes	Yes
Correlated effects	$\delta_t, \vartheta_G, \hat{r}_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	$\rho + \rho_\alpha = 0$							5.68(0.02)	5.73(0.02)
	$\alpha + \rho_\alpha = 0$							10.67(0.00)	11.04(0.00)
Link Residuals X^2_5*(p-val)*		22.58(0.00)	25.64(0.00)	22.66(0.00)	25.59(0.00)	22.71(0.00)	25.65(0.01)	22.99(0.00)	26.21(0.00)
LogLikelihood		-972.6	-972.6	-970.3	-971.2	-964.8	-965.8	-963.6	-964.7
Clusters		25	25	25	25	25	25	25	25
N		4,551	4,551	4,551	4,551	4,551	4,551	4,551	4,551

Notes: Random-effects complementary log-log estimation. Models 1-4 do not include average peer characteristics (i.e., contextual effects). Models 5-8 include these average peer characteristics (their coefficients and that of other controls are presented in appendix table 3.C1). Correlated effects include time fixed-effects, δ_t, link formation residuals, $\hat{r}_t$, and standard errors clustered at the village (i.e., network) level, in order to account for village factors that might drive peer behaviors to be correlated, ϑ_G [we did not use village dummies because of the need to avoid the incidental parameter problem (Lee et al., 2010) by having to include 25 village dummies, and also the fact that modularity is calculated for the entire network/village]. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

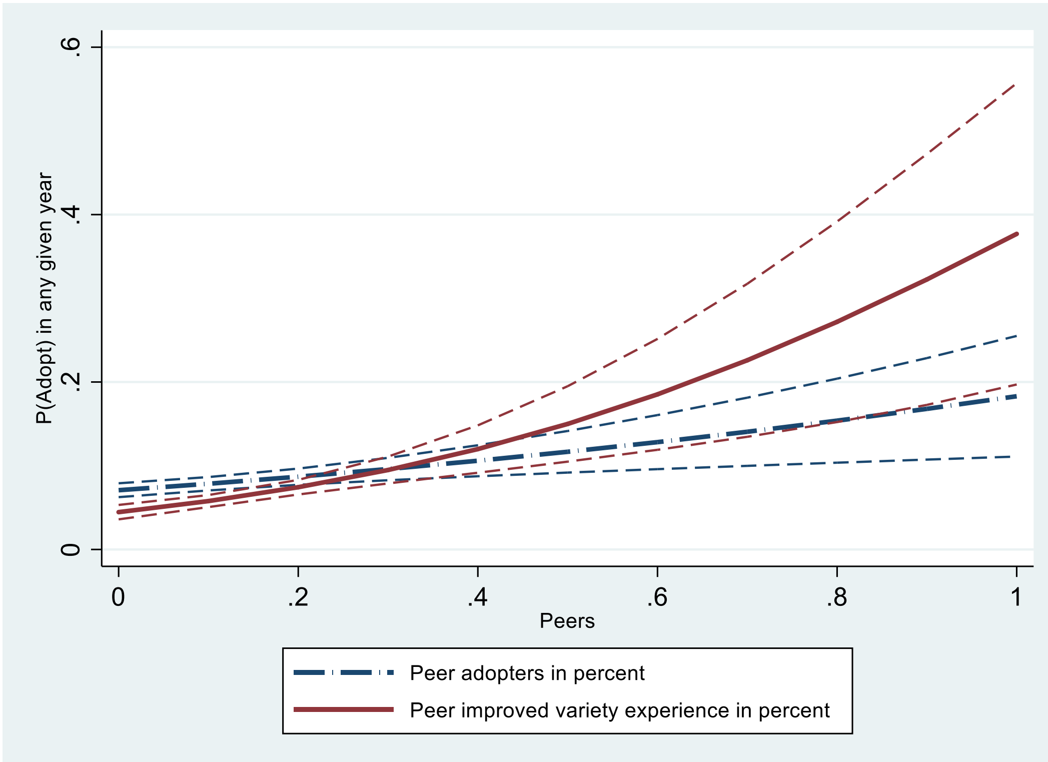

Figure 3.1 Marginal Effects of peer adoption and production experience

Notes: Marginal effects of the fully specified model (i.e., column 5 of table 3.6). In each case (e.g., peer adoption), all variables other than peer adoption are held constant at their mean values. Peer experience is expressed as a percent of the maximum average peer experience in the sample. Starting from baseline year adoption probabilities of about 9% and 6% for share of adopting and experienced peers, respectively, the probability of adoption marginally increases to about 18% with increased peer adoption of the improved variety (i.e., the thick-dot line), and to about 38% with increased peer experience in farming the improved variety soybean (i.e., the solid line).

To show the dependence between signals from past peer adoption decisions and peer experience in soybean farming, we also estimated the conditional network effects by interacting share of past adopting peers with peer experience [i.e., the first term of row two in specification (13)] in columns (7) and (8). The estimates reveal that whereas the main effect, ρ, and interaction effect, ρ_{α}, are each not statistically significant, the main effect of peer experience, α, remains positive and statistically significant. This suggests that a year increase in average peer experience with the improved variety is associated with a hazard rate of at least 77 percent.

Figure 3.2 shows the marginal effects of the interaction between share of peer adopters and peer experience on the conditional probability of adoption in any given year. The interaction effects between the two appear to be complementary on the probability of adoption. Specifically, the probability of adoption is generally low at lower shares of adopting peers and peer experience, and does not exceed 25 percent with 10 percent adopting peers and even with 4 years (on average) peer experience. Even at the maximum levels of peer adoption of the improved variety, the conditional probability of adoption in any given year is between 24 – 33 percentage points with lower (i.e., 2 year) average peer experience with the improved variety. However, a farmer who has peers with 6 years average experience and 80 percent share of adopting peers has about 79-89 percentage points likelihood of adoption in any given year.

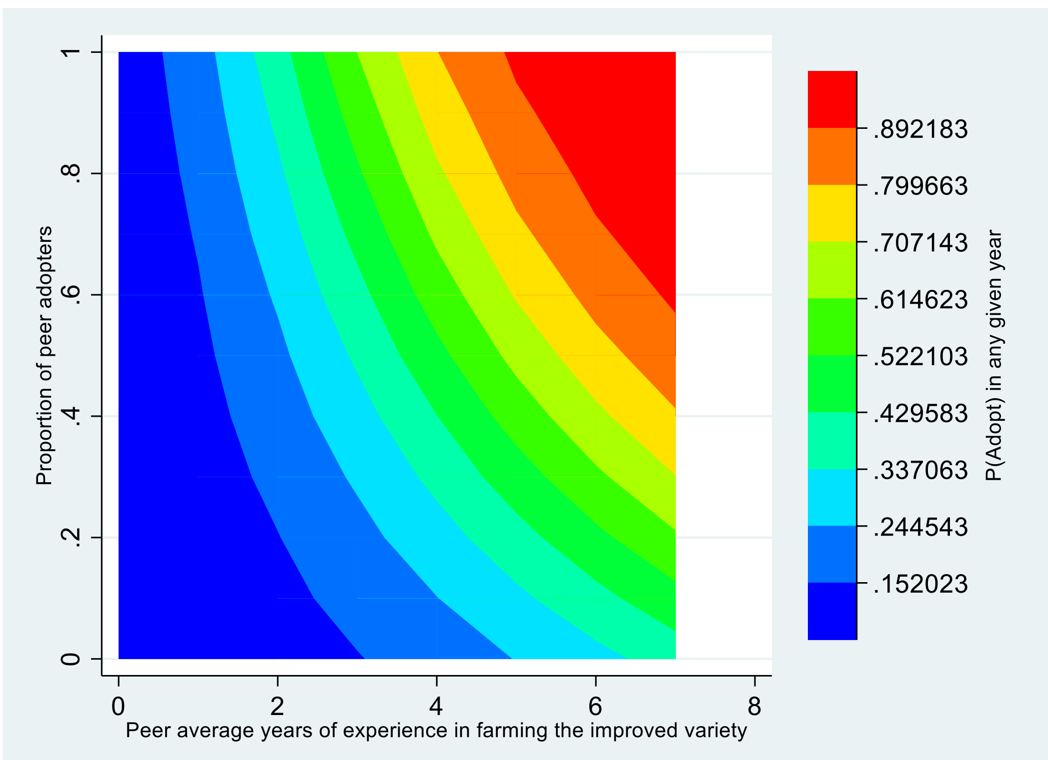

Figure 3.2 Predicted probability of adoption by peer adoption and production experience

Notes: Predicted probability of farm household adoption by peer adoption and production experience based on column 7 of table 3.6. There is a positive association between peer adoption and production experience. Starting from a baseline probability of 15% with lower levels of peer adoption and experience, the probability of adoption increases to at least 79-89% at high levels of peer adoption and production experience.

This finding suggests that although having many adopting and experienced peers can increase the learning opportunities and possibly reduces the duration of non-adoption, the effects of learning about know-how from peer experience on adoption is much higher than the effect of peer adoption decisions. This is expected because soybean production is quite demanding in terms of labor inputs, management and timing of other inputs application, making the marginal returns to learning about production relatively higher than just signal from peer adoption decisions.

3.5.2 Network statistics and diffusion

We next consider the network statistics by first focusing on the individual level statistics (i.e., transitivity, degree and eigenvector centralities). In respect of degree and eigenvector centralities, we focus on the averages of farmers' peer degree and eigenvector centralities because of our interest in showing the effects of a farmer's connection to highly connected or important peers on the probability of adoption, and not that of the farmer himself. The results, reported in table 3.6, show a positive and significant association between the transitivity and the conditional probability of adoption in any given year across all specifications. In addition, farmers' connections (i.e., degree) and farmers' average peer connections (i.e., farmers' average peer degrees) in column (7) as well as farmers' average peer eigenvector centrality in column (8) each significantly increases the hazard rate in any given year. Interestingly, however, the hazard rate of transitivity is significantly higher than the hazard rate of peer degree (p=0.022), but not significantly different from the hazard rate of farmers' average peer eigenvector centrality (p>0.1)[34].

[34] The coefficient of transitivity is also significantly higher than the coefficient of farmers' own degree (p=0.00) in column (7).

This finding suggests that obtaining information on the new technology from multiple and interconnected sources is very important than from a highly connected farmer. This could be due to the fact that the influence of central nodes is more local[35] (i.e., limited to few known direct nodes and the unknown nodes just learn by imitation) (e.g., see Banerjee et al. 2014; Beaman and Dillon 2018), and/or because the central node's trustworthiness is low. It could also be associated with the fact that central nodes are unable to communicate intensively over a certain time for other farmers to get the required information (especially if learning is not easy) (Beaman et al. 2018).

We earlier on argued that the extent of partitioning of the network into groups, which defines modularity, can affect the rate of interaction and diffusion of the improved variety, particularly if a network has high modularity statistics (i.e., highly segregated). Estimates of modularity show significant and negative association with adoption across all specifications in table 3.6. Thus, farmers who belong to highly segregated networks (i.e., higher modularity network) tend to have longer duration of non-adoption of the improved variety. Thus, whereas increasing transitivity of a farmer's neighborhood is associated with higher hazard rate due to less structural holes and increased efficiency in information flow and diffusion, increasing modularity leads to lower hazard rate due to the highly structured latent groups in the networks. This confirms the arguments by Rogers (1995), Alatas et al. (2016), and Jackson et al. (2017) that the likelihood of information or behavior to spread from one node to other nodes is high in networks with less latent community structures and/or highly cohesive subgroups.

[35] Beaman and Dillon (2018) found that information does not diffuse to people who are far from the first recipient of the information

3.5.3 Network modularity versus transitivity and centrality on diffusion

To examine whether network modularity conditions the effects of information about peer adoption decisions, – and for that matter profitability beliefs –, and peer experiences in soybean production on the conditional probability of adoption by farmers, we interact past peer adoption decision and peer experiences with modularity in columns (1) and (2) of table 3.7. Although the main effects of peer adoption decisions and experiences remained significantly positive, it is the interaction effects of peer experience with modularity that is significant, suggesting that there is some dependence of learning from peer experiences on modularity.

This is clearly shown in Figure 3.3 where the conditional probability of adoption continues to increase with increasing peer adoptions but with higher probability at higher levels of adopting peers and lower modularity (Fig. 4A). Similarly, the conditional probability of adoption increases with increasing peer experience but appears to show high effect of learning from peer experiences at higher peer experiences and modularity (Fig. 4B). These relationships suggest that farmers depend more on their direct peers or peers within their components in the network in learning from peer experiences, and possibly on both direct and indirect peers or even peers across components in observing peer adoption decisions.

Our findings substantiate the argument by Jackson et al. (2017) that flow of information or behavior among nodes is stronger and can possibly reach all nodes, if these nodes belong to the same component in a network, and that of Nourani (2019) that farmers tend to learn about production knowledge from strong ties, and about profitability from weak ties. In effect, the figures show that when the proportion of peer adopters and years of experience are low changes in the modularity has little effect on adoption. When these values are high changes in the modularity are highly effective.

Table 3.7. Impact of network modularity on farmers' adoption

		(1)	(2)	(3)	(4)
Share of peer adopters	ρ	2.223***	2.194***	2.480**	2.485***
		(0.610)	(0.588)	(0.788)	(0.776)
Peer experience	α	1.934***	1.987***	1.773***	1.793***
		(0.223)	(0.221)	(0.214)	(0.204)
Modularity	β_1	0.159*	0.109**	0.134**	0.127**
		(0.115)	(0.085)	(0.123)	(0.119)
Transitivity	β_2	3.107**	3.176**	3.462**	3.417**
		(1.328)	(1.427)	(1.531)	(1.593)
Degree	β_2	1.117**		1.060	
		(0.055)		(0.052)	
Average peer degree	β_3	1.171**		1.084	
		(0.082)		(0.076)	
Eigenvector	β_2		1.257		1.204
			(0.413)		(0.407)
Average peer eigenvector	β_3		2.450**		2.194*
			(1.067)		(0.866)
Modularity × Share of peer adopters	ρ_M	1.541	1.297		
		(7.895)	(6.514)		
Modularity × Peer experience	α_M	4.273*	3.544**		
		(3.349)	(2.679)		
Modularity × Transitivity	β_M			2.38E-5***	1.16E-5***
				(8.43E-5)	(4.45E-5)
Modularity × Average peer degree	β_M			0.372**	
				(0.154)	
Modularity × Average peer eigenvector	β_M				0.004**
					(0.010)
Controls	γ_1	Yes	Yes	Yes	Yes
Contextual effects	γ_2	Yes	Yes	Yes	Yes
Correlated effects	$\delta_t, \vartheta_G, \hat{r}_t$	Yes	Yes	Yes	Yes
LogLikelihood		-961.4	-963.2	-958.6	-959.1
Clusters		25	25	25	25
N		4,551	4,551	4,551	4,551

Notes: Random-effects complementary log-log estimation of equation (13). Column 1 controls for the interactions of modularity on one hand and peer adopters and experience on the other hand as well as agent's degree and average peer degree. Column 2 controls for the interactions of modularity on one hand and peer adopters and experience on the other hand but with agent's eigenvector centrality and average peer eigenvector centralities. Column 3 controls for the interactions of modularity on one hand and agent's local transitivity, degree and average peer degree, whiles column 4 controls for the interactions of modularity on one hand and agent's local transitivity, eigenvector centrality and average peer eigenvector centrality. The coefficients of agents' controls and that of peer characteristics are presented in appendix table 3.C2). Peer experience is the number of years of peer experience in cultivating the improved variety. Correlated effects include time fixed-effects, δ_t, link formation residuals, $\hat{r}_t$, and standard errors clustered at the village (i.e., network) level, in order to account for village factors that might drive peer behaviors to be correlated, ϑ_G [we did not use village dummies because of the need to avoid the incidental parameter problem (Lee et al., 2010) by having to include 25 village dummies, and also the fact that modularity is calculated for the entire network/village]. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Thus, it is beneficial to target share of adopters through extension services and training workshops in promoting adoption in the short run, and then focus on measures that facilitate interactions among farmers at the village level in order to minimize the constraining effects of modularity on social learning in the long run. We next check whether the latent network structures (modularity) condition the roles of transitivity and centrality in the social learning process, which is the last term of row two in specification (13). This is important because, the effectiveness of transitivity and centrality in the diffusion process depend on the extent of modularity of the network. High modularity networks are expected to constrain the role of transitivity and centrality in enhancing learning and diffusion in the network and the vice versa.

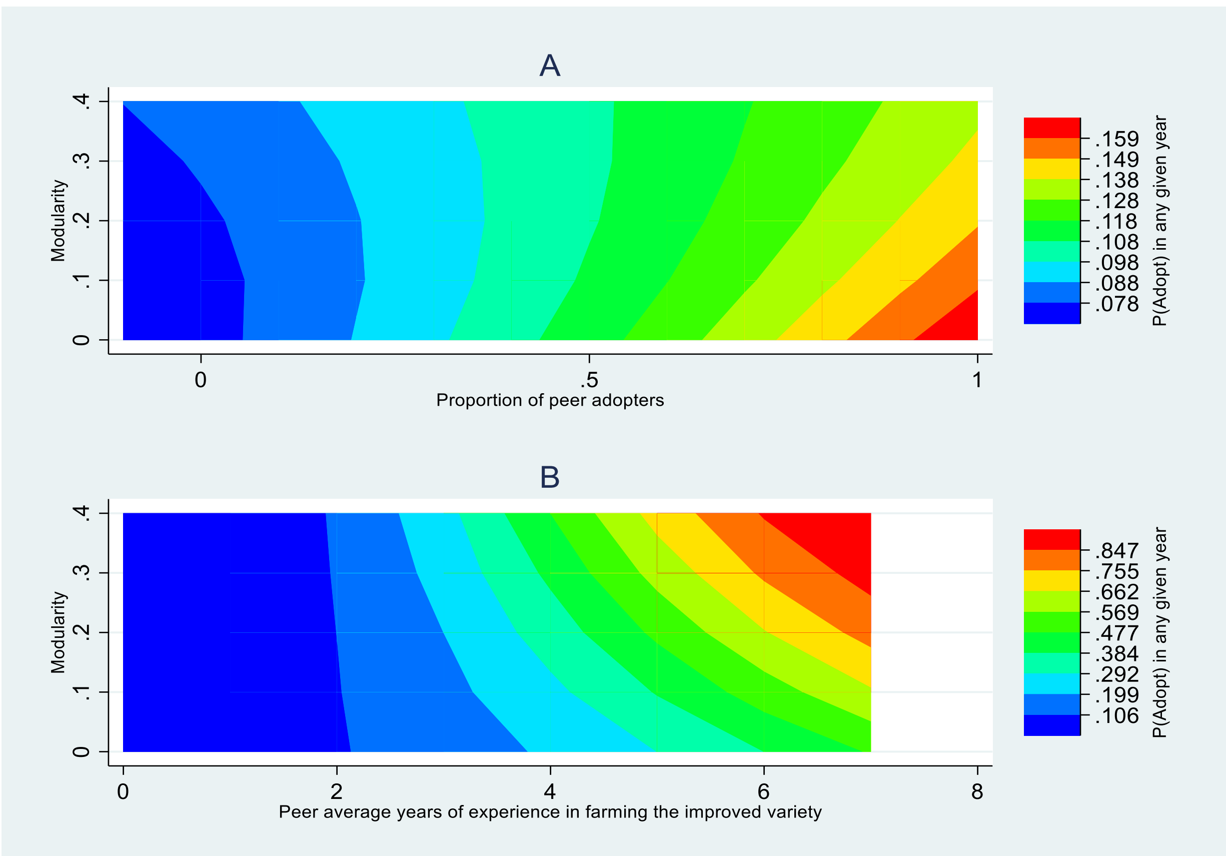

Figure 3.3 Predicted probability of adoption by modularity, peer adoption and experience

Notes: The figure depicts the predicted probability of household adoption by modularity and peer adoption (A) and by modularity and peer experience (B). Starting from lower levels of adoption probabilities of 7.8% and 11% respectively for A and B, the probability of adoption increases to about 16% and 85%, with increasing peer adoption and peer experience but at lower and higher modularity, respectively.

Columns (3) and (4) of table 3.7 show how modularity conditions the effects of these micro-network structures by interacting transitivity, average peer degree and eigenvector centrality with modularity. Whereas the main effects of transitivity show that increase in transitivity of a farmer's neighborhood is associated with higher hazard rate, the coefficients of modularity and the interaction with transitivity in both columns show lower hazard rates.

Similar effects are observed in the main and interaction effects of average peer degree, and eigenvector centrality with modularity. The interaction effects of modularity with average peer degree in column (3), and with average peer eigenvector centrality in column (4) are significant and less than one. These suggest that latent network structures significantly limit the role of these node level statistics in promoting social learning and diffusion. Figure 3.4 shows the interaction plots of modularity and average peer degree (A), average peer eigenvector (B) and farmer's local transitivity (C). We find that the association between transitivity, average peer degree and eigenvector centrality, and the conditional probability of adoption in any given year changes, based on the level of modularity. Generally, the conditional probability of adoption in any given year increases with increase in each of these statistics at lower levels of modularity.

The conditional probability of adoption reaches about 14, 10 and 9 percentage points at the highest levels of local transitivity, average peer eigenvector centrality and average peer degree, respectively, and at the lowest levels of modularity. However, the conditional probabilities of adoption are at most about 4 percentage points at the highest levels of local transitivity, average degree and eigenvector centrality when modularity is above 0.3. Thus, the higher the modularity of the network, the less effective is the influence of the local transitivity of a farmer's neighborhood, and the effect of peers with higher connections and importance in the network. The rationale is that when the network has many small components, information or behavior that originates among neighbors or from central and influential nodes in a given component –

especially when important nodes are targeted in placement of intervention – will probably take more time to spread to nodes in other components.

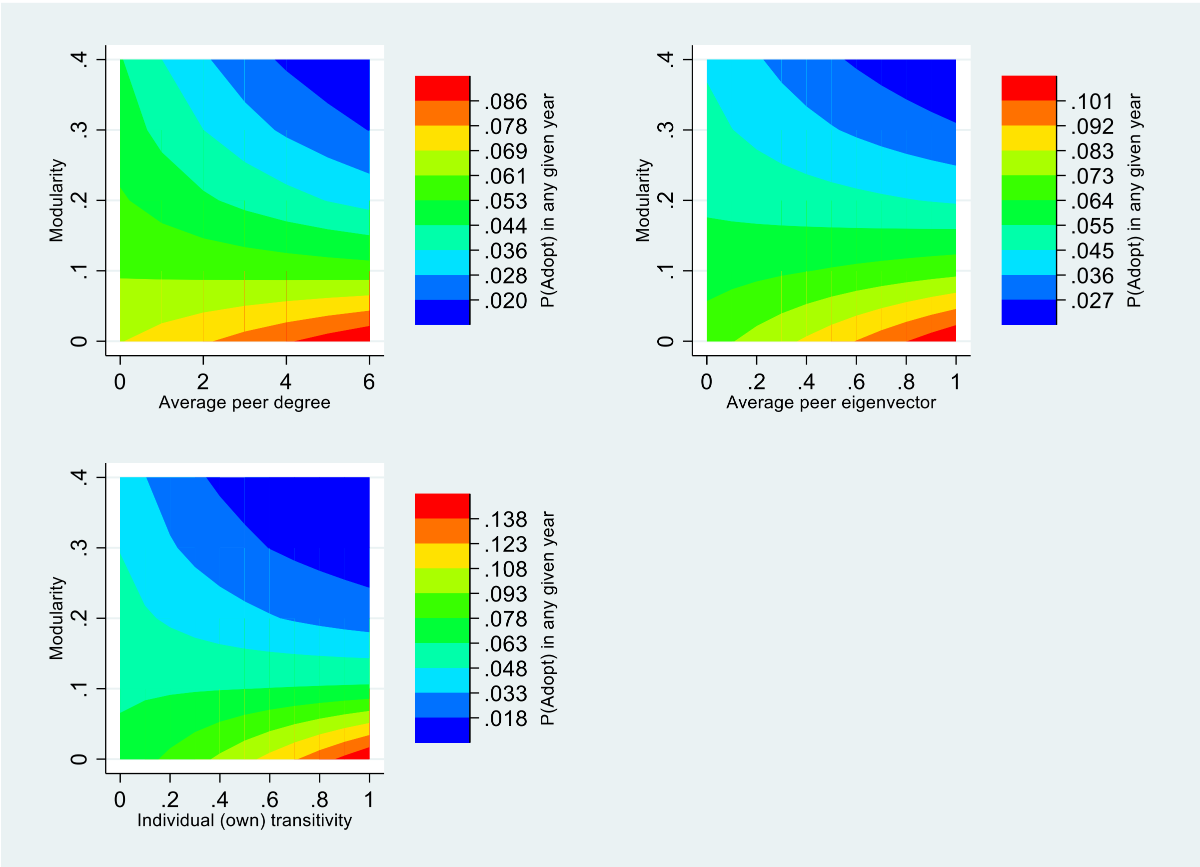

Figure 3.4 Predicted probability of adoption by modularity, centrality and transitivity

Notes: The figure shows the interaction plots of the probability of household adoption by modularity and average peer degree (A), modularity and average peer eigenvector centrality (B) and modularity and peer transitivity (C). In all cases, the effect of these local measures on the probability of adoption is limited when the modularity of the network is high.

This finding demonstrates the importance of social groups (i.e., latent network segregation pattern) in social learning and the technology diffusion process, as well as the need to consider social diversity and structures in interventions that are aimed at promoting information dissemination and technology diffusion. This is in line with the studies by Girvan and Newman (2002) and Newman (2002) who argue that communities in a network might signify actual social groupings based on interest, backgrounds or identities that are important in understanding and exploiting networks effectively. The implication of this finding is that the common strategy of targeting initial adopters who are central in their networks may not be sufficient for promoting diffusion of improved soybean in these villages, if the community structures and diversities that underlie farmers' interactions are ignored. The reason being that, the effect of a central member in a network will be limited in the presence of network structures and diversities. Hence, the use of approaches (such as farmer field days, self-help groups or multiple targeting) that lead to more interactions and subsequently creating more connection and increasing the density of contacts among farmers (as documented by Centola 2010; Magnan et al. 2015; Alatas et al. 2016) will be appropriate in promoting diffusion at the village (network).

3.5.4 Other possible effects and robustness checks

This section presents robustness checks by investigating the possibility of concerns that might threaten the effects observed in our analysis. Despite the fact that our specifications account for some correlated unobservables, with the residuals of the network formation model, and that all the study villages are in the Northern region of Ghana and have similar agricultural, climatic and market conditions, we nevertheless cannot completely rule out the possibility that our estimates could be driven by village and other environmental effects.

Individual ability and spurious correlations

The first concern is the possibility of the peer adoption effects to be spuriously correlated due to differences in farmers' and household abilities rather than due to social learning. To check this, we estimated our baseline models in columns (5) and (6) of table 3.6 with the squared term of peer adoption decisions, which are reported in column (1) of table 3.8. The coefficients of share of peer adopters and the share of peer adoption squared show a nonlinear relationship between peer adoption and the conditional probability of adoption of the improved variety, which partly suggests these effects are not driven by spurious correlations. This suggests that the total impact of peer adoption share is much stronger for low levels of peer adoption and then levels out for moderate levels of peer adoption. The effect tends to negative at high levels of peer adoption, which is consistent with the social learning literature that the marginal benefit of peer adoption decreases with increased peer adoption (Bandiera and Rasul 2006).

Table 3.8. Peer adoption squared and resource pooling

	Peer adoption squared		Excludes sample below the 5th and above the 95th average peer		
		Excludes landholding below 5th and above 95th percentile	Landholding	Household size	Liquidity constraints
	(1)	(2)	(3)	(4)	(5)
Share of peer adopters	3.031***	3.004***	0.855**	1.067***	1.333***
	(0.689)	(0.824)	(0.370)	(0.309)	(0.426)
Peer experience	0.554***	0.497***	0.569***	0.608***	0.506***
	(0.117)	(0.143)	(0.129)	(0.128)	(0.136)
Modularity	-1.676**	-1.537	-1.976**	-1.814**	-1.435*
	(0.707)	(0.949)	(0.743)	(0.814)	(0.863)
Transitivity	1.156**	1.134**	1.111**	1.165**	1.630***
	(0.427)	(0.424)	(0.496)	(0.437)	(0.396)
Degree	0.084	0.099*	0.123*	0.090*	0.089
	(0.049)	(0.051)	(0.061)	(0.053)	(0.068)
Average peer degree	0.142**	0.155**	0.172**	0.170**	0.195**
	(0.067)	(0.069)	(0.068)	(0.077)	(0.079)
Share of peer adopters squared	-3.697***	-3.565***			
	(1.053)	(1.272)			
Controls	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes	Yes
Correlated effects	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-961.2	-812.1	-833.7	-901.3	-787.2
Clusters	25	25	25	25	25
N	4,551	3,811	4,055	4,136	3,582

Notes: Random-effects complementary log-log estimation of equation (11). Column 1 controls for peer adoption squared, and column 2 controls for peer adoption squared but without households below the 5th percentile and above the 95th percentile of household land holding. Columns 3-5 present estimates of our baseline model excluding households with average peer landholding, household size and liquidity constraints below the 5th percentile and above the 95th percentile of the distribution of peer landholding, household size, and liquidity constraints. Correlated effects include time fixed-effects, δ_t, link formation residuals, $\hat{r}_t$, and standard errors clustered at the village (i.e., network) level, in order to account for village factors that might drive peer behaviors to be correlated, v_G [we did not use village dummies because of the need to avoid the incidental parameter problem (Lee et al., 2010) by having to include 25 village dummies, and also the fact that modularity is calculated for the entire network/village]. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

However, Bandiera and Rasul (2006) argue about the possibility of heterogeneities in abilities to spuriously drive such nonlinear peer relationship, particularly, when relatively low-ability households tend to be constrained in adoption, and high-ability households with investment options tend to be less likely to adopt. Thus, we estimated the same specification in column (1) of table 3.8 by excluding households with landholding below the 5th and above the 95th percentiles. The results, which are reported in column (2) of table 3.8, show the inverse U-shaped relationship still persists, suggesting that social learning does play a role in the diffusion process.

Resource effects and not learning

The next concern is resource-sharing effects, where exchanges of resources among peers can speed up the ability of resource constrained farm households to adopt the improved variety. The assumption is that households who are relatively resource poor can depend on relatively better households for resources required for cultivation. Also, gains from peer adoption that ease input constraints such as land, labor and liquidity can enhance the ability of poor and resource constrained households to access these inputs for cultivation. This has the potential of showing effects that are similar to social learning, where a farmer's conditional probability of adoption increases as a result of past adoption decisions of peers in the farmer's network.

To investigate this, we first replicated the results of the baseline model in column (5) of table 3.6 excluding households with average peer landholding, household size and liquidity constraints below the 5th and the 95th percentiles. These resources are important for soybean production in the area because the crop is labor intensive and also requires application of inputs such as inoculant, fertilizer and herbicides to obtained desired output (Heatherly and Elmore 2004). Farmers who are constrained in these inputs can benefit through increased access, following adoption of their peers, or from better-off peers. Reassuringly, the results remain stable, with positive and significant peer effects on the conditional probability of adoption in any given year.

Furthermore, we interact farmers' and peers' landholding and household size to examine whether households with more or less own and peer landholding and household size are more or less likely to adopt faster, and how such dependence in terms of resources affect our results. We report the results in columns (1) and (2) of table 3.9. Both estimates are small and statistically insignificant, suggesting that increase in peer landholding (household size), given the farmer's landholding (household size) is associated with a delayed (faster) adoption, but statistically not significant. The estimates of peer adoption decisions and the other network effects remain robust to this exercise.

Threats of geographic proximity

Another challenge has to do with residential and/or farm proximity between farmers and their peers, where farmers with similar soil quality and features on their plots, that favor a particular variety, might appear to have similar varietal choices. This may drive adoption decisions between peers and farmers to be correlated without social learning effect. Column (3) of table 3.9 contains interaction of farmers' soil quality with average peer soil quality, and the term shows that farmers who have peers with high (on average) soil quality have higher conditional probability of adoption, *albeit* not statistically significant. This suggests weak dependence in soil quality of farmers and peers. Columns (4) of table 3.9 investigate the validity of this issue in respect of residential proximity. We control for the average distance between household locations of farmers and their peers in this specification. Despite these specifications, the results in terms of magnitudes and directions of our estimates remain qualitatively similar to the baseline model, suggesting that social learning does play a role in the adoption of the improved variety.

Table 3.9. Geographic proximity, soil and experience

	Land	Household size	Soil	Household distance	Correlated effects
	(1)	(2)	(3)	(4)	(5)
Share of peer adopters	0.866**	0.868**	0.876**	0.857**	0.138
	(0.319)	(0.318)	(0.322)	(0.315)	(0.319)
Peer experience	0.602***	0.605***	0.600***	0.606***	0.225**
	(0.121)	(0.123)	(0.125)	(0.123)	(0.084)
Modularity	-1.628**	-1.717**	-1.792**	-1.617**	
	(0.763)	(0.765)	(0.768)	(0.736)	
Transitivity	1.190**	1.181**	1.174**	1.165**	1.061**
	(0.435)	(0.436)	(0.433)	(0.437)	(0.518)
Degree	0.088*	0.099**	0.100*	0.091*	0.158**
	(0.051)	(0.048)	(0.051)	(0.051)	(0.063)
Average peer degree	0.150**	0.148**	0.149**	0.147**	0.117
	(0.069)	(0.068)	(0.069)	(0.069)	(0.077)
Landholding	-0.036				
× average peer landholding	(0.044)				
Household		0.014			
× average peer household size		(0.026)			
Soil quality			0.140		
× average peer soil quality			(0.121)		
Distance: household and peers				0.015	
				(0.025)	
Controls	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes	Yes
Correlated effects	Yes	Yes	Yes	Yes	Yes
Correlated effects by village and time	No	No	No	No	Yes
Log Likelihood	-964.6	-964.6	-964.1	-962.1	-850.5
Clusters	25	25	25	25	25
N	4,551	4,551	4,551	4,549	3,469

Notes: Random-effects complementary log-log estimation of equation (11). Columns 1-3 control for the interactions of household and average peer soil quality, land holding and average peer landholding, and household size and average peer household size. Columns 4 control for the average distance between households and peers. Column 5 controls for correlated effects by village and time. The sample size in column 5 is 3,469 because the village by time interactions resulted in some village-time bins not having enough observation and as a result some observations were dropped in the estimation process due to collinearity. Correlated effects include time fixed-effects, δ_t, link formation residuals, $\hat{r}_t$, and standard errors clustered at the village (i.e., network) level, in order to account for village factors that might drive peer behaviors to be correlated, v_G [we did not use village dummies because of the need to avoid the incidental parameter problem (Lee et al., 2010) by having to include 25 village dummies, and also the fact that modularity is calculated for the entire network/village]. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Within village correlated effects

The next concern is the issue of correlated effects due to village-specific time trends, which might affect farmers' decisions to adopt the improved variety. One issue that arises in considering this is the fact that modularity is calculated for the whole network and only varies at the village level.

Hence, the inclusion of modularity, time and village fixed effects, and village × time fixed effects result in convergence problem during the estimation. As a result, modularity is dropped in this specification. Column (5) of table 3.9 presents results of the specification that includes time, village and village × time fixed effects, and shows, with the exception of share of adopters which loses its significance but still positively correlates with adoption, that most of the coefficients are qualitatively similar to the baseline results.

Sampled networks and robustness of results

Given that our network data is sampled and not based on a census of connections of households of these villages, there could be some bias in the estimates. Households were asked whether they know any of 5 households randomly drawn from the village sample and assigned to them, and links were defined based on whether the household knew the match or not. This implies that, when a household is not randomly assigned to a responding household, one cannot determine whether the responding household knows the non-sampled household ($g_{ij} = 1$) or not ($g_{ij} = 0$).

To investigate this issue, we use the graphical reconstruction technique developed by Chandrasekhar and Lewis (2016) to simulate the complete network for each village. We first estimate a model of network formation, using the sampled network of each village, and then use the estimated model to simulate the complete networks (i.e., predict the missing links of the network) (see appendix B for model, estimates and networks). We next calculate our social network statistics (i.e., modularity, transitivity, degree and eigenvector centrality) using the complete networks, and then use these statistics to estimate our baseline specification. The results are reported in columns (1) and (2) of table 3.10 for degree and eigenvector, respectively, and the key findings remain similar to the baseline estimates.

Furthermore, in order to investigate the direction of potential bias associated with the use of the sample networks in the calculation of the network statistics used in the estimations, we use an approach similar to Alatas et al. (2016). That is, we explore what would happen to the estimates if we progressively drop links of the simulated network up to the sample selection ratio of our sampled networks, which is 34 percent of households in the median village. To explore this, we first drop 25 percent of links uniformly at random, calculate the network statistics used in the analysis and estimate the baseline specification with these statistics, with the results, reported in columns (3) and (4) of table 3.10 with degree and eigenvector centrality, respectively.

We further drop 50 percent of the links, calculate the network statistics and re-estimate our baseline specification, and these results are reported in columns (5) and (6) of table 3.10. Finally, we drop 70 percent of the links and repeat the analysis and present the results in columns (7) and (8) of table 3.10. The results, generally, remain qualitatively similar to the baseline in terms of the direction of their effects, although with generally decreasing levels of the coefficients of these network statistics, as more links are dropped. This suggest that our point estimates of the effects of these network statistics using the sample networks are susceptible to measurement errors, which is shown to be an attenuation bias. Thus, the estimated parameters of the network statistics should best be considered as a lower bound on the true coefficients.

Table 3.10. Bias in estimation of network statistics (modularity, transitivity, degree and eigenvector centralities) based on model specification in columns (5) and (6)

	100% links		75% links		50% links		30% links	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of peer adopters	0.833**	0.861**	0.820**	0.855**	0.808**	0.836**	0.804**	0.828**
	(0.310)	(0.307)	(0.301)	(0.307)	(0.305)	(0.306)	(0.308)	(0.309)
Peer experience	0.596***	0.591***	0.604***	0.613***	0.621***	0.625***	0.624***	0.624***
	(0.123)	(0.118)	(0.119)	(0.118)	(0.120)	(0.112)	(0.117)	(0.111)
Modularity	-5.599*	-11.351***	-1.728	-5.337**	-2.080	-4.440**	-3.251*	-4.414**
	(3.109)	(2.457)	(2.614)	(2.716)	(2.055)	(1.982)	(1.757)	(1.700)
Transitivity	2.386**	2.707**	1.021**	0.778	0.677	0.591	0.628	0.562
	(0.992)	(1.014)	(0.503)	(0.552)	(0.474)	(0.506)	(0.459)	(0.458)
Degree	0.061**		0.047***		0.048**		0.026	
	(0.021)		(0.016)		(0.016)		(0.020)	
Average peer degree	0.137**		0.166**		0.171**		0.174**	
	(0.076)		(0.069)		(0.068)		(0.068)	
Eigenvector		0.627		0.408		0.496		0.214
		(0.387)		(0.351)		(0.346)		(0.265)
Average peer eigenvector		1.130**		1.161***		1.151***		1.200***
		(0.436)		(0.393)		(0.399)		(0.405)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Correlated effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LogLikelihood	-959.5	-961.1	-966.6	-969.2	-966.5	-968.8	-967.9	-968.7
Clusters	25	25	25	25	25	25	25	25
N	4,551	4,551	4,551	4,551	4,551	4,551	4,551	4,551

Notes: Random-effects complementary log-log estimation of equation (11). Columns (1) and (2) present estimates where network statistics (i.e., modularity, transitivity, degree and eigenvector centrality) are calculated using the simulated complete social networks. Columns (3) and (4) show estimates with 25% of links of the simulated complete social networks deleted (i.e., estimated with 75% of the links in each simulated village network). Columns (5) and (6) present the same estimates with network statistics computed from networks with 50% of the links deleted (i.e., calculated with 50% of links of the simulated network). Columns (7) and (8) depict estimates with only 30% of the links (i.e., 70% of links of the simulated social networks deleted). Correlated effects include time fixed-effects, δ_t, link formation residuals, $\hat{r}_t$, and standard errors clustered at the village (i.e., network) level, in order to account for village factors that might drive peer behaviors to be correlated, v_G [we did not use village dummies because of the need to avoid the incidental parameter problem (Lee et al., 2010) by having to include 25 village dummies, and also the fact that modularity is calculated for the entire network/village]. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

3.6 Conclusion

Although learning for technology adoption has become an important focus of research and policy interventions in promoting agricultural advancement, especially in developing countries, the complexity of the technology itself, heterogeneity of benefits and in understanding the technology, as well as in the structure of social interactions have often led to sub-optimal adoption and inconclusive evidence of social network effects. Policy interventions have operated based on the assumption that farmers can learn from their peers, with little friction in the flow of information. However, this assumption can be costly in the presence of heterogeneity in social network structures, which condition the flow of information. We investigated this assertion using observational data from a survey of 500 farm households in Northern Ghana and random matching within sample to generate social network contacts.

We first provide a dynamic framework of how social learning and heterogeneity of network structures influence farmers' adoption decisions. Second, we estimate the effect of learning from peers on the speed of adoption, conditional on the transitivity of farmers' neighborhoods, connectivity to important peers and modularity of the network. Our approach of accounting for contextual effects and correlated effects (using the control function approach, clustering at village/network level, and village and time fixed effects) are key to the identification of the different network effects.

Our empirical results reveal significant and positive duration dependence in the adoption process, justifying the relevance of the duration model in this study. Generally, having past adopting peers and high (on average) experienced peers tend to increase the speed of adoption, but the magnitude of peer experience on the speed of adoption is higher if the farmer has more peers already adopting the improved variety. Thus, we find evidence that both benefits and production know-how play important roles in how farmers learn from their network contacts, which suggests the existence of social learning among network members. The likelihood of adopting faster increases with high values of transitivity and centrality. However, we generally find the role of local transitivity in the learning process to be stronger and more efficient in enhancing diffusion, compared to centrality. This could be attributed to the limited influence of central members to farmers they have direct contacts with, especially when the frequency and intensity of interactions between groups of agents is limited by highly segregated network structures. On the other hand, highly cohesive networks favor the frequency and intensity of interactions, in segregated network structures, that seems important for social learning.

The findings generally suggest that the common extension strategy of targeting initial and influential adopters in the network for disseminating information may not be appropriate in engendering diffusion at the network level. Given the role of transitivity in promoting adoption and that of modularity in restricting diffusion, and the influence of the other network characteristics, it will be important for policymakers to consider introducing the technology through densely subgroups, or using policies and interventions aimed at engineering connections among farmers (such as farmer field days or self-help groups) to improve information flow. Also, network-oriented policies such as workshops and seminars or supporting adopters' association that is open also to non-adopters can increase the diffusion process. Furthermore, interventions such as extension services, public learning and training workshops, where people are specifically invited from different segments of the village at the early stages of adoption, can promote bridges between modules and diffusion. These would create more avenues for interactions in order to increase links among farmers and between groups which could overcome the limitations of lowly cohesive or highly segregated networks. Network oriented policies are likely to enhance the role of social networks in information and diffusion process of the technology.

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Appendix

Appendix A

Metrics of Transitivity, Degree and Eigenvector centrality

Transitivity or ***local cohesiveness/clustering coefficient*** τ_i measures how close the neighborhood $d_i(g)$ of a farmer (i) is to being a complete network. If farmer i has d_i neighbors (degree) in the network g, such that $jk \in d_i$, the local transitivity coefficient is calculated as

$$\text{(A1)} \quad \tau_i = \frac{\#\{jk \in g \mid k \neq j, j \in d_i(g), k \in d_i(g)\}}{d_i(g)[d_i(g)-1]/2}.$$

Transitivity lies in the range of 0 and 1, with 1 suggesting a full interconnected neighborhood and 0 indicating there are no contacts of a farmer that are linked to each other (e.g. a network in the form of a star).

Degree centrality measures how well a farmer is connected, in terms of direct connections and is simply calculated as $d_i(g)$. High values of degree centrality imply that the farmer is central/influential and low values mean that the farmer is less central.

Eigenvector centrality measures the centrality of a farmer i by considering how important (central) his neighbors are. The centrality of a farmer is proportional to the sum of the centrality of its neighbors. Thus, we calculate the eigenvector centrality, $\Lambda d_i^e(g)$, of i as

$$\text{(A3)} \quad \Lambda d_i^e(g) = \sum_j g_{ij} d_j^e(g)$$

where Λ is a proportionality factor and represents the corresponding eigenvalue of $d_i^e(g)$. This, when normalized, ranges from 0 to 1 with values close to 1 meaning the farmer is very important and values close to 0 implies the farmer is not important. Both degree and eigenvector centralities are represented in the theoretical framework by the same notation λ_i but can distinguished by the value λ_i. However, these three farmer level statistics are represented by D_t in the empirical specifications in eqns. (8), (11) and (12).

Appendix B

Network formation model and estimates

B.1 The network formation model

Our model of network formation is based on the behavior of utility maximization. In this framework, each group member is assumed to have some characteristics that are only observed by other group members in the same group, and the distances in these observable and unobservable characteristics between individuals explain their link formation (Hsieh and Lee 2016). Each individual i, chooses to link to j, that is $d_{ij,g} = 1$, if $U_{ij,g}(d_{ij,g} = 1) - U_{ij,g}(d_{ij,g} = 0) > 0$, and $d_{ij,g} = 0$ otherwise, where $U_{ij,g}$ denotes utility function from the link ij. We express the above utility differences as

$$\text{(B1)} \quad U_{ij,g}(d_{ij,g} = 1) - U_{ij,g}(d_{ij,g} = 0) = V_{ij,g}(L_g, \mathcal{A}) + r_{ij,g},$$

where $V_{ij,g}(L_g, \mathcal{A})$ is the observed link formation due to exogenous effects with specific elements, $l_{ij,g}$, as a vector of observed dyad-specific variables (such as age, sex, years of schooling etc.) and attributes of the link between i and j such as geographical and social distance between them. $r_{ij,g}$ is the error term and represents the unobservable characteristics that effect link formation between i, j, and $\mathcal{A}$ is a vector of parameter estimates.

We implement this by estimating a conditional edge independence model, which assumes links form independently, conditional on node- and link- level covariates (Fafchamps and Gubert 2007; Chandrasekhar and Lewis 2016) as follows;

$$\text{(B2)} \quad P_{ij} = a_0 + a_1|l_{i,g} - l_{j,g}| + a_2(l_{i,g} + l_{j,g}) + a_3|l_{ij,g}| + r_{ij,g}$$

where P_{ij} is an $N \times (N-1)$ matrix indicating whether there is a link between individuals i and j, $l_{i,g}$ and $l_{j,g}$ are characteristics of individual i and j. a_1 measures the influence of differences in their attributes, and a_2 measures the effect of combined level of their attributes. $l_{ij,g}$ captures attributes of the link between i and j such as geographical or social distance between them, and a_3 is the associated parameter estimate. The estimates of eq. (B1.1) are reported in table 3.B1.

With respect to potential endogeneity due to unobservables at the farmer link formation level, we retrieved the predicted residuals, $\hat{r}_{ij,g}$, and inserted these into our estimation equation to account for these threats. This also allows us to account for concerns of measurement errors due to the use of sampled networks (Chandrasekhar and Lewis 2016) by using the predicted probabilities of links in the respective village networks to simulate the completed networks of the villages. This is termed the graphical reconstruction approach by Chandrasekhar and Lewis (2016). With this, we are able to reconstruct the networks and thus able to predict what we would find if we had the missing part of the networks. This was used to perform sensitivity checks of our parameters to measurement errors due to the use of the sample data (see figures in table 3.B2 for a number of the sampled networks and their respective reconstructed versions).

B.2 The network formation estimates

Table 3.B1. Dyadic logit regression of network formation model

	Village1	Village2	Village3	Village4	Village5	Village6	Village7	Village8	Village9
Distance between peers in kilometres	-0.040	0.025	0.116**	-0.035	-0.025	-0.005	-0.075	-0.019	-0.006
	(0.062)	(0.044)	(0.050)	(0.039)	(0.079)	(0.045)	(0.059)	(0.048)	(0.044)
Difference in distance to road between peers in kilometres	-0.003	0.202*	-0.044	0.076	-0.020	0.094**	-0.171***	0.042**	0.041
	(0.030)	(0.104)	(0.055)	(0.058)	(0.030)	(0.038)	(0.029)	(0.019)	(0.025)
Relatives = 1	0.013	0.121	0.064	-0.323	0.304	0.294	0.407	-0.001	-0.685**
	(0.339)	(0.369)	(0.580)	(0.558)	(0.389)	(0.662)	(0.303)	(0.508)	(0.349)
Same religion = 1	n.a	n.a.	-0.095	-0.730**	-0.652**	-0.020	-0.610*	-0.013	-0.281
	n.a.	n.a.	(0.245)	(0.329)	(0.326)	(0.486)	(0.342)	(0.402)	(0.323)
Difference: Sex (= 1 if male)	1.150***	0.821***	7.767***	-0.306	0.428	0.013	0.334	0.976***	0.260
	(0.342)	(0.251)	(0.375)	(0.256)	(0.332)	(0.258)	(0.329)	(0.300)	(0.516)
Difference: Age	0.004	-0.031**	0.031**	-0.003	0.003	-0.037***	-0.044	-0.001	0.041***
	(0.008)	(0.013)	(0.013)	(0.015)	(0.013)	(0.012)	(0.031)	(0.016)	(0.014)
Difference: Years of schooling	0.090**	0.015	0.066	0.062	-0.046	-0.081**	-0.175***	6.946***	0.020
	(0.046)	(0.040)	(0.050)	(0.064)	(0.043)	(0.033)	(0.043)	(0.611)	(0.067)
Difference: Household size	-0.212**	-0.097	-0.080	0.067	0.074	0.157**	0.046	-0.177***	0.103
	(0.097)	(0.096)	(0.090)	(0.085)	(0.099)	(0.073)	(0.098)	(0.052)	(0.070)
Difference: Household landholding in hectares	-0.239	-0.200**	0.098	0.343***	-0.172	0.487**	0.369***	0.008	-0.071
	(0.218)	(0.096)	(0.173)	(0.119)	(0.201)	(0.217)	(0.130)	(0.082)	(0.132)
Difference: Village born = 1 if farmer was born in village	1.065**	0.287	-0.469	0.845***	0.374	-0.028	0.607**	0.143	-0.671**
	(0.513)	(0.353)	(0.310)	(0.290)	(0.342)	(0.323)	(0.266)	(0.448)	(0.307)
Difference: Household wealth (predicted) in GHS	1.173	-0.223	0.882	0.189	-0.181	-0.288	-0.589	-1.611	0.060
	(1.211)	(0.786)	(0.685)	(0.993)	(1.060)	(0.798)	(0.665)	(1.840)	(0.843)
Sum: Sex (= 1 if male)	-0.651***	0.483***	7.522***	-0.345	0.160	0.380*	-1.051***	0.637**	0.295
	(0.239)	(0.185)	(0.356)	(0.217)	(0.329)	(0.229)	(0.215)	(0.313)	(0.311)
Sum: Age	-0.005	0.011	-0.019	-0.023***	-0.010	0.001	-0.005	0.027***	-0.015
	(0.007)	(0.008)	(0.013)	(0.008)	(0.010)	(0.008)	(0.016)	(0.008)	(0.011)
Sum: Years of schooling	-0.018	0.028	0.012	-0.141**	0.008	0.042	0.008	-6.015***	-0.066
	(0.042)	(0.020)	(0.037)	(0.062)	(0.038)	(0.026)	(0.036)	(0.646)	(0.058)
Sum: Household size	-0.010	0.163***	0.112	-0.002	0.091	-0.040	0.140***	0.106*	0.121***
	(0.051)	(0.056)	(0.070)	(0.051)	(0.057)	(0.036)	(0.038)	(0.054)	(0.046)
Sum: Household landholding in hectares	-0.051	-0.005	0.011	0.113	0.174	-0.360**	0.134	0.083	0.173*
	(0.113)	(0.062)	(0.136)	(0.136)	(0.120)	(0.159)	(0.100)	(0.081)	(0.097)
Sum: Village born = 1 if farmer was born in village	1.019***	0.169	0.096	0.029	0.921***	0.259	0.794***	0.955**	-0.925***
	(0.367)	(0.331)	(0.283)	(0.217)	(0.342)	(0.255)	(0.266)	(0.394)	(0.190)
Intercept	-3.504*	-5.325***	-17.991***	0.004	-3.781*	-1.176	-3.036	-4.480	-1.282
	(1.983)	(1.838)	(1.825)	(1.742)	(1.941)	(1.986)	(1.876)	(4.427)	(1.827)
N	400	400	400	400	400	400	400	400	400
Pseudo R^2	0.114	0.072	0.092	0.082	0.061	0.077	0.146	0.083	0.080

Notes: the table reports results of the dyadic regression of network link formation in eq. (B2). The dependent variable = 1 if i (j) cites i (j) as knowing the other. Estimator is logit and all standard errors are clustered at the village level. Standard errors are in parenthesis. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 3.B1. (continued)

	Village10	Village11	Village12	Village13	Village14	Village15	Village16	Village17	Village18
Distance between peers in kilometres	0.011	-0.079	-0.058	-0.022	0.028	0.038	-0.065	-0.042	0.018
	(0.043)	(0.064)	(0.038)	(0.056)	(0.054)	(0.042)	(0.045)	(0.035)	(0.052)
Difference in distance to road between peers in kilometres	0.002	6.556**	-0.024	0.065	0.047**	0.069**	-0.142**	0.034	0.617
	(0.026)	(2.820)	(0.053)	(0.069)	(0.022)	(0.031)	(0.060)	(0.047)	(3.403)
Relatives = 1	0.026	0.274	0.051	-0.025	-0.346	0.570	-0.685**	0.103	-0.712
	(0.241)	(0.384)	(0.382)	(0.552)	(0.283)	(0.376)	(0.304)	(0.514)	(0.435)
Same religion = 1	0.324	-0.129	0.320	0.038	-0.369	0.349	-0.811*	0.183	0.759
	(0.389)	(0.361)	(0.317)	(0.268)	(0.307)	(0.503)	(0.439)	(0.342)	(0.506)
Difference: Sex (= 1 if male)	-0.400	0.254	0.522	-0.134	0.437	0.744**	0.381	0.821***	-0.919***
	(0.293)	(0.314)	(0.461)	(0.344)	(0.335)	(0.359)	(0.359)	(0.283)	(0.195)
Difference: Age	0.017	-0.028*	0.009	0.026***	-0.051***	0.038***	0.093***	0.033	0.010
	(0.014)	(0.014)	(0.012)	(0.010)	(0.017)	(0.010)	(0.036)	(0.023)	(0.009)
Difference: Years of schooling	1.131***	-0.033	0.060	1.402***	3.489***	-0.044*	3.064***	-0.143***	0.144*
	(0.073)	(0.050)	(0.052)	(0.103)	(0.189)	(0.025)	(0.386)	(0.055)	(0.075)
Difference: Household size	-0.117	0.087	0.005	0.163	-0.223**	-0.123	0.011	-0.043	-0.042
	(0.082)	(0.069)	(0.120)	(0.118)	(0.091)	(0.103)	(0.063)	(0.133)	(0.082)
Difference: Household landholding in hectares	0.137	-0.067	0.007	0.579***	0.130	-0.197*	0.089	-0.115	0.268*
	(0.169)	(0.085)	(0.146)	(0.152)	(0.153)	(0.110)	(0.113)	(0.149)	(0.155)
Difference: Village born = 1 if farmer was born in village	0.227	-0.395	0.907**	-0.570	-0.262	-0.865***	6.740***	-0.062	-0.122
	(0.272)	(0.320)	(0.444)	(0.382)	(0.239)	(0.262)	(0.516)	(0.232)	(0.313)
Difference: Household wealth (predicted) in GHS	-0.205	-0.709	0.541	0.152	0.826	-1.780***	2.738*	-0.858	2.433***
	(1.309)	(1.303)	(1.063)	(0.658)	(1.291)	(0.588)	(1.592)	(0.976)	(0.935)
Sum: Sex (= 1 if male)	0.535**	-0.027	0.500*	0.874***	0.942***	0.577**	0.548*	-0.068	0.426**
	(0.250)	(0.298)	(0.296)	(0.212)	(0.298)	(0.277)	(0.314)	(0.266)	(0.175)
Sum: Age	0.019**	0.000	-0.010	-0.011	0.012	-0.032***	-0.056**	-0.029**	-0.002
	(0.009)	(0.010)	(0.011)	(0.008)	(0.013)	(0.008)	(0.025)	(0.012)	(0.009)
Sum: Years of schooling	-1.125***	-0.043	-0.033	-1.482***	-3.470***	-0.014	-3.092***	0.071***	0.088
	(0.087)	(0.034)	(0.048)	(0.080)	(0.180)	(0.031)	(0.398)	(0.022)	(0.068)
Sum: Household size	-0.093	0.172***	0.130*	-0.153*	0.064	0.028	-0.037	0.171**	0.048
	(0.097)	(0.053)	(0.072)	(0.093)	(0.046)	(0.061)	(0.076)	(0.083)	(0.041)
Sum: Household landholding in hectares	0.083	0.091	-0.013	-0.539***	-0.246***	0.181*	-0.058	-0.129	-0.115
	(0.134)	(0.064)	(0.115)	(0.143)	(0.094)	(0.107)	(0.096)	(0.093)	(0.102)
Sum: Village born = 1 if farmer was born in village	0.422	0.392	0.572	0.362	-0.039	0.082	6.841***	0.078	-0.231
	(0.268)	(0.277)	(0.405)	(0.288)	(0.256)	(0.234)	(0.487)	(0.218)	(0.196)
Intercept	-3.558**	-2.183	-5.001**	0.240	-3.804**	0.751	-14.108***	1.407	-3.877**
	(1.657)	(2.780)	(2.115)	(1.978)	(1.606)	(1.442)	(2.475)	(2.590)	(1.602)
N	400	400	400	400	400	400	400	400	400
Pseudo R^2	0.049	0.059	0.047	0.117	0.096	0.113	0.122	0.073	0.073

Notes: the table reports results of the dyadic regression of network link formation in eq. (B2). The dependent variable = 1 if i (j) cites i (j) as knowing the other. Estimator is logit and all standard errors are clustered at the village level. Standard errors are in parenthesis. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 3.B1. (continued)

	Village19	Village20	Village21	Village22	Village23	Village24	Village25
Distance between peers in kilometers	-0.006	-0.040	0.044	0.060	-0.009	0.018	0.009
	(0.061)	(0.046)	(0.050)	(0.067)	(0.039)	(0.030)	(0.047)
Difference in distance to road between peers in kilometres	0.012	-1.666	0.024	0.059**	0.686	0.820	0.024
	(0.008)	(3.250)	(0.016)	(0.024)	(0.659)	(2.653)	(0.018)
Relatives = 1	-0.471*	0.227	-0.523	1.345	0.090	0.390*	0.717
	(0.268)	(0.307)	(0.538)	(1.195)	(0.272)	(0.205)	(0.605)
Same religion = 1	-0.304	n.a.	0.152	0.107	0.180	n.a.	-0.014
	(0.383)	n.a.	(0.423)	(0.578)	(0.479)	n.a.	(0.384)
Difference: Sex (= 1 if male)	-0.385	-0.457	0.744*	8.166***	-0.352	0.849*	0.435
	(0.275)	(0.278)	(0.392)	(0.399)	(0.423)	(0.447)	(0.336)
Difference: Age	0.003	-0.009	0.029	-0.000	-0.040**	-0.016	0.012
	(0.019)	(0.012)	(0.025)	(0.014)	(0.020)	(0.018)	(0.019)
Difference: Years of schooling	0.009	0.421***	0.142***	n.a.	0.043	-0.054*	0.803***
	(0.045)	(0.062)	(0.050)	n.a.	(0.065)	(0.030)	(0.060)
Difference: Household size	0.049	0.252***	0.229***	0.076	0.086	0.149*	0.020
	(0.063)	(0.093)	(0.081)	(0.097)	(0.088)	(0.089)	(0.082)
Difference: Household landholding in hectares	-0.066	0.619***	-0.263	0.126	-0.077	-0.088	0.289***
	(0.088)	(0.235)	(0.218)	(0.163)	(0.100)	(0.105)	(0.085)
Difference: Village born = 1 if farmer was born in village	6.526***	0.210	-0.235	0.638	8.173***	-0.273	-1.469***
	(0.422)	(0.327)	(0.412)	(0.490)	(0.403)	(0.315)	(0.419)
Difference: Household wealth (predicted) in GHS	1.450	-2.289***	-0.522	2.782***	-0.100	-1.353	-3.162***
	(1.150)	(0.794)	(1.269)	(0.976)	(0.639)	(0.884)	(0.861)
Sum: Sex (= 1 if male)	0.504*	0.219	0.161	8.878***	-0.293	0.810**	0.134
	(0.284)	(0.173)	(0.278)	(0.517)	(0.245)	(0.388)	(0.294)
Sum: Age	-0.012	0.030**	-0.002	0.017	0.010	-0.004	0.016
	(0.011)	(0.013)	(0.021)	(0.015)	(0.011)	(0.013)	(0.012)
Sum: Years of schooling	0.033	-0.460***	0.019	n.a.	0.210***	0.077***	-0.733***
	(0.024)	(0.047)	(0.059)	n.a.	(0.037)	(0.021)	(0.045)
Sum: Household size	-0.000	0.099	-0.284***	0.028	-0.072	-0.044	0.196***
	(0.048)	(0.085)	(0.056)	(0.062)	(0.062)	(0.054)	(0.055)
Sum: Household landholding in hectares	0.123	-0.413*	0.248	-0.382*	0.270***	-0.078	-0.063
	(0.092)	(0.213)	(0.169)	(0.198)	(0.082)	(0.085)	(0.080)
Sum: Village born = 1 if farmer was born in village	6.413***	0.725***	-0.821***	1.116**	7.525***	-0.381	0.213
	(0.380)	(0.228)	(0.278)	(0.435)	(0.430)	(0.240)	(0.374)
Intercept	-17.238***	-2.388	0.730	-26.287***	-18.598***	-0.160	-0.735
	(2.569)	(1.844)	(2.514)	(2.386)	(1.453)	(1.444)	(2.445)
N	400	400	400	400	400	400	400
Pseudo R^2	0.075	0.083	0.201	0.155	0.160	0.086	0.155

Notes: the table reports results of the dyadic regression of network link formation in eq. (B2). The dependent variable = 1 if i (j) cites i (j) as knowing the other. Estimator is logit and all standard errors are clustered at the village level. Standard errors are in parenthesis. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 3.B2. Sampled and simulated networks by quintiles of modularity

1. Sampled network	2. Simulated networks
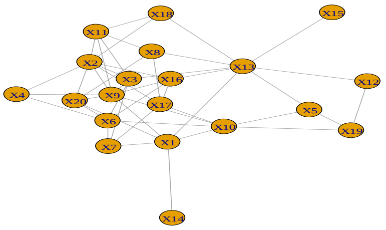	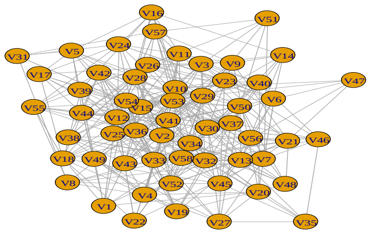
Fig. 1A. Lowest modularity network (0.143)	Fig. 2A. Lowest modularity network (0.163)
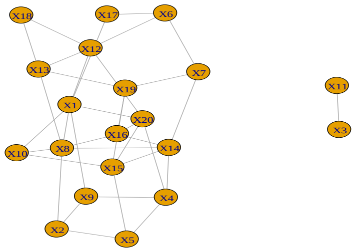	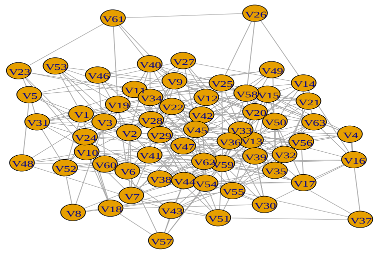
Fig. 1B. Mean modularity network (0.289)	Fig. 2B. Lowest modularity network (0.205)
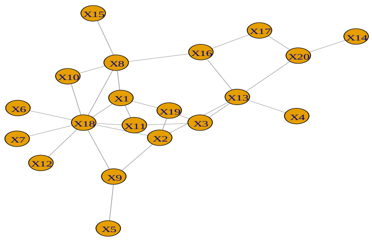	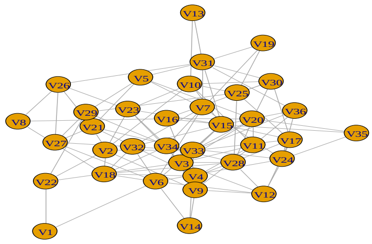
Fig. 1C. Median modularity network (0.345)	Fig. 2C. Lowest modularity network (0.233)
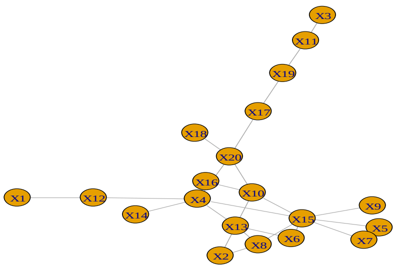	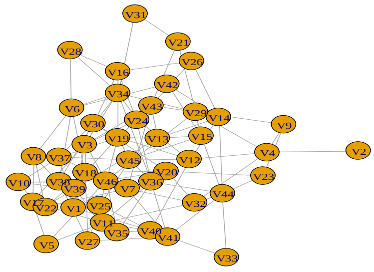
Fig. 1D. Highest modularity network (0.414)	Fig. 2D. Lowest modularity network (0.319)

Notes: the table shows plots of some of the social networks by quintiles of modularity in two columns. Column 1 shows a cross section of the sampled networks used categorized into the network at the lowest (Fig. 1A), at the mean (Fig. 1B), at the median (Fig. 1C) and at the highest (Fig. 1D) of modularity distribution. Column 2 shows the respective simulated (i.e., reconstructed) versions of these sampled networks based on the approach of Chandrasekhar and Lewis (2016). Figs. 1A and 1B have more interconnected nodes and lower modularity statistics, of 0.143 and 0.289, respectively, than figs. 1C and 1D. Similar trend is observed in the modularity statistics when calculated with simulated complete versions of these networks in figs. 2A-2D. We, therefore, expect learning and diffusion to be faster in the case of figures A and B.

Table 3.B3. Instrumenting regression for Wealth in Dyadic model

	Difference of wealth			Sum of wealth		
	Coefficient	**Robust S. E.**	**Dyadic S. E.**	**Coefficient**	**Robust S. E.**	**Dyadic S. E.**
	All regressors as difference			**All regressors as sums**		
	(1)	(2)	(3)	(4)	(5)	(6)
Sex = 1 if male	0.080	0.036	0.086	−0.237*	0.034	0.154
Years of education of farmer	−0.026**	0.004	0.010	−0.040**	0.004	0.017
Born = 1 if born in village	−0.106*	0.036	0.069	0.200*	0.034	0.144
Value of inherited land in GHS	0.277***	0.040	0.089	0.925***	0.048	0.142
District dummies						
1 if farmer resides in district 1	−0.322	0.052	0.262	−0.552*	0.066	0.397
1 if farmer resides in district 2	−0.493**	0.051	0.257	−0.757**	0.066	0.405
1 if farmer resides in district 3	0.298	0.068	0.327	0.429	0.090	0.539
1 if farmer resides in district 4	−0.150	0.082	0.426	−0.369	0.097	0.560
Intercept	1.488***	0.056	0.214	2.614***	0.088	0.429
N	9500			9500		

Notes: the table presents first-stage estimates for instrumenting wealth in the dyadic link formation model. Columns 1, 2 and 3 present results for the difference of wealth between neighbors. Value of inherited land is use as the instrument. Columns 4, 5 and 6 show results of the sum of wealth estimates. The table also show both the conventional robust standard errors (in columns 2 and 5) and the Fafchamps and Gubert (2007) group dyadic standard errors (columns 3 and 6). The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Appendix C

Other estimates

Table 3.C1. Control and contextual variables in Table 6

	(5)		(6)		(7)		(8)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Household controls, γ_1								
Age	-0.008	0.006	-0.008	0.006	-0.008	0.006	-0.008	0.006
Gender	0.325	0.213	0.355	0.217	0.325	0.210	0.356*	0.215
Education	0.131***	0.039	0.130***	0.039	0.129***	0.040	0.128***	0.040
Experience	-0.229***	0.041	-0.226***	0.040	-0.228***	0.042	-0.225***	0.040
Household	-0.083	0.054	-0.085	0.055	-0.082	0.054	-0.084	0.055
Landholding	0.270***	0.071	0.263***	0.071	0.228***	0.071	0.259***	0.070
Credit	-0.306	0.774	-0.195	0.780	-0.354	0.784	-0.238	0.790
Risk	0.021	0.074	0.027	0.076	0.023	0.075	0.029	0.076
Extension	1.024	0.866	1.157	0.868	0.998	0.870	1.139	0.872
Association	-0.322***	0.100	-0.325***	0.100	-0.322***	0.100	-0.326***	0.100
Price	-1.742**	0.621	-1.814***	0.610	-1.727**	0.616	-1.806***	0.605
Soil quality	0.530***	0.155	0.385***	0.111	0.526***	0.156	0.526***	0.157
Contextual (peer) controls, γ_2								
Gage	0.010	0.012	0.011	0.012	0.009	0.012	0.010	0.012
GGender	-0.596*	0.306	-0.551*	0.306	-0.588*	0.302	-0.543*	0.301
GEducation	-0.043	0.052	-0.041	0.052	-0.038	0.051	-0.035	0.050
GHousehold	-0.009	0.078	-0.005	0.078	0.010	0.076	0.007	0.078
GLandholding	-0.061	0.106	-0.053	0.106	-0.054	0.105	-0.046	0.107
GCredit	-0.400	0.267	-0.397	0.267	-0.390	0.263	-0.389	0.266
GRisk	0.237	0.164	0.241	0.164	0.233	0.166	0.237	0.163
GExtension	0.337	0.375	0.355	0.375	0.336	0.373	0.354	0.374
GAssociation	0.096	0.143	-0.105	0.143	0.086	0.142	0.095	0.139
GPrice	-0.859	0.684	-0.916	0.684	-0.889	0.685	-0.951	0.687
GSoil quality	-0.079	0.150	-0.079	0.150	-0.086	0.150	-0.086	0.147
Time effects, δ_t								
Year 3&4	0.736***	0.183	0.735***	0.180	0.739***	0.190	0.738***	0.187
Year 5&6	1.081***	0.339	1.111***	0.331	1.089***	0.350	1.120***	0.341
Year 7&8	1.509***	0.374	1.535***	0.367	1.544***	0.389	1.572***	0.382
Year 9&10	1.945***	0.432	1.964***	0.420	1.985***	0.445	2.006***	0.432
Year 11&12	1.798***	0.467	1.808***	0.456	1.841***	0.474	1.853***	0.462
Year 13&14	1.842***	0.520	1.785***	0.516	1.879***	0.528	1.820***	0.522
Link residuals, $\hat{r}_t$								
Av.Residual 1st quintile	-5.768***	1.970	-6.142***	2.011	-5.709***	1.939	-6.097***	1.983
Av.Residual 2nd quintile	10.067**	3.823	9.530**	3.945	9.433**	3.671	8.883**	3.791
Av.Residual 3rd quintile	1.265*	0.765	1.029	0.742	1.251*	0.752	1.015	0.729
Av.Residual 4th quintile	0.076	0.122	0.037	0.133	0.080	0.120	0.041	0.131
Av.Residual 5th quintile	-0.156	0.097	-0.170*	0.089	-0.162	0.098	-0.178*	0.091
District fixed-effects								
SaveluguNanton	-0.781***	0.229	-0.770***	0.229	-0.768***	0.234	-0.758***	0.234
Karaga	-0.668*	0.358	-0.580	0.356	-0.663*	0.360	-0.574	0.357
Gushegu	-0.984**	0.366	-0.886**	0.372	-0.989**	0.369	-0.888**	0.374
First-stage residuals								
Residuals Extension	-0.098	0.522	-0.158	0.527	-0.094	0.525	-0.158	0.529
Residuals Liquidity constr.	-0.288	0.408	-0.351	0.415	-0.264	0.414	-0.329	0.421

Notes: The table presents coefficients of controls of the models in columns 5-8 of table 3.6. D is the social network. Years 1 and 2 are the reference years. Av.Residual is the average residuals of the link formation model over a given quintile arranged in ascending order – 1st quintile is average of the predicted residuals of the first four set of peers of a household with the least predicted residuals (i.e., less likely to link up due to unobserved determinant of link formation). The 2nd quintile is the average residuals of the link formation model for the next set of four peers and so on until the 5th set of four peers as those with the highest residuals (i.e., those most likely to link up due to unobserved determinants of link formation). These are used as instruments to account for potential endogeneity due to correlated unobservables at the link formation level. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 3.C2. Control and contextual variables in Table 7

	(1)		(2)		(3)		(4)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Household controls								
Age	-0.008	0.006	-0.008	0.006	-0.009	0.006	-0.008	0.006
Gender	0.336*	0.201	0.365*	0.208	0.364*	0.210	0.395*	0.215
Education	0.128***	0.039	0.127***	0.039	0.133***	0.039	0.134***	0.039
Experience	-0.218***	0.043	-0.217***	0.042	-0.225***	0.040	-0.218***	0.038
Household	-0.076	0.052	-0.080	0.053	-0.077	0.053	-0.083	0.053
Landholding	0.263***	0.071	0.258***	0.071	0.256***	0.070	0.250***	0.069
Credit	-0.293	0.734	-0.176	0.746	-0.108	0.757	-0.003	0.773
Risk	0.019	0.073	0.025	0.076	0.026	0.069	0.024	0.070
Extension	0.897	0.851	1.055	0.861	1.306	0.843	1.319	0.865
Association	-0.314***	0.097	-0.318***	0.098	-0.344***	0.097	-0.339***	0.096
Price	-1.690**	0.638	-1.779**	0.629	-1.683**	0.605	-1.672***	0.574
Soil quality	0.515***	0.152	0.518***	0.153	0.497***	0.148	0.505***	0.148
Contextual (peer) controls								
Gage	0.010	0.012	0.011	0.012	0.007	0.012	0.008	0.012
GGender	-0.516*	0.271	-0.473*	0.277	-0.553*	0.326	-0.526*	0.315
GEducation	-0.042	0.052	-0.040	0.051	-0.036	0.054	-0.035	0.052
GHousehold	0.001	0.075	-0.002	0.078	0.001	0.072	0.001	0.076
GLandholding	-0.061	0.101	-0.051	0.104	-0.050	0.096	-0.061	0.098
GCredit	-0.397	0.263	-0.392	0.268	-0.391	0.280	-0.417	0.278
GRisk	0.232	0.161	0.238	0.159	0.210	0.153	0.221	0.154
GExtension	0.300	0.373	0.331	0.370	0.349	0.356	0.349	0.356
GAssociation	0.110	0.139	0.122	0.136	0.080	0.140	0.072	0.135
GPrice	-0.920	0.659	-0.970	0.666	-0.781	0.667	-0.874	0.671
GSoil quality	-0.093	0.150	-0.091	0.148	-0.097	0.145	-0.101	0.143
Time effects								
Year 3&4	0.726***	0.177	0.729***	0.176	0.745***	0.178	0.746***	0.175
Year 5&6	1.018***	0.335	1.058***	0.328	1.114***	0.344	1.137***	0.333
Year 7&8	1.413***	0.350	1.455***	0.351	1.535***	0.379	1.561***	0.366
Year 9&10	1.813***	0.404	1.850***	0.402	1.964***	0.444	1.987***	0.426
Year 11&12	1.613***	0.416	1.647***	0.417	1.804***	0.471	1.821***	0.456
Year 13&14	1.590***	0.483	1.545***	0.501	1.914***	0.539	1.900***	0.530
Link residuals								
Av.Residual 1st quartile	-5.441***	1.888	-5.932***	1.926	-5.671***	1.818	-5.820***	1.835
Av.Residual 2nd quartile	9.985**	3.675	9.447**	3.815	9.861**	3.642	9.436**	3.749
Av.Residual 3rd quartile	1.241	0.838	0.974	0.803	1.138	0.765	0.998	0.737
Av.Residual 4th quartile	0.075	0.116	0.029	0.128	0.091	0.122	0.077	0.130
Av.Residual 5th quartile	-0.186**	0.090	-0.196**	0.082	-0.095	0.099	-0.103	0.095
District fixed-effects								
SaveluguNanton	-0.813***	0.198	-0.799***	0.205	-0.668***	0.231	-0.679***	0.224
Karaga	-0.655*	0.335	-0.563*	0.339	-0.618*	0.353	-0.577*	0.343
Gushegu	-0.981***	0.322	-0.879**	0.338	-0.890**	0.377	-0.813**	0.378
First-stage residuals								
Residuals Extension	-0.033	0.507	-0.103	0.517	-0.245	0.509	-0.243	0.526
Residuals Liquidity constr.	-0.305	0.392	-0.373	0.400	-0.361	0.409	-0.428	0.415

Notes: The table presents coefficients of controls of the models in columns 5-8 of table 3.6. D is the social network. Years 1 and 2 are the reference years. Av.Residual is the average residuals of the link formation model over a given quintile arranged in ascending order – 1st quintile is average of the predicted residuals of the first four set of peers of a household with the least predicted residuals (i.e., less likely to link up due to unobserved determinant of link formation). The 2nd quintile is the average residuals of the link formation model for the next set of four peers and so on until the 5th set of four peers as those with the highest residuals (i.e., those most likely to link up due to unobserved determinants of link formation). These are used as instruments to account for potential endogeneity due to correlated unobservables at the link formation level. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Appendix D

Endogeneity of credit-constraint and extension contact

The final issue we address is the potential endogeneity of credit-constraint and extension contact. Credit-constraint could be endogenous because farmers with higher yields and incomes will be less credit-constrained as a result of the associated increased yields and incomes from adoption. On the other hand, extension contact could be endogenous because extension officers may be more inclined to visit farmers who adopted than farmers who did not adopt. We used a two-stage generalized residual inclusion estimation procedure suggested by Wooldridge (2015), where we first estimate a probit model for each of these endogenous variables using the variables in the diffusion model (to be estimated in the second-stage) and two instruments in each case as explanatory variables. The generalized residuals from the first-stage estimation are then included with the observed values of the potentially endogenous variables in the second-stage specification.

We use credit-constraint and extension contacts of farmer i's indirect, $X_{it}' G_t^{2,\text{n}}$, [i.e., first $(i, j + 1)$ generation] peers (neighbors) as instruments. These are considered valid and relevant instruments because the credit-constraint and extension contacts of the $j + 1$ peers of farmer i relate indirectly to his own credit-constraint and extension contacts through the credit-constraints and extension contacts of his direct neighbors j, (i.e., $X_t' G_t^{\text{n}}$) who are direct peers of the $j + 1$ peers. These variables, however, are not expected to directly affect the farmer's conditional probability of adoption. Bramoulle et al. (2009) show that these are valid instruments once there are intransitive triads[36] in the network, so that the characteristics of the first and higher generation neighbors of the farmer affect the characteristics and outcomes of

[36] The average transitivity statistics in table 3.4 is less than 0.2 across the networks, suggesting that majority of triads on average are intransitive.

the farmer through his direct neighbors. Estimates of the first-stage probit are presented in table 3.D1.

Table 3.D1. First stage probit estimates for credit constraints and extension contact

Variable	Credit constraint		Extension	
	Coefficient	**S.E.**	**Coefficient**	**S.E.**
Age	-0.004	0.005	0.003	0.005
Gender	-0.489***	0.141	-0.078	0.147
Education	0.045*	0.022	-0.002	0.021
Experience	-0.016	0.020	-0.029	0.019
Household	-0.025	0.030	0.001	0.032
Landholding	-0.069	0.046	0.094**	0.044
Credit			-0.394**	0.141
Risk	0.104*	0.055	-0.157**	0.061
Extension	-0.391**	0.147		
Association	-0.146**	0.057	-0.206***	0.054
Price	-1.410***	0.417	2.251***	0.441
Soil quality	-0.103	0.071	0.068	0.075
DAge	-0.003	0.009	-0.004	0.009
DGender	0.115	0.237	-0.119	0.240
DEducation	0.056**	0.036	-0.039	0.038
DExperience	0.004	0.034	-0.003	0.032
DHousehold	0.044	0.048	-0.017	0.058
DLandholding	-0.021	0.077	-0.022	0.086
DCredit	-0.267	0.270	-0.080	0.278
DRisk	-0.137	0.092	0.123	0.097
DExtension	0.093	0.248	-0.554*	0282
DAssociation	-0.014	0.093	0.089	0.095
DPrice	-0.279	0.633	0.628	0.661
DSoil quality	-0.037	0.109	0.108	0.119
D^2Credit	2.942***	0.483	-	-
D^2Extension	-		2.741***	0.572
Constant	2.113	1.161	-5.462***	1.214
Instrument validity $\boldsymbol{X^2}$(p-value)	37.12(0.000)		23.01(0.000)	
Log likelihood	-252.34		-227.64	
Wald ($\boldsymbol{X^2_{25}}$)	144.35		140.94	
p-value	0.000		0.000	
Pseudo $\boldsymbol{R^2}$	0.265		0.288	

Notes: the table presents first-stage estimates of credit constraints and extension contacts of households. S.E. is robust standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

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Chapter Four

Social networks, adoption of improved variety and household welfare: Evidence from Ghana

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Abstract

In this study, we examine the effects of own and peer adoption of improved soybean variety on household yields, food and nutrients consumption, using observational data from Ghana. We employ the marginal treatment effect approach to account for treatment effects heterogeneity across households, and a number of identification strategies to capture social network effects. Our empirical results show that households with higher unobserved gains are more likely to adopt because of their worse outcomes when not adopting. We also find strong peer adoption effect on own yield, only when the household is also adopting, and on food and nutrients consumption when not adopting. However, the peer adoption effect on consumption attenuates when the household adopts the improved variety. Furthermore, our findings reveal that adoption tends to equalize households in terms of observed and unobserved gains on consumption, and can thus serve as a mechanism for promoting food security and nutrition in this area.

JEL codes: C21, D60, D85, O13, O33

Keywords: Improved variety, Technology adoption, Social networks, Marginal treatment effects, Food and nutrition security

4.1 Introduction

Food insecurity remains a major concern across many sub-Saharan African countries, despite significant strives and improvements in agricultural technologies and crop varieties over the past few decades (Shiferaw et al. 2014; FAO, et al. 2019). Globally, the prevalence of hunger increased from 10.6% in 2015 to 10.8% in 2018, while that of sub-Saharan Africa increased from 20.9% in 2015 to 22.8% in 2018 (FAO, et al. 2019), suggesting the prevalence in sub-Saharan Africa is not only twice that of the world prevalence, but also a cumulative increase from 2015 of about nine times that of the world. This increasing food insecurity in the midst of increased availability of improved agricultural technologies, particularly in sub-Saharan Africa (Minten and Barrett 2008; Shiferaw et al. 2014), suggest the need to obtain better understanding of technology adoption and consumption of food and specific nutrients in order to enhance the effectiveness of improved technologies in addressing food insecurity in these areas.

While the literature has made significant strides in investigating the importance of improved crop varieties on household welfare, not much consideration has been given to the impact of improved crop varietal adoption by households and their peers on household food and nutrients consumption (Minten and Barrett 2008; Shiferaw et al. 2014; Smale et al. 2015; Verkaart et al. 2017). Also, studies that examined the impact of technology adoption on performance outcomes tend to focus on crop yield and income related measures (e.g., Becerril and Abdulai, 2010; Abdulai and Huffman 2014; Verkaart et al. 2017; Wossen et al. 2019). There is virtually no rigorous empirical evidence on the potential impact of improved crop varieties on the consumption of specific nutrient rich foods among households (Hotz et al. 2012; Smale et al. 2015; Larsen and Lilleør 2016; Ogutu et al. 2020)[37]. The few that examined the impact of

[37] Previous studies focused on production diversification on households' and children's dietary diversity and consumption of specific food groups (Dillon et al. 2015; Lovo and Veronesi 2019); caregivers nutrition knowledge on the types of foods

improved crop varietal adoption on food security and nutrition focused on food group diversity and vitamin A intake (Hotz et al. 2012; Smale et al. 2015; Larsen and Lilleør 2016), without much consideration given to the other components of nutrients such as protein rich food intake. In particular, improving household consumption of protein rich foods is important in the prevention of wasting, stunting and micronutrients deficiencies that cause diseases and deaths[38]. Thus, a better understanding of the link between adoption of improved technology and consumption of food and these specific nutrients is key in helping policy-makers design policies to promote food and nutrition security.

Despite the increasing interest in understanding the role of social interaction on households' decision-making and individual welfare (e.g., Bandiera and Rasul 2006; Fafchamps and Gubert 2007; Conley and Udry 2010; Garcia et al. 2014; De Giorgi et al. 2020), the voluminous literature on social interactions has virtually not provided evidence on the potential benefits of peer adoption of agricultural technologies on household food and nutrients consumption. With the exception of a few such as Maurer and Meier (2008), and De Giorgi et al. (2020) on endogenous consumption peer effects; and Kuhn et al. (2011) on lottery prices[39], this has not been done on peer adoption effects. There are various reasons one will expect spill overs from peer adoption on household food and nutrients consumption. First, peer adoption that leads to

consumed by children (Hirvonen et al. 2017) and the impacts of improved extension designs on smallholder sensitivity to nutrition (Ogutu et al. 2020). See Sibhatu and Qaim (2018) for a meta-analysis.

[38] The World Food Program (2015) argues that tackling vitamin A deficiency, before the age of five, can reduce mortality and infectious diseases up to a third.

[39] Maurer and Meier (2008) study intertemporal consumption effects among peers using panel data from US, and find moderate, but significant evidence of consumption externalities across peer-groups. De Giorgi et al. (2020) investigate consumption network effects, using administrative dataset and complementing it with data on consumption survey of households' expenditure on goods, and find peer consumption effects on household consumption to be non-negligible. Kuhn et al. (2011) study the effect of lottery prices on neighbors of winners, and find evidence for effects of lottery prices on winners' neighbors, but only for consumption of cars.

increased learning opportunities and productivity of the household can enhance the household's consumption, especially in rural Africa, where the issues of missing and inefficient markets are prevalent (de Janvry et al. 1991). Second, when peer adoption leads to increased peer productivity, and changes in peer consumption, can affect household consumption either due to endogenous peer effect, or through private cash transfers to the household in a form of safety net.

The purpose of this study is twofold: to investigate the effect of household adoption of improved crop variety on the consumption of food and specific nutrients among households; and to examine the effect of peer adoption of the improved crop variety on yield, food and nutrients consumption. We do this by using detailed data of 500 farm households from northern Ghana to examine the effect of household and peer adoption of improved soybean variety on crop yield, and the household's consumption of food, vitamin A and protein rich foods. Analytically, we exploit spatial econometric techniques to generate instruments (Bramoullé et al. 2009; Acemoglu et al. 2015), and then use the instruments, in addition to controlling for network fixed effects and potential endogeneity of network link formation with the control function approach by Brock and Durlauf (2001) to identify peer adoption effects on own adoption and outcomes. We employ the marginal treatment effects (MTE) approach, following Heckman and Vytlacil (2005) and Cornelissen et al. (2018) to estimate the treatment effects heterogeneities. This approach is significant in the sense that it allows us to identify, at least, a substantial part of the range of individual treatment effects, and as a result characterize the extent and pattern of treatment effects heterogeneity (Cornelissen et al. 2016; 2018)[40].

[40] Previous studies (e.g., Minten and Barrett 2008; Shiferaw et al. 2014) have assumed homogenous treatment effects, focusing mainly on addressing selectivity problems arising from unobserved characteristics, and aggregate parameter estimates. As argued by Cornelissen et al. (2016), this approach can mask important heterogeneity in treatment effects.

Poverty incidence and its extreme form have been consistently higher in northern Ghana than the national average and that of the rest of the country since 2005, and with worsening rates of extreme poverty, as the incidence increased from 29.7% in 2012/13 to 34.5% in 2016/17 (GSS 2018). This has resulted in higher incidence of food insecurity and malnutrition in the area, compared to the rest of the country, and the use of a number of strategies including credit purchases and borrowing from friends and relatives to cope with food insecurity (WFP and GSS 2012). This makes northern Ghana a suitable area for assessing the impact of improved crop varietal adoption by households and their peers on crop yield, and household food and nutrients consumption.

Our findings show strong evidence of heterogeneity in returns to adoption in both observed and unobserved characteristics. Specifically, we find positive selection on gains due to unobserved characteristics, mainly driven by worse outcomes, of households with less resistance to adopt, in the non-adoption state. However, adoption appears to make the potential outcomes of households quite homogenous, irrespective of their level of resistance to adoption. Peer adoption increases the household's food and nutrients consumption, when the household is not adopting the improved variety, but with attenuating effects when the household adopts, suggesting that non-adopters tend to depend more on adopting peers in terms of food and nutrients consumption than adopters. We, however, note that the estimated effects cannot be interpreted as causal-effects in its strictest sense, given that households were not randomly assigned to treatment and control groups, as in a randomized controlled trial[41].

Our study contributes to the literature in threefold: first, it provides empirical insights into the importance of improved crop varieties on welfare indicators such as crop yields and consumption of specific nutrient rich foods, while highlighting heterogeneity in returns to adoption in observed and unobserved characteristics. To the best of our knowledge, this is the

[41] We thank the reviewers and editor for suggesting this to us.

first study to use this approach to quantify the effects of improved crop variety on food and nutrients consumption. Second, the paper presents evidence of exogenous interaction effects (Manski 2013) on food and nutrients consumption of smallholders. As indicated previously, understanding the relationship between peer adoption and household consumption may present an alternative to public food and nutrition security interventions through private transfers among peers, given the challenges of sustainable and exit mechanisms of public food transfer modalities (Holden et al. 2006). Finally, the study provides insights into the effectiveness of policy options (i.e., whether to promote affordability or availability of the improved soybean seeds) that shift some non-adopting households to adopt on the outcomes.

The next section presents the conceptual framework of the analysis. In section 4.3, we present the context and data used in the analysis. Section 4.4 presents the analytical and empirical frameworks and estimation. In Section 4.5, we report the results, and then discuss in section 4.6. The final section presents a brief summary and conclusions.

4.2 Conceptual framework

In this section, we explore the conceptual mechanisms by which own and peer adoption may affect crop yield, food and nutrients consumption. To the extent that the improved variety is characterized as high yielding, early maturing and resistant to agricultural and climatic stress (CSIR-SARI 2013), own adoption of the improved variety can lead to increased yields and reduced production costs, which may result in increased farm income and subsequently increased food consumption. However, when own adoption and investments in the new variety is not complemented with good production "know-how", or soybean market, this may lead to reduced income and food consumption, since soybean is not a staple food in the area but is mainly produced for cash sales[42]. Similarly, food and nutrients consumption may decrease, if

[42] The other pathways through which agriculture production can affect food security and nutrition are changes in food prices, consumption of own production and intra-household dynamics related to gender and resource control. However, we do not

additional income from adoption of the improved variety is not spent on food and nutrients (Carletto et al. 2015, Sibhatu and Qaim 2018).

Given that smallholder farmers in the rural areas of developing countries often face missing or inefficient markets, making household production and consumption decisions jointly determined and thus "non-separable" (de Janvry et al. 1991), peer adoption decisions that affect household production can alter household consumption decisions as well. For example, peer adoption that provides learning opportunities and eases input constraints can lead to increased crop yield, farm income and consequently food consumption possibilities (Conley and Udry 2010; De Giorgi et al. 2020). However, when a household does not adopt, peer adoption can reduce (increase) learning opportunities (costs), especially if the production processes of the improved and traditional varieties are not complementary (Niehaus 2011), which can constrain household productivity, income and possibly consumption capabilities.

Peer adoption effects can also impact on own yield and food consumption through private transfers that result in a shift in the household's resources. In particular, if peer adoption leads to increased yield, income and wealth of peers, this can as well empower peers to undertake private transfers to the household. This can then lead to an increase in the household resource possibilities to (a) directly spend on food and/or (b) indirectly relax the liquidity constraint of the household in production, which may increase crop yield and food consumption possibilities. However, own adoption by the household which leads to increased productivity and income especially of poorer households may attenuate peer effects through private transfers on the households' food consumption, when the increase in productivity and income from adoption,

emphasize the food price and intra-household effects because the focus of the study is on farm-level effects and not on individual household members (Carletto et al. 2015). Also, consumption of own production is not emphasized here because soybean is not a staple food in the study area but a crop that mainly produced for cash sales and incomes (CSIR-SARI 2013).

leads to a decrease in the private transfers from peers or reduce dependence on peers. Studies have noted that, when the cost of sharing or altruistic effort is sufficiently higher than the benefit, then no member will undertake any effort to share (e.g., Alger and Weibull 2012; Di Falco and Bulte 2013). Finally, peer adoption effect on food consumption could decline, following own adoption, if own adoption by the household, leads to increased productivity and results in the need to settle past transfer commitments (Di Falco et al. 2018).

We deduce a number of implications from the foregoing discussion to guide our interpretation of the empirical results. When the household is not adopting, the impact of peer adoption on the household's yield and food consumption could be either positive, if the production processes of the improved and traditional varieties are complementary, or negative if otherwise, thereby constraining transferability of production "know-how" and other inputs. The impact of peer adoption on household food security should be positive, if peer adoption leads to increased private transfers from peers. When the household adopts, the impact of peer adoption on crop yield and food consumption could be positive, if own adoption enhances learning and relaxes input constraints, which leads to increased household productivity, income and spending on food. On the contrary, the impact of peer adoption on consumption in particular could be negative, if increased productivity and income due to own adoption either results in reduction of dependence on social transfers from peers, or in the need to return private transfers received from peers by the household, indicating peer and own adoption are substitutes (Di Falco et al. 2018).

4.3 Context and data

4.3.1 Context

Ghana is a lower middle-income country that has made steady progress in economic growth, food security, and in reducing poverty rate from 56.5% in 1991 to 23.4% in 2018 (GSS 2018). Despite this progress, substantial regional disparities exist, with some of the poorest indicators (i.e., high incidence of poverty, food insecurity and malnutrition) found in the northern part of the country. In the three northern regions (Northern, Upper East and Upper West regions) of Ghana, about 16% of all households are food insecure, with diets consisting of staple foods and occasionally accompanied by oil and vegetables (WFP and GSS 2012). Food insecurity in these regions is largely associated with poverty, weather constraints, seasonal effects and high food prices. The major sources of food for households are own production and market purchases, with more than 65% of food consumption coming from cash purchases during the lean season months. Similarly, households in this area resort to borrowing food or money from friends and relatives in coping with food insecurity (WFP and GSS 2012).

Soybean is a viable crop that can enhance the incomes and resilience of the poor households, because of its commercial potential and also the fact that it is mainly produced in the northern regions, which are the poorest regions in the country. The climatic conditions in this area are suitable for soybean cultivation, because of the high temperature requirement of $20^{o}C$ to $30^{o}C$ for successful cultivation. Among the regions of the north, the Northern region, in particular, which is the study region, accounts for over 65% of the total area cultivated to the crop and produces about 72% of the national output. The crop is cultivated mostly by smallholder farmers under rain-fed conditions, and with an average area cultivated of less than two acres. It has received significant promotion by the Ministry of Food and Agriculture (MoFA) and the Ghana ADVANCE[43] program in value chain enhancement and through seed price subsidies to farmers aimed at increasing productivity and incomes (MoFA 2017).

The Council for Scientific and Industrial Research (CSIR) and the Savanna Agricultural Research Institute (SARI) developed and introduced the improved variety in order to

[43] ADVANCE refers to the Feed the Future Ghana Agricultural Development and Value Chain Enhancement Project funded by the United States Agency for International Development (USAID).

circumvent the problems associated with the traditional variety[44]. The improved variety has higher yield potential of over 2.0 MT/ha, resistant to pod-shattering, matures in about 35 days earlier, and is resistant to other agricultural and climatic variabilities (CSIR-SARI 2013). Despite these interventions, the average national yield of 1.68MT/ha has remained below the national achievable yields of 2.50 – 3.10MT/ha (CSIR-SARI 2013). Also, available evidence shows that the use of improved soy seed is still quite low, with estimates ranging between 16% and 33% (CSIR-SARI 2013) of soybean farmers. Although, SARI and the Ministry of Food and Agriculture (MoFA) have worked with private seed companies and other local input dealers to enhance supply at the district level, farmers in some communities still travel long distances to acquire the seeds from input dealers (MoFA 2017).

4.3.2 Data

Data on farm households

We conducted a survey in 25 villages across 5 districts in the Northern region of Ghana between June and September 2017. A random sample of 500 farm households was drawn in three stages. In the first step, we purposively sampled five (5) soybean producing districts in the region, based on their intensity of soybean production. In the second stage, we used a list of soybean producing villages in each district obtained from the Ministry of Food and Agriculture (MoFA) offices to randomly sample 8 villages in Savelugu-Nanton, 6 in Gushegu, 5 in Tolon, 4 in Karaga and 2 in Kumbungu districts, in proportion to the number of households engaged in agriculture in each district (GSS 2014).

In the third stage, (i.e., the village level), we conducted a listing of households in each village and randomly selected 20 households in each village for interview and a structured

[44] The traditional variety, Salintuya, has been described as low yielding (about 1.0 MT/ha), early shattering of pods and susceptible to disease and pests, which sometimes lead to complete loss of output (CSIR-SARI 2013).

questionnaire was administered to them. We obtained information from households about their agricultural production for the 2016 cropping year, household land, assets and wealth, 7-day recall daily food and nutrients consumption; and distance to the nearest soybean seed source among others. Finally, we organized a focus group discussion with 4 to 6 village leaders in each village, and village level information such as local farm input prices, wage rate, and distance to the nearest paved road, market and the district capital was collected from this medium.

Data on social networks

We used the random matching within sample, which involves drawing a random sample from a population and collecting information on the links among them (Conley and Udry 2010). This approach offers the advantage of having both households (i.e., nodes[45]) in any link, randomly selected (Fafchamps and Gubert 2007). At the beginning of the interview for each household, we randomly matched 5 households from the rest of the village sample to the household, and information was collected on the matched households the respondent knew. In particular, we collected information on exchanges of agricultural information, labor, credit and land; social relations (i.e., whether relatives and friends) and geographic proximity (i.e., whether farm neighbors) between the household and the assigned matches the household knew.

We then define the matched households the household shared any of the above exchanges, social relation and geographical proximity with as the social contacts. Using these social contacts and denoting the responding household as i and a given village as v, we next construct a 20 x 20 village social network, which we denote as $N(v)$. Thus, $N(v)$ denotes a symmetric matrix of the set of 20 households randomly sampled in a village, with undirected entries, being equal to one if the respondent has any of these social contacts with a known match (which

[45] **Nodes** represent agents (i.e., households in this study) in a network. **Degree** is the number of links of a household (i.e., node) in an undirected network (Chandrasekhar and Lewis 2016).

defines the peers), and zero if otherwise. A household in the network [i.e., $N_i(v)$][46] has an average of 4 links (i.e., degree) with other sampled households in the village, and an average node transitivity of 0.46, suggesting that 46% of triads of a household head and the peers have links with one another.

Descriptive statistics

This section describes the data used by focusing on the main outcomes which are soybean yields, food consumption score (food) and nutrient rich food consumption scores. Soybean yield is measured as the total soybean output in kilograms divided by the acres[47] cultivated to the crop by household. Given that the food and nutrients outcomes measure the frequency of consumption of food and nutrient rich foods, we ask households the question "How many days in the last 7 days your household ate the following foods?" We calculated the food consumption score by first grouping all food items consumed by households into main staple, pulses, vegetables, fruit, meat and fish, milk, sugar, oils and condiments, and the food consumption score-nutrition by grouping food items into 15 food groups.

We then categorized these groups into vitamin A rich foods as dairy, organ meat, eggs, orange and green vegetables, and orange fruits, and protein rich foods as pulses, dairy, flesh meat, organ meat, fish and eggs (WFP 2015). We next sum all the consumption frequencies of the food and nutrient rich food items of the same group. For the food consumption score, we multiply the value obtained for each food group by the group weight to obtain weighted food group scores, and then add the weighted food groups to generate the food consumption score

[46] $N_i(v)$ is the ith row of the network matrix $N(v)$.

[47] The acres cultivated to soybean exclude the proportion of the plots cultivated to vegetables by the 1% of farmers who planted some vegetables on their soybean plots.

for a household[48]. For each nutrient rich food group, we sum the number of days the food sub-group belonging to this was consumed to obtain the food consumption score-nutrition for the household (WFP 2015).

The descriptive statistics of these outcome variables are presented in table 4.1 for the whole sample and by own adoption status and quintiles of average peer adoption. With a mean soybean yield of 631 kilograms per acre (kgs/ac), the mean yield for adopters is 726 kgs/ac, which is significantly higher than the mean yield, 439 kgs/ac, of non-adopters.

Table 4.1. Descriptive statistics of outcomes by own and quintiles of average peer adoption

		By quintiles of average peer adoption				
	All	1st	2nd	3rd	4th	5th
Main outcomes						
Soybean yield	630.7	551.8	621.8	610.9	667.9	701.1
Adopters	725.8	688.5	727.7	705.1	751.7	739.8
Nonadopters	439.5	420.5	433.7	443.5	472.3	442.3
Adopters – nonadopters	286.3***					
Food	33.6	29.5	33.2	32.4	35.2	37.3
Adopters	34.9	34.1	33.6	33.0	36.2	37.2
Nonadopters	30.7	25.1	32.6	32.0	33.1	38.6
Adopters – nonadopters	4.2***					
Vitamin A	12.4	10.1	12.4	12.0	13.5	14.3
Adopters	13.4	12.9	12.9	12.4	13.9	14.3
Nonadopters	10.5	7.3	11.5	11.0	12.4	14.4
Adopters – nonadopters	2.9***					
Protein	6.2	4.5	6.3	5.8	6.8	7.2
Adopters	7.4	7.7	7.4	6.7	7.6	7.5
Nonadopters	3.8	2.2	4.4	4.1	4.9	5.2
Adopters – nonadopters	3.8***					
Nadoption at means	0.69	0.38	0.61	0.71	0.81	0.94

Notes: The table presents means of the main outcomes, and proportion of adopting peer for the sample and by quintiles of proportions of adopting peers. For each variable, the table presents the mean for all the sample, adopters and non-adopters. Nadoption denotes the proportion of peers who adopted the improved variety. The table also presents the differences between adopters and non-adopter for all the variables. *** denotes significance at 1%.

[48] The food consumption score (FCS) is highly correlated with the household dietary diversity score (HDDS) given that they both measure the frequency of consumption of different food groups at the household level (FAO 2010). However, whereas the FCS weights the various food groups based on nutrient quality, the HDDS uses the unweighted food groups in the computation. The limitation of these measures is that they do not provide information on food consumption, dietary diversity and specific nutrient intake of individuals in the household, which make them suitable only for household level analysis (FAO 2010; WFP 2015).

The mean food consumption frequency is 34 for the entire sample, with the mean consumption of 35 for adopters, being significantly higher than the mean food consumption of 31 for non-adopters. Similarly, adopters of the improved variety have significantly higher consumption frequencies of nutrient rich foods (i.e., vitamin A and protein rich foods). These observations motivate the empirical investigation, where there is significant unequal consumption frequencies of food and nutrient rich foods that appear to coincide with adoption status.

Given the association between household adoption and food and nutrients consumption frequencies, we next explore whether peer adoption can possibly be associated with household food and nutrients consumption by providing descriptive statistics according to quintiles of peer adoption. The mean soybean yield increases from 552, 689 and 421 kgs/ac for the lowest quintile to 701, 740 and 442 kgs/ac for all the sample, adopters and non-adopters, respectively, in the top quintile, an increase that is statistically significant for all sample ($p = 0.000$) and only adopters ($p = 0.015$). The mean food consumption frequency also increases from 30, 34 and 25 for the bottom quintile to 37, 37 and 39 for the top one for the entire sample, adopters and non-adopters respectively, an increase which is statistically significant ($p = 0.000$). However, the food consumption difference between adopters and non-adopters markedly narrows at the top quintile of peer adoption ($p = 0.449$).

Similarly, the mean consumption frequencies of nutrient rich foods closely follow that of food consumption in general. While the consumption of vitamin A and protein rich foods by non-adopters significantly increase from 7.3 and 2.2 for the bottom quintile to 14.4 and 5.2 for the top one, respectively, the consumption frequencies of adopters do not witness significant changes. The weaker correlation between peer adoption and yield of non-adopters and the stronger association between peer adoption and non-adopters' food and nutrients consumption, suggest the possibility of stronger peer adoption effects in the form of risks sharing and private transfers when the farmer is not adopting.

We present definition, measurement and descriptive statistics of characteristics of the sample and peers in table 4.2. Of particular interest is panel B, which presents the main instrument, distance to the nearest soybean seed source used to identify household adoption of the improved variety. In our sample, the average distance from the household location to the nearest seed source is about 6 kilometres (km). Even though some households are located in less than 2 km to the nearest soybean seed source, the distance increases to an average of about 11 km for the households in the highest distance quintile in the sample (see Table 4.A1 in appendix A3). Panels C of table 4.2, shows that a household has an average of 65% of the peers being males, aged 44 years and with landholding of 2.7 hectares. Also, 63% of a household's peers of peers are males, aged 44 and with landholding of 2.7 hectares (panel D).

4.4 Methodology

4.4.1 Analytical framework

The significant differences between the outcomes of adopters and non-adopters, and the heterogeneity in these outcomes across the distribution of adopting peers, shown in section 4.3, suggest the need for a framework that can estimate the effects of own adoption on these outcomes, while accounting for heterogeneity in gains from peer adoption, as well as other observed and unobserved characteristics of these farm households. Thus, we use the marginal treatment effects framework, which is based on the generalized Roy model (Heckman and Vytlacil 2005; Cornelissen et al. 2016; 2018).

We assume that treatment (adoption) of a household, i, is a binary variable denoted by A_i, and the household's potential outcome (e.g., yield, food and nutrients consumption) under the hypothetical situation of being an adopter ($A_i = 1$) and non-adopter ($A_i = 0$) as Y_{1i} and Y_{0i}, respectively. Let A_j represent peer adoption, with ρ_1 and ρ_0 as the parameter estimates showing the effects of peer (j's) adoption on own (i) potential outcomes under the situation of the household adopting and not adopting, respectively.

Table 4.2. Variable definition, measurement and descriptive statistics

Variables	Definition and measurement	Mean	SD
Panel A: *Household characteristics*			
Adoption	1 if farmer adopted the improved variety; 0 otherwise	0.67	0.47
Nadoption	Proportion of peers who adopted the improved variety	0.69	0.01
Sex	1 if male; 0 otherwise	0.59	0.49
Age	Age of farmer (years)	44.03	12.04
Education	Number of years in school	1.27	3.27
Hsize	Household size (number of persons)	5.64	2.14
HLand	Total land size of household (in hectares)	2.56	1.56
HWealth	Value of household durable assets in 10,000 GHS	1.29	2.00
HRisk	Risk of food insecurity (No. of months household was food inadequate)	0.93	1.37
Soil fertility	4=fertile; 3=moderately fertile; 2=less fertile; and 1=infertile	2.97	0.97
Seed use	Quantity of soybean seeds used per acre in kilograms	9.58	4.37
Fertilizer cost	Cost of fertilizer applied per acre in GHS	151.4	226.1
Pesticide cost	Cost of pesticides applied per acre in GHS	1.45	5.26
Weedicide cost	Cost of weedicides applied per acre in GHS	22.52	37.18
Machinery	Log of machinery cost per acre	4.16	0.50
Local wage rate	Log of local wage rate per day	1.80	0.23
Labor use	Number of man-days per acre	14.95	10.21
Extension	1 if ever had extension contact; 0 otherwise	0.34	0.47
Farm revenue	Total farm revenue of household in 1000 GHS	6.37	4.23
Soybean income	Net income from soybean in GHS calculated as total soybean revenue per acre minus the cost of seeds, fertilizer, weedicide, labor and machinery used on soybean farm per acre.		
Association	Number of associations the farmer is a member in the community	1.07	1.27
Town center	Distance from community to main town center in kilometers	15.46	11.86
Panel B: *Instruments*			
SoySeed price	Soybean seed price in GHS/kilograms	1.06	0.19
SoySeed distance	Distance from household location to soybean seed source in kilometers	5.54	3.51
NResident distance	Average distance from farmer to peers' residence in kilometers	5.33	3.48
N^2Resident distance	Average distance from peers to peers of peers' residence in kilometers	5.22	2.06
Panel C: *Direct peer characteristics*			
NSex	Proportion of male peers	0.65	0.17
NAge	Average age of peers	43.65	4.37
NEducation	Average years of schooling of peers	1.58	1.12
NHsize	Average households' size (number of persons) of peers	5.74	0.79
NLandholding	Average landholdings of peers	2.67	0.67
NWealth	Average value of household durable assets of peers (normalized)	0.03	0.34
NSoil	Average soil fertility of peers	3.02	0.31
NExtension	Proportion of peers with extension contact ever	0.38	0.15
NFarm revenue	Log of average total farm revenue of peers	8.55	0.52
NSoySeed distance	Average distance from peers' household locations to soybean seed source in kilometers	5.52	3.30
Panel D: *Indirect peer characteristics*			
N^2Sex	Proportion of male peers of peers	0.63	0.13
N^2Age	Average age of peers of peers	43.73	3.82
N^2Education	Average years of schooling of peers of peers	1.51	0.92
N^2Hsize	Average households' size (number of persons) of peers of peers	5.73	0.74
N^2Landholding	Average landholdings of peers of peers	2.65	0.59
N^2Wealth	Average value of household durable assets of peers of peers	0.04	0.31
N^2Soil	Average soil fertility of peers of peers	3.01	0.29
N^2Extension	Proportion of peers of peers with extension contact ever	0.38	0.14
N^2Farm revenue	Log of average total farm revenue of peers of peers	8.56	0.51
N^2SoySeed distance	Average distance from peers of peers household locations to soybean seed source in kilometers	5.51	3.28

Also, let X_i denote a vector of farmer and household characteristics, with η_1 and η_0 being the associated vector of parameter estimates under the situation of being an adopter and non-adopter, respectively; G_i represents a vector of village characteristics and network fixed effects. Given these definitions, we model the potential outcomes as

$$Y_{1i} = \rho_1(A_j) + \eta_1(X_i) + G_i'\tau + U_{1i},$$
(1)
$$Y_{0i} = \rho_0(A_j) + \eta_0(X_i) + G_i'\tau + U_{0i}$$

where τ is a vector of parameters to be estimated, while U_{1i} and U_{0i} represent deviations from the mean and are assumed to have means of zero. The peer adoption variable, A_j, is obtained by multiplying the adoption variable, A_i, by the ith row of the social network matrix $N(v)$ [i.e., $N_i(v)A_i$], which we discussed in subsection 4.3.2

We express adoption decision of i in the following latent variable (i.e., A_i^*) discrete choice model:

(2) $$A_i^* = \Theta_A(A_j, X_i, G_i, R_i) - \varepsilon_i \text{ with } A_i = \begin{cases} 1 \text{ if } A_i^* \geq 0 \\ 0 \text{ otherwise} \end{cases}$$

where A_i is a binary indicator that equals 1 if household i adopts the improved soybean variety and zero otherwise. The other variables are as defined earlier, and R_i is an instrument excluded from eq. (1), and used to identify the effect of household adoption decisions on the outcomes. Θ_A is a vector of parameters to be estimated. ε_i is an i.i.d. error term, and because it enters the selection equation with a negative sign, it represents the unobserved characteristics, also referred to as resistance, that make individuals less likely to adopt.

If we assume a cumulative distribution function (*c.d.f.*) of ε_i as $\Phi(\varepsilon_i)$, then the mean part of eq. (2) [i.e., $\Theta_A(.)$] will represent the propensity score of adoption [defined as $\Phi(\Theta_A(.)) \equiv P(Z)$], which is based on the observed characteristics. The *c.d.f.* of ε_i represents the quantiles of distribution of the unobserved resistance to adoption [defined as $\Phi(\varepsilon_i) \equiv U_A$]. A farm household will adopt, if the propensity score of adoption is greater than the unobserved resistance to adoption [i.e., $\Phi(\Theta_A(.)) \geq \Phi(\varepsilon_i)$]. Given the propensity score and eq. (1), we can estimate the outcome equation as a function of the observed regressors (A_j, X_i, D_i, G_i) and the propensity score $P(Z)$ as

$$
\begin{aligned}
(3) \qquad & E\left[Y \middle| A_j = a, X_i = x,\ G_i = g,\ P(Z) = p\right] \\
& \qquad = A_j\rho_0 + X_i'\eta_0 + G_i\tau + A_j{}'(\rho_1 - \rho_0)p + X_i'(\eta_1 - \eta_0)p + E(U_{1i} - U_{1i})p
\end{aligned}
$$

where $Y = Y_{1i} - Y_{0i}$, $(\rho_1 - \rho_0)p$ and $(\eta_1 - \eta_0)p$ measure the returns to adoption for households with different levels of peer adopters, A_j, and other observable covariates, X_i, respectively. These observed gains could be positive or negative depending on whether households with higher values (such as more adopting peers) have higher or lower than average returns to adoption (Carneiro et al. 2011). $E(U_{1i} - U_{1i})p$ represents the returns to adoption due to unobserved ability of the household. Suppose that Y is yield, a positive (negative) effect of $E(U_{1i} - U_{1i})p$ will imply a negative (positive) selection on unobserved gains.

Following Heckman and Vytlaci (2005) and Cornelissen et al. (2018) we obtain the marginal treatment effects (MTE) for A_j, X_i and $U_A = p$ by taking the derivative of eq. (3) with respect to p as

$$
(4) \qquad \text{MTE}(a, x, p) = \frac{\partial E[Y|\,.\,, P(Z)=p]}{\partial p} = A_j{}'(\rho_1 - \rho_0) + X_i'(\eta_1 - \eta_0) + \frac{\partial K(p)}{\partial p}
$$

where $K(p)$ is a nonlinear function of the propensity score. Equation (4) suggests that treatment effects heterogeneity can result from both observed and unobserved characteristics. Estimation of the treatment effects requires a first-stage in which the instrument, R_i, in eq. (2) causes variation in the probability of adoption, conditional on the observed characteristics [i.e., $R_i \perp (U_{0i}, U_{1i}, \varepsilon_i)\big|(A_j, X_i, G_i)$]. Given the exclusion instrument, we estimate a first-stage probit eq. (2) to obtain estimates of the propensity score $\hat{p} = \Phi(\Theta_A(.))$. Modeling $K(\hat{p})$ as a polynomial in degree 2, we estimate the marginal treatment effects (MTE), using the local instrumental variable (IV) estimator by expressing eq. (3) as a function of observed regressors (A_j, X_i, G_i) and the propensity score $P(Z)$. This is specified as

$$(5) \qquad Y = A_j\rho_0 + X_i'\eta_0 + G_i\tau + A_j(\rho_1 - \rho_0)\hat{p} + X_i'(\eta_1 - \eta_0)\hat{p} + K(\hat{p}) + \mu_i$$

where $K(\hat{p})$ is a non-linear function of the propensity score and μ_i is the error term. Equation (5) expresses the returns to adoption for an individual with adopting peers $A_j = a$, and observed characteristics $X_i = x$, who is in the U_Ath quantile of the distribution of ε. We compute the unconditional treatment effects of household adoption [i.e., the average treatment effects (ATE), treatment effects on the treated (TT) and treatment effects on the untreated (TUT)] by aggregating the MTE over the U_A and the appropriate distributions of the covariates. Given our interest in evaluating policy intervention that seeks to subsidize soybean seed price or reduce distance to soybean seeds source, we also use the Policy Relevant Treatment Effects (PRTE) to estimate the aggregate effects of such policy changes (Heckman and Vytlacil 2005) (refer to appendix A1 for expression of these treatment effects measures).

4.4.2 Exclusion restriction and identification of the peer effect

The first identification concerns are issues of standard endogeneity and omitted variable biases of own adoption in eq. (1), due to the fact that own adoption is endogenously determined. Our strategy for dealing with this is to rely on the distance of the household to the closest source of soybean seeds, and not necessarily where soybean seeds are actually purchased. We argue that distance to soybean seed source indicates the availability of the soybean seeds in the district, and will likely alter the relative cost of adoption by a household (see also Suri 2011). Thus, households located close to improved soybean seed source will have lower costs and possibly higher net benefits from adoption, which will make them more likely to adopt than those not closer. We further argue that distance to soybean seed source is not directly related to our outcome variables, except through the effect on adoption, because the main sources of the improved soybean variety are agricultural input dealers some of who are located in the district capitals (CSIR-SARI 2013)[49].

Two main possible concerns about the exogeneity of our instrument are that; if soybean seed dealers chose their location strategically close to their buyers, and if households' location was endogenously determined based on the location of input dealers. In respect of the first concern, we show that this is not the case with results of t-test of differences in means, across different distance bandwidths, for variables at the village level, household levels and the outcomes in table 4.A1 in appendix A3. The tests suggest that villages and households located closer to soybean seed source are not systematically different from those located further away. The second concern is not likely the case, because soybean is not the main crop cultivated by these households and thus, it is unlikely that a household will change location because it wants to access improved soybean seeds. Table 4.A1 further shows no significant difference in distance and adoption status among households who changed location over the past 5 and 10 years as at the time of the interviews.

The next critical issue of identification is the peer effects in eqs. (1) and (2). The first concern is the endogeneity of the peer effects. First, the peer adoption effect (i.e., A_j), in eq. (1) cannot generally be consistently estimated, especially with OLS, because of the correlation of the error term in this equation with this term [i.e., $\mathrm{cov}(A_j, U_{1,0i}) \neq 0$], possibly due to the omitted effects of the peer outcomes (Acemoglu et al. 2015). The second aspect is that, the estimation of own

[49] Of course, distance to seed source could be correlated with distance to town centre, where households who have their closest seed source located in the town centre inadvertently live closer to the town centre and therefore more likely to be wealthy and to be able to buy or trade for food, increasing food security. This could threaten our identification strategy because distance to soybean source in this case can affect our outcomes through closeness to town centre and household wealth, and not only through adoption. For this reason, we controlled for distance to town centre and household wealth in all specifications.

and peer adoption (A_j is endogenous effect) in eq. (2) poses endogeneity concerns because of the Manski's (1993) "reflection problem" and correlated unobservables [i.e., $\text{cov}(A_j, \varepsilon_i) \neq 0$]. The reflection problem is the result of the coexistence of the endogenous peer effect and the contextual effect in eq. (2)[50].

In order to identify the contextual effect in eq. (1), and the contextual and endogenous effects in eq. (2), we follow the approaches of Bramoullé et al. (2009) and Acemoglu et al. (2015), who use the average characteristics of peers of peers [i.e., $N^2(v)$] as an instrument for the average adoption of peers. Intuitively, since the characteristics of a household's peers of peers are correlated with the behavior and outcome of the household's peers, but are exogenous to the behavior and outcome of the household, these satisfy the exclusion restriction of being valid instruments for the adoption decision of the household's peers (see Appendix A2 for a case on social network structures and identification of peer effects). Two key requirements for the use of this strategy are that the peers of peers characteristics (such as distance to soybean seed source by peers of peers) that are used as instruments should be uncorrelated with the instrument used to identify own adoption, and that the peers of peers instrument must be independent of own outcomes, except through average peer adoption (Acemoglu et al. 2015).

However, given that our main instrument is the distance to soybean seed source, it is likely that the household's own distance to seed source will be correlated with the average distance to soybean seed source by peers of peers. As a result, we use the average distance between the residence of the household's peers and the peers of peers as an instrument to identify the effect of average peer adoption on household own adoption and the outcomes. The reasoning is that, when farmers are residentially close to each other, they are more likely to interact and exchange

[50] These identification issues are discussed in the social networks and peer effects literature (Bramoullé et al. 2009; Acemoglu et al. 2015; De Giorgi et al. 2020). The formal development of these issues is beyond the scope of this paper. We refer the reader to Acemoglu et al. (2015) for the formal development and identification problems therein.

information and resources, which can increase the likelihood of them influencing the behavior and decisions of each other. Thus, if a farmer has geographically closed peers whose closer peers have new and more access to information about the improved variety, that farmer could receive this information and advice from the peers of peers through the farmer's peers.

Indeed, whereas the distance to soybean seed source of peers of peers appears to be highly correlated with own distance (0.942), the average distance between the residence of farmer's peers and the peers of peers is uncorrelated with own distance to the seed source (0.010) as shown in table 4.A2. To test the second assumption, we followed the approach of Di Falco et al. (2011) by regressing the outcomes of non-adopters on the own and average peer adoption instruments in table 4.A3. Whereas the estimate generally show that these instruments do not significantly correlate with the outcomes, tables 4.B1.1 and 4.C1-4.C3 in the supplementary material show that the instruments significantly explain average peer adoption and own adoption, respectively.

Thus, to account for the endogeneity of peer adoption, we regress peer adoption on own, X_i, and peer characteristics ($N_i(v)X_i$), as well as the characteristics of the peer of peers ($N_i^2(v)X_i$), obtain the predicted peer adoption, and use this as the peer adoption variable in the outcome (eq.1) and selection (eq.2) equations (see table 4.B1.1 in appendix B1). Finally, we partly capture correlated effects by including village dummies to account for network fixed effects G_i (i.e., individuals self-select into networks based on network-specific characteristics). To account for correlated effects at the link formation level, we estimated a network formation model and inserted the predicted generalized residuals of this model into eqs. (1) and (2) as control functions (Brock and Durlauf 2001) (see Appendix B2.).

4.5 Empirical Results

4.5.1 First-stage adoption

Table 4.3 reports the marginal effects estimates of the first-stage probit selection model in column (1) for soybean yield, and in column (2) for food and nutrients consumption. The distance to the closest soybean seed source is a strong predictor of adoption, and as expected, the coefficients of the distance suggest a strong relationship between the availability of the improved seeds and the decision to adopt.

Table 4.3. First-stage adoption results of yield and food and nutrients consumption specifications

	(1) Yield		**(2) Food and nutrients**	
	Coefficient	S. E.	Coefficient	S. E.
	$\boldsymbol{\Theta_A}$		$\boldsymbol{\Theta_A}$	
Nadoption (Predicted)	0.168***	0.047	0.110**	0.049
Sex	0.050	0.052	0.011	0.053
Age	−0.002	0.001	−0.002	0.001
Education	0.002	0.008	0.004	0.008
Hsize	−0.035**	0.013	−0.041***	0.013
HLand	0.052**	0.022	0.041*	0.021
HWealth (predicted)	0.163***	0.045	0.169***	0.045
Soil fertility	0.022	0.026	0.038	0.027
Seed use	−0.014**	0.006	−0.015**	0.006
Fertilizer cost	−1.8E−5	7.0E−5	−3.9E-5	6.0E−5
Pesticide cost	0.001	0.004	0.003	0.004
Weedicide cost	3.6E-4	0.001	−2.6E-5	0.001
Machinery	−0.006	0.052	−0.066	0.059
Labor use	0.001	0.002	0.001	0.002
Extension (predicted)	0.568***	0.110	0.572***	0.108
Soy selling price	0.166	0.203	0.088	0.194
Farm revenue (predicted)			0.270***	0.070
Residuals_NWLink	−0.054	0.034	−0.046	0.034
Local wage rate	0.137	0.101	−0.266*	0.151
Network Fes	Yes		Yes	
Town center	0.004*	0.002	0.005**	0.002
NSex	−0.240	0.151	−0.498***	0.163
NAge	0.003	0.005	0.002	0.005
NLand	−0.098**	0.040	−0.116**	0.040
SoySeed Distance	−0.478***	0.089	−0.483***	0.094
N^2SoySeed Distance	0.147***	0.027	0.144***	0.029
SoySeed price	−0.481**	0.193	−0.497**	0.194

The table reports the first-stage adoption results of the yield equation in column (1) and food and nutrients consumption equation in columns (2). The estimates are marginal effects from probit selection model of adoption decisions (first-stage eq. 2). Our instrument is distance to soybean seed source, which is normalized about its overall mean. Θ_A is a vector of parameter estimates from equation (2). Network FEs is network fixed effects and Residuals_NWLink is residuals of the link formation model. S.E. are bootstrapped standard errors with 50 replications. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

As expected, the soybean seed price shows a strong negative correlation with the decision to adopt. We also report the chi-squared test of the excluded instruments at the bottom panels of these tables, and based on this, we can, throughout, reject the hypotheses that the excluded instruments are not relevant. The results suggest that there is a strong and significant relationship between the adoption decisions of peers and one's own decision to adopt the improved variety. To facilitate interpretation, we normalize peer adoption over its mean. Specifically, a standard deviation (SD) increase in the number of adopters of the improved variety among a household's peers, raises the probability of the household's (own) adoption by at least about 11 percentage points. The estimated peer adoption effects correct for the potential endogeneity of the peer adoption variable by using predicted peer adoptions, and account for correlated unobservables with the network fixed effects and residuals of the link formation model (Residuals_NWLink) in all specifications.

The first-stage probit generates a large common support for the propensity score P(Z) and this ranges from 0.1 to at least 0.99 (figure 4.1) for both soybean yield (part A) and food and nutrients (part B). This satisfies the requirement that the instrument should generate enough common support for the estimation of the MTE (Cornelissen, et al. 2016).

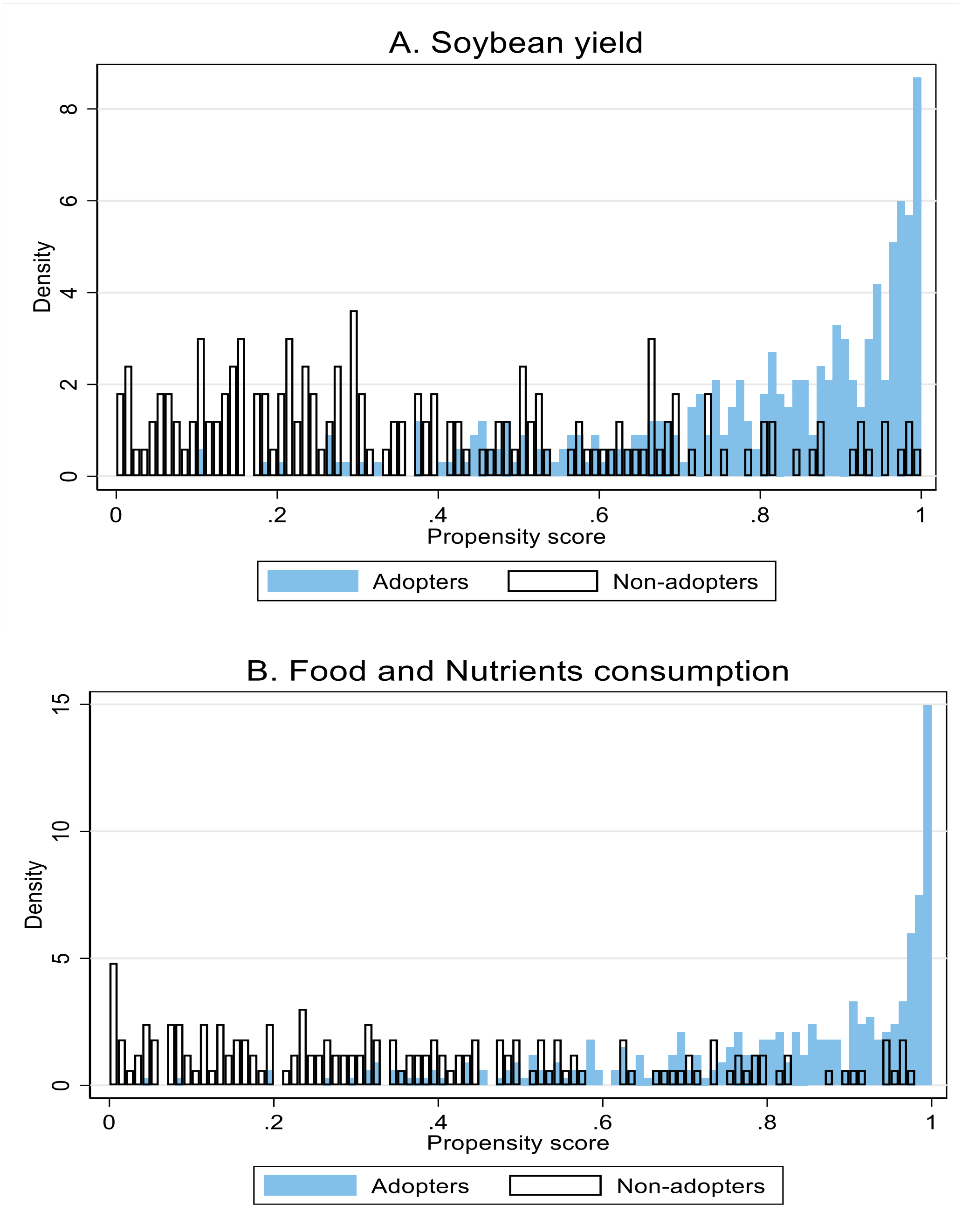

Figure 4.1 Common support for Soybean yield and food and nutrition security

The figure plots the frequency distribution of the propensity score by adopters and non-adopters. The propensity score is predicted from the baseline first-stage regressions. Part A is based on the regression for soybean yield and part B is based on the regressions on food and nutrition. We have two different specification of the first-stage equation, and thus the two propensity score plots because we included extension contact in both the selection and the outcome stages in the yield equation, but included it only in the first-stage of the food and nutrients consumption equations. The reason is that whereas extension was conceived as having potential effects on both adoption and yield directly, we considered the effect of extension on food and nutrients consumption will be through farm income which we controlled for.

4.5.2 Summary treatment effects and marginal treatment effects of household adoption

We report the summary treatment effect estimates of eq. (5) in panel A of table 4.4 (refer to table 4.C1-4.C3 in appendix C for the complete estimates). The ATE indicates that for a soybean producing household chosen at random from the population of soybean producing households, adopting the improved variety increases soybean yield by 61 percentage points. Our results for the TT imply that for an average adopting household, adoption significantly results in about 77 percentage points increase in soybean yield. In the TUT case, for an average non-adopting household, adoption would significantly increase soybean yield of the household by 28 percentage points.

Table 4.4. Aggregate Treatment effects of adoption on Yield, food and nutrients consumption

	(1) Yield	(2) Food	(3) Vitamin A	(4) Protein
Panel A				
ATE	0.606***	0.294***	0.526***	1.041***
	(0.095)	(0.080)	(0.121)	(0.198)
TT	0.772***	0.299**	0.596***	1.128***
	(0.149)	(0.118)	(0.173)	(0.284)
TUT	0.278**	0.283***	0.384***	0.864***
	(0.098)	(0.078)	(0.089)	(0.185)
Panel B				
Nadoption ρ_0	−0.051	0.087**	0.198***	0.292***
	(0.033)	(0.033)	(0.049)	(0.086)
TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$	0.128**	−0.107***	−0.214***	−0.346***
	(0.051)	(0.034)	(0.055)	(0.087)
p-values for essential heterogeneity	0.010	0.001	0.000	0.000
Observations	500	500	500	500

Notes: The table reports the average treatment effect (ATE), average treatment effect on the treated (TT), average treatment effect on the untreated (TUT), effect of peer adoption (i.e., Nadoption ρ_0), treatment effect of peer adoption, [i.e., TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$] using the baseline specification and the ρ's are as defined in equations (1) and (3). The yield column (1) refers to the soybean yield equation. The food, vitamin A and protein columns (2 to 4) refer to the food consumption, and vitamin A and protein rich food consumption equation (estimates of other variables are in tables 4.C1 to 4.C3). The p-value for the test of essential heterogeneity tests for a nonzero slope of the MTE curve. Bootstrapped standard errors with 50 replications are reported in parentheses. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Similarly, for a soybean producing household picked at random from the soybean producing population, adoption of the improved variety increases food and nutrients consumption from 29 percentage points, for food, to about 104 percentage points for protein. These estimated parameters are all statistically significant at the 1% level. Also, the TT estimates show that for an average adopting household, adoption results in 30 percentage points increase in food consumption, and 60 to 113 percentage points increase in nutrients consumption. These parameters are significantly different from zero, at least, at the 5% level. The significance of adoption is still observed, even in the untreated case, where the food and nutrients consumption of non-adopters will increase by 28 to 86 percentage points, if they adopt the improved variety.

The summary measures of treatment effects suggest possible treatment effect heterogeneity among soybean producing households. In particular, all parameter estimates in table 4.4 show that the TT is greater than the ATE, which is also greater than the TUT. This is suggestive of positive selection on gains, where individuals who are more likely to adopt (perhaps because of their innate ability or variation in the quality of adoption and production conditions) tend to benefit more from adoption in terms of yield and food/nutrients consumption. However, as indicated earlier, these summary measures mask such treatment effects heterogeneity and thus, we show the marginal treatment effects (MTEs) in figures 4.2. These figures relate the unobserved parts of the outcomes ($U_1 - U_0$) to that of the adoption decision (U_A). Higher values of U_A imply lower probabilities of adoption (i.e., higher resistance to adoption).

The MTE curves decline with increasing resistance to treatment in all instances, and indicate a pattern of positive selection on gains. In effect, given the unobserved characteristics, households who are most likely to adopt the improved variety appear to benefit the most from adoption. Thus, the slopes of the MTE curves in each case suggest a pattern of heterogeneity in returns to adoption, that is significantly different from zero at the 5% level (see the p-values for the test of essential heterogeneity at the bottom of table 4.4). Part A of figure 4.2 depicts the MTE for yield and shows that for households who are more likely to adopt than the average household ($U_A < 0.5$), their returns to adoption are higher than the average household *albeit* not significantly different from the returns to adoption of an average household. For the households with higher resistance to adoption than the average household, their yield returns to adoption is significantly lower than that of the average household selected at random for the 30% of households with the highest resistance to adoption ($U_A > 0.7$).

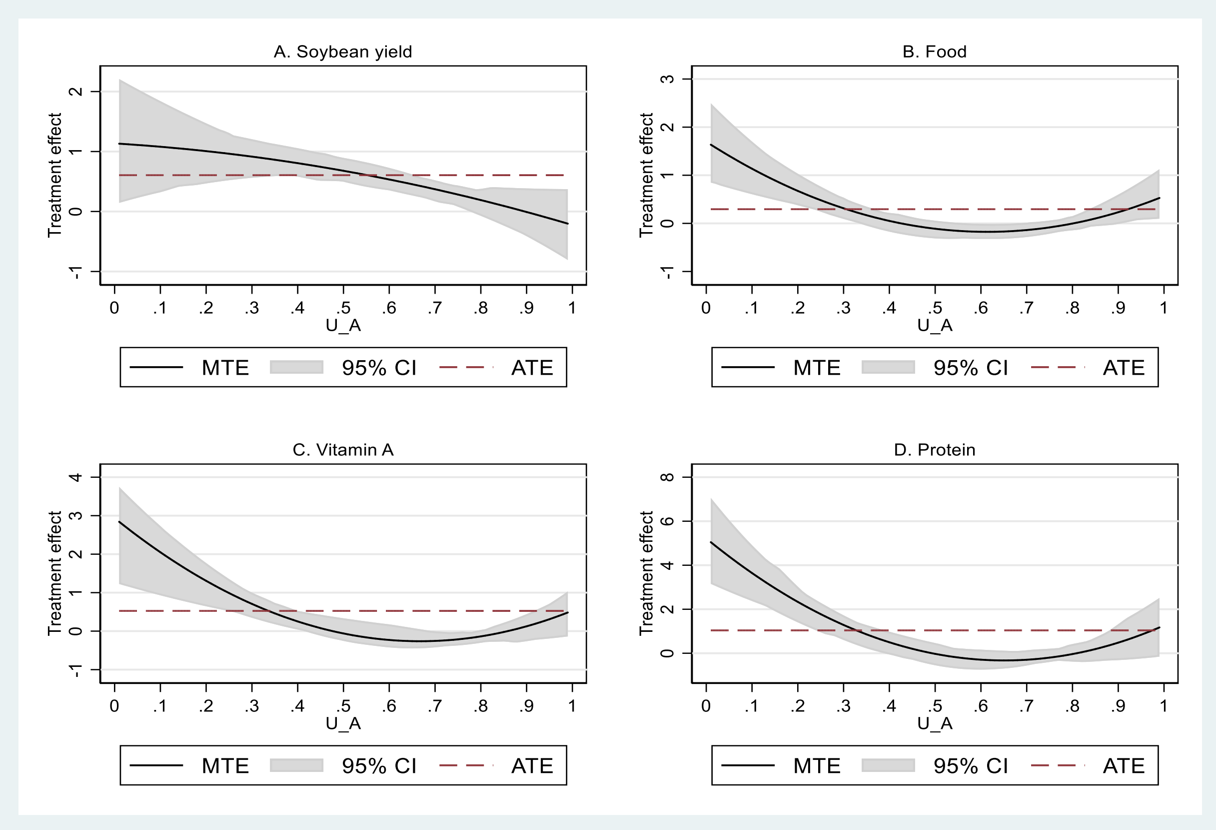

Figure 4.2 MTE curves for soybean yield

The figure shows the marginal treatment effect (MTE) curves for yield, food and nutrient rich food consumption at the average values of the covariates based on specifications in equations (4 and 5). U_A denotes unobserved resistance to treatment/adoption. Part A is the MTE curve for soybean yield. Part B depicts the MTE curve for food consumption, part C shows the MTE curve for vitamin A rich foods consumption and part D is the MTE curve for protein rich foods consumption. The dashed lines are the average treatment effects (ATE). The 95% confidence interval (95% CI) is based on bootstrapped standard errors with 50 replications.

Figure 4.2 also shows there is clear heterogeneity in returns to adoption in terms of food and nutrients consumption. We observe a similar pattern of positive selection on gains, with returns to adoption significantly higher than the average household, at least, for the 20%, for food consumption, and 25% for nutrients consumption of households who are most likely to adopt. Figure 4.2 further shows that returns to adoption in terms of food and nutrients consumption decrease and fall below that of the average soybean producing household, for the households with over 33% (i.e., $U_A > 0.33$) resistance to adoption.

In order to probe for the source of this treatment effect heterogeneities, we check whether the positive gains on selection on unobserved characteristics (i.e., $U_1 - U_0 | U_A = u_A$) are because of heterogeneity in the outcomes when not adopting [i.e., upward sloping in $E(Y_0 | U_A = u_A)$], when adopting [i.e., downward sloping $E(Y_1 | U_A = u_A)$], or both. We report the plot of Y_1 and Y_0 for the various outcomes in figure 4.C1. The figure shows, across all outcomes that, the differences in the outcomes are driven by worse outcomes in the non-adoption state, as shown by the increasing dashed-dotted lines. However, the outcomes in the adoption state (i.e., dotted lines) are more homogenous throughout.

4.5.3 Treatment effect heterogeneity in peer adoption

For easy reference, we report the estimates of peer adoption effects in panel B of table 4.4, where we first present the effect for the case when the household is not adopting (i.e., ρ_0) and when the household is adopting [i.e., $(\rho_1 - \rho_0)\,\hat{p}$]. The results show that in the non-adoption state, a standard deviation increase in the number of adopting peers of the improved soybean variety, is associated with a decrease in one's own soybean yield, although not statistically significant. However, the treatment effect of peer adoption is significantly positive and increases own yield by about 13 percentage points.

In respect of food and nutrients consumption, the results show that when not adopting, a standard deviation increase in peer adoption increases food consumption of the household by 9 percentage points, and consumption of vitamin A and protein rich foods by 20 and 29 percentage points, respectively. These effects are significant at least at the 5% level, and suggest that non-adopting households benefit from their adopting peers in terms of enhanced food and nutrients consumption. Interestingly, when the household adopts, the treatment effect of a standard deviation increase in adopting peers is negative (i.e., $(\rho_1 - \rho_0)\,\hat{p}$), suggesting that household adoption of the improved variety significantly reduces the heterogeneity in food and nutrients consumption due to adopting peers by 11, 21 and 35 percentage points for food, vitamin A and protein consumption, respectively. These results indicate that households with more (fewer) adopting peers tend to gain more in terms of increased soybean yields (food and nutrients consumption), when they adopt than their counterparts with fewer (more) adopting peers. This is not surprising because as shown in table 4.1, non-adopters appear to have lower yields and food consumption.

4.5.4 Effect mechanisms

Given the generally positive effects of adoption of the improved variety on yields, food and nutrients consumption, we next investigate the mechanisms by which adoption can affect food and nutrients consumption in particular. Our conceptual framework suggests that own adoption can enhance consumption through increased yields and changes in household income, consumption of own production, food prices and intra-household dynamics[51]. This analysis is shown explicitly in table 4.5, where we first estimate the levels and heterogeneity effects of gains in yield from adoption on soybean income, food and nutrients consumption (cols. 1-4). The estimates reveal a significantly positive association between gains in yield and income from soybean. In particular, a log percentage point increase in yield from adoption of the improved variety significantly increases the gains in soybean income by over GHS 700 [i.e., $(\eta_1 - \eta_0)p$], which is about 30% higher than the mean soybean income of non-adopters.

[51] Given the macro nature of food prices and the focus of the analysis on farm level links, and the limitation of data on the sources of households' food and nutrients consumption (i.e., whether from own production or purchases), we are unable to show the effects of changes in food prices and consumption of own produce on food and nutrients consumption.

In addition, food and nutrients consumption gains from increased yield due to adoption is positive, but significant for food and vitamin A and not for protein. This is expected, given that soybean is not a staple food consumed by households, but a crop that is primarily produced for sale to enhance household income. Following this, we next check the effects on food and nutrients consumption given income gains from adoption (cols. 5-7). In effect, whereas at the non-adoption state increase in household income is significantly and positively associated with increased food and nutrients consumption, the nutrients consumption, in particular, is significantly higher for non-adopters when they adopt, as revealed by the negative treatment effects for income.

Table 4.5. Estimates of effects mechanisms

Soybean	(1) Soybean income	(2) Food	(3) Vitamin A	(4) Protein	(5) Food	(6) Vitamin A	(7) Protein
Yield η_0	653.4***	0.084	0.027	0.112			
	(34.1)	(0.208)	(0.335)	(0.545)			
TE for Yield	764.5***	0.467*	0.833**	1.057			
$(\eta_1 - \eta_0)\hat{p}$	(50.6)	(0.247)	(0.414)	(0.740)			
Income η_0					0.211***	0.476***	0.545***
					(0.069)	(0.143)	(0.163)
TE for Income					-0.030	-0.395**	-0.497**
$(\eta_1 - \eta_0)\hat{p}$					(0.079)	(0.165)	(0.196)
Sex η_0					0.103*	0.148	0.140
					(0.055)	(0.102)	(0.117)
TE for Sex					-0.905	-0.130	-0.126
$(\eta_1 - \eta_0)\hat{p}$					(0.069)	(0.126)	(0.158)
Observations	500	500	500	500	500	500	500

Notes: the table shows the effect pathways of adoption of the improved soybean variety. η_0 presents effects of yield and income on soybean income and food and nutrients consumption when the household is not adopting as in equations (3). $(\eta_1 - \eta_0)\hat{p}$ shows the treatment effects on consumption due to yield and income gains from adoption also as in equation (3). TE denotes treatment effects.

We also noted in the conceptual framework that the effect of agricultural production on food and nutrients consumption can be mediated by gender-related issues (Carletto et al 2015). Interestingly, table 4.5 shows that the treatment effect of adoption is not statistically significant across gender for all the outcomes, although the negative sign suggests females tend to benefit more from adoption in terms of food and nutrients consumption compared to males. This finding confirms that the main mechanism by which adoption affects food and nutrients consumption is through increased soybean yields and household income. It further suggests that the attenuating treatment effects of peers observed when a farmer adopts can be attributed to increased household income following own adoption.

4.5.5 Policy strategies

Our results so far, have demonstrated that adoption of the improved variety does not only lead to increased soybean yield, but also contributes to increasing food and nutrients consumption of not only adopters, but that of non-adopters should they adopt. This implies that policies that seek to overcome structural barriers and induce people to adopt can be much rewarding. Thus, we show the effects of a policy that reduces soybean seed price by 50% (in line with current Government policy in Ghana), and a policy that reduces the distance of the household to the nearest soybean seed source to a maximum of four kilometres, using the policy-relevant treatment effects (PRTE). Whereas the subsidy policy seeks to improve affordability, the distance policy attempts to enhance availability of the seeds of the improved variety.

Table 4.6 (col. 1) shows the propensity score at the baseline policy, columns (2) and (3) show the propensity scores and the PRTE, respectively, for soybean seed price subsidy, and columns (4) and (5) show the propensity scores and PRTE, respectively, for the policy of reducing distance to soybean seed source. The estimates show that subsidizing soybean seed price by 50%, and reducing the distance to soybean seed source to a maximum of four kilometres shift households with high unobserved resistance to adoption into adoption, and as a result significantly increase soybean yield by 42 and 36 percentage points, respectively, per household shifted from non-adoption into adoption. The magnitude of the price subsidy effect on yield is higher than that of the distance to seed source. We find statistically significant policy effects for both policies in food and nutrients consumption, but with marginally higher effects for the reduction in distance to seed source. These findings show that, whereas reducing distance to soybean seeds source appears to be more effective in promoting food and nutrients consumption through adoption than the price subsidy, the subsidy appears to produce higher yield effect than the policy of reducing the distance to soybean seed source.

Table 4.6. Policy simulations of the effects of changes in soybean price and distance to soybean seed source on soybean yield, food and nutrients consumption

	Soybean seed price			Distance seed source	
	(1)	(2)	(3)	(4)	(5)
	Baseline propensity score	**Policy propensity score**	**PRTE**	**Policy propensity score**	**PRTE**
Soybean yield	0.664	0.819	0.421***	0.829	0.361***
			(0.082)		(0.109)
Food	0.665	0.823	0.205***	0.828	0.275***
			(0.055)		(0.055)
Vitamin A	0.665	0.823	0.323***	0.828	0.373***
			(0.078)		(0.072)
Protein	0.665	0.823	0.733***	0.828	0.859***
			(0.099)		(0.109)

Notes: The table presents the policy-relevant treatment effects (PRTE) per net household shift into adoption for two different policies. Column 1 reports the baseline propensity score, and columns 2 and 4 report the increase in the propensity induced by the soybean price subsidy and increase proximity to seed source, respectively, based on the baseline specification for the various outcomes. Columns 3 and 5 are the policy-relevant treatment effects for the soybean seed and seed proximity policies respectively. Bootstrapped standard errors (50 replications) are reported in parentheses. The asterisks *** indicates significance at 1% level.

4.5.6 Robustness

In order to examine the robustness of our estimates, we examine the sensitivity of our results to changes in alternative specifications of the MTE functional form, outcome and selection equations, as well as in the peer effects. We first consider the baseline pattern of our MTE curve of positive selection on gains. This is because the estimation of the MTE depends on the functional form assumptions invoked, and also the MTE obtained under different functional form assumptions may yield different weighted effects of the instrument (i.e., IV effects) (Heckman and Vytlaci, 2005). In figure 4.C2 in appendix C, we present MTE curves that include specifications based on the parametric normal model (which assumes returns to adoption decreases monotonically with resistance to adoption), parametric cubic and a semiparametric approach. These curves suggest that the basic shape of the MTE curve is robust to different functional forms, and generally show a similar pattern as in the baseline specification.

We next consider the sensitivity of our ATE, TT and TUT to different specifications, as these put most weights in different segments of the MTE, and therefore could be sensitive to changes in the estimated MTE (Carneiro, et al. 2011). In panel A of table 4.C5, we present estimates from a model where we control for other contextual peer effects (i.e., peers' sex, age, landholding and soil fertility) in the outcome equations (cols. 1-3) to assess whether the observed peer and treatment effects could be driven by contextual effects or correlation in soil conditions between farmers and their peers. In columns 4 to 6, we present estimates of a specification that excludes the effects of peer adoption to examine these estimates under the stable unit treatment value assumption (SUTVA)[52]. The estimates are marginally low and high for yield and food consumption (col. 4-6), and suggest expansion and attenuation biases, respectively, *albeit* similar in directions and significance to the baseline estimates.

In columns 1 to 3 of panel B, we report estimates when estimating the first-stage with a squared term of distance to nearest soybean seed source as additional instrument to account for the fact that at longer distances to seed sources, the probability of adoption will become very low. In columns 4 to 6 of panel B, we interact distance to soybean seed source with household wealth and household size, because the effect of our instrument is likely to vary across households, based on their observed resource status (Carneiro, et al. 2011). Table 4.C6 reports results that show the sensitivity of the estimates to the use of standard errors clustered at the village level in columns (1) to (3) (Cameron, et al. 2008), and when we control for mobile phone network

[52] The SUTVA requires that the potential outcomes of treatment observed on one farm household should not be affected by the treatment of other farm households. The inclusion of the peer adoption effects violates this assumption but Manski (2013) provides characterization of bounds on the treatment effects under social interactions, and thus our estimates should be interpreted as bounds and not necessarily as the point estimates.

coverage in the village in columns (4) and (5). In order to show the sensitivity of the results to changes in the measure of household food consumption, we report treatment effects of adoption on household dietary diversity in column (6) of table 4.C6 (FAO 2010). In spite of these exercises, the treatment effects estimates remain qualitatively similar to those reported in table 4.4.

Finally, table 4.C7, columns (1) to (3) of panel A explore the sensitivity of the estimates to peer effects through means other than peer adoption. Recall from subsection 4.3.2 that links in our networks are defined using social and farm plot proxies, and some of these (such as labor and land exchanges) can present effects similar to peer adoption effects. We explore this by accounting for household (node) degree, which is the total number of connections a household has in the network. A related concern is the issue of the use of the sampled networks which truncate the number of households' social connections and could lead to important links and nodes not observed, which can bias the estimates (Chandrasekhar and Lewis 2016).

In order to examine the sensitivity of our estimates to this issue, we follow the approach of Liu et al. (2017) by re-running our models without households with links with all the 5 randomly matched households to them. Finally, in columns (1) to (3) of panel B, we report estimates with difference in adopting peers of a household between a year after the introduction of the improved variety (i.e., 2004) and the 2016 cropping season. The results of these exercises remain very similar to our baseline results in table 4.4, suggesting that our findings of the pattern of selection and the treatment effects are robust to various functional forms and specifications.

4.6 Discussion

We find significant effects of household adoption on yield, food and nutrients consumption as expected, which can be partly attributed to the yield, income and agro-climatic advantages of the improved over the traditional variety (CSIR-SARI, 2013). The high magnitudes of these effects, especially on food and nutrients consumption can be explained by the interplay of two factors: one is the timing of the survey, as it was conducted in the lean season when households rely heavily on food consumption from cash purchases, and the commercial status of soybean, as an income enhancing crop for households (see also WFP and GSS 2012; Carletto et al. 2015).

Our findings of heterogeneity in returns to adoption show that households with low resistance to adoption do much worse than an average soybean producing household without adoption of the improved variety. However, these households become relatively similar with adoption. This is perhaps because the production of the traditional variety is more demanding (in terms of time and labor), and requires farmers to invest more resources to minimize the production challenges. This could increase the risk of vulnerable households who are not able to meet these production requirements of losing their crops or entire investment due to early shattering. But the improved variety is quite resistant to these issues (CSIR-SARI 2013).

Whereas peer adoption effect has significant and positive effect on households' yields when adopting, we find no significant peer effect on yield when the household is not adopting. A potential interpretation is that when the household is not adopting, increased peer adoption could reduce private learning opportunities from peers, especially if the production processes of the improved and traditional varieties are not complementary. However, household adoption increases private learning and imitation opportunities from adopting peers (Niehaus 2011).

Our findings on peer adoption effect on food and nutrients consumption in the non-adoption state are suggestive of some form of private transfer among peers, since consumption increases with peer adoption in the non-adoption state. However, own adoption leads to attenuating peer adoption effects and this can primarily be attributed to the yield and income gains from the improved soybean variety that tend to substantially increase the consumption of non-adopters when they adopt. This indicates that consumption benefits from peer adoption tend to decline with own adoption, suggesting that increased own productivity and household income lead to reduction in farmers' dependence on peers (Alger and Weibull 2012; Di Falco et al. 2018).

4.7 Conclusion

This paper examined the impact of adoption of improved soybean variety on soybean yield, and household food and nutrients consumption, using household survey data from Ghana. In particular, we estimated the marginal treatment effects of adoption of the improved variety on these outcomes, and thus, show heterogeneities in returns to adoption due to observed and unobserved characteristics of households. The results generally show positive association between adoption and the outcomes, but do not necessarily establish causality. We note three main findings: First, a pattern of positive selection on unobserved gains from adoption of the improved variety is observed across all outcomes, which is due to the fact that households who are more likely to adopt the improved variety have lower returns, than that of an average soybean producing household, when not adopting. This finding is in line with the hypothesis of adoption based on comparative advantage (Suri, 2011). However, adoption of the improved variety tends to make these households quite homogeneous across these outcomes, suggesting that adoption can serve as means by which poorer households can narrow the gaps in yields, and food and nutrients consumption with better and richer households.

Second, we find that households benefit, in terms of increased soybean yield, from having peers who are adopters only when the households also adopt, suggesting the possibility of social learning, imitation and/or exchange of resources that are complementary in the soybean cultivation process. However, on food and nutrients consumption, we find that having adopting peers results in increased household food and nutrients consumption, when the household is not adopting, but attenuates when the household adopts. This suggests that households tend to depend on peers more in meeting food and nutrients consumption, when not adopting (possibly in the form of private transfers) which decreases when the household adopts. These findings suggest that network effects can be an important means of promoting adoption of the improved variety and food and nutrients consumption of vulnerable households. Interventions, such as self-help groups and/or farmer field-days, aimed at promoting interactions among farm households, and enhancing exchange can increase the effectiveness of social networks in promoting adoption, soybean yield, and household food security and nutrition.

Finally, subsidizing soybean seed price, and reducing distance to soybean seed source are estimated to increase adoption, soybean yield, and household food and nutrients consumption. This implies that interventions to minimize production and structural constraints to adoption could be an important strategy in mitigating the cost associated with technology adoption, at least in the setting at hand. Whereas our evidence suggests that input subsidy is likely to be a move in the right direction in enhancing adoption and household outcomes, the option of increasing access by reducing the distance to soybean seed source could produce some additional gains in food and nutrients consumption. Hence, government and development partners can consider increasing access through availability of the improved seeds at the local levels, such as empowering village level shops or community-based groups to engage in input marketing.

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Appendix

Appendix A1: Expressions of treatment effects measures

A.1.1 Conventional treatment effects measures

E.1 ATE $= E[Y_1 - Y_0] = E[\eta_1(X_i) - \eta_0(X_i)]$;

E.2 TT $= E[Y_1 - Y_0|A_i = 1] = E[\eta_1(X_i) - \eta_0(X_i)|A_i = 1] + E[U_{1i} - U_{0i}|A_i = 1]$

E.3 TUT $= E[Y_1 - Y_0|A_i = 0] = E[\eta_1(X_i) - \eta_0(X_i)|A_i = 0] + E[U_{1i} - U_{0i}|A_i = 0]$.

A.1.2 Policy Relevant Treatment Effects (PRTE)

Given that the conventional treatment parameters often present estimates of effects of interventions in gross terms (Heckman & Vytlacil 2005), we use the Policy Relevant Treatment Effects (PRTE) to estimate the aggregate effects of policy intervention that seek to subsidize soybean seed price or reduce distance to soybean seeds source. Such a policy only changes who selects into adoption but does not change the underlying distribution of treatment effects or preference for treatment (Cornelissen et al. 2016). Suppressing the i subscript, if A represents adoption under the prevailing state, and $\tilde{A}$ as the adoption under the alternative policy (i.e., after the subsidy or seed availability intervention), the unconditional PRTE is defined as

$$(6) \qquad \text{PRTE}= E\big[Y_1 - Y_0\big|\tilde{A} = 1\big]E\big[\tilde{A}\big] - [Y_1 - Y_0|A = 1]E[A] + \frac{E[U_1-U_0|\tilde{A}=1]E[\tilde{A}]-[U_1-U_0|A=1]E[A]}{E[\tilde{A}]-E[A]}.$$

This is the mean effect of going from the prevailing policy to the alternative policy per net person shift (Heckman & Vytlacil 2005; Cornelissen et al. 2016).

Appendix A2: Note on social network structures and identification of peer effects

Manski's linear-in-means model assumed individuals in a group are affected by all members of the group, and not by members outside. The simultaneity in behaviour of same group members creates perfect collinearity between the behavioural peer effect and the contextual effects, which causes identification problem. However, in majority of social networks, individuals are influenced by their direct connections or peers, making the impact of members on individuals not even in the network. In this case, the structure of the social network can be relied on to identify peer effects. This makes it possible to identify the two effects if there exist intransitivities in the network such that if individuals i and j are connected and j and k are connected but i and k are not connected, then the characteristics of k can be used as an instrument to identify the effect of j on i (Bramoullé et al. 2009; Di Giorgi et al 2019).

Appendix A3: Excluded instruments

Table 4.A1. Difference in community and key household characteristics across different bandwidths of distance to soybean seed source

Quartiles	**1**	**2**	**1-2**	**3**	**1-3**	**4**	**1-4**	**5**	**1-5**
Distance bandwidth in kilometres (km)	**0.30 to 2.50**	**2.70 to 4.00**		**4.10 to 5.40**		**5.5 to 8.00**		**8.30 to 17.00**	
Community characteristics									
Periodic market (0,1)	0.45	0.53	-0.08	0.43	0.02	0.40	0.05	0.41	0.04
	(0.05)	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)
Mobile phone network (0,1)	0.75	0.71	0.04	0.73	0.02	0.64	0.11*	0.77	-0.02
	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.04)	(0.06)
Nearest paved road (Distance in km)	7.81	9.26	-1.45	7.90	-0.09	9.41	-1.60	8.13	-0.32
	(0.68)	(0.78)	(1.04)	(0.68)	(0.96)	(0.74)	(1.00)	(0.53)	(0.87)
Local wage rate (in GHS)	6.21	6.20	0.01	6.08	0.12	6.49	-0.28	6.22	-0.01
	(0.11)	(0.13)	(0.18)	(0.15)	(0.18)	(0.13)	(0.17)	(0.12)	(0.16)
Local soybean price (in GHS)	1.06	1.06	0.00	1.04	0.02	1.05	0.01	1.05	0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Household									
Wealth (in 10,000 GHS)	1.61	1.23	0.34	1.20	0.41	1.22	0.39	1.16	0.45
	(0.31)	(0.16)	(0.35)	(0.18)	(0.36)	(0.13)	(0.33)	(0.17)	(0.36)
Landholding (in hectares)	2.89	2.44	0.46*	2.48	0.41*	2.62	0.27	2.36	0.53**
	(0.17)	(0.16)	(0.23)	(0.15)	(0.22)	(0.17)	(0.23)	(0.12)	(0.21)
Household size	5.37	5.24	0.12	5.52	-0.15	5.47	-0.10	6.67	-1.31***
	(0.20)	(0.20)	(0.28)	(0.20)	(0.29)	(0.22)	(0.29)	(2.16)	(0.29)
Farmer education (in years)	1.55	2.13	-0.57	0.86	0.69	0.80	0.75*	1.01	0.54
	(0.37)	(0.42)	(0.56)	(0.24)	(0.45)	(0.24)	(0.44)	(0.31)	(0.49)
Change location in 5yrs (0,1)	0.02	0.03	-0.01	0.02	0.00	0.01	0.01	0.03	-0.01
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Change location in 10yrs (0,1)	0.04	0.06	-0.02	0.03	0.01	0.06	-0.02	0.05	-0.01
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Outcomes									
Soybean yield	638.6	641.3	-2.6	626.2	12.4	626.4	12.1	620.0	18.6
	(15.4)	(15.7)	(22.0)	(17.2)	(23.0)	(15.5)	(21.9)	(18.0)	(23.5)
Food cons. score	32.6	33.9	-1.4	33.4	-0.8	33.5	-0.9	34.4	-1.8
	(0.7)	(0.7)	(1.1)	(0.8)	(1.1)	(0.8)	(1.1)	(0.9)	(1.2)
Vitamin A Cons.	12.0	12.7	-0.7	12.4	-0.4	12.6	-0.6	12.3	-0.3
	(0.4)	(0.4)	(0.5)	(0.4)	(0.5)	(0.4)	(0.5)	(0.4)	(0.6)
Protein Cons.	6.4	6.7	-0.3	6.0	0.4	5.9	0.4	5.9	0.5
	(0.4)	(0.3)	(0.5)	(0.3)	(0.5)	(0.3)	(0.5)	(0.4)	(0.5)
Hem iron Cons.	3.9	4.1	-0.2	3.7	0.2	3.6	0.3	3.6	0.3
	(0.2)	(0.2)	(0.3)	(0.2)	(0.3)	(0.2)	(0.3)	(0.2)	(0.3)
Mean (in km)	1.46	3.46		4.95		6.79		11.46	
	(0.73)	(0.46)		(0.27)		(0.75)		(2.15)	
Observations	101	103		96		107		93	

Notes: the table reports results of t-test of community and household level characteristics by different bandwidths of the distance of farm households to the closest soybean seed source. Distance to seed source was categorized into 5 quantiles and the closest bandwidth (i.e., columns 1) was compared with the rest of the bandwidths. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively

Table 4.A2. Pairwise correlations between own instruments and peers of peers' instruments

	(1) SoySeed Distance	(2) N^2SoySeed Distance	(3) SoySeed price	(4) NResident distance	(5) N^2Resident distance
SoySeed Distance					
N^2SoySeed Distance	0.942				
	(0.000)				
SoySeed price	0.008	-0.009			
	(0.857)	(0.825)			
NResident distance	-0.029	-0.016	-0.048		
	(0.505)	(0.717)	(0.275)		
N^2Resident distance	0.010	0.013	-0.007	0.019	
	(0.823)	(0.767)	(0.859)	(0.666)	
Adopted	-0.238	-0.157	-0.011	-0.090	0.091
	(0.000)	(0.000)	(0.798)	(0.044)	(0.042)

Note: Values in parenthesis are p-values.

Table 4.A3. OLS estimates of the effect of distance to soybean seed source on outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Instruments for own adoption				Instruments for peer adoption			
Panel A	Yield	Food	Vitamin A	Protein	Yield	Food	Vitamin A	Protein
SoySeed Distance	-0.041	-0.046	-0.036	0.017				
	(0.025)	(0.032)	(0.042)	(0.071)				
N^2SoySeed Distance	0.013*	0.012	0.020	0.009				
	(0.008)	(0.010)	(0.014)	(0.023)				
SoySeed price	-0.036	-0.049	-0.012	-0.032				
	(0.066)	(0.085)	(0.124)	(0.228)				
NResident distance					0.004	-0.004	-0.010	0.001
					(0.003)	(0.006)	(0.010)	(0.010)
N^2Resident distance					0.003	0.002	0.011	0.023
					(0.005)	(0.007)	(0.014)	(0.017)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farm inputs and revenue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contextual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Network Fes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	5.666***	1.297***	-0.182	-2.095***	5.511***	0.756	-1.603*	-3.089**
	(0.145)	(0.220)	(0.358)	(0.572)	(0.305)	(0.510)	(0.822)	(1.230)
R-squared	0.815	0.476	0.472	0.500	0.504	0.551	0.523	0.585
Observation	166	166	166	166	166	166	166	166

Notes: the table presents an ordinary least square (OLS) regression to test the effect of the distance to soybean seed source (i.e., the exclusion instrument) on our outcomes. Conditional on the household, network (also village) and district controls, the instrument (SoySeed Distance) does not significantly affect any of the outcomes. Values in parenthesis are standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively

Appendix B1: First stage estimates

Table 4.B1.1. First-stage estimates of peers' adoption of improved soybean variety

	Peer adoption	
	Coefficients	S.E.
Sex	0.004	0.010
Age	-0.000	0.000
Education	-0.002	0.001
Hsize	0.005**	0.002
HLand	0.002	0.003
HWealth (predicted)	0.001	0.005
Soil fertility	-0.009	0.005
Seed use	0.001	0.001
Fertilizer cost	0.000	0.000
Pesticide cost	0.001	0.001
Weedicide cost	0.000	0.000
Machinery	-0.005	0.008
Labor use	-0.001**	0.000
Local wage rate	-0.192***	0.032
Soyseed price	-0.002	0.019
Extension (predicted)	-0.037	0.032
Residuals_NWLink	0.007	0.006
Degree	0.006	0.004
NSex	0.053*	0.030
NAge	-0.002	0.002
NEducation	-0.000	0.009
NHsize	0.007	0.014
NLandholding	0.042**	0.017
NWealth	0.111***	0.041
NSoil	-0.110**	0.047
NExtension	-0.198	0.129
NResident distance	-0.002**	0.001
N^2Sex	-0.312***	0.055
N^2Age	0.001	0.002
N^2Education	0.016	0.012
N^2Hsize	-0.055***	0.014
N^2Landholding	-0.081***	0.017
N^2Wealth	0.110**	0.055
N^2Soil	0.294***	0.058
N^2Soyseed price	0.822***	0.137
N^2Extension	-0.154	0.162
N^2Resident distance	-0.005***	0.002
Town centre	-0.002***	0.001
Network Fes	Yes	
Intercept	-0.229	0.181
R-squared	0.882	
Observation	500	

Notes: table reports first-stage estimates of peer adoption equations used to predict the peer adoption variable. Columns 1 and 2 present results for the soybean yield specification, whereas columns 3 and 4 display the results for the food and nutrition specification. S.E. are reported robust standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

B1.2. Further empirical Issues

Our final concern is the potential endogeneity of household wealth, extension contact and farm revenue. In the adoption and outcome equations, household wealth and farm revenues are potentially endogenous because households who adopted the improved variety are expected to have higher yields, which will likely translate into higher farm revenues, incomes and more assets. Also, given that soybean is a market-oriented crop, one can expect that households who are food secured will more likely invest in the new variety, which could lead to increased yield, farm revenues and enhanced wealth. Extension contact could also be endogenous because extension officers may be more inclined to visit farmers who adopted (or performing farmers) than non-adopting (or nonperforming farmers).

To account for this, we use predicted instead of the observed values of these variables obtain from a regression of each of these variables on the entire set of exogenous characteristics and at least an instrument. For the wealth equation, we use whether any parent of the farmer or spouse ever had authority in the community, as instrument. We believe this to be valid and relevant instrument because the authority of the parents in the traditional political system are mostly predetermined by lineage, and can therefore be reasonably assumed to be exogenous. Also, the traditional authority system gives the parent access to land and other natural resources in the village, which the children can benefit from. One issue that might threaten the use of these as instruments is when access to these resources are able to affect our outcomes through a different route, such as household landholding, as well. For this reason, we control for household landholding in all specifications. In the extension contact and farm revenue, following the network literature, we use the extension contact and farm revenues, respectively, of direct and indirect peers, respectively, as instruments. The first-stage instrumenting regressions are presented in table 4.B1.2.

Table 4.B1.2. Instrumenting regressions for wealth, extension contact and farm revenue

	(1) Wealth		(2) Extension		(3) Extension	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Adoption	0.131**	0.057	0.168***	0.038	0.066	0.043
Nadoption	0.100	0.227	-0.007	0.144	0.017	0.145
Sex	-0.079	0.058	-0.013	0.039	0.033	0.036
Age	0.001	0.002	0.001	0.001	0.001	0.001
Education	-0.012	0.009	0.003	0.006	-0.002	0.006
Hsize	0.004	0.016	0.008	0.009	0.015*	0.009
HLand	0.056**	0.023	0.008	0.014	0.024**	0.012
HWealth(predicted)			0.012	0.027	0.011	0.022
HRisk	-0.015	0.019	-0.034**	0.013	-0.010	0.014
Soil fertility	0.045	0.031	0.034*	0.018	-0.024	0.020
Seed use	0.012*	0.007	0.007	0.005	0.006	0.004
Fertilizer cost	0.000*	0.000	0.000	0.000	0.000**	0.000
Pesticide cost	0.002	0.005	-0.002	0.003	0.001	0.003
Weedicide cost	0.000	0.001	-0.000	0.000	0.001*	0.000
Machinery	0.084	0.077	0.004	0.030	0.105**	0.042
Labor use	-0.002	0.003	0.002	0.002	0.001	0.002
Soybean seed price	0.103	0.164			0.223***	0.081
Extension (predicted)					-0.047	0.072
Local wage rate	-0.038	0.123			0.106	0.088
Town center	-0.003	0.003	-0.001	0.002	-0.001	0.002
Contextual effects and link residual						
NSex	0.103	0.172	0.179*	0.102	0.055	0.102
NAge	-0.008	0.006	-0.001	0.004	-0.001	0.004
NLandholding	0.003	0.045	0.019	0.031	0.021	0.030
Residuals_NWLink	-0.009	0.037	0.000	0.024	0.006	0.022
Instruments						
Parent authority	2.200***	0.132				
NExtension			-2.756***	0.253		
N^2Extension			3.671***	0.262		
Association			0.063***	0.014		
NFarm Revenue					-5.747***	0.892
N^2Farm Revenue					-2.636	2.283
N^3Farm Revenue					9.333***	3.034
Network FEs	Yes		Yes		Yes	
Intercept	-0.713	0.553	-0.269	0.274	-0.722*	0.406
R-squared	0.678		0.446		0.746	
Observation	500		500		500	

Notes: the table presents first-stage estimates for instrumenting wealth, extension and revenue used in the soybean yield and food and nutrition estimations. Columns 1 and 2 present results for the household wealth equation. Columns 3 and 4 shows the extension contact results and columns 5 and 6 presents the results of the revenues equation. Network FEs is network fixed effects and Residuals_NWLink is residuals of the link formation model. S.E. are reported robust standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Appendix B2 First-stage network formation model and estimates

B2.1. Network formation model

The section describes the network formation model estimated. We estimated a conditional edge independence model, which assumes links form independently, conditional on node- and link-level covariates as follows;

(B2.1) $L_{ij} = \beta_0 + \beta_1|c_i - c_j| + \beta_2(c_i + c_j) + \beta_3|\mathcal{L}_{ij}| + \mu_{ij}$

where L_{ij} is an $N \times (N-1)$ matrix indicating whether there is a link between individuals i and j, c_i and c_j are characteristics of individual i and j. β_1 measures the influence of differences in their attributes, and β_2 measures the effect of combined level of their attributes. $\mathcal{L}_{ij}$ captures attributes of the link between i and j such as geographical or social distance between them, and β_3 is the associated parameter estimate. The estimates of eq. (B2.1) are reported in table 4.B2.1. We next use the average of the predicted residuals of the link formation model as control functions in our selection and outcome equations to account for the endogeneity of peer effects due to unobserved factors that determine link formation.

Table 4.B2.1. Dyadic regression of network link formation

	Village1	Village2	Village3	Village4	Village5	Village6	Village7	Village8	Village9
Distance between peers in kilometers	-0.040	0.025	0.116**	-0.035	0.028	-0.005	0.038	-0.065	-0.006
	(0.062)	(0.044)	(0.050)	(0.039)	(0.054)	(0.045)	(0.042)	(0.045)	(0.044)
Difference in distance to road between peers in kilometres	-0.003	0.202*	-0.044	0.076	0.047**	0.094**	0.069**	-0.142**	0.041
	(0.030)	(0.104)	(0.055)	(0.058)	(0.022)	(0.038)	(0.031)	(0.060)	(0.025)
Relatives = 1	0.013	0.121	0.064	-0.323	-0.346	0.294	0.570	-0.685**	-0.685**
	(0.339)	(0.369)	(0.580)	(0.558)	(0.283)	(0.662)	(0.376)	(0.304)	(0.349)
Same religion = 1	n.a	n.a.	-0.095	-0.730**	-0.369	-0.020	0.349	-0.811*	-0.281
	n.a.	n.a.	(0.245)	(0.329)	(0.307)	(0.486)	(0.503)	(0.439)	(0.323)
Difference: Sex (= 1 if male)	1.150***	0.821***	7.767***	-0.306	0.437	0.013	0.744**	0.381	0.260
	(0.342)	(0.251)	(0.375)	(0.256)	(0.335)	(0.258)	(0.359)	(0.359)	(0.516)
Difference: Age	0.004	-0.031**	0.031**	-0.003	-0.051***	-0.037***	0.038***	0.093***	0.041***
	(0.008)	(0.013)	(0.013)	(0.015)	(0.017)	(0.012)	(0.010)	(0.036)	(0.014)
Difference: Years of schooling	0.090**	0.015	0.066	0.062	3.489***	-0.081**	-0.044*	3.064***	0.020
	(0.046)	(0.040)	(0.050)	(0.064)	(0.189)	(0.033)	(0.025)	(0.386)	(0.067)
Difference: Household size	-0.212**	-0.097	-0.080	0.067	-0.223**	0.157**	-0.123	0.011	0.103
	(0.097)	(0.096)	(0.090)	(0.085)	(0.091)	(0.073)	(0.103)	(0.063)	(0.070)
Difference: Household landholding in hectares	-0.239	-0.200**	0.098	0.343***	0.130	0.487**	-0.197*	0.089	-0.071
	(0.218)	(0.096)	(0.173)	(0.119)	(0.153)	(0.217)	(0.110)	(0.113)	(0.132)
Difference: Village born = 1 if farmer was born in village	1.065**	0.287	-0.469	0.845***	-0.262	-0.028	-0.865***	6.740***	-0.671**
	(0.513)	(0.353)	(0.310)	(0.290)	(0.239)	(0.323)	(0.262)	(0.516)	(0.307)
Difference: Household wealth (predicted) in GHS	1.173	-0.223	0.882	0.189	0.826	-0.288	-1.780***	2.738*	0.060
	(1.211)	(0.786)	(0.685)	(0.993)	(1.291)	(0.798)	(0.588)	(1.592)	(0.843)
Sum: Sex (= 1 if male)	-0.651***	0.483***	7.522***	-0.345	0.942***	0.380*	0.577**	0.548*	0.295
	(0.239)	(0.185)	(0.356)	(0.217)	(0.298)	(0.229)	(0.277)	(0.314)	(0.311)
Sum: Age	-0.005	0.011	-0.019	-0.023***	0.012	0.001	-0.032***	-0.056**	-0.015
	(0.007)	(0.008)	(0.013)	(0.008)	(0.013)	(0.008)	(0.008)	(0.025)	(0.011)
Sum: Years of schooling	-0.018	0.028	0.012	-0.141**	-3.470***	0.042	-0.014	-3.092***	-0.066
	(0.042)	(0.020)	(0.037)	(0.062)	(0.180)	(0.026)	(0.031)	(0.398)	(0.058)
Sum: Household size	-0.010	0.163***	0.112	-0.002	0.064	-0.040	0.028	-0.037	0.121***
	(0.051)	(0.056)	(0.070)	(0.051)	(0.046)	(0.036)	(0.061)	(0.076)	(0.046)
Sum: Household landholding in hectares	-0.051	-0.005	0.011	0.113	-0.246***	-0.360**	0.181*	-0.058	0.173*
	(0.113)	(0.062)	(0.136)	(0.136)	(0.094)	(0.159)	(0.107)	(0.096)	(0.097)
Sum: Village born = 1 if farmer was born in village	1.019***	0.169	0.096	0.029	-0.039	0.259	0.082	6.841***	-0.925***
	(0.367)	(0.331)	(0.283)	(0.217)	(0.256)	(0.255)	(0.234)	(0.487)	(0.190)
Intercept	-3.504*	-5.325***	-17.991***	0.004	-3.804**	-1.176	0.751	-14.108***	-1.282
	(1.983)	(1.838)	(1.825)	(1.742)	(1.606)	(1.986)	(1.442)	(2.475)	(1.827)
Observation	400	400	400	400	400	400	400	400	400
Pseudo R^2	0.114	0.072	0.092	0.082	0.096	0.077	0.113	0.122	0.080

Notes: the table reports results of the dyadic regression of network link formation in eq. (B2.1). The dependent variable = 1 if i (j) cites i (j) as ever having any of the social and locational contact dimensions discussed under section 4.2.2. Estimator is logit and all standard errors are clustered at the village level. Standard errors are in parenthesis. n.a. denotes not available. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.B2.1. (continued)

	Village10	Village11	Village12	Village13	Village14	Village15	Village16	Village17	Village18
Distance between peers in kilometers	-0.022	-0.079	-0.058	0.011	-0.025	-0.075	-0.019	0.009	-0.042
	(0.056)	(0.064)	(0.038)	(0.043)	(0.079)	(0.059)	(0.048)	(0.047)	(0.035)
Difference in distance to road between peers in kilometres	0.065	6.556**	-0.024	0.002	-0.020	-0.171***	0.042**	0.024	0.034
	(0.069)	(2.820)	(0.053)	(0.026)	(0.030)	(0.029)	(0.019)	(0.018)	(0.047)
Relatives = 1	-0.025	0.274	0.051	0.026	0.304	0.407	-0.001	0.717	0.103
	(0.552)	(0.384)	(0.382)	(0.241)	(0.389)	(0.303)	(0.508)	(0.605)	(0.514)
Same religion = 1	0.038	-0.129	0.320	0.324	-0.652**	-0.610*	-0.013	-0.014	0.183
	(0.268)	(0.361)	(0.317)	(0.389)	(0.326)	(0.342)	(0.402)	(0.384)	(0.342)
Difference: Sex (= 1 if male)	-0.134	0.254	0.522	-0.400	0.428	0.334	0.976***	0.435	0.821***
	(0.344)	(0.314)	(0.461)	(0.293)	(0.332)	(0.329)	(0.300)	(0.336)	(0.283)
Difference: Age	0.026***	-0.028*	0.009	0.017	0.003	-0.044	-0.001	0.012	0.033
	(0.010)	(0.014)	(0.012)	(0.014)	(0.013)	(0.031)	(0.016)	(0.019)	(0.023)
Difference: Years of schooling	1.402***	-0.033	0.060	1.131***	-0.046	-0.175***	6.946***	0.803***	-0.143***
	(0.103)	(0.050)	(0.052)	(0.073)	(0.043)	(0.043)	(0.611)	(0.060)	(0.055)
Difference: Household size	0.163	0.087	0.005	-0.117	0.074	0.046	-0.177***	0.020	-0.043
	(0.118)	(0.069)	(0.120)	(0.082)	(0.099)	(0.098)	(0.052)	(0.082)	(0.133)
Difference: Household landholding in hectares	0.579***	-0.067	0.007	0.137	-0.172	0.369***	0.008	0.289***	-0.115
	(0.152)	(0.085)	(0.146)	(0.169)	(0.201)	(0.130)	(0.082)	(0.085)	(0.149)
Difference: Village born = 1 if farmer was born in village	-0.570	-0.395	0.907**	0.227	0.374	0.607**	0.143	-1.469***	-0.062
	(0.382)	(0.320)	(0.444)	(0.272)	(0.342)	(0.266)	(0.448)	(0.419)	(0.232)
Difference: Household wealth (predicted) in GHS	0.152	-0.709	0.541	-0.205	-0.181	-0.589	-1.611	-3.162***	-0.858
	(0.658)	(1.303)	(1.063)	(1.309)	(1.060)	(0.665)	(1.840)	(0.861)	(0.976)
Sum: Sex (= 1 if male)	0.874***	-0.027	0.500*	0.535**	0.160	-1.051***	0.637**	0.134	-0.068
	(0.212)	(0.298)	(0.296)	(0.250)	(0.329)	(0.215)	(0.313)	(0.294)	(0.266)
Sum: Age	-0.011	0.000	-0.010	0.019**	-0.010	-0.005	0.027***	0.016	-0.029**
	(0.008)	(0.010)	(0.011)	(0.009)	(0.010)	(0.016)	(0.008)	(0.012)	(0.012)
Sum: Years of schooling	-1.482***	-0.043	-0.033	-1.125***	0.008	0.008	-6.015***	-0.733***	0.071***
	(0.080)	(0.034)	(0.048)	(0.087)	(0.038)	(0.036)	(0.646)	(0.045)	(0.022)
Sum: Household size	-0.153*	0.172***	0.130*	-0.093	0.091	0.140***	0.106*	0.196***	0.171**
	(0.093)	(0.053)	(0.072)	(0.097)	(0.057)	(0.038)	(0.054)	(0.055)	(0.083)
Sum: Household landholding in hectares	-0.539***	0.091	-0.013	0.083	0.174	0.134	0.083	-0.063	-0.129
	(0.143)	(0.064)	(0.115)	(0.134)	(0.120)	(0.100)	(0.081)	(0.080)	(0.093)
Sum: Village born = 1 if farmer was born in village	0.362	0.392	0.572	0.422	0.921***	0.794***	0.955**	0.213	0.078
	(0.288)	(0.277)	(0.405)	(0.268)	(0.342)	(0.266)	(0.394)	(0.374)	(0.218)
Intercept									
	0.240	-2.183	-5.001**	-3.558**	-3.781*	-3.036	-4.480	-0.735	1.407
	(1.978)	(2.780)	(2.115)	(1.657)	(1.941)	(1.876)	(4.427)	(2.445)	(2.590)
Observation	400	400	400	400	400	400	400	400	400
Pseudo R^2	0.117	0.059	0.047	0.049	0.061	0.146	0.083	0.155	0.073

Notes: the table reports results of the dyadic regression of network link formation in eq. (B2.1). The dependent variable = 1 if i (j) cites i (j) as ever having any of the social and locational contact dimensions discussed under section 4.2.2. Estimator is logit and all standard errors are clustered at the village level. Standard errors are in parenthesis. n. a. denotes not available. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.B2.1. (continued)

	Village19	Village20	Village21	Village22	Village23	Village24	Village25
Distance between peers in kilometers	-0.006	0.018	-0.009	0.060	0.018	-0.040	0.044
	(0.061)	(0.030)	(0.039)	(0.067)	(0.052)	(0.046)	(0.050)
Difference in distance to road between peers in kilometres	0.012	0.820	0.686	0.059**	0.617	-1.666	0.024
	(0.008)	(2.653)	(0.659)	(0.024)	(3.403)	(3.250)	(0.016)
Relatives = 1	-0.471*	0.390*	0.090	1.345	-0.712	0.227	-0.523
	(0.268)	(0.205)	(0.272)	(1.195)	(0.435)	(0.307)	(0.538)
Same religion = 1	-0.304	n.a.	0.180	0.107	0.759	n.a.	0.152
	(0.383)	n.a.	(0.479)	(0.578)	(0.506)	n.a.	(0.423)
Difference: Sex (= 1 if male)	-0.385	0.849*	-0.352	8.166***	-0.919***	-0.457	0.744*
	(0.275)	(0.447)	(0.423)	(0.399)	(0.195)	(0.278)	(0.392)
Difference: Age	0.003	-0.016	-0.040**	-0.000	0.010	-0.009	0.029
	(0.019)	(0.018)	(0.020)	(0.014)	(0.009)	(0.012)	(0.025)
Difference: Years of schooling	0.009	-0.054*	0.043	n.a.	0.144*	0.421***	0.142***
	(0.045)	(0.030)	(0.065)	n.a.	(0.075)	(0.062)	(0.050)
Difference: Household size	0.049	0.149*	0.086	0.076	-0.042	0.252***	0.229***
	(0.063)	(0.089)	(0.088)	(0.097)	(0.082)	(0.093)	(0.081)
Difference: Household landholding in hectares	-0.066	-0.088	-0.077	0.126	0.268*	0.619***	-0.263
	(0.088)	(0.105)	(0.100)	(0.163)	(0.155)	(0.235)	(0.218)
Difference: Village born = 1 if farmer was born in village	6.526***	-0.273	8.173***	0.638	-0.122	0.210	-0.235
	(0.422)	(0.315)	(0.403)	(0.490)	(0.313)	(0.327)	(0.412)
Difference: Household wealth (predicted) in GHS	1.450	-1.353	-0.100	2.782***	2.433***	-2.289***	-0.522
	(1.150)	(0.884)	(0.639)	(0.976)	(0.935)	(0.794)	(1.269)
Sum: Sex (= 1 if male)	0.504*	0.810**	-0.293	8.878***	0.426**	0.219	0.161
	(0.284)	(0.388)	(0.245)	(0.517)	(0.175)	(0.173)	(0.278)
Sum: Age	-0.012	-0.004	0.010	0.017	-0.002	0.030**	-0.002
	(0.011)	(0.013)	(0.011)	(0.015)	(0.009)	(0.013)	(0.021)
Sum: Years of schooling	0.033	0.077***	0.210***	n.a.	0.088	-0.460***	0.019
	(0.024)	(0.021)	(0.037)	n.a.	(0.068)	(0.047)	(0.059)
Sum: Household size	-0.000	-0.044	-0.072	0.028	0.048	0.099	-0.284***
	(0.048)	(0.054)	(0.062)	(0.062)	(0.041)	(0.085)	(0.056)
Sum: Household landholding in hectares	0.123	-0.078	0.270***	-0.382*	-0.115	-0.413*	0.248
	(0.092)	(0.085)	(0.082)	(0.198)	(0.102)	(0.213)	(0.169)
Sum: Village born = 1 if farmer was born in village	6.413***	-0.381	7.525***	1.116**	-0.231	0.725***	-0.821***
	(0.380)	(0.240)	(0.430)	(0.435)	(0.196)	(0.228)	(0.278)
Intercept							
	-17.238***	-0.160	-18.598***	-26.287***	-3.877**	-2.388	0.730
	(2.569)	(1.444)	(1.453)	(2.386)	(1.602)	(1.844)	(2.514)
Observation	400	400	400	400	400	400	400
Pseudo R^2	0.075	0.086	0.160	0.155	0.073	0.083	0.201

Notes: the table reports results of the dyadic regression of network link formation in eq. (B2.1). The dependent variable = 1 if i (j) cites i (j) as ever having any of the social and locational contact dimensions discussed under section 4.2.2. Estimator is logit and all standard errors are clustered at the village level. Standard errors are in parenthesis. n.a. denotes not available. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.B2.2. Instrumenting regression for Wealth in Dyadic model

	Difference of wealth			Sum of wealth		
	Coefficient	Robust S. E.	Dyadic S. E.	Coefficient	Robust S. E.	Dyadic S. E.
	All regressors as difference			All regressors as sums		
Sex = 1 if male	0.080	0.036	0.086	−0.237*	0.034	0.154
Years of education of farmer	−0.026**	0.004	0.010	−0.040**	0.004	0.017
Born = 1 if born in village	−0.106*	0.036	0.069	0.200*	0.034	0.144
Value of inherited land in GHS	0.277***	0.040	0.089	0.925***	0.048	0.142
District dummies						
1 if farmer resides in district 1	−0.322	0.052	0.262	−0.552*	0.066	0.397
1 if farmer resides in district 2	−0.493**	0.051	0.257	−0.757**	0.066	0.405
1 if farmer resides in district 3	0.298	0.068	0.327	0.429	0.090	0.539
1 if farmer resides in district 4	−0.150	0.082	0.426	−0.369	0.097	0.560
Intercept	1.488***	0.056	0.214	2.614***	0.088	0.429
Observations	9500			9500		

Notes: the table presents first-stage estimates for instrumenting wealth in the dyadic link formation model. Columns 1, 2 and 3 present results for the difference of wealth between neighbors. Columns 4, 5 and 6 show results of the sum of wealth estimates. The table also show both the conventional robust standard errors (in columns 2 and 5) and the Fafchamps and Gubert (2007) group dyadic standard errors (columns 3 and 6). S.E. denotes standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Appendix C: Results

Table 4.C1. Soybean varietal adoption and yield

	Selection		Outcome	
	Coefficient	S. E.	Coefficient	S. E.
Panel A	$\boldsymbol{\Theta_A}$		$\boldsymbol{\rho_0, \eta_0}$	
Nadoption (Predicted)	0.168***	0.047	-0.051	0.033
Sex	0.050	0.052	-0.028	0.053
Age	-0.002	0.001	0.001	0.002
Education	0.002	0.008	0.029***	0.008
Hsize	-0.035**	0.013	-0.005	0.011
HLand	0.052**	0.022	0.047	0.029
HWealth (predicted)	0.163***	0.045	0.069	0.074
Soil fertility	0.022	0.026	0.009	0.026
Seed use	-0.014**	0.006	0.005	0.006
Fertilizer cost	-1.8E-5	7.0E-5	-2.4E-5	8.4E-5
Pesticide cost	0.001	0.004	-0.006	0.012
Weedicide cost	3.6E-4	0.001	0.002**	0.001
Machinery	-0.006	0.052	0.102	0.095
Labor use	0.001	0.002	-0.001	0.002
Extension (predicted)	0.568***	0.110	-0.021	0.127
Soy selling price	0.166	0.203	-0.046	0.130
Residuals_NWLink	-0.054	0.034	0.055*	0.031
Intercept			5.435***	0.406
Panel B			$\boldsymbol{(\rho_1 - \rho_0)\,\hat{p}, (\eta_1 - \eta_0)\,\hat{p}}$	
Nadoption (Predicted)			0.128**	0.050
Sex			0.053	0.061
Age			-0.002	0.002
Education			-0.013	0.010
Hsize			0.001	0.014
HLand			-0.036	0.032
HWealth (predicted)			-0.061	0.078
Soil fertility			0.012	0.032
Seed use			-0.004	0.007
Fertilizer cost			6.1E-5	1.0E-4
Pesticide cost			0.008	0.014
Weedicide cost			-0.003***	0.001
Machinery			-0.106	0.104
Labor use			0.001	0.002
Extension (predicted)			0.066	0.139
Soy selling price			0.018	0.176
Residuals_NWLink			-0.042	0.042
Intercept			1.106**	0.460
Panel C			$\boldsymbol{(\tau)}$	
Local wage rate	0.137	0.101	-0.013	0.042
Network FEs	Yes		Yes	
Town center	0.004*	0.002	-0.001	0.001
NSex	-0.240	0.151		
NAge	0.003	0.005		
NLand	-0.098**	0.040		
SoySeed Distance	-0.478***	0.089		
N^2SoySeed Distance	0.147***	0.027		
SoySeed price	-0.481**	0.193		
X^2: excluded instruments	36.99			
p-value: excluded instruments	0.000			
p-value: observed heterogeneity			0.000	
Observations	500		500	

Notes: The "selection" column reports the marginal effects from probit selection model of adoption decisions, with Θ_A as the vector of parameter estimates, equation (2). Our instrument is distance to soybean seed source, which is normalized about its overall mean. $\hat{p}$ is the predicted propensity score from the estimated first-stage adoption equation. The "outcome" column shows the estimates of the soybean yield equations (1 and 5). ρ_0, η_0 in panel A denote effects of covariates on the outcome when the household is not adopting as in equations (3). $(\rho_1 - \rho_0)\,\hat{p}$, $(\eta_1 - \eta_0)\hat{p}$ in panel B denote the treatment effects of the covariates on the outcome due to gains from adoption as in equation (3). τ is a parameter vector of village characteristics and network fixed effects (Network Fes). Residuals_NWLink is residuals of the link formation model. S.E. are bootstrapped standard errors with 50 replications. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.C2. Soybean variety adoption, food and vitamin A consumption

	Selection		Outcome			
			Food		Vitamin A	
	Coefficient	S. E.	Coefficient	S. E.	Coefficient	S. E.
Panel A	$\boldsymbol{\Theta_A}$		$\boldsymbol{\rho_0, \eta_0}$		$\boldsymbol{\rho_0, \eta_0}$	
Nadoption (predicted)	0.110**	0.049	0.087**	0.033	0.198***	0.048
Sex	0.011	0.053	0.103*	0.055	0.148	0.102
Age	-0.002	0.001	-0.002	0.002	0.003	0.003
Education	0.004	0.008	0.022**	0.010	0.040***	0.011
Hsize	-0.041***	0.013	-0.035***	0.011	-0.016	0.027
HLand	0.041*	0.021	0.058**	0.027	0.036	0.043
HWealth (predicted)	0.169***	0.045	0.127*	0.076	0.190**	0.087
Soil fertility	0.038	0.027	0.030	0.035	-0.045	0.048
Seed use	-0.015**	0.006	0.003	0.007	0.007	0.010
Fertilizer cost	-3.9E-5	6.0E-5	2.4E-5	6.8E-5	-3.8E-5	1.3E-4
Pesticide cost	0.003	0.004	0.012*	0.007	0.015	0.011
Weedicide cost	-2.6E-5	0.001	-8.6E-5	0.001	1.7E-4	0.001
Machinery	-0.066	0.059	0.056	0.090	0.023	0.128
Labor use	0.001	0.002	0.007**	0.002	0.010**	0.004
Farm revenue (predicted)	0.270***	0.070	0.211***	0.064	0.476***	0.127
Residuals_NWLink	-0.046	0.034	0.017	0.029	0.049	0.057
Soybean selling price	0.088	0.194	0.227*	0.137	0.073	0.270
Intercept			0.519	0.669	-2.980***	0.920
Panel B			$\boldsymbol{(\rho_1 - \rho_0)\,\hat{p}, (\eta_1 - \eta_0)\,\hat{p}}$		$\boldsymbol{(\rho_1 - \rho_0)\,\hat{p}, (\eta_1 - \eta_0)\,\hat{p}}$	
Nadoption (predicted)			-0.107***	0.033	-0.214***	0.055
Sex			-0.095	0.069	-0.130	0.126
Age			0.003	0.003	-0.002	0.004
Education			-0.024**	0.010	-0.042***	0.014
Hsize			0.041**	0.015	0.026	0.035
HLand			-0.075**	0.030	-0.035	0.047
HWealth (predicted)			-0.135	0.083	-0.195*	0.100
Soil fertility			-0.030	0.047	0.068	0.062
Seed use			0.003	0.009	-0.004	0.013
Fertilizer cost			-1.2E-5	8.7E-5	1.1E-4	1.8E-4
Pesticide cost			-0.013*	0.008	-0.017	0.013
Weedicide cost			3.4E-4	0.001	3.6E-5	0.002
Machinery			-0.006	0.098	0.050	0.149
Labor use			-0.011***	0.003	-0.014**	0.005
Farm revenue (predicted)			-0.030	0.068	-0.395**	0.145
Residuals_NWLink			-0.039	0.040	-0.091	0.073
Soybean selling price			-0.232	0.179	-0.120	0.337
Intercept			1.072	0.761	3.931***	0.995
Panel C			$\boldsymbol{(\tau)}$		$\boldsymbol{(\tau)}$	
Extension (predicted)	0.572***	0.108				
Local wage rate	-0.266*	0.151	0.015	0.040	0.166**	0.065
Network FEs	Yes		Yes		Yes	
Town center	0.005**	0.002	0.001	0.001	0.005***	0.001
NSex	-0.498***	0.163				
NAge	0.002	0.005				
NLand	-0.116**	0.040				
SoySeed Distance	-0.483***	0.094				
N^2SoySeed Distance	0.144***	0.029				
SoySeed price	-0.497**	0.194				
X^2: excluded instruments	38.10					
p-value: excluded instruments	0.000					
p-value: observed heterogeneity			0.000		0.000	
Observations	500		500		500	

Notes: The "selection" column reports the marginal effects from probit selection model of adoption decisions, with Θ_A as the vector of parameter estimates, equation (2). Our instrument is distance to soybean seed source, which is normalized about its overall mean. $\hat{p}$ is the predicted propensity score from the estimated first-stage adoption equation. The "outcome" column shows the estimates of the food and vitamin A foods consumption equations (1 and 5). ρ_0, η_0 in panel A denote effects of covariates on the outcomes when the household is not adopting as in equations (3). $(\rho_1 - \rho_0)\,\hat{p}$, $(\eta_1 - \eta_0)\hat{p}$ in panel B denote the treatment effects of the covariates on the outcomes due to gains from adoption as in equation (3). τ is a parameter vector of village characteristics and network fixed effects (Network Fes). Residuals_NWLink is residuals of the link formation model. S.E. are bootstrapped standard errors with 50 replications. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.C3. Soybean variety adoption and protein consumption

	Selection		Protein	
	Coefficient	S. E.	Coefficient	S. E.
Panel A		$\boldsymbol{\Theta_A}$		$\boldsymbol{\rho_0, \eta_0}$
Nadoption (predicted)	0.110**	0.049	0.292***	0.086
Sex	0.011	0.053	0.140	0.117
Age	-0.002	0.001	0.001	0.005
Education	0.004	0.008	0.074**	0.027
Hsize	-0.041***	0.013	-0.031	0.036
HLand	0.041*	0.021	0.076	0.058
HWealth (predicted)	0.169***	0.045	0.440***	0.118
Soil fertility	0.038	0.027	0.068	0.065
Seed use	-0.015**	0.006	0.019	0.019
Fertilizer cost	-3.9E-5	6.0E-5	-2.4E-5	2.1E-4
Pesticide cost	0.003	0.004	-0.005	0.024
Weedicide cost	-2.6E-5	0.001	0.002	0.003
Machinery	-0.066	0.059	-0.070	0.243
Labor use	0.001	0.002	0.010	0.007
Farm revenue (predicted)	0.270***	0.070	0.546***	0.157
Residuals_NWLink	-0.046	0.034	0.008	0.068
Soybean selling price	0.088	0.194	-0.194	0.253
Intercept			-4.702***	1.440
Panel B			$\boldsymbol{(\rho_1 - \rho_0)\,\hat{p}, (\eta_1 - \eta_0)\,\hat{p}}$	
Nadoption (predicted)			-0.346***	0.087
Sex			-0.126	0.158
Age			0.003	0.007
Education			-0.101***	0.033
Hsize			0.030	0.047
HLand			-0.045	0.065
HWealth (predicted)			-0.510***	0.145
Soil fertility			-0.001	0.096
Seed use			-0.012	0.025
Fertilizer cost			1.6E-4	2.5E-4
Pesticide cost			0.009	0.029
Weedicide cost			-0.002	0.004
Machinery			0.219	0.295
Labor use			-0.015*	0.008
Farm revenue (predicted)			-0.497**	0.200
Residuals_NWLink			-0.039	0.095
Soybean selling price			0.185	0.316
Intercept			4.319**	1.837
Panel C			$\boldsymbol{(\tau)}$	
Extension (predicted)	0.572***	0.108		
Local wage rate	-0.266*	0.151	0.310**	0.121
Network FEs	Yes		Yes	
Town center	0.005**	0.002	0.011***	0.002
NSex	-0.498***	0.163		
NAge	0.002	0.005		
NLand	-0.116**	0.040		
SoySeed Distance	-0.483***	0.094		
N^2SoySeed Distance	0.144***	0.029		
SoySeed price	-0.497**	0.194		
X^2: excluded instruments	38.10			
p-value: excluded instruments	0.000			
p-value: observed heterogeneity			0.000	
Observations	500		500	

Notes: The "selection" column reports the marginal effects from probit selection model of adoption decisions, with Θ_A as the vector of parameter estimates, equation (2). Our instrument is distance to soybean seed source, which is normalized about its overall mean. $\hat{p}$ is the predicted propensity score from the estimated first-stage adoption equation. The "outcome" column shows the estimates of the protein foods consumption equations (1 and 5). ρ_0, η_0 in panel A denote effects of covariates on the outcome when the household is not adopting as in equations (3). $(\rho_1 - \rho_0)\,\hat{p}$, $(\eta_1 - \eta_0)\hat{p}$ in panel B denote the treatment effects of the covariates on the outcome due to gains from adoption as in equation (3). τ is a parameter vector of village characteristics and network fixed effects (Network Fes). Residuals_NWLink is residuals of the link formation model. S.E. are bootstrapped standard errors with 50 replications. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.C4. Soybean variety adoption, yield and food consumption with mobile phone coverage

	Selection		Outcome			
			Yield		Food	
	Coefficient	S. E.	Coefficient	S. E.	Coefficient	S. E.
Panel A	$\boldsymbol{\Theta_A}$		$\boldsymbol{\rho_0, \eta_0}$		$\boldsymbol{\rho_0, \eta_0}$	
Nadoption (predicted)	0.138**	0.052	-0.064	0.037	0.097***	0.097
Sex	0.043	0.052	-0.027	0.045	0.103**	0.103
Age	-0.002	0.001	0.001	0.002	-0.002	-0.002
Education	0.001	0.008	0.030***	0.009	0.022**	0.022
Hsize	-0.034**	0.013	-0.004	0.011	-0.035**	-0.035
HLand	0.054**	0.022	0.049	0.034	0.057**	0.057
HWealth (predicted)	0.159***	0.045	0.056	0.139	0.128	0.128
Soil fertility	0.021	0.026	0.011	0.027	0.032	0.032
Seed use	-0.014**	0.006	0.005	0.006	0.003	0.003
Fertilizer cost	-1.7E-05	7.0E-05	-1.9E-05	8.9E-05	2.2E-05	2.2E-05
Pesticide cost	0.001	0.004	-0.009	0.010	0.013	0.013
Weedicide cost	0.001	0.001	0.002***	0.001	-9.9E-05	-9.9E-05
Machinery	-0.008	0.051	0.125	0.089	0.048	0.048
Labor use	0.001	0.002	-0.001	0.002	0.007***	0.007
Extension (predicted)	0.580***	0.111	-0.021	0.114		
Farm revenue (predicted)	-0.064	0.029			0.215***	0.215
Residuals_NWLink	-0.052	0.034	0.055	0.033	0.015	0.015
Soybean selling price	0.161	0.205	-0.052	0.148	0.234*	0.234
Intercept			5.376***	0.477	0.524	0.524
Panel B			$\boldsymbol{(\rho_1-\rho_0)\,\hat{p}, (\eta_1-\eta_0)\,\hat{p}}$		$\boldsymbol{(\rho_1-\rho_0)\,\hat{p}, (\eta_1-\eta_0)\,\hat{p}}$	
Nadoption (predicted)			0.137**	0.059	-0.111***	0.033
Sex			0.049	0.051	-0.094*	0.055
Age			-0.001	0.002	0.002	0.003
Education			-0.014	0.010	-0.024**	0.011
Hsize			0.001	0.015	0.039**	0.016
HLand			-0.039	0.037	-0.075***	0.024
HWealth (predicted)			-0.047	0.150	-0.137	0.092
Soil fertility			0.009	0.031	-0.032	0.031
Seed use			-0.004	0.007	0.003	0.008
Fertilizer cost			5.0E-05	1.1E-04	-7.6E-06	9.2E-05
Pesticide cost			0.011	0.012	-0.014	0.009
Weedicide cost			-0.003***	0.001	0.001	0.001
Machinery			-0.135	0.099	0.008	0.087
Labor use			0.002	0.003	-0.011***	0.003
Extension (predicted)			0.066	0.131		
Farm revenue (predicted)					-0.033	0.077
Residuals_NWLink			-0.041	0.044	-0.036	0.034
Soybean selling price			0.043	0.192	-0.241	0.152
Intercept			1.163**	0.536	1.082	0.745
Panel C			$\boldsymbol{(\tau)}$		$\boldsymbol{(\tau)}$	
Local wage rate	0.145	0.101	-0.019	0.036	0.014	0.046
Mobile network	0.112	0.098	0.018	0.029	0.033	0.027
Network FEs	Yes		Yes		Yes	
Town center	0.004	0.002	0.001	0.001	0.002***	0.001
NSex	-0.254*	0.154				
NAge	0.002	0.005				
NLand	-0.068	0.046				
SoySeed Distance	-0.483***	0.091				
N^2SoySeed Distance	0.154***	0.029				
SoySeed price	-0.465**	0.197				
p-value: observed heterogeneity			0.000		0.000	
Observations	500		500		500	

Notes: The “selection” column reports the marginal effects from probit selection model of adoption decisions, with Θ_A as the vector of parameter estimates, equation (2). Our instrument is distance to soybean seed source, which is normalized about its overall mean. $\hat{p}$ is the predicted propensity score from the estimated first-stage adoption equation. The “outcome” column shows the estimates of the soybean yield and food consumption equations (1 and 5). ρ_0, η_0 in panel A denote effects of covariates on the outcomes when the household is not adopting as in equations (3). $(\rho_1-\rho_0)\,\hat{p}$, $(\eta_1-\eta_0)\hat{p}$ in panel B denote the treatment effects of the covariates on the outcomes due to gains from adoption as in equation (3). τ is a parameter vector of village characteristics and network fixed effects (Network Fes). Residuals_NWLink is residuals of the link formation model. S.E. are bootstrapped standard errors with 50 replications. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

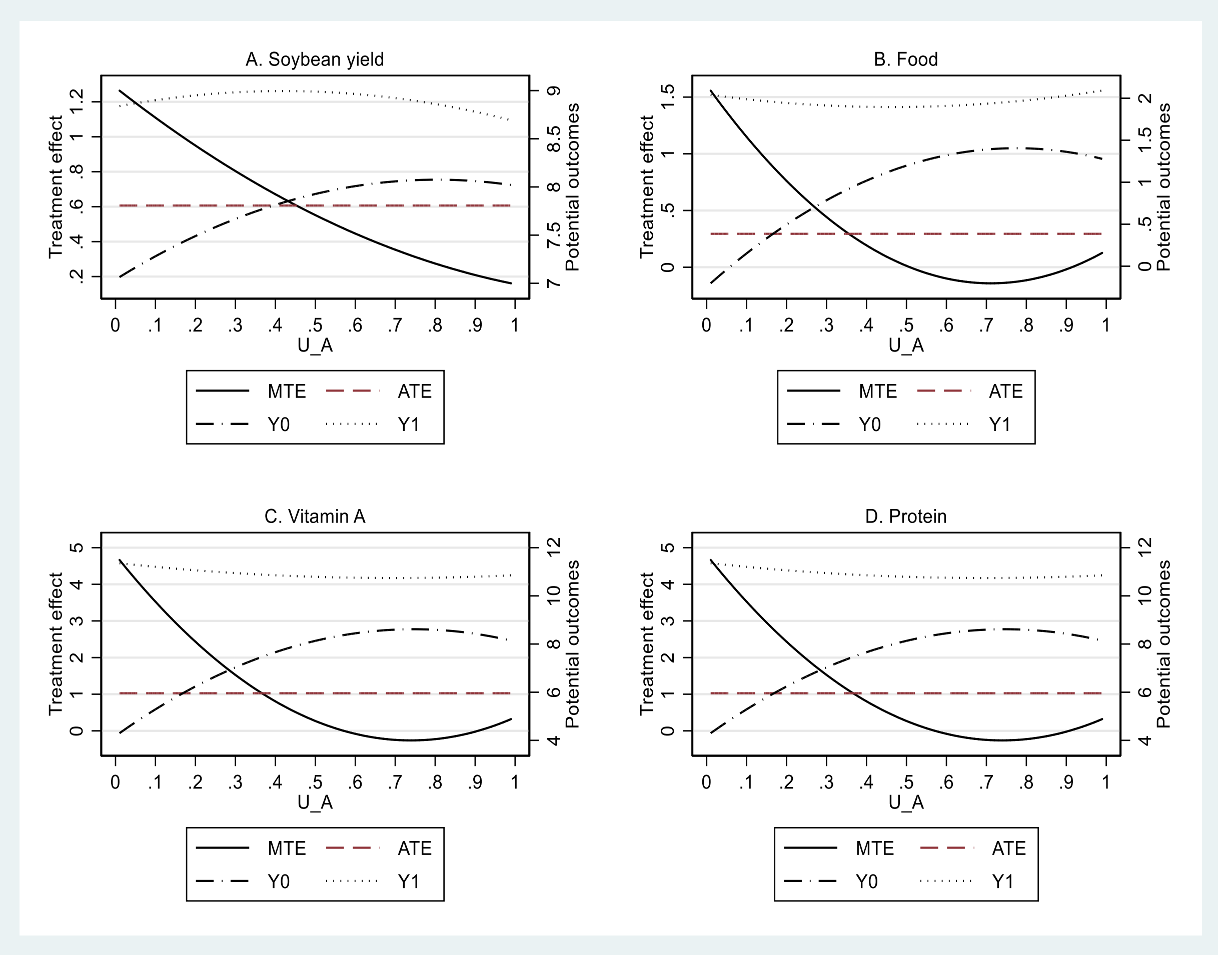

Figure 4.C1 Counterfactual outcomes

The figure shows the treatment effects and potential outcomes (unobserved) as a function of resistance to treatment (U_A) for all the outcomes, based on the baseline specification. In each case, it displays the marginal treatment effects, MTE (solid line), and average treatment effects, ATE (dashed line). More importantly, it shows the distribution of the outcomes, Y0 and Y1, in the non-adoption (dashed-dot line) and adoption (dotted line) states, respectively.

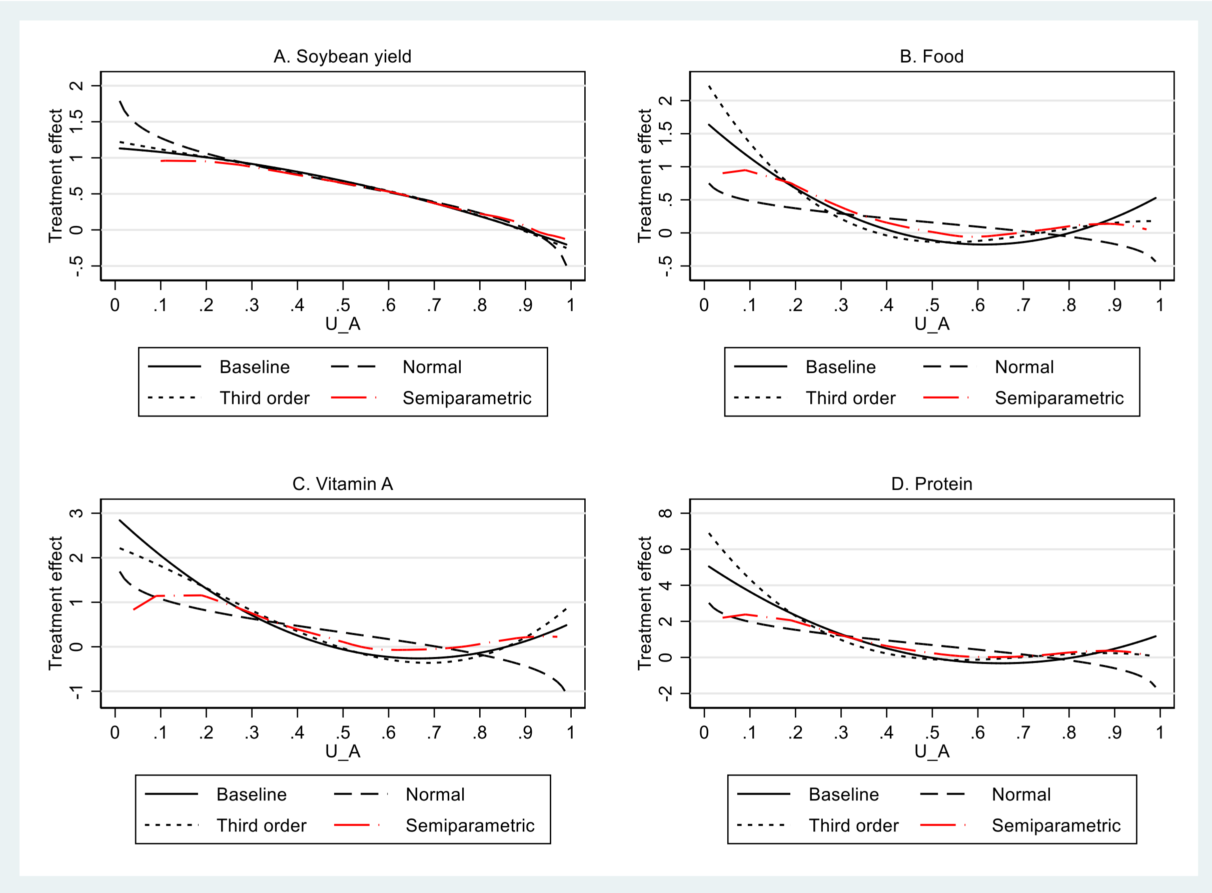

Figure 4.C2 MTE Functional form sensitivity for food and nutrition security

Figure 4.C2 shows the marginal treatment effects (MTE) functional form robustness checks based on the same specifications in figure 4.3, evaluated at average values of the covariates. U_A denotes unobserved resistance to treatment/adoption. Part A depicts MTE curves for soybean yield, part B shows the MTE curve for food consumption, part C is the MTE curve for vitamin A rich foods consumption, while part D is the MTE curve for protein rich foods consumption. The solid MTE curve refers to our baseline specification, where we include the propensity score and its square in the specification. The figure also displays three additional specifications that allow for a specification without square of the propensity score (i.e., normal), one with cubic of the propensity score (third order) and a specification obtained from semiparametric approach (Semiparametric).

Table 4.C5. Aggregate treatment effects of adoption on Soybean yield, food and vitamin A: Sensitivity to different specification of the outcomes and selection equations

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**Sensitivity to different specification of the outcome equation**					
	Contextual network effects and peer soil			Exclude peer effects for SUTVA		
	Yield	Food	Vitamin A	Yield	Food	Vitamin A
ATE	0.671***	0.276***	0.589***	0.527***	0.329***	0.566***
	(0.119)	(0.093)	(0.164)	(0.122)	(0.070)	(0.128)
TT	0.867***	0.279**	0.677***	0.625***	0.374***	0.716***
	(0.164)	(0.129)	(0.234)	(0.163)	(0.103)	(0.188)
TUT	0.284**	0.271***	0.411***	0.333**	0.241***	0.267***
	(0.115)	(0.076)	(0.101)	(0.127)	(0.077)	(0.086)
Nadoption ρ_0	−0.070	0.088**	0.155**			
	(0.037)	(0.040)	(0.069)			
TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$	0.157***	−0.085**	−0.135*			
	(0.043)	(0.047)	(0.079)			
p-values for essential heterogeneity	0.002	0.011	0.001	0.041	0.001	0.000
Panel B	**Sensitivity to the specification of the choice equation**					
	Distance squared			Distance interacted with wealth and household size		
	Yield	Food	Vitamin A	Yield	Food	Vitamin A
ATE	0.569***	0.342***	0.621***	0.622***	0.292***	0.535***
	(0.124)	(0.072)	(0.133)	(0.105)	(0.071)	(0.118)
TT	0.723***	0.380**	0.742***	0.791***	0.287**	0.604***
	(0.172)	(0.111)	(0.190)	(0.159)	(0.107)	(0.161)
TUT	0.265**	0.265***	0.379***	0.287**	0.299***	0.394***
	(0.124)	(0.063)	(0.079)	(0.103)	(0.074)	(0.086)
Nadoption ρ_0	−0.050	0.075**	0.180***	−0.059	0.089**	0.198***
	(0.034)	(0.027)	(0.056)	(0.035)	(0.033)	(0.058)
TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$	0.135**	−0.089**	−0.188**	0.136**	−0.108	−0.211***
	(0.049)	(0.031)	(0.065)	(0.048)	(0.038)	(0.063)
p-values for essential heterogeneity	0.003	0.000	0.000	0.001	0.001	0.001

Notes: The table reports the average treatment effect (ATE), average treatment effect on the treated (TT), average treatment effect on the untreated (TUT), effect of peer adoption (i.e., Nadoption ρ_0), treatment effect of peer adoption, [i.e., TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$] using different specification for soybean yield, food and nutrients consumption. The ρ's are as defined in equations (1) and (3). Panel A shows the sensitivity of the outcome equations to different specifications. Panel B dwells on sensitivity of the selection equation, which includes the square of the instrument and the instrument interacted with household size and wealth. The p-value for the test of essential heterogeneity tests for a nonzero slope of the MTE curve. Bootstrapped standard errors (50 replications) are reported in parentheses. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.C6. Aggregate treatment effects of adoption on outcomes: Sensitivity to use of clustered standard errors, mobile phone network coverage and household dietary diversity

	(1)	(2)	(3)	(4)	(5)	(6)
	Sensitivity to:					
	Use of clustered errors			Mobile network		HDDS
	Yield	Food	Vitamin A	Yield	Food	
ATE	0.606***	0.294***	0.526***	0.617***	0.295***	1.317**
	(0.105)	(0.078)	(0.143)	(0.103)	(0.077)	(0.521)
TT	0.772***	0.299**	0.596**	0.788***	0.296**	1.206*
	(0.142)	(0.101)	(0.188)	(0.166)	(0.107)	(0.727)
TUT	0.278**	0.283***	0.384***	0.280**	0.294***	1.532***
	(0.121)	(0.086)	(0.106)	(0.119)	(0.065)	(0.451)
Nadoption ρ_0	-0.051	0.087**	0.198***	0.064	0.097***	0.455**
	(0.033)	(0.028)	(0.057)	(0.037)	(0.030)	(0.226)
TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$	0.128**	-0.107***	-0.214***	0.137**	-0.111***	-0.613**
	(0.045)	(0.033)	(0.053)	(0.059)	(0.033)	(0.245)
p-values for essential heterogeneity	0.004	0.001	0.003	0.016	0.001	0.045
Observations	500	500	500	500	500	500

Notes: The table reports the average treatment effect (ATE), average treatment effect on the treated (TT), average treatment effect on the untreated (TUT), effect of peer adoption (i.e., Nadoption ρ_0), treatment effect of peer adoption, [i.e., TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$]. The ρ's are as defined in equations (1) and (3). Columns (1) to (3) report estimates where standard errors are clustered at the village level following Cameron et al. (2008). Columns (4) and (5) present estimates where we accounted for village mobile phone network coverage, whiles column (6) presents estimates where household food dietary diversity score (HDDS) is used as the outcome. The p-value for the test of essential heterogeneity tests for a nonzero slope of the MTE curve. Bootstrapped standard errors (50 replications) are reported in parentheses in columns (4) to (6). The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.C7. Aggregate treatment effects of adoption on Soybean yield, food and vitamin A: Sensitivity to Network Fixed Effects, Unobserved Link formation and differences in peers

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**Sensitivity to farmers' degree and truncation of links due to sampling**					
	Degree			Without those with links with all 5		
	Yield	Food	Vitamin A	Yield	Food	Vitamin A
ATE	0.627***	0.312***	0.547***	0.618***	0.316***	0.549***
	(0.115)	(0.082)	(0.128)	(0.096)	(0.093)	(0.123)
TT	0.796***	0.346***	0.671***	0.789***	0.335**	0.629***
	(0.165)	(0.119)	(0.188)	(0.139)	(0.146)	(0.181)
TUT	0.293**	0.244***	0.301***	0.296**	0.279***	0.396***
	(0.113)	(0.066)	(0.090)	(0.108)	(0.059)	(0.096)
Nadoption ρ_0	-0.046	0.128**	0.279***	-0.045	0.082***	0.198***
	(0.046)	(0.046)	(0.074)	(0.032)	(0.032)	(0.049)
Degree $\rho_{0,d}$	0.042	-0.071	-0.122			
	(0.070)	(0.061)	(0.121)			
TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$	0.113*	-0.165***	-0.328***	0.122**	-0.101**	-0.215***
	(0.058)	(0.055)	(0.098)	(0.047)	(0.037)	(0.054)
TE for Degree $(\rho_{1,d} - \rho_{0,d})\,\hat{p}$	0.045	0.146	0.278*			
	(0.078)	(0.072)	(0.147)			
p-values for essential heterogeneity	0.005	0.006	0.018	0.000	0.000	0.000
	500	500	500	478	478	478

Panel B	**Sensitivity to changes in adopting peers over time and use of HDDS**		
	Difference in peer adopters: 2016 – 2004		
	Yield	Food	Vitamin A
ATE	0.598***	0.298***	0.540***
	(0.119)	(0.076)	(0.131)
TT	0.760***	0.307***	0.615***
	(0.169)	(0.106)	(0.179)
TUT	0.279**	0.281***	0.390***
	(0.109)	(0.078)	(0.091)
Nadoption ρ_0	-0.055	0.075**	0.176***
	(0.039)	(0.029)	(0.075)
TE for Nadoption $(\rho_1 - \rho_0)\,\hat{p}$	0.131**	−0.101***	−0.203***
	(0.050)	(0.031)	(0.059)
p-values for essential heterogeneity	0.006	0.000	0.000
Observations	500	500	500

Notes: The table reports the average treatment effect (ATE), average treatment effect on the treated (TT), average treatment effect on the untreated (TUT), effect of peer (i.e., ρ_0 and $\rho_{0,d}$ for peer adoption and degree, respectively), treatment effect of peers [i.e., $(\rho_1 - \rho_0)\,\hat{p}$ and $(\rho_{1,d} - \rho_{0,d})\,\hat{p}$ for peer adoption and degree, respectively] and the p-value for the test of essential heterogeneity using different specification for soybean yield, food and nutrients consumption. Panel A shows the sensitivity of our estimates to household degree and measurement errors due to the use of the sampled networks. Panel B dwells on sensitivity of the estimates the use of differenced peer adoption. The p-value for the test of essential heterogeneity tests for a nonzero slope of the MTE curve. Bootstrapped standard errors (50 replications) are reported in parentheses. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 4.C8. Estimates of network fixed effects (Tables C1 and C2 continued)

	(1)	(2)	(3)	(4)
	Selection equations		Outcome equations	
	Yield	Food	Yield	Food
Village 2	184.375***	178.404***	0.063	-0.030
	(64.354)	(62.591)	(0.077)	(0.074)
Village 3	128.749***	124.759***	-0.031	-0.123*
	(44.421)	(43.226)	(0.076)	(0.067)
Village 4	126.167***	122.800***	0.002	-0.065
	(44.058)	(42.831)	(0.057)	(0.067)
Village 5	117.003***	113.338***	0.052	-0.124**
	(41.210)	(40.053)	(0.091)	(0.062)
Village 6	43.525***	42.898***	-0.032	-0.142**
	(14.861)	(14.426)	(0.075)	(0.069)
Village 7	375.646***	363.032***	-0.024	-0.053
	(130.379)	(126.753)	(0.057)	(0.064)
Village 8	78.181***	75.635***	-0.030	0.015
	(28.067)	(27.265)	(0.098)	(0.080)
Village 9	121.510***	115.719***	-0.024	-0.037
	(41.596)	(40.539)	(0.066)	(0.093)
Village 10	-100.812***	-99.107***	0.113	0.021
	(34.630)	(33.657)	(0.076)	(0.085)
Village 11	-100.972***	-99.779***	-0.086	-0.053
	(35.957)	(34.953)	(0.073)	(0.105)
Village 12	-78.137***	-77.489***	-0.007	-0.036
	(27.630)	(26.847)	(0.054)	(0.094)
Village 13	-9.003*	-9.642**	-0.151	-0.061
	(4.933)	(4.772)	(0.095)	(0.121)
Village 14	-50.025***	-48.998***	0.050	-0.027
	(17.612)	(17.047)	(0.071)	(0.072)
Village 15	-18.533**	-18.862**	-0.183**	-0.101
	(8.561)	(8.315)	(0.091)	(0.114)
Village 16	-5.114*	-5.135*	-0.071	-0.054
	(2.727)	(2.687)	(0.068)	(0.085)
Village 17	138.474***	132.801***	-0.013	-0.011
	(48.015)	(46.701)	(0.058)	(0.069)
Village 18	-38.725***	-37.550***	-0.019	-0.048
	(13.670)	(13.328)	(0.051)	(0.057)
Village 19	-6.225***	-6.795***	0.005	0.037
	(1.926)	(1.913)	(0.063)	(0.073)
Village 20	30.308***	28.587***	0.022	0.024
	(10.833)	(10.501)	(0.056)	(0.058)
Village 21	-92.361***	-90.162***	-0.157	-0.026
	(30.394)	(29.590)	(0.142)	(0.128)
Village 22	-134.078***	-129.525***	-0.180	0.015
	(44.845)	(43.647)	(0.186)	(0.138)
Village 23	59.334***	58.869***	-0.126	-0.147
	(19.061)	(18.561)	(0.077)	(0.100)
Village 24	65.202***	63.404***	-0.038	-0.171**
	(22.110)	(21.540)	(0.067)	(0.067)
Village 25	n.a.	n.a.	0.024	0.090
	n.a.	n.a.	(0.103)	(0.078)

Notes: Bootstrapped standard errors (50 replications) are reported in parentheses. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively. n.a. denotes not available.

Chapter Five

Informing Food Security and Nutrition Strategies in Sub-Saharan African countries: An Overview and Empirical Analysis

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Abstract

This article presents a systematic review of the literature on policy options to improve food security and nutrition in developing countries, and an empirical analysis of the impact of smallholder market participation on food security and nutrition in Ghana. The review focuses on the impacts of policy strategies such as structural changes in relative prices, agricultural infrastructure, economic incentives and agricultural technologies. In order to account for threats of selection bias and omitted variable problem, the empirical analysis uses an ordered probit selection model to jointly estimate households' market orientation decisions and food and nutrients consumption. The empirical results show that transitioning from one market orientation to another significantly increase households' food and nutrients consumption.

Keywords: Food security, Nutrition, Market orientation, Crop commercialization, Treatment effects

JEL codes: D12, Q13, Q18

5.1 Introduction

Food insecurity in sub-Saharan Africa remains a major developmental challenge, despite several interventions to improve food security and nutrition in many developing regions. Recent official estimates suggest that hunger and malnutrition appear to be increasing in most sub-Saharan African countries, a situation that is in contrast to the rest of the world (FAO, ECA and AUC 2020)[53]. The increasing food insecurity in Africa, combined with the fact that persistent food insecurity contributed to the failure of countries in the region in meeting the Millennium Development Goal (MDG) of halving the number of hungry people by 2015 (Abdulai and Kuhlgatz 2012), suggest the need for continuous efforts in supporting and promoting measures to improve food security in the region. While the worsening food situation can partly be attributed to climate change (Abdulai 2018; FAO, ECA and AUC 2020), as well as poor and weakening market conditions, the impact of agricultural markets on food security and nutrition appears to be far from being conclusive (Carletto et al. 2017; Linderhof et al. 2019; Ehui 2020).

Many authors have emphasized the role of new agricultural technologies, specialization and commercialization in increasing farm productivity and household welfare through enhanced efficiency, competitiveness and gains from comparative advantage (Govereh and Jayne 2003; Ochieng et al. 2019). However, prohibitive transaction costs imposed by underdeveloped market systems and infrastructure, market failures, and inadequate access to finance and technologies in most developing countries have often hindered the efficiency of food market systems, and limited the potentials of agricultural marketing in these areas (Fafchamps 1992; Abdulai and Birachi 2009; Abdul-Rahaman and Abdulai 2020). Notwithstanding these

[53] Whereas there was no increase in the prevalence of undernourishment in the rest of world between 2014-2018, growth in prevalence for the whole of Africa and sub-Saharan Africa was 1.7 and 2.0 percentage points, respectively, over the same period (FAO, ECA and AUC 2020).

constraints, smallholder marketing has been shown to increase farmers' access to improved crop inputs, productivity and income (Ashraf et al. 2009; Abdul-Rahaman and Abdulai 2020).

Despite the widespread agreement on the role of smallholder marketing in improving food security and nutrition, the empirical evidence on this issue remain scanty, with mixed findings (Carletto et al. 2017; Linderhof et al. 2019; Kuma et al. 2018). While studies such as Ochieng et al. (2019) analyzed the impact of commercialization of bananas and legumes on dietary diversity in central Africa, and Kuma et al. (2018), who examined the effects of coffee production on household food security in Ethiopia show that commercialization improved household dietary diversity and food security, others authors report that the impacts of commercialization on food consumption and nutrition is either negative or non-existent (e.g., Carletto et al. 2017; Linderhorf et al. 2019).

Moreover, most of these studies have often failed to consider the possible market orientation[54] of smallholders' crop sales, which may mask the extent and pattern of gains from crop sales, given that smallholders' crop sales are driven by profit and non-profit motives (Pingali and Rosegrant 1995; Jacoby and Minten 2009). Production and marketing decisions of smallholders in Africa are often fragmented and characterized by a blend of subsistence, surplus, commercial and distress[55] motives, which may have various implications on the gains and impacts of commercialization across farmers (Pingali and Rosegrant 1995). For instance, if households are

[54] Household market orientation in developing countries has been classified into three (FAO 1989; Pingali and Rosegrant 1995). 1) ***Subsistence farmer*** where the farmer's objective is food self-sufficiency, produces wide range of products and/or sells not more than 25% of the output; 2) ***Transitional or surplus farmer*** where the farmer produces for household consumption and sale of surplus, but sells at least 25% and less than 50% of the output; and 3) ***Commercial farmer*** where the farmer is profit oriented, highly specialized and with high market engagement, and sells more than 50% of the output.

[55] Distress sales usually arise when farmers are forced to sell their harvest to meet immediate financial requirements (such as servicing of debts or meeting other household needs) (Jacoby and Minten 2009).

subsistence-oriented or surplus-oriented, they may choose to produce different crop mix in order to secure food self-sufficiency, and to spread market-related risks due to market imperfections and lack of risk mitigating mechanisms such as insurance and credit markets (Zanello 2012; Ecker 2018). If, however, farm households are commercial-oriented, then production and marketing decisions could be based on profit and some market intelligence, which can result in higher 'gains' from trade, increased household income and improved food security and nutrition (Pingali and Rosegrant 1995; Abdulai and Huffman 2000).

In this paper, our goal is twofold: First, to provide an overview of the literature on food security and nutrition strategies in developing countries. While food security and nutrition are of interest in their own rights, we focus on the survey of the literature on economic policies and micro strategies of promoting smallholder food security and nutrition in sub-Saharan Africa. Second is to provide an empirical example of how smallholder market orientation impacts on food security and nutrition in Ghana. The empirical analysis builds on the review by showing how commercially/profit-oriented market engagement by smallholders can serve as a food security and nutrition enhancing strategy in the area. While previous studies have considered the role of smallholder market participation and commercialization on food security and nutrition, there is almost no study on how smallholder market orientation affects the impacts of commercialization on food security and nutrition[56]. The empirical analysis is partly justified by the fact that the extent of smallholder market integration is closely associated with the motive

[56] Some studies examine the impacts of smallholder market participation and commercialization by focusing on market participation decisions, cultivation and sale of cash crops, as well as the value of total crop harvest sold. Strasberg et al. (1999), Govereh and Jayne (2003), Zanello (2012) and Kuma et al. (2018), for instance, focus on smallholder marketing decisions, and cultivation and sales of cash crops, and Carletto et al. (2017) and Linderhof et al. (2019) focus on the value of crops sold. Notable exceptions are Ochieng et al. (2019) who focus on the effect of households moving from non-commercialized to commercialized, and Ogutu et al. (2019) who emphasis the effects of commercialization in a continuum (i.e., continuous treatment effects), but not on how market orientation affects food security and nutrition.

of production, which tends to have varied impacts on household welfare (Abdulai and Huffman 2000; Ecker 2018). This, therefore, allows us to delineate smallholder market participation effects on household food security and nutrition under different motives of market engagement by smallholders.

Second, the empirical analysis allows us to highlight the impact of smallholder transition from subsistence to commercial on the consumption of specific nutrient rich foods. The analysis on specific nutrients intake is significant in this setting for at least two reasons: First, unlike most previous studies that focused on calorie and/or food consumption (Kuma et al. 2018; Ochieng et al. 2019), which do not enhance the understanding of individual nutrients intake patterns, analysis of the consumption of nutrient rich foods provide insights into specific nutrients intake and therefore, serve as a wedge between food patterns and food quality (Freisling et al. 2010). Second, the distinction between food/calorie and specific nutrient rich foods is important, because many African countries, including the study country, face deficiencies in specific nutrients such as vitamins, protein and iron, in spite of appreciable or relatively normal levels of food and calorie intake (Abdulai and Kuhlgatz 2012; Colen et al. 2018). This, coupled with the fact that the recent deteriorating food security and nutrition situation in Africa has been partly attributed to adverse food market conditions, underscore the need to further understand how smallholder market orientation affects the impact of commercialization on household food security and nutrition.

The rest of the paper is organized into three main sections as follows: The next section presents an overview of food security research in Africa, with particular emphasis on food security and nutrition promotion strategies in the literature. Section 5.3 shows the empirical example of smallholder market participation as a food security and nutrition enhancing strategy. Section 5.4 concludes and highlights some policy and future research implications.

5.2 Food Security in Africa

The recent increase in the incidence of food insecurity and malnutrition in sub-Saharan African (SSA) countries calls for the need to seriously assess and find ways to promote food security in the sub-region. Evidence shows that the prevalence of food insecurity and malnutrition have risen from 18.2% in 2014 to 20% in 2018 in Africa, with that of sub-Saharan Africa, increasing from 20.8% to 22.8% over the same period (FAO, ECA and AUC 2020). Estimates from the FAO, ECA and AUC (2020) reveal that about 239 million in the region were undernourished in 2018. The number of undernourished people in Nigeria, which is the most populated country in the region, was estimated to be over 25 million in 2018, which is about 180% increase over the past decade (FAO, ECA and AUC 2020). This development suggests that, as was in the case of the failure to achieve the Millennium Development Goal of halving the incidence of hunger by 2015, the realization of the Sustainable Development Goal two of eradicating hunger and improving nutrition by 2030 may not be realized, if concerted efforts are not made to overcome the barriers to improving food security and nutrition in the region (OECD 2016).

The state of food security and nutrition in developing countries has been a consequence of environmental and economic factors including climate shocks; conflicts; unemployment; low wages and food price inflation; lack of access to and adoption of improved technologies; and lack of institutions, structures and markets for farmers and consumers (Weber et al. 1988; Abdulai and Kuhlgatz 2012; Abdulai and Huffman 2014; FAO, ECA and AUC 2020). In this section, we provide an overview of the literature on how these factors have impacted food security and nutrition, as well as general household welfare.

5.2.1 Economic Policies and Food Security

In most African countries, the fundamental agricultural policy objectives have been to increase productivity and private sector engagement in agriculture, reduce state involvement, improve innovation and technology, opening up markets and allowing prices to determine the allocation of factors of production (Abdulai and Huffman 2000). Food security policies in many of these economies have also focused on improving food trade and market integration through enhanced infrastructure, private and state trade support policies, and public buffer stocks. These policies have resulted in key policy initiatives such as the Comprehensive Africa Agricultural Development Programme (CAADP) and the African Regional Nutrition Strategy (ARSN) aimed at increasing investment in research and development, agricultural infrastructure, extension services and the subsidization of farm inputs to increase productivity, trade and food security (Sheahan and Barrett 2017; FAO, ECA and AUC 2020). Also, in the wake of the COVID-19 pandemic, which has resulted in border closures, lockdowns and curfews, and the consequent disruption in supply chains as well as projected contraction of agricultural production, ministers for agriculture of African Union members have publicly committed to implementing measures to minimize food system disruptions and ensure food security and nutrition for their citizens (Ehui 2020).

The issue of food prices has been a key focus of interest in food security policies in many developing countries. Such policies aim at improving food access through lower market prices and stabilization of consumption in times of high food price inflation (Barrett 2002; OECD 2016). Two main approaches have been widely used to implement these policies in the past. These included universal price subsidies that benefit net buyers of food, and limited access subsidies that provide rationed quantities at reduced prices (Byerlee et al. 2006; Abdulai and Kuhlgatz 2012). However, the limitations of these policies have been the lack of sustainability and exit mechanisms, and the accruals of greater shares of rationed food gains to political actors and groups at the expense of the poor. Moreover, a number of these price policies did not sufficiently incorporate country specific price and production risk factors. This resulted in the failure of several food price policies to produce the desired results with respect to food security and nutrition measures (Barrett 2002; Byerlee et al. 2006).

Similarly, the Structural Adjustment Programs that were implemented by many African governments in the 1980s also contributed to food security dynamics in many of these countries. Available evidence shows that the response of the agriculture sector in Africa to these policy reforms was encouraging, because output and productivity increased in the countries that pursued reforms compared to countries that failed to implement these reforms (Byerlee et al. 2006; Abdulai and Kuhlgatz 2012). However, the reduction or removal of subsidies on farm inputs following the structural reforms also led to increased input prices, which later led to reduced farm output and productivity, and increased food insecurity and malnutrition (Abdulai and Huffman 2000). This suggests the need for policy-makers and researchers to put particular emphasis on how long-term policies and interventions can ensure a balance between state efficiency and productivity, without compromising food security and nutrition goals.

5.2.2 Climate Change and Food Security

Climate change and shocks continue to have serious adverse effects on agricultural production and food security, particularly in developing countries (Abdulai 2018; Eastin 2018; Shahzad and Abdulai 2020; FAO, ECA and AUC 2020). In particular, high temperatures, heat, water stress and related weather extremes tend to affect poor people in developing countries the most, because of their heavy reliance on agriculture for their livelihoods, low economic diversification and their inability to cope with food price inflation and income shocks (Abdulai and CroleRees 2001; Eastin 2018). Several attempts have been made to address or mitigate the adverse impacts of climate change in Africa, with some prominent strategies being the development of irrigation systems and the adoption of climate-smart agricultural practices (Lipper et al. 2014; Abdulai 2018). Climate-smart agriculture is an embodiment of practices that seek to promote the reliance on agricultural systems and livelihoods to promote production, and reduce risks of food insecurity and malnutrition for the current and future generations (Lipper et al. 2014; Issahaku and Abdulai 2020).

The literature has shown a variety of climate-smart practices that include conservation agriculture, use of improved and drought-tolerant crop varieties, adoption of improved technologies, crop rotation and mixed cropping, matching livestock to supply of grazing land as well as crop diversification and economic diversification into non-farm income activities (Abdulai and CroleRees 2001; Di Falco and Veronesi 2013; FAO 2016; Shahzad and Abdulai 2020). Earlier studies on the impact of climate change focused on crop productivity at the country, regional and global levels, and only provided insights into the impacts of climate change in aggregate terms (Di Falco et al. 2011). However, the need to promote resilience of the poorest and vulnerable segments of rural population in developing countries (Eastin 2018), resulted in the need to understand smallholder adaptation strategies (Di Falco et al. 2011; Issahaku and Abdulai 2020). Thus, recent studies have focused on understanding the drivers of smallholder adaptation to climate change in developing countries, and also quantifying the effects of adaptation strategies on farm performance and household welfare measures such as yields, net returns, poverty reduction, and food security and nutrition (FAO 2016; Eastin 2018; Issahaku and Abdulai 2020; Shahzad and Abdulai 2020).

Promotion of drought resistant crop varieties, and conservation agriculture remain top of the list of climate change adaptation practices, since these have been shown to have substantial impacts on household resilience to climate change and on household welfare in Africa (Di Falco et al. 2011; Abdulai 2018). Many studies have shown positive effects of climate change adaptation practices such as changing crop varieties, soil and water conservation practices, water harvesting and irrigation, tree planting, matching livestock to supply of grazing land, and economic diversification on household welfare in Africa and Asia (e.g., Di Falco et al. 2011; FAO 2016; Issahaku and Abdulai 2020; Shahzad and Abdulai 2020). For instance, Issahaku and Abdulai (2020) show that smallholder adaptation to climate change increases household dietary diversity and reduces household food insecurity by about 15% and 35%, respectively in Ghana.

Despite the benefits of these practices, adoption of specific climate-smart practices remains low in many African countries (Walker et al. 2014; Abdulai and Huffman 2014; Issahaku and Abdulai, 2020). Whereas available evidence estimates the average adoption of climate-smart practices at about 66% (Di Falco et al. 2011; Issahaku and Abdulai 2020), the incidence of adoption of specific strategies have been quite low. For instance, Di Falco and Veronesi (2013) show that farmers' adoption of water strategies ranges from 4 to 16%, while their adoption of other strategies such as the use of new technologies and diversification into off-farm jobs stand at 1.35% and 6.83%, respectively. Also, in spite of the burgeoning literature on impact of adaptation to climate change, discourse between adaptation and food security and nutrition in developing countries is quite limited (Di Falco et al. 2011; Di Falco and Veronesi 2013; Issahaku and Abdulai 2020).

5.2.3 Adoption of Technology and Food Security

In addition to the issues of climate-smart and sustainable agriculture, the association between adoption of improved agricultural technologies and household welfare has received considerable attention among policymakers and researchers (Abdulai and Huffman 2005; Foster and Rosenzweig 2010). This is due to the long recognition that productivity growth in agriculture partly depends on the availability of improved technologies and the adoption of these technologies (Foster and Rosenzweig 2010; Pannell and Zilberman 2020). Studies on this front can be broadly categorized into those that focus on understanding the drivers of technology adoption and diffusion in developing countries, and those that examine the impacts of adoption on household welfare (Foster and Rosenzweig 2010; Abdulai and Huffman 2014; Wossen et al. 2019; Huffman 2020).

In the case of the former, many factors have been found to be associated with the lack of adoption of improved technologies, particularly in sub-Saharan Africa. Prominent among these factors are credit constraints, absence of insurance and other risk mitigating schemes, high transaction costs due to lack of market infrastructure and efficient markets, lack of access to extension services and some behavioral limitations (Foster and Rosenzweig 2010; Pannell and Zilberman 2020). Information failure has also been identified as an important factor that limits farmers awareness, understanding and adoption of improved technologies in many developing countries. This contributed to increased interest in understanding the role of social learning and other peer effects in the adoption and diffusion of improved technologies in Africa (Abdulai and Huffman 2005; Foster and Rosenzweig 2010; Huffman 2020).

The other strand of adoption studies focused on understanding the impacts of adoption on household welfare (e.g., Becerril and Abdulai 2010; Abdulai and Huffman 2014; Kassie et al. 2017; Wossen et al. 2019). Most of these studies show that adoption of improved technologies tends to increase household productivity, income and consumption, with some of the studies reporting impacts of 24% and 16% increase in smallholder crop yields and farm net returns, respectively (Abdulai and Huffman 2014; Kassie et al. 2017; Wossen et al. 2019). Unfortunately, despite the significance of improved technologies for farm productivity and income, Africa has lagged behind in the use of improved and modern technologies, and as such has not been able to reap the productivity and welfare benefits of the so-called Green revolution (Sheahan and Barrett 2017). For instance, Walker et al. (2014) estimate the mean level of adoption across 20 improved crop varieties at 35% in Africa, with two-thirds of these crops having adoption rates lower than this mean level.

Similarly, in spite of the high interest in understanding the impact of agricultural technologies on household welfare, not much has been done on the impacts of adoption of improved crop varieties on food security and, in particular, on the consumption of specific nutrient rich foods in Africa. Previous studies mostly focused on adoption, farm returns and to a lesser extent on food security (Abdulai and Huffman 2014; Kassie et al. 2017; Wossen et al. 2019), and when attempts are made in the realm of specific nutrients consumption, the focus has been on calorie-income and price elasticities (Abdulai and Aubert 2004; Colen et al. 2018). There is therefore the need for an in-depth examination and understanding of the impacts of specific food security promotion strategies such as adoption of new technologies, smallholder diversification and marketing, as well as the associated impact mechanisms on specific food nutrients intake. Such information would be relevant in informing the design and implementation of pro-poor policies in Africa, and in increasing the effectiveness of food security and nutrition policies in realizing the Sustainable Development Goal of eradicating hunger, achieving food security and improved nutrition, and promoting sustainable agriculture (Abdulai 2018; Colen et al. 2018).

Thus, the empirical analysis considers the role of smallholder market engagement as a diversification strategy that can enhance the resilience of smallholders to food and nutrition insecurity. Smallholder farmers market engagement generally include non-farm employment, diversification into cash cropping, selling of harvest and purchases of food to minimize seasonal variation in food availability (Abdulai and CroleRees 2001; Wiggins et al. 2011; Di Falco and Veronesi 2013; Kuma et al. 2018), and these have been recognized as food insecurity coping mechanisms (Di Falco and Veronesi 2013; Shahzad and Abdulai 2020). Also, the integration of smallholders into output and input markets can result in increased motivation of smallholders to produce for profit maximization, which may lead to increased household welfare (Abdulai and Huffman 2000). Thus, the next section focuses on the issues of agricultural commercialization and household food security and nutrition.

5.2.4 Market Engagement and Food Security

Agricultural marketing or commercialization has been conceived in the literature as involving smallholder participation in non-farm economic activities, participation in output and input markets, as well as the profit motive or orientation of the farm business (Pingali and Rosegrant 1995; Abdulai and Delgado 1999; Wiggins et al. 2011; Dithmer and Abdulai 2017; Carletto et al. 2017). A considerable body of empirical research has focused on understanding the role of smallholder non-farm work and market participation on household welfare (Abdulai and Delgado 1999; Abdulai and CroleRees 2001; Zanello 2012; Carletto et al. 2017). This is due to the fact that non-farm engagement or marketing has long been recognized as a means by which smallholders can move from subsistence farming to a more commercialized one, and also minimize agricultural risks, given the failure or absence of consumption and insurance markets in developing countries (Pingali and Rosegrant 1995; Reardon et al. 2006). These studies place more emphasis on understanding the determinants of smallholder participation in non-farm work or marketing, and the impact of such participation on smallholder welfare indicators such as productivity, net returns and income (Abdulai and Delgado 1999; Abdulai and CroleRees 2001; Wiggins et al. 2011; Zanello 2012).

Many factors such as education, availability of markets and other infrastructure, household access to credit, income and capital have been reported as influencing smallholders' decisions to participate in non-farm work or economic diversification, since the lack of access to these factors appears to make it difficult for smallholders in many developing countries to diversify away from subsistence agriculture (Abdulai and CroleRees 2001; Wiggins et al. 2011). Also, studies have shown that transaction costs, wealth and assets, contractual and cooperative marketing substantially affect smallholders' marketing decisions and the quantities of inputs and outputs traded (Abdulai and Birachi 2008; Zanello 2012; Abdul-Rahaman and Abdulai 2020). In particular, recent studies show that smallholder contract and cooperative marketing tend to reduce market risks, increase smallholders' bargaining power, and contribute to increase farm productivity, income and household welfare in some Asian and African countries (Abdulai and Birachi 2008; Ma et al. 2018; Abdul-Rahaman and Abdulai 2020).

In addition, several studies have examined the impacts of non-farm work and diversification (Holden et al. 2004; Owusu et al. 2011; Ecker 2018), sale and purchase of food (Zanello 2012; Ogutu et al. 2019), and contracting or cooperative marketing (Ma et al. 2018; Abdul-Rahaman and Abdulai 2020) on household welfare. Smallholder marketing has contributed to increased household productivity and farm returns in Asia and Africa (Ma et al. 2018; Abdul-Rahaman and Abdulai 2020; Ogutu et al. 2019; Ochieng et al. 2019), although its impacts on food security and particularly nutrients intake remain inconclusive (Zanello 2012; Carletto et al. 2017; Ogutu et al. 2019).

One possibility of resolving the mixed and inconclusive findings on the impacts of smallholder marketing on food security and nutrition is to consider the fact that consumption gains from commercialization could be heterogeneously distributed among households, and also within household members (Carletto et al. 2017; Ogutu et al. 2019). However, studies have mostly failed to consider these dimensions in examining the impacts of commercialization on household welfare (Carletto et al. 2017). In addition, existing studies have completely neglected smallholder profit or market orientation on welfare gains, in spite of the fact that smallholders' production and marketing decisions in developing countries are characterized by different motives, including "distress sales" (Pingali and Rosegrant 1995; Reardon 2006; Jacoby and Minten 2009). A notable exception is Ogutu et al. (2019), who examined the heterogeneity in the impacts of agricultural commercialization on household calorie and micronutrients consumption, but did not consider the profit motive or market-orientation of smallholders.

The empirical analysis builds on these previous studies, by examining the impact of smallholder market-orientation on household food and nutrient rich food consumption. This is partly justified by the fact that the extent of smallholder market integration is closely associated with the motive of production, which has been argued as having varied impacts on household welfare

(Abdulai and Huffman 2000; Ecker 2018). Another motivation for the analysis is the fact that, the recent upsurge in malnutrition in Africa has been attributed to the adverse impact of climate change and worsening food markets' conditions in the region (FAO, ECA and AUC 2020).

5.3 Empirical Analysis

This section presents the empirical analysis of the impact of smallholder market participation as household food security and nutrition strategy. The section consists of the conceptual framework, the study area and data, analytical and empirical strategies, as well as the results of the analysis.

5.3.1 Conceptual Framework

In this section, we outline three pathways highlighting the conditions under which smallholder market orientation may lead to different levels of food and nutrients consumption among households.

The first is the pure income effect. The underlying premise of this pathway is that agricultural commercialization and specialization through high value crops, or selling higher quantities at higher prices for current crops can lead to increased farm incomes and consequently increased household consumption possibilities of food and other essential household needs (Carletto et al. 2017; Kuma et al. 2018). Increased household income from commercialization can also enhance the household's ability to purchase food items that are not produced by the household through cash purchases from the market (Abdulai and Aubert 2004; Ecker 2018). However, increased specialization in cash crops and sale of output may lead to reduced production of diverse foods and availability of staples for home consumption, which can predispose commercially-oriented households to food insecurity and malnutrition, especially if the additional income is not spent on food, or if output prices are low (von Braun et al. 1989; Carletto et al. 2017).

Second is that cash income from crop sales can enhance households' access to and affordability of improved farm inputs and better technologies that can be used for staple crop production (Minten et al. 2011). Likewise, households who diversify their crops may enjoy economies of scope, where skills, experiences and inputs acquired to grow staple crops for domestic consumption can also be used to produce cash crops, and vice versa (Abdulai and CroleRees 2001; Govereh and Jayne 2003; Ecker 2018). However, missing, inefficient or very volatile food markets can lead to high transaction costs or interrupted input supply, which may tend to limit households access to inputs and other market opportunities, and can result in reduced household income, food purchases and consumption (Fafchamps1992; Abdul-Rahman and Abdulai 2020). This could present a situation where subsistence or surplus-oriented households tend to have higher food and calorie intake than commercially-oriented households.

Finally, when there is considerable seasonal variation in household food availability and food prices, which is often due to climatic shocks and inadequate infrastructure, this can lead to farmers who grow more cash or high valued crops benefiting more in terms of food and nutrients consumption (WFP and GSS 2012; Kuma et al. 2018; Issahaku and Abdulai 2020). In sum, the effects of crop commercialization on household food and nutrients consumption will be higher for commercial and perhaps surplus than subsistence households, if market conditions are favorable and additional incomes from crop sales are spent on food consumption, and lower if otherwise. In addition, commercially-oriented households may benefit more if seasonality of food supply tends to increase households' reliance on purchased food in times of household food deficits. Finally, the magnitude of the effects of commercialization will be much higher for the consumption of food items that are largely purchased from the market. We examine these issues based on the case of smallholder farmers in the Northern region of Ghana.

5.3.2 Study Area

Despite the importance of agriculture as a source of livelihood of the majority of the population in Ghana, the incidence of poverty was highest among households engaged in the agriculture sector (42.7%) in 2016-2017. Also, the incidence of poverty in the northern regions have been higher than the rest of the country since 2006 (GSS 2018). Food insecurity and malnutrition have also been the highest in these regions, compared to the rest of the country, with an average of 18% of households being severely food insecure. Farm households in these regions are faced with inadequate rains, structural constraints and poor soils, which have often led to low agricultural output, fluctuation in food prices, and food insecurity (WFP and GSS 2012). In spite of efforts made to promote commercialization of agriculture and smallholders in the northern regions, the average marketed crop surplus across the three regions remains low, ranging from 15% in the Upper East region to 34% in the Northern region (IFAD-IFPRI 2011). The high incidence of poverty, food insecurity and malnutrition in the Northern region amid slightly higher proportion of marketed crops than the national average of 33%, presents an apparent paradox that provides an appropriate context for the investigation of the impact of households' crop commercialization on food and nutrients consumption.

5.3.3 Data and Descriptive Statistics

We conducted a survey of 500 farm households in the Northern region of Ghana between July and September 2017. Five districts were purposively selected based on their intensity of cultivation of both staple and cash food crops, and then 25 villages were randomly selected across these districts, with the allocation of villages done in proportion to the total households in each district. These villages are remote and small, with less than 150 households in each. Given this, we randomly selected 20 household heads in each village, and then used structured questionnaires to interview the primary decision-makers in the households. In addition, a detailed discussion using an interview guide was administered in each village to a focus group of village leaders and representatives to obtain information on village characteristics. The survey combined modules of household characteristics, agricultural production and marketing to collect household data for the 2015-2016 cropping season.

Given our interest in measuring commercialization from the output market participation side, and in terms of sales of all crops cultivated by the household in the 2015-2016 season, we use the Household crop commercialization index (HCCI) suggested by Strasberg et al. (1999). The index is expressed as:

$$HCCI = \frac{\sum_{c=1}^{\bar{c}} \bar{P}_{v,c} M_{i,c}}{\sum_{c=1}^{\bar{c}} \bar{P}_{v},c,Q_{i,c}} \times 100 \qquad [1]$$

where $\bar{P}_{v,c}$ is the average village level crop c price in village v, $M_{i,c}$ is the quantity of crop c marketed by household i, $Q_{i,c}$ is total quantity of crop c produced by the household i, and c is an index of crops produced, with c =1,…, $\bar{c}$. On the basis of this measure, a household's degree of commercialization can be expressed in a continuum that ranges from pure subsistence of HCCI = 0 to completely commercialized production of HCCI = 100. In order to characterize households' market orientation, we use the categorization by FAO (1989), which categorizes households into three orientations, based on the proportion of crop output sold (see also Pingali and Rosegrant 1995). Thus, we classify our farmers into subsistence-oriented, if the farmer sells less than 25% of the output; surplus-oriented, if the farmer sells at least 25%, but less than 50% of the output; and commercial-oriented if the farmer sells more than 50% of the output.

The outcomes of interest in this study are food consumption score (food) and food consumption scores-nutrition. Given that these outcomes measure the frequency of consumption of food and nutrient rich foods, we asked households the question "How many days in the last 7 days your household ate the following foods?" (refer to notes under table 5.1 for details). We next sum all the consumption frequencies of the food and nutrient rich food items of the same group. For the food consumption score, we multiply the value obtained for each food group by the group weight to obtain weighted food group scores, and then add the weighted food groups to generate the food consumption score for a household. With regards to the nutrient consumption, we sum the number of days that foods belonging to each nutrient sub-group (i.e., vitamin A, protein and hem iron) were consumed in the household to obtain the food consumption score-nutrition for the household (WFP 2015).

In order to explore how food and nutrients consumption vary by household market orientation, we present the mean differences in food and nutrient rich foods consumption by household market orientation in table 5.1. We first present the means for the whole sample in column (1). In columns (2) to (4), we compare the mean differences of households who did not report any sales and those who reported sales of 0 < HCCI < 25%. The table suggests that households who did not sell any of their harvest have slightly lower food and nutrient rich food consumption than those who sold at most 25% of the harvest, *albeit* not statistically significant across all outcomes. This justifying our classification of households with less than 25% HCCI as subsistence-oriented.

Columns (5) to (7) present the means and the mean differences between subsistence and surplus-oriented households, while columns (8) to (10) report the comparison between commercial on the one hand and surplus and subsistence households, on the other hand. The comparison shows that both surplus and commercial-oriented households have significantly (at the 1% level) higher income, food and nutrient rich foods consumption than subsistence-oriented households. At the same time, commercial-oriented farm households appear to have significantly higher income, food and nutrients consumption than surplus-oriented households. These suggest the possibility of significant differences in the returns to household crop commercialization across market orientations.

Table 5.1. Means and differences in means of food and nutrient rich food consumption outcomes across market orientation

	All sample	Sell none	Sell < 25%	Difference	Subsistence-oriented	Surplus-oriented	Difference	Commercial-oriented	Difference	Difference
	(1)	(2)	(3)	(4) = (3-2)	(5)	(6)	(7) = (6-5)	(8)	(9) = (8-5)	(10) = (8-6)
Food consumption score	33.55	27.95	30.08	2.13	29.83	33.73	3.90***	39.11	9.28***	5.38***
	(8.23)	(1.03)	(0.67)	(1.85)	(0.61)	(0.52)	(0.79)	(0.59)	(0.89)	(0.83)
Vitamin A	12.43	10.18	10.56	0.38	10.52	12.55	2.03***	15.23	4.71***	2.68***
	(3.83)	(0.69)	(0.34)	(0.94)	(0.31)	(0.24)	(0.38)	(0.18)	(0.41)	(0.34)
Protein	6.18	3.13	4.26	1.12	4.13	6.14	2.01***	9.52	5.39***	3.38***
	(3.46)	(0.57)	(0.24)	(0.69)	(0.23)	(0.22)	(0.31)	(0.15)	(0.31)	(0.31)
Hem iron	3.77	1.91	2.48	0.57	2.41	3.75	1.34***	5.96	3.55***	2.21***
	(2.26)	(0.37)	(0.16)	(0.45)	(0.15)	(0.14)	(0.21)	(0.09)	(0.19)	(0.20)
Log income	8.39	7.93	8.23	0.30***	8.19	8.33	0.14**	8.83	0.64***	0.49***
	(0.71)	(0.14)	(0.04)	(0.12)	(0.04)	(0.04)	(0.06)	(0.09)	(0.09)	(0.08)

Notes: the table shows the descriptive statistics and the differences in means across household market orientation for the food and nutrient rich foods consumption outcomes and household annual income. Column (1) presents the means of household consumption of food and nutrients, and household income for the entire sample. Columns (2) and (3) depict the means for households who did not sell any of the output and those who sold less than 25% of the output, respectively, while column (4) shows the differences in these means. Columns (5), (6) and (8) present the means for subsistence-oriented, surplus-oriented and commercial-oriented households. Column (7) reports the differences in means between subsistence and surplus-oriented households, whiles column (9) presents the differences in means between subsistence and commercial-oriented households. Column (10) shows the differences in means between surplus and commercial-oriented households. Values in parenthesis are standard deviations in column (1) and standard errors in columns (2) to (10). The asterisks *** and ** are significance at 1% and 5% levels, respectively.

We calculated the food consumption score by first grouping all food items consumed by households into main staple, pulses, vegetables, fruits, meat and fish, milk, sugar, oils and condiments and the food consumption score-nutrition by grouping food items into 15 food groups under vitamin A rich foods (i.e., dairy, organ meat, eggs, orange and green vegetables; and orange fruits), protein rich foods (pulses, dairy, flesh meat, organ meat, fish and eggs) and iron rich foods (flesh meat, organ meat and fish) (WFP 2015).

Table 5.2. Variable definition, measurement and descriptive statistics

Variables	Definition and measurement	Mean	S.D.
Panel A: C*ommercialization*			
HCCI	Household crop commercialization index (in percentage)	36.76	19.02
Subsistence-oriented	1 if household sells less than 25% of harvest; 0 otherwise	0.36	0.48
Surplus-oriented	1 if household sells between 25% & 49.99% of harvest; 0 otherwise	0.41	0.49
Commercial-oriented	1 if household sells at least 50% of harvest; 0 otherwise	0.23	0.41
Panel B: *Household characteristics*			
HHAge	Age of household head (years)	44.03	12.04
HHSex	1 if household head is male; 0 otherwise	0.59	0.49
HHEducation	Number of years in school by household head	1.27	3.27
HHSize	Household size (number of persons)	5.63	2.14
HHLandholding	Total land size of household (in hectares)	2.56	1.56
CB_Assoiations	Number of associations the farmer is a member in the community	1.07	1.27
Log HHIncome	Log of total household annual income	8.39	0.71
Log HHLivestock	Log value of household livestock at beginning of 2015 season	7.65	2.19
Log HHDAsset	Log value of household durable assets at beginning of 2015 season	9.11	0.88
Extension	1 if ever had extension contact; 0 otherwise	0.34	0.47
Save money	1 if household regularly save money; 0 otherwise	0.72	0.45
Save food	1 if household at least save some food surplus; 0 otherwise	0.06	0.23
Panel C: *Community variables and district Fes*			
Town distance	Distance from community to main town centre in kilometres	15.46	11.86
Local wage	Local wage rate per day in GHS	6.22	1.34
Gushegu	1 if household resides in Gushegu district; 0 otherwise	0.24	0.43
Karaga	1 if household resides in Karaga district; 0 otherwise	0.15	0.36
Savelugu-Nanton	1 if household resides in Savelugu-Nanton district; 0 otherwise	0.32	0.46
Tolon	1 if household resides in Tolon district; 0 otherwise	0.19	0.39
Kumbungu	1 if household resides in Kumbungu district; 0 otherwise	0.09	0.28
Panel D: *Instruments*			
PreProductContract	1 if farmer has no pre-planting input contract in the past 5 years, 0 otherwise	0.18	0.39
HHMobileNetwork	1 if household location has a telecommunication network coverage, 0 otherwise	0.72	0.45
CMarket	1 if household resides in community with market, 0 otherwise	0.44	0.49
Farm_shock	1 if household experience any shock in farming due to weather or bush/wildfires in the past 5 years, 0 otherwise	0.59	0.49
NonEmployTravel	1 if a household member left the community for non-employment reasons (such as marriage, education or religion) in the past year, 0 otherwise	0.23	0.42
Panel E: *Other covariates of the First-stage household income model*			
Tractor	Tractor cost per acre in GHS	57.28	40.85
SeedUse	Quantity of crop seeds used per acre in kilograms	67.15	207.32
SeedPrice	Average seed price in GHS	32.01	177.68
Fertilizer	Cost of fertilizer applied per acre in GHS	56.94	67.01
Pesticides	Cost of pesticides applied per acre in GHS	1.47	5.98
Weedicides	Cost of weedicides applied per acre in GHS	20.65	30.28
Labor	Number of man-days per acre	22.98	10.68
Soil fertility	4=fertile; 3=moderately fertile; 2=less fertile; and 1=infertile	1.20	0.36

Notes: the table depicts the definition, measurement and descriptive statistics of household crop commercialization, instruments and other controls. Panel A shows the household crop commercialization index (HCCI) and the proportion of households under each market orientation. Panels B and C consist of household, community and district controls, while panel D contains the instruments used for exclusive restriction in the first-stage market orientation model as well as the first-stage household income regression to account for potential endogeneity of household income. Panel E consists of farm inputs and soil characteristics of households. GHS is Ghana cedis, which is the Ghanaian currency.

Table 5.2 presents the definition, measurement and descriptive statistics of all the variables used in the analysis for the entire sample. Panel A shows that 36% of the farm households surveyed are subsistence-oriented, 41% are surplus-oriented, and 23% are commercial-oriented. Also, the average household head is 44 years old and with 1.27 years of schooling. The average household size and landholding are 5.63, and 2.6 hectares, respectively (panel B). The average distance from the villages to the nearest town centre is about 15 kilometres, and the mean village wage rate is about 6 GHS. We also compare the differences in the main controls between market orientation in table 5.A1 in the appendix, and this shows significant differences mostly in the household characteristics across market orientation.

5.3.4 Analytical Framework and Empirical Strategy

Our conceptual framework shows how smallholder food and nutrients consumption tend to depend on household market orientation and market conditions. Given the categorization of smallholders' market orientation into subsistence, surplus and commercial-oriented, based on the proportion of output marketed, we model household market orientation as an ordered choice (Heckman et al. 2006). We define the latent variable C_{ij}^{*}, which denotes sorting of farm households i into the 3 categories of market orientation, based on an ordered probit selection rule as;

$$C_{ij}^{*} = \alpha_j' \boldsymbol{Z}_i + \mu_{ij},$$

where

$$C_{ij} = \mathbf{1}[\tau_j(w_j) < \alpha_j' \boldsymbol{Z}_i + \mu_{ij} \leq \tau_{j+1}(w_{j+1})], \qquad [2]$$

$$j = 1, 2 \ldots \bar{J}$$

and the cutoffs satisfy

$$\tau_j(w_j) \leq \tau_{j+1}(w_{j+1}), \qquad \tau_0(w_0) = -\infty, \qquad \text{and } \tau_{\bar{J}}(w_{\bar{J}}) = \infty$$

where C_{ij} is a multivalued observed treatment variable, $\boldsymbol{Z}_i$ is a vector of observed controls, $\alpha_j' \boldsymbol{Z}_i + \mu_{ij}$ is a latent linear index, α_j is a vector of parameters to be estimated, w_j is a vector of observed regressors, $\tau_j(w_j)$ are threshold parameters, which are allowed to depend on the regressors[57], and μ_{ij} are error terms. To the extent that we are interested in the estimation of the impact of farm household market orientation (C_{ij}) on food and nutrients consumption, we denote the observed food and nutrients consumption outcomes as Y_{ij} for the three market orientations. We express the outcomes as linear functions of a vector of observed independent variables, X_i as;

$$Y_{ij} = \begin{cases} \beta_1' X_i + \epsilon_{i1} & if\ C_i = 1 \\ \beta_2' X_i + \epsilon_{i2} & if\ C_i = 2 \\ \beta_3' X_i + \epsilon_{i3} & if\ C_i = 3 \end{cases} \qquad [3]$$

where the vector of coefficients, β_j, of X_i are allowed to depend on the treatment options, and ϵ_{ij} is assumed to have a zero mean and variance of σ_j^2, for each j = 1,2,3.

Households' market orientation in this study are non-random and implies that orientation status of farmers could differ systematically due to self-selection of households into categories. Selection bias can result from both observed factors (such as education, landholding, wealth etc) and unobserved factors (such as innate abilities). Such factors may simultaneously drive correlations in households' market orientation and the outcomes, which will result in omitted variable problem (Heckman et al. 2018). As a result, estimation of equation (3) with ordinary least squares will generally result in biased and inconsistent estimates. We can control for the observed sources of selection (to the extent possible) with detailed household and contextual data, but the unobservable factors remain a source of concern for this analysis.

In order to account for the threats of selection bias and omitted variable problem in the light of the ordered nature of the selection variable, we employ the ordered probit selection model

[57] Such a model is referred to as the generalized ordered probit model, as opposed to the classical ordered choice model which assumes the distribution of w_j are degenerate, and thus the thresholds τ_j are assumed constants (Heckman et al. 2006).

(Heckman et al. 2006). This is a parametric model that assumes joint normality of the errors in equations (2) and (3) (i.e., ϵ_{ij}, μ_{ij}), and utilizes full information maximum likelihood procedure to jointly estimate a first-stage ordered probit of household market orientation in equation (2), and a second-stage outcome models for the three regimes of market orientation (equation 3). The process accounts for selection bias and omitted variable problem by inserting calculated inverse Mills ratios from the first-stage ordered choice model into the second-stage food and nutrients consumption model. The coefficients of the inverse Mills ratios, which we denote as $\rho_j = \text{Corr}(\epsilon_{ij}, \mu_{ij})$, define the correlation between the errors in equations (2) and (3). Significance of the correlation coefficients, ρ_j, will suggest the presence of selection bias indicating that households' market orientation decisions are endogenous. The signs of the ρ_j's show the pattern of correlation.

A critical concern is that the estimation of the selection and outcome equations requires an exclusion restriction, or a source of variation to avoid collinearity and enhance identification. However, an issue that complicates the exclusion restriction in the ordered choice setting is the need for an instrument for each transition (Heckman et al. 2006). The three ordered choices give two transitions (i.e., subsistence to surplus, and surplus to commercial) which intuitively suggest the need for at least two instruments. In this study, we use farmers' access to pre-planting input contract for the past 5 years prior to the 2015 cropping season, telecommunication network coverage at the location of the household and the presence of at least periodic market in the village as instruments.

Past pre-planting input contract, is correlated with farmer market orientation, because it contributes to minimizing market risks and transaction costs (Mishra et al. 2018). Whereas we do not expect past pre-planting contract to directly affect current food and nutrients consumption, it is possible that it may affect current consumption through past food stored for current consumption. Table 5.2 (panel B) shows this is not a threat, because very few (6%)

households reported saving food from previous season. Also, these households do not systematically differ across market orientation (table 5.A1, panel C) and past pre-planting contract status in table 5.B1 in appendix B. Access to telecommunication network coverage and village markets in Ghana vary substantially across villages (Zanello 2012), and are expected to be good predictors of household market orientation, because these can increase households' access to real-time market information, and reduce transaction cost of marketing, which are key constraints to market engagement in these areas (MoFA 2017). However, these instruments should not directly affect households' current food and nutrients consumption, other than through households' market engagement. We further control for distance to the town centre, household income and assets to ensure that the instruments are not picking up any proximity, wealth and income effects.

The final issue is the potential endogeneity of household income. Household income may be endogenous in the market orientation equation, because increased commercialization can lead to increased farm income through high price premiums. In the food and nutrients consumption equation, household income may be endogenous because of the joint production and consumption decisions among agricultural households in developing countries (Fafchamps 1992). To account for the potential endogeneity, we employ the Control Function approach (Woodridge 2010; Abdulai and Huffman 2014), using households experience of any shock on the farm due to weather or wildfires in the past 5 years as instrument. Such shocks are usually exogenously determined by idiosyncratic factors and are expected to be good predicters of households' total income, because of the association between such shocks and household crop output and income. Given this, we estimate a first-stage generalized linear model of household income on the instrument and other controls, and then insert the predicted residuals into the selection and the outcome equations to account for the potential endogeneity of household income.

Given the correction for sample selection and the identification issues, we estimate the average treatment effects for transitioning between two orientations, j and $j + 1$, on the population ($ATE^{\dagger}$), on everyone at the transition point between j and $j + 1$ (ATE), on the treated (ATT) and on the untreated (ATU). The difference between $ATE^{\dagger}$ and ATE shows the difference in the characteristics of farmers in the entire population and those at the transition between two market orientations. In addition, the difference between the ATT and ATE measures sorting on gains, whereas the difference between ATU and ATE measures sorting losses (Heckman et al. 2018). Finally, the relationship among ATE, ATT and ATU shows the pattern of sorting on gains, such that if ATT > ATE >ATU, this will suggest positive selection on gains, and if ATU >ATE>ATT will indicate reverse selection on gains (Cornelissen et al. 2018).

5.3.5 Results and Discussion

This section presents and discusses the results of our estimations. We first present the results of the first-stage estimates of households' market orientation and the second-stage estimates of food and nutrient rich foods consumption. We next report the results of the treatment effects of households' market orientation.

First- and Second-Stage Results

We report the marginal effects of the first-stage ordered probit estimates of determinants of household market orientation in table 5.3, with subsistence-oriented as the base category. The estimates show that household income and wealth significantly affect market orientation. In particular, a percentage increase in household income decreases the probabilities of being subsistence and surplus-oriented by 0.14 and 0.13, respectively, and increases the probability of being commercial-oriented by about 0.27. The estimates show that a percentage increase in household livestock value significantly increases the probability of being commercial-oriented by about 0.04.

Table 5.3. First-stage determinants of market orientation

	Subsistence-oriented (1)		Surplus-oriented (2)		Commercial-oriented (3)	
	Marginal effect	S.E.	Marginal effect	S.E.	Marginal effect	S.E.
HHAge	-0.001	0.001	0.001	0.001	9.1E-5	0.001
HHSex	-0.029	0.053	0.137**	0.057	-0.108**	0.042
HHEducation	-0.009	0.008	0.005	0.008	0.003	0.005
HHSize	0.013	0.011	-0.017	0.012	0.004	0.008
HHLandholding	-0.014	0.017	0.007	0.018	0.006	0.012
CB_Assoiations	0.022	0.019	-0.047**	0.020	0.025	0.015
Log HHIncome	-0.144**	0.064	-0.130**	0.064	0.274***	0.047
Log HHLivestock	-0.016	0.011	-0.020	0.014	0.036***	0.012
Log HHDAsset	-0.107***	0.029	0.096***	0.030	0.010	0.021
Town distance	-0.001	0.021	0.006**	0.003	-0.005**	0.002
Local wage	0.041*	0.021	-0.062**	0.023	0.020	0.018
Gushegu	0.060	0.084	-0.246**	0.108	0.186*	0.092
Karaga	0.041	0.087	-0.352***	0.110	0.310***	0.094
Savelugu-Nanton	0.140	0.085	-0.386***	0.097	0.245***	0.084
PreProductContract	0.272***	0.061	-0.220***	0.063	-0.051	0.046
HHMobileNetwork	-0.228***	0.054	0.100*	0.056	0.128***	0.037
CMarket	-0.039	0.048	-0.099*	0.053	0.138***	0.040
HHIncomeResid	0.139	0.089	0.075	0.089	-0.214***	0.056
Log likelihood			-426.27			
LR X^2(36)			217.65			
Prob X^2			0.000			
X^2 (3) Excluded Instruments			39.60			
Prob X^2			0.000			
Number of observations		180	206		114	

Notes: First-stage generalized ordered probit estimation of equation (2). Column (1) presents the marginal effects and the standard errors (S.E.) of the various covariates on the likelihood of being a subsistence-oriented household. Columns (2) and (3) report the marginal effects and standard error of the covariates on the likelihood of being a surplus-oriented and commercial-oriented household respectively. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Similarly, the probability of being subsistence-oriented household decreases by about 0.11, while that of being surplus and commercial-oriented households increase by 0.09 and 0.01 respectively, when the value of household durable assets increases by 1%, *albeit* not significant for commercial-oriented. These estimates generally suggest that wealthy households appear to be more commercially inclined than less wealthy households. These results confirm the finding by Abdulai and CroleRees (2001) that household income and wealth play important roles in households' diversification away from subsistence agriculture. Wealthy households tend to be less vulnerable to risks of market failures and exposure to food insecurity, because of the relatively high security due to their wealth and income, compared to poorer households who are severely affected by market imperfections and inefficiencies (von Braun et al. 1989; Abdulai and Aubert 2004; Ogutu et al. 2019).

Our results further show that the instruments strongly predict the probability of either being subsistence, surplus or commercial-oriented household. The estimates show that households with past pre-planting input contracts are more likely to be surplus-oriented, whereas those with access to telecommunication network and markets in the village are more likely to be commercial-oriented. We test the validity of the instrument by regressing the respective outcomes on our set of controls and the instruments in part B of table 5.B3, and the results show that all the instruments are valid, as they do not significantly explain food and nutrients consumption.

We further check the relevance and validity of these instruments by presenting test diagnostics of a generalized method of moments (IV-GMM)[58] estimations of the effect of commercialization on the outcomes in table 5.B2. The diagnostics test statistics reported at the bottom of table 5.B2 (col. 1) further suggest the instruments are together relevant, and as such, good predictors of household degree of commercialization. Specifically, the Cragg-Donald F-statistic of 14.75, the Kleibergen-Paap rk Wald F-statistic of 45.98 and the associated Angrist and Pischke (2009) p-value (p=0.000) all reject the null hypothesis that the instruments are weak. Moreover, given the Hansen J test statistic of 3.452 and the p-value of 0.178, we cannot reject the null hypothesis of zero correlation between the instruments and the error term (the second-stage estimates are reported in part A of table 5.B3).

[58] We use the IV-GMM estimator because of its efficiency over the conventional two-stage least squares when the equation is over-identified (which is the case in our application as the number of instruments, three, exceed the number of endogenous regressors of one) and its robustness to heteroskedasticity (Kuma et al. 2018).

We report results of the second-stage estimates of food and nutrients consumption in tables 5.C1 and 5.C2. The estimates show that education significantly increases the consumption of food, protein and hem iron rich foods for subsistence-oriented households, and the consumption of food and only vitamin A rich foods for surplus-oriented households. This confirms past findings that education is positively associated with better food and dietary diversity (Issahaku and Abdulai 2020). In addition, an increase in household size results in increased consumption of food and vitamin A rich foods, although weakly significant at the 10% level, for surplus-oriented households. This suggests the labor effect of household size, which contributes to increased crop production, outweighs the dependency effect for the surplus-oriented households, and thus, explains the positive effect of the household size[59] in this case.

The results further reveal that household income significantly increases food and vitamin A food consumption for surplus-oriented households, and the consumption of protein and hem iron foods for surplus and commercial-oriented households, lending support to past studies that income growth tend to increase calorie intake (Abdulai and Aubert 2004; Colen et al. 2018; Kuma et al. 2018). However, household income generally reduces food and nutrient rich food consumption for subsistence-oriented households, although not statistically significant. This suggests that some sales of crops by subsistence-oriented households are due to distress that results in a trade-off between household food and nutrients consumption on one hand and the household income on the other hand. This incidence has been reported in the context of developing countries where farmers are forced to sell their harvest to meet immediate financial requirements (such as servicing of debts or other household needs) and later on have to buy food from the market, or borrow food to meet household food needs (Reardon et al. 2006; Jacoby and Minten 2009).

[59] Family labour is an important part of household labor in the sample and constitutes about 74% of the total labor days used on households' farms in the sample.

Similarly, household wealth plays an important role in enhancing food and nutrients consumption. In particular, an increase in the value of household livestock significantly increases household food and nutrient rich food consumption for subsistence, while significantly increasing the consumption of only nutrient rich foods for surplus-oriented households. Furthermore, an increase in the value of household durable assets is estimated to significantly increase food consumption for subsistence and surplus-oriented households, and increase nutrient rich foods consumption for all groups.

We report the ρs, which show the correlation between the errors in equations (2) and (3) at the bottom of tables 5.C1 and 5.C2. The estimated correlations are weakly significantly different from zero ($p<0.1$) for protein and hem iron foods consumption in the commercial-oriented category, indicating the presence of self-selection. This implies that transitioning into commercial-orientation may not have the same effect on protein and hem iron foods consumption for the other two market orientations if they transition (Heckman et al. 2006; Abdulai and Huffman 2014). The positive signs of the coefficients indicate reverse selection on unobserved gains, suggesting that farm households with more than average protein and iron rich food consumption have lower probabilities of transitioning into commercial-oriented category.

Treatment Effects Measures

Table 5.4 presents the treatment effects estimates of farm households' transition between market orientation. Panel A presents the treatment effects between subsistence and surplus-oriented, while panel B reports the treatment effects between surplus and commercial-oriented. We report the treatment effects between subsistence and commercial-oriented in panel A of table 5.5, although we mainly focus on table 5.4 in what follows.

In respect of transitioning between subsistence and surplus orientation (panel A), the ATE† estimates for the entire population show that moving from subsistence to surplus-oriented increases food consumption by 14.9%, and the consumption of vitamin A, protein and iron rich foods by 18%, 25% and 26%, respectively, for an average household chosen at random. This is higher than the other treatment effects measures (i.e., ATE, ATT and ATU) that condition on those making this transition. This suggests that the characteristics of those at the transition between subsistence and surplus are somewhat less favourable than those in the population, possibly due to the better characteristics of commercial-oriented households (Heckman et al., 2018). For those transitioning from surplus to commercial orientation, the average treatment effects (ATE†) of a farm household chosen at random from the population is estimated as 18% for food consumption, and 15%, 39% and 44% for vitamin A, protein and iron rich foods consumption, respectively (panel B).

We next focus on the specific treatment effects across the outcomes, as their relationships indicate the pattern of selection as stated in the analytical framework. Regarding food consumption in column (1), the treatment effects (i.e., ATE, ATT and ATU) are all statistically significant at the 1% level across the transitions (table 5.4). Recall that the ATE measures the average effects only for households transitioning between two market orientation. The results show that food consumption significantly increases by 11.6% and 14.3% for a randomly chosen farm household at the transition between subsistence and surplus-orientation and between surplus and commercial-orientation, respectively. With regards to nutrient rich foods consumption, the ATE suggests that going from subsistence to surplus-orientation tend to increase vitamin A, protein and iron rich foods consumption by about 13%, 18% and 19%, respectively, for an average household transitioning between subsistence and surplus-orientation (panel A).

Table 5.4. Treatment effects estimates of household market orientation on food and nutrients outcomes

	(1) Food		(2) Vitamin A		(3) Protein		(4) Hem iron	
	Treatment effect	% of base choice	Treatment effect	% of base choice	Treatment effect	% of base choice	Treatment effect	% of base choice
Panel A								
Subsistence vs. Surplus								
ATE†	4.405***	14.89	1.893***	17.73	1.231***	25.27	0.780***	26.42
	(0.159)		(0.087)		(0.072)		(0.049)	
ATE	3.462***	11.62	1.338***	12.51	0.825***	17.89	0.517***	18.66
	(0.151)		(0.079)		(0.065)		(0.046)	
ATT	3.971***	13.34	1.705***	15.72	1.102***	21.89	0.668***	21.66
	(0.530)		(0.254)		(0.179)		(0.117)	
ATU	2.879***	9.65	0.919***	8.73	0.509**	12.33	0.345***	14.30
	(0.490)		(0.245)		(0.179)		(0.115)	
Panel B								
Surplus vs. Commercial								
ATE†	6.107***	17.97	1.892***	15.05	2.360***	38.67	1.635***	43.79
	(0.206)		(0.087)		(0.078)		(0.053)	
ATE	4.959***	14.29	1.639***	12.41	1.917***	27.67	1.303***	30.42
	(0.256)		(0.116)		(0.099)		(0.067)	
ATT	2.664***	7.31	0.831***	5.77	1.164***	13.93	0.724***	13.81
	(0.619)		(0.261)		(0.228)		(0.149)	
ATU	6.229***	18.46	2.087***	16.63	2.333***	38.02	1.623***	43.25
	(0.427)		(0.179)		(0.130)		(0.085)	

Notes: the table shows ordered Heckman treatment effects estimates of the impact of household market orientation on households' food, vitamin A, protein and hem iron rich foods consumption between subsistence and surplus in panel A, and between surplus and commercial in panel B. ATE† is the average treatment effects for the entire population; ATE is the average treatment effects for those at the point of deciding between two orientation, ATT is average treatment effects on the treated and ATU is average treatment effects on the untreated. Values in parenthesis are robust standard errors. The asterisks *** and ** are significance at 1% and 5% levels, respectively.

Similarly, going from surplus to commercial-orientation increases consumption of foods rich in vitamin A, protein and iron by about 12%, 28% and 30%, respectively, for an average household transitioning between surplus and commercial-orientation (panel B). The ATT estimates for food consumption indicate that for a surplus-oriented household, going from subsistence to surplus-orientation results in 13.3% increase in food consumption, whereas for a commercial-oriented household, going from surplus to commercial-orientation increases food consumption by 7.3%.

The results of the ATT for vitamin A, protein and iron rich foods consumption suggest that for an average surplus-oriented household, going from subsistence to surplus-orientation increases the consumption of foods rich in these nutrients by 16%, 22% and 22%, respectively. At the same time, going from surplus to commercial-orientation increases vitamin A, protein and iron rich foods consumption by about 6%, 14% and 14%, respectively, for a commercial-oriented household. We also considered what the returns to marketing will be should subsistence-oriented households become surplus-oriented, or surplus-oriented households become commercial-oriented in the estimates of the ATU.

For subsistence-oriented household, going from subsistence to surplus-orientation increases food consumption by 9.7%, while transitioning from surplus to commercial-orientation increases food consumption by 18.5%. The estimates for the nutrient rich food consumption show that for a subsistence-oriented household, going from subsistence to surplus-orientation increases consumption of vitamin A, protein and iron rich foods by 8.7%, 12.3% and 14.3%, respectively, if they transition into surplus-orientation. Similarly, going from surplus to commercial-orientation increases the consumption of vitamin A, protein and iron rich foods by about 16.6%, 38% and 43.3%, respectively.

Table 5.5. Treatment effects between subsistence and commercial, and difference in treatment effects between subsistence to surplus for non-sellers and those selling less than 25%

	Food	Vitamin A	Protein	Hem iron
Panel A				
Subsistence to commercial	(1)	(2)	(3)	(4)
ATE†	10.512***	3.785***	3.592***	2.415***
	(0.172)	(0.095)	(0.076)	(0.049)
ATE	10.730***	3.781***	3.701***	2.502***
	(0.218)	(0.120)	(0.095)	(0.060)
ATT	10.263***	4.602***	3.769***	2.393***
	(0.576)	(0.259)	(0.187)	(0.119)
ATU	11.026***	3.261***	3.658***	2.571***
	(0.399)	(0.202)	(0.135)	(0.087)
Panel B				
Subsistence to surplus				
ATU for 0< sales < 25% of output	2.912	0.986	0.569	0.391
	(0.232)	(0.120)	(0.095)	(0.068)
ATU for 0 sales of output	2.642	0.434	0.078	0.011
	(0.721)	(0.325)	(0.095)	(0.184)
Difference in ATUs	0.270	0.552	0.490*	0.379*
	(0.675)	(0.344)	(0.275)	(0.194)

Notes: the table shows ordered Heckman treatment effects estimates of the impact of household market orientation on household food and nutrient rich foods consumption. In panel A, ATE† is the average treatment effects for the entire population; ATE is the average treatment effects for those at the point of deciding between two transition, ATT is average treatment effects on the treated and ATU is average treatment effects on the untreated. Panel B compares the treatment effects of subsistence farmers transitioning from subsistence to surplus-oriented (i.e., ATU) between non-selling farm households and those who sell less than 25% of the output. Values in parenthesis are robust standard errors. The asterisks *** and * are significance at 1% and 10% levels, respectively.

5.4 Conclusions and Policy Implications

Food insecurity and malnutrition remain major challenges in sub-Saharan Africa, despite many interventions like the Millennium Development Goals and the Sustainable Development Goals, which aimed at reducing poverty and hunger in the world. Similarly, several authors have analyzed the policy options which have been implemented and their impacts on household welfare measures such as income, wages, as well as food security and nutrition. In this article, we presented a systematic overview of the literature on policies and strategies to improve food security and nutrition in Africa, as well as an empirical analysis on the impact of smallholder market participation as a strategy for enhancing food security and nutrition in Ghana.

The survey of the literature shows that most food security and nutrition policies and interventions in Africa have centred around indirect measures such as improving agricultural infrastructure and economic incentives, as well as providing smallholders with new agricultural technologies, and climate-smart practices to increase farm output and productivity. These indirect policy options have gained considerable attention over the past three decades. In addition to these, some direct interventions such as structural changes in relative prices and targeted food subsidies have been implemented with the aim of improving food access through lower market prices and the stabilization of consumption in times of high food price inflation. However, lack of proper targeting of the poor, removal of subsidies, as well as the lack of sustainability and exit mechanisms of these direct interventions have often led to the failure of many of these policies. These have led to governments using measures that stimulate sufficient levels of demand to improve food security and nutrition. These measures commonly involve cash transfers, income diversification strategies and increased access to markets.

To this end, several studies have examined the effects of market participation on household productivity, income and calorie intake. However, the impacts of smallholder market participation, especially on food security and nutrition, varies across food and nutrition outcomes, and also over smallholder market orientation. The results from the empirical analysis on Ghana show that gains from commercialization are higher for protein and iron rich foods consumption compared to that of food and vitamin A rich food consumption, which are mainly due to increased farm and household incomes. Household income tend to increase vitamin A rich food consumption of surplus oriented smallholders, and protein and iron rich foods consumption of both surplus and commercial oriented smallholders. This is not surprising, given the low dietary quality in the area and the fact that most foods rich in protein and iron such as meat, fish and eggs are generally from cash purchases compared to staple foods, which are mostly from own production (WFP and GSS 2012; GSS 2018).

In addition, food and nutrient rich foods consumption are generally higher for smallholders transitioning from surplus to commercial, compared to their counterparts transitioning between subsistence and surplus. This is probably because the level of market integration, *albeit* generally low among the farmers, is comparatively higher for commercial-oriented households, due to the high profit and market orientation (von Braun et al. 1989; Pingali and Rosegrant 1995). In fact, we see that there is no substantial difference in consumption between pure subsistence smallholders and those who sell some but not more than 25% of the output in panel B of table 5.5. These findings imply that smallholders will benefit more from marketing if they are able to sell more with the motive of making profit.

Furthermore, the pattern of consumption gains differs across market orientation. There is positive selection on gains in transitioning from subsistence-orientation to surplus-orientation, suggesting that more endowed subsistence-oriented households tend to benefit more in terms of consumption when they move to surplus-oriented, than their less endowed counterparts. However, less endowed households appear to benefit more in going from surplus to commercial-orientation, suggesting reverse selection on gains, where disadvantaged households who are less likely to transition from surplus to commercial tend to benefit more if they move from surplus to commercial. Thus, when less endowed subsistence and surplus-oriented households are able to overcome existing market constraints and transition into commercial orientation, this will substantially increase their food and nutrients consumption through increased income (Pingali and Rosegrant 1995; Abdulai and Huffman 2000). In effect, the overview of the literature and the empirical analysis suggest the following policy directions:

- To the extent that ineffective targeting of the poor has been partly responsible for the failure of many policies in sub-Saharan Africa, public policies need to move beyond “broader targeting”, where sectors and subsectors that are conceived to strongly affect the poor are targeted. Thus, “narrow targeting”, where poor locations and segments of the population are earmarked and targeted for food security and nutrition interventions could be considered. It is also important to promote collaboration between government and other development partners at national and local levels to develop workable criteria, and to supervise the intervention process to eschew the accrual of intervention gains to political actors and influential groups.

- Structural reforms that were implemented by many African countries, initially contributed to increased output and productivity. However, the reduction or removal of subsidies on farm inputs in many cases led to increased input prices, reduced productivity, and increased food insecurity and malnutrition in the long run. Policymakers should put emphasis on how policies and interventions can ensure a balance in state efficiency and productivity, without compromising food security and nutrition in the long run. Governments can consider measures such as promotion of market access and efficient supply chains, income diversification and other productivity enhancing interventions that stimulate sufficient and sustained levels of production and demand.

- Smallholder commercialization can promote household food security and nutrition through increased household income, as shown by the empirical analysis. Smallholder commercialization therefore can serve as a strategy for stimulating household demand for food and nutrients, although inadequate market information and access often limit their market participation. Thus, policies should consider providing platforms such as mobile agriculture services and trainings on market intelligence and promotion services to increase smallholder commercial orientation and market integration.

- Smallholder transition from subsistence to surplus-orientation tend to favor more endowed households in terms of consumption. Policymakers can consider measures that minimize smallholders resource constraints and stimulate household crop productivity in order to enhance the capacity of less endowed subsistence households. Such measures may include cash crop programmes that support farmers with inputs, and training to increase their access to improved inputs and innovations, and also to facilitate other spill-over benefits between food and cash crop cultivation (Govereh and Jayne 2003).

- Conversely, less endowed households appear to benefit more in transitioning from surplus to commercial-oriented. Thus, promotion of higher smallholder commercialization will require in addition to output augmenting measures the mitigation of some of the market barriers and failure (such as, market availability, physical access and information, market standards, inadequate credits etc) that limit poor smallholders from engaging in sales for profit (see also Wiggins et al. 2011; Abdul-Rahaman and Abdulai 2020). Interventions such as market information platforms, farmer cooperatives and collective actions as well as contract buying, which provides ready markets for farmers, will be quite rewarding (Ma et al. 2018).

In addition to these policy directions, there are some potential areas future research efforts could consider to increase our understanding of the role of smallholder market engagement, and the impacts of policies and strategies to enhance food security and nutrition in developing countries. One of such areas will be to examine how smallholder engagement in input markets, and the integration into the rural cash economy impact food security and nutrition (von Braun et al. 1989). This is because past studies in this area tend to focus on output market participation and drivers of diversification (Abdulai and Delgado 1999; Abdulai and ColeRess 2001). Also, studies that examined the impacts of non-farm work mostly neglect the nutritional aspect of food security, in spite of the income elasticity differences among various food and nutrient elements (Abdulai and Aubert 2004; Colen et al. 2018; Owusu et al. 2011).

Another area related to the empirical analysis in this article is how farmers' market orientation, and marketing affect intra-household production decisions and food consumption distribution, since their effects could be heterogeneously distributed across individuals and various demographic groups of household members (Carletto et al. 2017; Ogutu et al. 2019). In particular, there is the need to understand the effects of smallholder marketing and diversification on intra-household power and decision-making, domestic violence, and poverty. It will be interesting to also know which demographic groups are the most affected by food and nutrition insecurity, and to what extent do smallholder market engagement and related policies contribute to intra-household distributive impacts on food and nutrition insecurity.

Moreover, not much has been done on how heterogeneities in costs and returns to climate-smart adaptation practices affect smallholder adaptation, although there is some growing interest in the literature (Di Falco et al. 2011; Issahaku and Abdulai 2020). There is, therefore, the need for future studies to also examine heterogeneities in returns to climate change adaptation practices, given that such returns may be different across households and adaptation strategies. In particular, it will be interesting to examine how climate change, climate shocks and socio-cultural norms impact vulnerable groups (such as the physically challenged, aged, women and children) who are normally disadvantaged in productive capacities, and in economic and geographical mobility. It is also important to understand how smallholder market and non-farm engagement can be used as climate change resilience strategies, particularly for vulnerable groups in developing countries, given the reliance of many of such groups on crop marketing, and the fact that agriculture is the hardest hit sector by climate change in these regions.

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Appendix

Appendix A: Differences in characteristics between market orientations

Table 5.A1. Mean differences in household characteristics across market orientation

	Subsistence (1)	Surplus (2)	Difference (3) = (2-1)	Commercial (4)	Difference (5) = (4-1)	Difference (6) = (4-2)
Panel A: ***Household characteristics***						
HHAge	43.73	44.45	0.73	43.74	0.01	-0.72
	(0.86)	(0.86)	(1.22)	(1.16)	(1.42)	(1.44)
HHSex	0.58	0.62	0.04	0.58	0.00	-0.04
	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
HHEducation	0.65	1.18	0.53*	2.43	1.79***	1.23***
	(0.18)	(0.22)	(0.28)	(0.40)	(0.39)	(0.42)
HHSize	5.64	5.55	0.09	5.73	0.08	0.17
	(0.16)	(0.14)	(0.22)	(0.21)	(0.26)	(0.25)
HHLandholding	2.20	2.57	0.37**	3.09	0.89***	0.51**
	(0.09)	(0.11)	(0.15)	(0.16)	(0.18)	(0.19)
CB_Assoiations	1.11	1.01	0.10	1.13	0.02	0.12
	(0.10)	(0.08)	(0.13)	(0.11)	(0.15)	(0.14)
Log HHIncome	8.19	8.33	0.14**	8.82	0.63***	0.49***
	(0.04)	(0.04)	(0.05)	(0.08)	(0.08)	(0.08)
Log HHLivestock	7.01	7.65	0.64**	8.68	1.66***	1.02***
	(0.20)	(0.13)	(0.23)	(0.11)	(0.27)	(0.19)
Log HHDAsset	8.83	9.19	0.36***	9.40	0.57***	0.21**
	(0.05)	(0.06)	(0.08)	(0.09)	(0.10)	(0.10)
Panel B: ***Community level variables and districts***						
Town distance	15.33	15.78	0.44	15.09	-0.24	-0.69
	(0.92)	(0.80)	(1.22)	(1.09)	(1.45)	(1.35)
Local wage	6.29	6.18	-0.11	6.19	-0.10	0.01
	(0.09)	(0.10)	(0.13)	(0.12)	(0.15)	(0.16)
Gushegu	0.27	0.23	-0.04	0.21	-0.06	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Karaga	0.11	0.14	0.04	0.24	0.14***	0.10**
	(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)
Savelugu-Nanton	0.37	0.27	-0.10**	0.32	-0.05	0.05
	(0.04)	(0.03)	(0.05)	(0.04)	(0.06)	(0.05)
Tolon	0.16	0.24	0.08**	0.15	-0.01	-0.09**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)
Kumbungu	0.08	0.09	0.01	0.07	-0.01	-0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
Panel C: ***Identification instruments***						
PreProductContract	0.29	0.14	-0.14***	0.07	-0.22***	-0.07*
	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)	(0.04)
HHMobileNetwork	0.59	0.75	0.15***	0.85	0.26***	0.11**
	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)	(0.05)
CMarket	0.42	0.41	-0.01	0.53	0.10*	0.11*
	(0.04)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
Save money	0.71	0.70	-0.01	0.76	0.06	0.07
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.05)
Save food	0.07	0.06	-0.01	0.04	0.03	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)

Notes: the table reports the means and the differences in means of the controls in panels A and B, and the instruments, in panel C, across household market orientation. Columns (1), (2) and (4) show the means of these variables for subsistence-oriented, surplus-oriented and commercial-oriented households. Column (3) shows the differences in the means of subsistence and surplus-oriented households. Column (5) shows the mean differences in the variables for subsistence and commercial-oriented households, while column (6) depicts the mean differences in these covariates for surplus and commercial-oriented households. Values in parenthesis are standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Appendix B: Instruments diagnostics

Table 5.B1. Tests of systematic difference among households based on instrument status

	Pre-planting inputs contract between 2001-2015			Telecommunication network coverage at household location			At least periodic market in village		
	No	Yes	Mean Difference	No	Yes	Mean Difference	No	Yes	Mean Difference
Panel A: Endogenous targeting									
Village level characteristics									
Local wage rate in GHS	6.23	6.22	-0.01	6.40	6.15	-0.25*	6.46	5.91	-0.56***
	(0.14)	(0.07)	(0.16)	(0.11)	(0.07)	(0.13)	(0.06)	(0.10)	(0.12)
Distance to town in Km	16.07	15.32	-0.75	19.64	13.83	5.81***	15.22	15.76	0.55
	(1.42)	(0.56)	(1.36)	(1.23)	(0.54)	(1.15)	(0.65)	(0.86)	(1.06)
Household level characteristics									
Household income in 1000 GHS	4.90	5.32	0.41	5.24	5.24	0.00	5.44	4.99	-0.45
	(0.39)	(0.25)	(0.56)	(0.41)	(0.25)	(0.48)	(0.29)	(0.33)	(0.44)
Household non-farm income in 1000 GHS	0.29	0.60	0.31**	0.57	0.54	0.03	0.51	0.59	0.07
	(0.05)	(0.07)	(0.14)	(0.13)	(0.06)	(0.12)	(0.06)	(0.10)	(0.11)
Household durable asset value in 1000 GHS	13.95	14.33	0.37	13.57	14.53	-0.95	15.37	12.85	2.52*
	(1.75)	(0.81)	(1.89)	(1.35)	(0.87)	(1.64)	(1.03)	(1.02)	(1.48)
Household livestock value in 1000 GHS	4.98	6.08	1.11	5.83	5.91	-0.08	5.76	6.03	0.26
	(0.81)	(0.33)	(0.78)	(0.57)	(0.36)	(0.67)	(0.39)	(0.48)	(0.61)
Household size	5.77	5.59	-0.17	5.82	5.55	0.27	5.59	5.67	0.08
	(0.21)	(0.11)	(0.24)	(0.18)	(0.11)	(0.21)	(0.12)	(0.15)	(0.19)
Landholding (in hectares)	2.33	2.61	0.27	2.52	2.57	0.05	2.50	2.63	0.13
	(0.14)	(0.08)	(0.17)	(0.13)	(0.08)	(0.16)	(0.09)	(0.11)	(0.14)
Education (in years)	0.66	1.41	0.75	1.11	1.34	-0.24	1.23	1.34	0.11
	(0.23)	(0.17)	(0.37)	(0.26)	(0.17)	(0.32)	(0.19)	(0.22)	(0.29)
Save money	0.68	0.72	0.04	0.74	0.71	0.03	0.72	0.72	0.00
	(0.05)	(0.02)	(0.05)	(0.04)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Save food	0.04	0.06	0.02	0.07	0.05	0.02	0.05	0.06	0.01
	(0.02)	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Panel B: Endogenous location of household									
Head Change village of birth (0,1)	0.32	0.29	-0.03	0.34	0.29	0.05	0.29	0.32	0.02
	(0.05)	(0.02)	(0.05)	(0.04)	(0.02)	(0.05)	(0.03)	(0.03)	(0.04)
Change location in 5yrs (0,1)	0.02	0.02	0.00	0.01	0.03	-0.02	0.02	0.02	0.00
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	92	408		140	360		280	220	

Notes: the table reports result of t-test of community and household level characteristics by access to past pre-planting input contract, access to telecommunication network coverage and whether village has market. Values in parenthesis are standard errors. The asterisks *** and * are significance at 1% and 10% levels, respectively.

Table 5.B2. First-stage regressions of the IV-GMM and potential endogeneity of household income

	First-stage IV-GMM (1)		First-stage Household Income (2)	
	Coefficient	S.E.	Coefficient	S.E.
HHAge	5.3E-5	0.001	-3.1E-5	1.2E-4
HHSex	-0.029*	0.016	0.010**	0.005
HHEducation	0.001	0.002	0.002**	0.001
HHSize	-0.002	0.003	-0.002**	0.001
HHLandholding	0.004	0.005	0.002*	0.001
CB_Assoiations	0.005	0.006		
Log HHIncome	0.125***	0.020		
Log HHDAsset	0.009**	0.003	0.007**	0.002
Log HHLivestock	0.015*	0.009	0.003**	0.001
Town distance	-1.6E-4	0.001	5.0E-4*	3.0E-4
Local wage	-2.9E-4	0.007	0.001	0.001
Gushegu	0.030	0.027	-0.019**	0.009
Karaga	0.029	0.025	-0.024***	0.007
Savelugu-Nanton	0.039	0.026	-0.055***	0.008
HHIncomeResid	-0.093**	0.038		
PreProductContract	-0.083***	0.020		
HHMobileNetwork	0.069***	0.016		
CMarket	0.041**	0.016	-0.009*	0.004
HHExtension			0.020***	0.006
Tractor			-1.2E-4*	6.9E-5
SeedUse			6.3E-5**	2.7E-5
SeedPrice			-3.4E-5	5.8E-5
Fertilizer			4.9E-5*	2.8E-5
Pesticides			-2.4E-4	3.0E-4
Weedicides			1.1E-4	1.0E-4
Labor			6.1E-5	4.1E-5
Soil fertility			0.089***	0.009
Farm_shock			-0.033***	0.007
NonEmployTravel			-0.018***	0.005
Constant	-0.961***	0.170	1.946***	0.031
R^2	0.849			
Weak identification tests:				
Cragg-Donald F-statistic	14.49			
Kleibergen-Paap rk Wald F statistic	45.17			
P-value of Angrist-Pischke F-test	0.000			
Over identification test:				
Hansen J	3.452			
p-value	0.178			
Log likelihood			-287.46	
AIC			1.25	
BIC			-2859.49	
Number of observations	500		500	

Notes: the table presents firsts-stage estimations of the IV-GMM regression of household HCCI on the set of controls and the instruments as in our first-stage market orientation model reported in table 5.3, and the first-stage household income regression. S.E. denotes robust standard errors, AIC denotes Akaike information criterion and BIC represents the Bayesian information criterion. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 5.B3. Household crop commercialization and food and nutrients rich food consumption

	Part A: IV-GMM								Part B: OLS							
	Food (1)		Vitamin A (2)		Protein (3)		Hem iron (4)		Food (5)		Vitamin A (6)		Protein (7)		Hem iron (8)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
HCCI	14.20**	5.37	6.05**	2.58	4.84**	2.34	3.02*	1.53	12.93***	1.71	6.60***	0.89	8.01***	0.65	5.29***	0.43
HHAge	-0.01	0.02	-0.01	0.01	0.01	0.01	0.01	0.01	-0.02	0.02	-0.01	0.01	0.01	0.01	0.01	0.01
HHSex	0.39	0.61	0.28	0.27	0.11	0.26	0.07	0.16	0.37	0.64	0.28	0.27	0.20	0.25	0.14	0.13
HHEducation	0.28***	0.09	0.11***	0.03	0.06*	0.03	0.04*	0.02	0.30***	0.08	0.12***	0.04	0.06	0.04	0.04*	0.02
HHSize	0.04	0.13	0.08	0.06	0.01	0.05	0.01	0.03	0.05	0.15	0.08	0.07	0.01	0.06	0.01	0.03
HHLandholding	0.01	0.18	0.07	0.09	0.10	0.08	0.06	0.05	0.02	0.20	0.05	0.09	0.08	0.07	0.05	0.05
CB_Assoiations	0.30	0.24	0.01	0.10	-0.08	0.09	-0.09	0.05	0.30	0.23	0.01	0.12	-0.09	0.08	-0.10*	0.05
Log HHIncome	2.33**	1.03	0.67	0.45	1.05**	0.40	0.75***	0.26	2.38**	0.84	0.53	0.39	0.62**	0.28	0.43**	0.16
Log HHLivestock	0.28*	0.14	0.26***	0.07	0.22***	0.05	0.14***	0.03	0.32**	0.15	0.26***	0.06	0.20***	0.05	0.12***	0.03
Log HHDAsset	1.60***	0.32	0.73***	0.14	0.68***	0.13	0.45***	0.08	1.64***	0.36	0.72***	0.16	0.62***	0.12	0.42***	0.07
Town distance	-0.01	0.03	-0.03**	0.01	-0.02*	0.01	-0.01*	0.01	-0.01	0.03	-0.03**	0.01	-0.02*	0.01	-0.01*	0.01
Local wage	0.14	0.26	0.06	0.12	0.08	0.11	0.03	0.07	0.14	0.29	0.06	0.11	0.08	0.11	0.03	0.06
Gushegu	-6.79***	1.03	-2.47***	0.46	-0.41	0.41	-0.29	0.25	-6.29***	1.04	-2.33***	0.46	-0.47	0.35	-0.33	0.23
Karaga	-3.69***	0.98	-0.28	0.40	1.43***	0.39	0.88***	0.25	-3.29***	1.01	-0.20	0.36	1.35***	0.38	0.82***	0.22
Savelugu-Nanton	-4.54***	1.03	-2.61***	0.48	-0.47	0.44	-0.27	0.28	-4.36***	1.04	-2.63***	0.50	-0.60*	0.34	-0.38	0.29
PreProductContract									0.51	0.72	0.30	0.31	0.30	0.38	0.17	0.20
HHMobileNetwork									0.96	0.71	0.27	0.33	-0.11	0.26	-0.07	0.18
CMarket									-0.50	0.52	-0.17	0.24	-0.22	0.26	-0.21	0.13
HHIncomeResid	-0.76	1.17	0.01	0.52	-0.26	0.49	-0.28	0.32	-0.68	1.33	0.14	0.47	0.07	0.39	-0.02	0.26
Constant	-5.56	7.99	-3.34	3.35	-13.40***	3.02	-9.33***	1.95	-6.82	7.34	-2.54	2.70	-10.16***	1.94	-6.89***	1.27
R^2	0.48		0.50		0.47		0.47		0.48		0.50		0.50		0.50	
Wald X^2									606.76		759.58		1788.07		1136.52	
p-value									0.00		0.00		0.00		0.00	
F-statistic	25.50		27.64		30.55		31.54									
p-value	0.00		0.00		0.00		0.00									
Number of observations	500		500		500		500		500		500		500		500	

Notes: the table shows the second-stage of the two-stage least squared generalized methods of moments (IV-GMM) and the ordinary least square (OLS) estimations of the impact of household crop commercialization on food and nutrient rich foods consumption. The coef. and S.E. are coefficient and standard errors, respectively. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Appendix C: Second-stage estimates of the model

Table 5.C1. Second stage estimates of determinants of food and vitamin A rich food consumption

	Food						Vitamin A					
	Subsistence- oriented		Surplus-oriented		Commercial-oriented		Subsistence- oriented		Surplus-oriented		Commercial-oriented	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
HHAge	-0.041	0.042	-0.043	0.029	0.022	0.048	0.001	0.021	-0.018	0.014	-0.011	0.014
HHSex	0.631	1.174	-0.101	0.888	0.087	1.255	0.112	0.593	0.614	0.416	-0.194	0.345
HHEducation	0.451*	0.229	0.391***	0.116	0.171	0.164	0.196	0.124	0.221***	0.047	0.028	0.040
HHSize	-0.221	0.239	0.442*	0.235	0.107	0.229	0.023	0.120	0.210*	0.113	0.008	0.075
HHLandholding	0.584	0.409	-0.011	0.216	-0.618	0.409	0.299	0.223	0.001	0.118	-0.102	0.112
CB_Assoiations	0.238	0.432	0.823*	0.411	0.023	0.420	0.050	0.208	0.213	0.147	-0.143	0.131
Log HHIncome	-1.400	2.003	4.556***	1.358	1.811	2.134	-1.289	0.944	1.968***	0.524	0.599	0.545
Log HHLivestock	0.401*	0.234	0.210	0.217	0.023	0.434	0.350***	0.115	0.186*	0.110	0.105	0.130
Log HHDAsset	2.489***	0.791	0.930*	0.468	0.982	0.613	1.102***	0.311	0.517**	0.233	0.546***	0.183
Town distance	0.040	0.071	-0.091*	0.048	0.118	0.082	2.505**	1.123	-0.081	0.586	-0.649	0.494
Local wage	0.130	0.592	0.341	0.382	0.091	0.471	-0.044	0.031	-0.032	0.021	0.017	0.020
Gushegu	-7.979***	2.090	-6.090***	1.484	-3.124*	1.785	-3.490***	0.930	-1.512**	0.624	-1.435**	0.657
Karaga	-4.544**	2.016	-3.335**	1.458	-2.660	1.935	-0.978	0.924	0.619	0.614	-0.521	0.542
Savelugu-Nanton	-6.899***	2.061	-2.798*	1.649	-1.961	1.933	-4.570***	0.984	-1.363*	0.759	-1.294**	0.579
HHIncomeResid	3.466	2.390	-0.375	1.462	-1.903	1.661	0.104	0.283	0.235	0.184	-0.167	0.151
Constant	19.330	18.397	-14.045	11.852	14.832	26.894	9.925	8.072	-11.621**	4.919	6.202	6.318
$\rho_{\epsilon\mu}$	-0.304	0.316	-0.082	0.212	-0.292	0.676	-0.225	0.229	0.101	0.235	0.192	0.470
LR $X^2(3)$ ($\rho_{\epsilon\mu} = 0$)	1.29						1.01					
Prob X^2	0.732						0.798					
Log likelihood	-2029.44						-1603.46					
LR $X^2(18)$	143.42						142.73					
Prob X^2	0.000						0.000					
Number of observations	180		206		114		180		206		114	

Notes: the table shows the second-stage ordered Heckman estimations of equation (3) for food consumption score and vitamin A rich foods consumption frequencies. $\rho_{\epsilon\mu}$ denotes the correlation between the unobservables in the first-stage ordered probit selection equation (2) and the second-stage outcome equations (3). S.E. denotes robust standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively.

Table 5.C2. Second stage estimates of determinants of protein and iron rich food consumption

	Protein						Hem iron					
	Subsistence- oriented		Surplus-oriented		Commercial-oriented		Subsistence- oriented		Surplus-oriented		Commercial-oriented	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
HHAge	0.011	0.017	0.014	0.014	-0.002	0.012	0.006	0.010	0.005	0.009	-0.002	0.007
HHSex	-0.195	0.512	0.599	0.467	-0.257	0.294	-0.073	0.330	0.432	0.310	-0.221	0.176
HHEducation	0.170**	0.076	0.113	0.072	-0.024	0.029	0.117**	0.052	0.068	0.046	-0.013	0.018
HHSize	-0.049	0.072	0.036	0.110	-0.016	0.067	-0.030	0.045	0.053	0.071	-0.014	0.041
HHLandholding	0.351**	0.171	-0.016	0.135	-0.057	0.137	0.214*	0.110	-0.009	0.087	-0.046	0.083
CB_Assoiations	-0.087	0.164	-0.100	0.156	0.105	0.123	-0.097	0.107	-0.114	0.105	0.041	0.072
Log HHIncome	-0.281	0.696	1.904***	0.584	0.930***	0.307	-0.248	0.443	1.330***	0.387	0.597***	0.187
Log HHLivestock	0.222***	0.074	0.257**	0.100	0.065	0.100	0.151***	0.048	0.151**	0.065	0.035	0.061
Log HHDAsset	1.037***	0.232	0.627**	0.244	0.301*	0.163	0.694***	0.146	0.411**	0.161	0.201**	0.094
Town distance	-0.038	0.027	-0.023	0.026	0.006	0.014	-0.026	0.017	-0.015	0.016	0.002	0.008
Local wage	0.160	0.204	0.107	0.185	0.053	0.134	0.071	0.132	0.088	0.121	-0.024	0.083
Gushegu	-1.350*	0.748	0.472	0.652	0.156	0.489	-0.959**	0.465	0.369	0.421	0.004	0.303
Karaga	-0.043	0.855	2.310***	0.663	1.491***	0.469	-0.042	0.566	1.552***	0.435	0.723**	0.296
Savelugu-Nanton	-2.207**	0.779	-0.046	0.756	1.018**	0.491	-1.484***	0.493	0.109	0.487	0.475	0.301
HHIncomeResid	0.989	0.817	0.157	0.743	-0.787**	0.337	0.642	0.516	-0.036	0.488	-0.506**	0.216
Constant	-4.447	6.017	-19.547***	5.592	-3.222	2.608	-2.434	3.784	-13.744***	3.694	-1.488	1.601
$\rho_{\epsilon\mu}$	-0.006	0.218	0.245	0.239	0.307*	0.158	0.033	0.212	0.258	0.239	0.269*	0.153
LR $X^2(3)$ ($\rho_{\epsilon\mu} = 0$)	2.05						2.03					
Prob X^2	0.562						0.566					
Log likelihood	-1563.33						-1339.87					
LR $X^2(18)$	142.76						142.65					
Prob X^2	0.000						0.000					
Number of observations	180		206		114		180		206		114	

Notes: the table shows the second-stage ordered Heckman estimations of equation (3) for protein and hem iron rich foods consumption frequencies. $\rho_{\epsilon\mu}$ denotes the correlation between the unobservables in the first-stage ordered pobit selection equation (2) and the second-stage outcome equations (3). S.E. denotes standard errors. The asterisks ***, ** and * are significance at 1%, 5% and 10% levels, respectively

Chapter Six

Summary, conclusions and policy implications

The low uptake of innovations and improved technologies, and the recent increase in food insecurity and malnutrition in sub-Saharan Africa, in the midst of increased availability of improved agricultural technologies in the continent motivated the need to investigate the role of social networks in technology adoption, and the implications of improved technology adoption and crop commercialization on household welfare. This study contributes to the existing literature by examining the impact of social networks, technology adoption and smallholder market-orientation on household welfare in developing countries. First, the study examined the impacts of smallholders' peer adoption of two improved and competing soybean varieties on their adoption decisions of these varieties, showing the instances under which a given improved variety is likely to become dominant in terms of adoption in a farmer's social networks and when a farmer is likely to defer adoption of any of the improved varieties.

Second, the study investigated the role of learning about both production techniques and expected benefits of improved soybean varieties from peers on diffusion of these varieties, and the influence of social network structures, specifically *transitivity* and *modularity* on diffusion of these improved soybean varieties. Following these, the study then examined the effects of own and peer adoption of the improved variety on household soybean yield, food consumption, as well as the consumption of vitamin A, and protein rich foods. Finally, the study explored the impacts of smallholder market-orientation on household food consumption, and on the consumption of nutrient (such as vitamin A, protein and hem iron) rich foods.

6.1 Summary of empirical methods

Given the endogeneity and identifications concerns of social network effects, and the threats of sample selection and missing variable biases, this study utilized a number of empirical methods in the analysis depending the nature of the problem and the issue of being investigated. In particular, the study used the spatial autoregressive multinomial approach, Bayesian estimation approach, Markov Chain Monte Carlo (MCMC), random-effects complementary log-log hazard model, graphical reconstruction of social networks, marginal treatment effects, and ordered-Probit selection model.

Chapter two employed a spatial autoregressive multinomial probit model (SAR Probit) to examine how neighbors' varietal and cross varietal adoption of improved varieties, affect a farmer's adoption decision in the social network. Due to challenges of multidimensional integrals, correlations in the error terms and the complexity of the spatial dependence in the estimation of spatial models in a multinomial setting, the study used the Markov Chain Monte Carlo (MCMC) sampling, which is a Bayesian estimation framework, to estimate the SAR Probit model since this allows for the higher dimensional integrals to be re-specified into sequence of draws. This spatial autoregressive model directly accounts for contextual network effects in order to identify the endogenous network effect. Finally, network fixed-effects and the control function approach were used to account for correlated network effects due to similar institutional and environment conditions faced by farmers in the same network and unobserved determinants of link formation between individuals, respectively.

In chapter three, a Random-effects complementary log-log hazard function was employed to estimate the conditional probability of adoption in a small-time interval for a farmer who has not adopted the technology up to this time. Given that adoption of the improved varieties was observed on annual basis, the duration to adoption was modelled in a discrete-time method to account for the banded nature of the survival time. In order to identify endogenous from exogenous, the model controlled for contextual peer characteristics. Given that the network structure, *modularity*, was measured at the network level, which makes the use of network dummies to control for network fixed-effects challenging due to the incidental parameter problem, the study accounted for correlated effects in a network by controlling for time fixed-effects, use of residuals of link formation model as control functions and clustering standard errors at the village (i.e., network) level. To investigate the extent of bias due to the use of sampled networks, instead of complete networks, in the construction of the network structures, the study used the graphical reconstruction approach to simulate complete networks, and then used these to calculate the network structures for estimation of the hazard model as robustness.

Chapter four used spatial econometric techniques to generate instruments, and then use the instruments, in addition to controlling for network fixed-effects and for potential endogeneity of network link formation with the control function approach to identify peer adoption effects on own adoption and outcomes. The marginal treatment effects (MTE) approach was used to estimate the treatment effects heterogeneities across households. The MTE approach allows an identification of a substantial part of the range of individual treatment effects, and as a result characterize the extent and pattern of treatment effects heterogeneity from adoption due to observed and unobserved characteristics. It also shows the pattern of selectivity and allows for computation of average treatment effects (ATE), average treatment effects on the treated (TT) and the average treatment on the untreated (TUT). The Policy Relevant Treatment Effect (PRTE) was used to estimate the effects of policies that either increase affordability of soybean seeds through input subsidy, or increase access to soybean seeds by reducing distance to the nearest soybean seed source.

Chapter five provides a review of food security and nutrition strategies in sub-Saharan Africa countries, and an empirical analysis of smallholder market participation as a food security and nutrition strategy. Smallholders were classified based on their market-orientation into subsistence-oriented, surplus-oriented and commercial-oriented. To the extent that the treatment of farm households in this study is non-random implies that market-orientation status of farmers could differ systematically due to self-selection of households into categories. In order to account for the threats of selection bias and omitted variable problem due to observed and unobserved factors in the light of the ordered nature of the selection variable, the study employed the ordered-Probit selection model. This is a parametric model that utilizes full information maximum likelihood procedure to jointly estimate a first-stage ordered-Probit of smallholder market-orientation, and a second-stage outcome models for the three regimes of market-orientation. The process accounts for selection bias and omitted variable problem by inserting calculated inverse Mills ratios from the first-stage ordered choice model into the second-stage food and nutrients consumption model. Finally, the approach allows for the calculation of average treatment effects (ATE) for the entire population and for those at one of the transition stages, the average treatment effects on the treated (ATE) and the average treatment effects on the untreated (ATU).

6.2 Summary of results

The results of chapter two show that a farmer's likelihood of adopting an improved variety is lower than the proportion of adopting neighbors of that variety when the proportion is below a threshold. However, the likelihood of adoption becomes higher than the proportion of adopting neighbors when the share of neighbors adopting that variety is above this threshold. The results also show that a farmer's adoption decision of a given improved variety is positively influenced by the adopting neighbors of this variety, but negatively by the adopting neighbors of the competing improved variety. Furthermore, when the relative share of adopting neighbors are equal, farmers are more likely to wait and not to switch from the old variety. Similarly, when the proportion of adopters of both improved varieties in a farmer's neighborhood are less than 25% or greater than 25%, then the farmer is more likely to defer adoption of improved varieties.

In chapter three, the results reveal a positive and significant effect of past share of adopting peers on the conditional probability of adoption across all specifications. Similarly, there is a positive and significant effect of peer experience in the cultivation of the improved varieties on the speed of adoption. These suggest that both learning about benefits and production process are important in accelerating adoption, although the effects of experience are higher when sufficient peers adopt the improved varieties. The interaction effects between the past adopting peers and peer experience with the improved varieties appear to be complementary on the conditional probability of adoption up to an average peer experience of 5 years, after which it begins to exhibit decreasing probability of adoption with increasing peer experience. The results of the network structures show the role of *transitivity* in the learning and diffusion processes to be stronger, compared to *centrality*. However, *modularity* tends to slow down the diffusion process, and limits the significance of both *transitivity* and *centrality*.

The results of chapter four show that own adoption tend to significantly increase yield, food and nutrients consumption of the household, *albeit* the effects of adoption on nutrients rich food consumption are stronger and higher in magnitudes than the effect on food consumption. The results reveal positive selection on gains due to unobserved characteristics, mainly driven by worse outcomes, of households with less resistance to adopt, in the non-adoption state. However, adoption tends to make the potential outcomes of households quite homogenous, irrespective of their level of resistance to adoption. The results show that peer adoption tends to strongly affect own yield, only when the household is also adopting, which is in line with the notion of social learning or contagion effects. In terms of food and nutrients consumption, the results show that peer adoption tends to increase own food and nutrients consumption when not adopting, and attenuating peer adoption effects when adopting, which are suggestive of stronger private transfers received from peers in the form of cash or food safety nets when the household is not adopting.

The impact of commercialization on food and nutrients rich food consumption is generally shown to be positive across transitions of smallholder market-orientation in Chapter five, which is mainly due to increased farm and household income. Specifically, transitioning from subsistence to surplus orientation increases household consumption across all food and nutrient items. Also, transitioning from surplus to commercial orientation substantially increases household food and nutrients consumption. However, the magnitudes of the treatment effects for protein and iron rich food consumption are higher compared to that of food and vitamin A food consumption. The results also show substantial heterogeneities in gains (i.e., sorting gains and losses), where positive selection on gains is shown, in transitioning between subsistence and surplus orientations, while reverse selection on gains is revealed in transitioning between surplus and commercial orientations. These suggest that less (more) endowed and constrained households who are less (more) likely to transition from surplus (subsistence) to commercial (surplus) orientation tend to gain more in food and nutrients consumption if they go from surplus (subsistence) to commercial (surplus)-oriented.

6.3 Policy implications

The findings of this study show that social networks are important in promoting technology adoption, diffusion, and household welfare. These have some implications for policy. The findings of the differential adoption rates of competing technologies and the ultimate dominance of varieties in networks suggest the need to do a stepwise introduction of improved varieties before a full-scale promotion in the villages. It will be rewarding to first expose some farmers in the network (i.e., village) to the improved varieties, observe the extent of adoption and then following-up with a wide-scale introduction and promotion of the variety that leads in adoption in the network. This will reduce the prohibitive costs associated with promotion of several varieties at the same time. The finding that information about benefits and production process matter in the diffusion process, and that farmers are likely not to adopt the improved varieties when the proportion of adopting neighbors of the improved varieties are equal suggest the need for policymakers to focus promotion efforts on demonstrating the relative benefits and production process of improved varieties introduced to farmers, since these would motivate farmers to adopt.

The finding on the role of *transitivity* in promoting adoption and that of *modularity* in restricting diffusion, and the influence of the other network characteristics suggest that the common extension strategy of targeting initial and influential adopters in a network for disseminating information may not be appropriate in enabling diffusion at the network level. Given that networks can be important means of increasing yield, and promoting welfare of vulnerable households, interventions, such as self-help groups and/or farmer field-days, aimed at promoting interactions among farm households, and enhancing exchange can increase the effectiveness of social networks in these respects. Also, training workshops, where people are specifically invited from different segments of the village at the early stages of adoption, can promote bridges between network components and diffusion. The policy simulation suggests that interventions to minimize production and structural constraints to adoption could be an important strategy in mitigating the cost associated with technology adoption. Hence, government and development partners can consider increasing access through availability of the improved seeds at the local levels, such as empowering village level shops or community-based groups to engage in input marketing.

Finally, the findings show substantial heterogeneity in consumption gains across market-orientations and suggest the need for transition-sensitive policies in promoting smallholder food security and nutrition through crop commercialization. Thus, promoting food security and nutrition among subsistence-oriented households need to consider productivity enhancing measures such as cash crop programmes that support farmers with inputs to facilitate spill-over benefits between food and cash crop cultivation, and promotion of policies to increase their access to improved inputs and innovations. Also, the promotion of higher smallholder commercialization will require in addition to output augmenting measures the mitigation of some of the market barriers and failures (such as, markets availability, physical access and information) that limit poor smallholders from engaging in sales for profit. Interventions such as promotion of market information platforms, farmer cooperatives and collective actions as well as contract buying, which provides ready markets for farmers, will be more rewarding.

Appendices

Appendix 1: Household survey questionnaire

Christian-Albrechts University of Kiel, Germany

Institute of Food Economics and Consumption Studies

Social Networks, Technology Adoption and Agriculture Commercialization on Smallholder Welfare in the Northern Region of Ghana

Introduction

Good day Sir/Madam and thank you for talking to me. We are conducting a survey of smallholder farmers to examine the impacts of farmer individual social and economic networks, adoption of technologies and agricultural commercialization on their welfare. The specific purposes of this survey are to assess the impacts of farmers' perceptions about technology features and social networks on technology adoption; roles of social networks and technology adoption on household agriculture commercialization processes and to examine the impacts of agriculture commercialization on household welfare. The information gathered will provide significant input into the write-up of a PhD thesis in Agriculture and Food Economics at the University of Kiel, Germany. The interview will take about 1 hour 30 minutes and your participation is entirely by choice. Your name, identity and individual responses will be kept confidential.

Do you wish to participate in this survey? 0 =No 1 =Yes

Survey identification

Questionnaire number: ___________ Name of enumerator: ______________________________ Enumerator's ID: ____________

Date of interview: |_____|_____|_______| Start time (24hr Clock): |___:____| End time (24hr Clock): |___:____|

Location

1. District name: ____ 2. District code: ___________________________________
3. Name of community: ____ 4. Community ID: __________________________________
5. Head of Household (name): __________________________________ 6. Household ID: __________________________________

Note on soybean varieties: **Afayak:** (a bit yellowish compared to jenguma & matures in 85 to 90 days) **Jenguma:** (Short, whitish & matures in 90 days) **Suong-Pungun:** (More yellowish at maturity and matures in 75 days) **Salintuya:** (tall, can be intercropped and matures in 120 days)

Put "99" for "Not Applicable" and "Don't know"

Section A: General information

A1	A2	A3	A4
What is/are the main languages spoken at home? **Codes A**	What is the ethnicity of the household head **Codes B**	What is the family type of the household? **Codes D**	What type of marriage is the household head practicing? **Codes E**

Section B: Socio-demographic characteristics

B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13
What is the farmer's relationship with the household head? **Codes F**	Sex of farmer? 0=F 1=M	How old is the farmer?	What is farmer's educational level? *(In completed years of schooling*)	What is farmer's religion? **Codes C**	What is farmer's marital status? **Codes G**	What is farmer's main occupation? **Codes H**	Number of years farmer is living in the village	Farmer's experience (years) in own farming activities	Farmer's experience (years) in cultivating maize	Does the household head hold any of the following authorities at the community level? **Codes I**	Does the household head's **spouse** hold any of the following authorities at the community level? **Codes I**	Household size *(number of persons who share cooking arrangement/ under your care*)

Codes A

1. Likpakpaln (Konkomba)	10. Sissali
2. Chekosi	11. Gruni
3. Mampruli	12. Kasem
4. Dagbali (Dagbani)	13. Nankan
5. Nanunli	14. Kusaal
6. Gonja	15. Twi
7. Hausa	16. Ewe
8. Bimoba	17. Ga
9. Dagaare/Wali	18. Other (specify)

Codes B

1. Konkombas	10. Sissalas
2. Chekosi	11. Grunsi
3. Mamprusi	12. Kassenas
4. Dagombas	13. Nankan
5. Nanumbas	14. Kusasi
6. Gonjas	15. Akans
7. Hausas	16. Ewes
8. Bimobas	17. Gas
9. Dagaabas/Walas	18. Other (specify)

Codes C
0 No religion
1 Muslim
2 Christian
3 Traditional
4 Other (specify)
____

Codes G
0 Never married
1 Married
2 Consensual union
3 Separated
4 Divorced
5 Widowed

Codes I
0 None
1 Chief/community leader
2 Chief council member
3 Assembly/unit committee member
4 Religious leader
5 Youth leader
6 Women leader
7 Political party leader

Codes E
1 Polygynous
2 Monogamous
3 Other (specify)
____

Codes D
1 Nuclear
2 Extended
3 Other (specify)
____

Codes F

1 Head	6 Son/Daughter-in-law
2 Spouse	7 Other relative
3 Child	8 Adopted/Foster/Stepchild
4 Grandchild	9 House help
5 Parent/Parent-in-law	10 Non-relative

Codes H
1 Farming (crop and/or livestock)
2 Housekeeping
3 Casual labour on another farm
4 Non-farm business (shops, trade, etc)

Please complete the table below on the age composition and non-farm work of the household members

B14		B15		B16		B17		B18	B19
(less than 16 years)		(16 - 30 years)		(31 - 60 years)		(above 60 years)		Family non- farm workers	
Male	Female	Male	Female	Male	Female	Male	Female	Male	Female

Please complete the table on the household and household head's social issues

#	Question I	#	Question II	#	Question III
B20	What is household head's settlement status in the community? 0 =Settler 1 =Native	**B28**	If no, how long has the household head been in this community? _______ (Years)	**B36**	Did any member of the household experience any court, police or major theft incidence in last 5 years? 0 =No 1 =Yes
B21	Has the household head a royal lineage? 0 =No 1 =Yes	**B29**	How many times has the household head travelled outside the village in last 12 months? _______ (times)	**B37**	Did you or any member of the household undertake any lumpy expenditure (such as construction of house and/or room) in last 5 years? 0 =No 1 =Yes
B22	Has any of the parents of the household head or spouse any important position or representation in the traditional political or authority system? 0 =No 1 =Yes	**B30**	Has the household change location in the past…. 5 years? 0 =No 1 =Yes 10 years? 0 =No 1 =Yes	**B38**	Did you experience any shock or loss in your farming activities in last 5 years? 0 =No >>B41 1 =Yes
B23	Has any member of the household been away from the community for more than 6 months in the last 12 months? 0 =No >>B26 1 =Yes	**B31**	Did you have a wedding ceremony in the household in the past 2 years? 0 =No >>B33 1 =Yes	**B39**	If yes, which of the following did you experience? 1 =Weather shocks 2 =bush/wildfires 3 =Other (specify)______________________
B24	If yes, how many people? _________	**B32**	If yes, how many times? _______ (times)	**B40**	If yes, how regular is the incidence of these shocks/losses? 1 =Very regular 2 =Regular 3 =Occasional
B25	For what reason did the person move away? **Codes A**	**B33**	Did you have an outdooring ceremony in the household in the past 2 years? 0 =No >>B35 1 =Yes	**B41**	Did you experience a sudden death of any household/family member in last 5 years? 0 =No >>B43 1 =Yes
B26	Was the household head born in this community? 0 =No 1 =Yes	**B34**	If yes, how many times? _______ (times)	**B42**	If yes, how many times did you experience this in the past 5 years? _________ (times)
B27	Did the household head grow-up in this community? 0 =No 1 =Yes >>B29	**B35**	Did any household member fall sick in the in last 12 months? 0 =No 1 =Yes	**B43**	Did you experience a long period of sickness of a household member which led to his/her death in last 5 years? 0 =No 1 =Yes

Codes A

1. Job transfer	2. Seeking employment	3. Spouse's employment
4. Marriage	5. Other family reason	6. Education
7. Political/religious	8. Ethnic/chieftaincy conflict	9. Other (specify)____

Section CI: Social networks

Contact Name/ID	CI1	CI2	Have any of you ever sought or exchanged (S/E) any of the following from each other?							
			Information on improved soybean variety (Jenguma)			**Seeds of Jenguma variety**	**Information on other soybean varieties Codes A**			**Seeds of other soybean varietie/s**
			CI3	**CI4**	**CI5**	**CI6**	**CI7**	**CI8**	**CI9**	**CII08**
	Do you know (X) 0=No >> next contact 1=Yes	How long have you known (X)?	S/E 0=No 1=Yes	No. of times in the past 12 months	Type of information **Codes C**	S/E 0=No 1=Yes	S/E 0=No 1=Yes	No. of times in the past 12 months	Variety **Codes A**	S/E 0=No 1=Yes
1										
2										
3										
4										
5										

Contact ID	Have any of you ever sought or exchanged (S/E) any of the following from each other?							CI18	CI19
	Information on other crops (specify)				**Seeds of other crop varieties**	**Information on soybean marketing**	**Information on other crop marketing**	If yes, type of information exchanged? **Codes D**	In the past 12 months, how many times did you have such exchanges?
	CI11	**CI12**	**CI13**	**CI14**	**CI15**	**CI16**	**CI17**		
	S/E 0=No 1=Yes	Crop **(Codes B)**	No. of times in the past 12 months	Type of information **Codes C**	S/E 0=No 1=Yes	S/E 0=No 1=Yes	S/E 0=No 1=Yes		
1									
2									
3									
4									

Code A
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Crops B
1 Rice
2 Maize
3 Millet
4 Sorghum
5 Cassava
6 Soya bean
7 Cowpea
8 Groundnut
9 Cotton
10 Yam
11 Vegetables
12 Fruits
13 Other (specify): ________________________

Codes C
1 Crop choice
2 Agronomic practices
3 Fertilizer application
4 Weedicides
5 Harvesting
6 Pesticides
7 Storage
8 Other(specify)_________

Codes D
1 Prices
2 Demand situation
3 Buyers
4 Inputs availability
5 Other (specify)____

Contact ID	Have any of you ever sought or exchanged (S/E) any of the following from each other?									
	Labor for soybean activities			**Credit and/or gift transactions**				**Land exchange/transaction**		
	CI20	**CI21**	**CI22**	**CI23**	**CI24**	**CI25**	**CI26**	**CI27**	**CI28**	**CI29**
	S/E 0=No 1=Yes	No. of times in the past 12 months	No. of man-days per exchange	S/E 0=No 1=Yes	Nature of exchange **Codes A**	No. of times in the past 12 months	Amount received GHS______ and/or given GHS______	S/E 0=No 1=Yes	Nature of the exchange **Codes B**	If rented, how much was paid? (GHS)
1										
2										
3										
4										
5										

Section CII Social learning

Please tell me about contact (X) soybean farming activities during the 2015/16 season

***(NOTE: Ask if respondent at least know contact even if nothing was sought or no exchange between respondent and contact)*. Put "99" for "Don't know"**

Contact ID	**CII1**	If yes, i.e. (X) cultivated soybean									
	Did (X) cultivate soybean 0 =No >> next contact 1=Yes	**CII2**	**CII3**	**CII4**	**CII5**	**CII6**	**CII7**	**CII8**	**CII9**	**CII10**	**CII11**
		When did (X) started cultivating soybean? **Codes C**	Soybean varieties cultivated **Codes D**	Where did (X) get seeds of soybean varieties? **Codes E**	Did (X) use fertilizer on soybean plot? 0= No 1= Yes	Did (X) use manure on soybean plot? 0= No 1= Yes	Did (X) use pesticides on soybean plot? 0= No 1.=Yes	Did (X) use weedicides on soybean plot? 0=No 1=Yes	How much soybean did (X) harvest (100kg)?	Did (X) sell the soybean harvest? 0= No 1= Yes	If yes, at what price (GHS/kg)?
1											
2											
3											
4											
5											

Codes A
1 Credit
2 Gift
3 Both

Codes B
1 Purchased
2 Tenant rented (for cash or kind)
3 Sharecropped
4 Allocated free of charge
5 Begged
6 Borrowed
6 Other (specify)______________________________________

Codes C
1 Not yet
2 Before me
3 At the same time as me
4 After me

Code D
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Codes E
0 Own storage
1 Agro-input dealer
2 Purchased from market
3 Exchange (farmer)
4 Private aggregator
5 FBO (cooperative)
6 Local seed producers
7 Extension officer (MoFA)
8 NGO
9 Gift
10 SARI/CSI
11 Other (specify) ___________

Contact ID	CII12	CII14	CII15	CII16	CII17	CII18	CII19	CII20	CII21	CII22
	I will now ask you information about contacts' maize cultivation									
	Did X cultivate maize? 0=No 1=Yes	Was crop of modern variety? 0=No 1=Yes	Where did (X) get seeds of crop varieties? **Codes A**	Did (X) use fertilizer on crop plot? 0=No 1=Yes	Did (X) use manure on crop plot? 0=No 1=Yes	Did (X) use pesticides on crop plot? 0=No 1=Yes	Did (X) use weedicides on crop plot? 0=No 1=Yes	How much maize did (X) harvest (100kg)?	Did (X) sell the maize harvest? 0=No 1=Yes	If yes, at what price (GHS/kg)?
1										
2										
3										
4										
5										

I will like to ask you about the social and physical proximity issues between you and the matched contacts

Contact ID	CII23	CII24	CII25	CII26	CII27	CII28	CII29	CII30
	How is (X) related to you? **Codes B**	Have same family name 0=No 1=Yes	Do you and contact families trace your origin to same region? 0=No 1=Yes	Have you ever visited the home of (X)? 0=No >> CII28 1=Yes	If yes, number of visits per month to (X) home?	Where does this person live? **Codes C**	Approximately how far does this person live from you *(in minutes of walking)*?	Is (X)'s field/ plot adjacent to yours? 0=No 1=Yes
1								
2								
3								
4								
5								

Codes A
0 Own storage
1 Agro-input dealer
2 Purchased from market
3 Exchange (farmer)
4 Private aggregator
5 FBO (cooperative)
6 Local seed producers
7 Extension officer (MoFA)
8 NGO
9 Gift
10 SARI/CSI
11 Other (specify) ____________

Codes B
1 Parent
2 Child
3 Sibling
4 Grandparent
5 Grandchild
6 In-law
7 Other relative
8 Friend
9 Same family lineage;
10 Neighbor;
11 Attend same church/ mosque
12 belong to same association
13 Professional/business colleague
14 Other (specify)____________

Codes C
1 Next house/neighbor
2 Neighbor of my neighbor
3 Not neighbor of me or of my neighbor

Contact ID	CII31	CII32	CII33	CII34	CII35	How frequent do you attend…	
						CII36	CII37
	Do you pass by X's field when going to field? 0=No 1=Yes >> CII33	If no, have you ever passed by the field of (X)? 0=No 1=Yes	Do you perceive the soil conditions of your farm(s) as similar with (X)? 0=No 1=Yes	How many of these contacts know one another?	Generally speaking, would you say that most people can be trusted? **Codes A**	…social events (such as weddings, funerals and festivals)? **Codes E**	…religious events (such as visiting mosque, church or shrine)? **Codes E**
1							
2							
3							
4							
5							

Section CIII: Famers networks of family and friends/acquaintances

I will like to ask you about your network of close relatives and friends your share farming information and resources with, in the community.

Network members	CIII1	CIII2	CIII3	CIII4	CIII5	CIII6	CIII7	CIII8	CIII9	CIII10	CIII11	CIII12	CIII13	CIII14	CIII15
	How many people do you consider relevant for exchanging information about agronomic issues with?	How many of them know each other?	How many of them cultivate soybean?	How many of them cultivate soybean variety? **(varieties codes B)**										In general, how many cultivators of soybean do you know in the community?	How many of them cultivate maize?
				1	2	3	4	5	6	7	8	9	10		
Family															
Friends/acquaintances															
Family & Friends															

Network members	CIII17	CIII18	CIII19	CIII20	CIII21	CIII22	CIII23	CIII24	CIII25	CIII26
	How many of them implement the following agronomic practices on the soybean farm? **(Practice codes C)**						How many of them uses the following in threshing soybean? **(Threshing code D)**			
	1	2	3	4	5	6	0	1	2	3
Family										
Friends/acquaintances										

Codes A scale of 1 to 6
1 = Cannot be too careful
2
3
4
5
6 = Most can be trusted

Code B
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Codes C
1 Recommended depth of planting
2 Row planting
3 Inoculant use
4 Crop rotation
5 No burn of crop residue
6 Other (specify) _____________

Codes D
0 Manual with sticks
1 Tractor
2 Thresher
3 Other (specify) _____

Codes E
1 Daily
2 Biweekly
3 Weekly
4 Fortnightly
5 Monthly
6 Yearly

Source of information	CIII27	CIII28	CIII29	CIII30	CIII31	CIII32	CIII33	CIII34	CIII35
	Do you know any external officer from the following…? 0=No 1=Yes	How long (in years) have you known officer?	Have you ever sought or received soybean information from any of the following in the past? 0=No 1=Yes	If yes to CIII29,					
				How many of them do you discuss with?	In a normal month, how many times do you talk with…?	In a normal month, how many times do you discuss soybean varieties with…?	In a normal month, how many times do you discuss soybean agronomic practices with…?	In a normal month, how many times do you general farming issues with…?	In a normal month, how many times do you discuss marketing with…?
Neighbours									
Family									
Friends/acquaintances									
External officer									
Agric. Ext Officer (MoFA)									
Research organization									
NGOs									
Other farmer organizations									

Network member	CIII37	CIII38	CIII39	CIII40	CIII41	CIII42	CIII43	CIII44
	Have you ever sought or received any of the following from any of the following in the past?							
	Soy seeds		**Labour**		**Credit**		**Land**	
	0/1	No. of contacts	0/1	No. of contacts	0/1	No. of contacts	0/1	No. of contacts
Family								
Friends/acquaintances								

Agricultural Production

Section DI: Soybean varieties

I will like to ask you about your farming activities now starting with issues of soybean cultivation

DI1	DI2	DI3	DI4	DI5	DI6		DI7		DI8		DI9		DI10		DI11	DI12	DI13	DI14
Which soybean varieties do you know? **Codes A**	When (year) did you first hear about the variety?	From whom did you first hear about it?, rank up to three **Code F**	Have you ever planted the variety? 0=No >> next variety 1=Yes	How many times have you planted it in the past?	Years cultivated soybean and acreage										Did you cultivate variety in the 2015/2016 cropping season? 0=No 1=Yes	Did you use certified seed? 0=No 1=Yes	Acres under certified seeds	If No, to DI11 why not? **Codes G,** rank 3
					Yr1	Acre	Yr2	Acre	Yr3	Acre	Yr4	Acre	Yr5	Acre				

DI15	DI16	DI17		DI18		DI19		DI20		DI21	DI22	DI23	DI24
Hypothetical question, what is the minimum addition to net benefit that made you adopt for sure? (%)	If No to DI4, hypothetical question, please estimate the average yield of soybean varieties if you had adopted last year? (%)	Which of the following agronomic practices do you implement and what proportion of the field is under this? **Codes B**								If the farmer rotated soybean with another crop, which crop(s)? **Codes D**	Before adopting did you see the variety in the field? 0=No >> DI24 1=Yes	If yes, where was this plot located? **Codes C**	Have you ever attended any training on soybean cultivation?
		Prac. code	Acres	Prac. code	Acres	Prac. code	Acres	Prac. code	Acres				

Codes B
1 Recommended depth of planting
2 Row planting
3 Inoculant use
4 Crop rotation
5 No burn of crop residue
6 Other (specify) ______________

Codes D
1 Rice
2 Maize
3 Millet
4 Sorghum
5 Cassava
6 Soya bean
7 Cowpea
8 Groundnut
9 Cotton
10 Yam
11 Vegetables
12 Fruits
13 Other (specify): ______________

Codes F
1 Telephone/cell phone
2 Friends or relatives
3 Neighbor
4 Radio/TV
5 Traders
6 Newspaper
7 Extension officer
8 Demonstrations/Field days
9 Agro-input dealer
10 GOs/NGOs
11 FBO
12 ICT platform (e.g ESOKO)
13 Neighboring community
14 Other, specify _______

Codes G
1 Cannot get seed at all
2 Lack of cash to buy seed
3 Susceptible to field pests/diseases
4 Susceptible to storage pests
5 Poor taste
6 Requires more rainfall
7 Don't know how to use it
8 Low yielding variety
9 Poor prices
10 No market
11 Requires high skills
12 Seeds are expensive
13 Cannot get credit
14 Need for other crops
15 Other (specify) ____

Codes C
1 Next to my plot
2 On the way to my plot
3 Different locality area in the community
4 Outside the community

Code A
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Section DII: Farmers' perception

Please I will like to ask you of your perception about characteristics of Jenguma and Afayak compared with the traditional soybean variety.

Which is better? [Use Codes: 0= Traditional 1=Afayak 2=Jenguma]

#	Characteristics	Afayak	Jenguma	#	Characteristics	Afayak	Jenguma
	Production				**Market and economics**		
DII1	High grain yield			**DII8**	Quality grain		
DII2	Climate stress tolerance			**DII9**	Marketability (demand)		
DII3	Striga resistant			**DII10**	Good price		
DII4	Field resistant to pod shattering				**Post-harvest**		
DII5	Easy threshability			**DII11**	Longer shelf life in storage		
DII6	Less labour demand			**DII12**	Ease of processing		
DII7	Easier to understand and cultivate			**DII13**	**Overall comparison**		

Section E: Land, crops cultivated, farm operations and extension

I will now like to ask you about your farming activities during the 2015/2016 season.

E1	E2	E3	E4		E5					E10	E11
Which crops did you cultivate in the 2015/16 season? **Codes A and B**	Farm location **Codes E**	How far is this farm from your home? **Codes B**	Approximate size of this entire farm, including uncultivated acreage or acreage being farmed by someone outside your household? **Unit Codes C**		Do you keep some part of your land fallow? 0=No >> E10 1=Yes					Did you cultivate other crop on this land? 0=No 1=Yes	If yes, what portion of land is cultivated to this <u>main</u> crop? (%)
					E6		**E7**	**E8**	**E9**		
					Size of land under fallow **Unit Codes C**		How long (years) have you left this fallow?	Could you leave the land fallow for several months without being worried about losing it? 0=No 1=Yes	If no, how or why might you lose the land? **Codes D**		
			Num.	Unit	Num.	Unit					
Soybean:											
Other crops:											

Code A
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Codes B
1 Rice
2 Maize
3 Millet
4 Sorghum
5 Cassava
6 Cowpea
7 Groundnut
8 Cotton
9 Yam
10 Vegetables
11 Fruits
12 Other (specify): __

Codes B
1 Meter
2 Km
3 Mile

Codes C
1 Acre
2 Hector
3 Pole
4 Rod
5 Other (specify)_________

Codes D
1 I would lose title to the land
2 Land would be given to somebody else
3 Somebody else would start to use the land
4 Other (specify)_____________________

Codes E
1 Within the homestead
2 Outside the homestead, same village
3 Outside the homestead, different village

Crop Codes	E12	E13	E14	E15	E16	E17	E18	E19	E20
	How fertile is the soil on this farm? **Codes A**	What is the dominant texture of soils on this farm? **Codes B**	How wet is this land compared to other lands in your community? 1…less wet 2….same 3…more wet	Slope of this land 1 = Plain 2 =Gentle 3 =Hilly	Is the land watered from a source other than rain? 0=No 1=Yes	If yes, what is your primary source of watering? **Codes C**	How did you obtain this plot, or gain the right to farm this plot? **Codes D**	If tenant, what type of tenancy arrangement do you operate? **Codes E**	If fixed rent, what is the duration of tenure?
Soy:									
Other:									

Crop Codes	E21	E22	E23	E26	E27	E28	Did you use items on plot in the 2015/16 farming season?			
							E29	**E30**	**E31**	**E32**
	If share cropping, what are the terms of this rent? ***(i.e. harvest shared)***	How long have you been farming this land? (Yrs)	Do you practice soil and water conservation? 0=No 1=Yes	If yes, which type(s) do you practice? **Codes F**	Average size of land under this practice (acres)	Does water log on plot? 0=No 1=Yes	Tractor 0=No 1=Yes	Cost (give money value if in kind) GHS	Drought animal 0=No 1=Yes	Cost (give money value if in kind) GHS
Soy:										
Other:										

Codes A
1 Fertile
2 Moderately fertile
3 Less fertile
4 Infertile

Codes B
1 Sandy
2 Rocky/gravely
3 Clay-filled
4 Silty
5 Loamy

Codes C
1 Well
2 Borehole
3 Pond/tank
4 Weir
5 River/stream
6 Other (specify)____

Codes D
1 Owner
2 Purchased
3 Inherited from deceased family member
4 Tenant Rented (cash/kind)
5 Allocated free of charge
6 Begged
7 Borrowed
8 Other (specify)__________

Codes E
1 Fixed rent
2 Sharecropped

Codes F
1 Crop rotation
2 Land enriching cover crops
3 Legumes
4 Zero tillage
5 Minimal tillage
6 Composting
7 Agroforestry
8 Other (specify) ________

Section F: Inputs (seeds and materials)

Please I will like to ask you about your inputs applications during the 2015/2016 cropping season

Crop Codes	F1 What quantity of crop seeds did you use on farm? (Kg)	F2 What type or variety of the seed did you plant on farm? **Codes D**	F3 How did you obtain the crop seeds planted on this farm? **Codes C**	F4 If any seeds were purchased, what quantity was purchased? (kg)	F5 How much did you pay for the purchased seeds used on farm? (GHS)	F6 Did you apply fertilizer to farm? 0=No 1=Yes	F7 Which type did you apply? **Codes E**	F8 What quantity was applied? (Kg)	F9 What was the unit price? (GHS)
Soy:									
Other:									

Crops Codes	F10 Did you apply pesticides? 0=No 1=Yes			F14 Did you apply weedicides? 0=No 1=Yes			F18	F19	F20
	F11 Which types did you apply? **Codes F**	F12 Quantity applied on farm (litres/kg)	F13 Total expenditure on pesticides? (GHS)	F15 Which types did you apply? **Codes F**	F16 Quantity applied on farm (litres)	F17 Total expenditure on weedicides? (GHS)	Did you apply green manure? 0=No 1=Yes	Did you apply animal manure? 0=No 1=Yes	Did you apply composted manure? 0=No 1=Yes
Soy:									
Other:									

Code A
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Codes E
1 Rice
2 Maize
3 Millet
4 Sorghum
5 Cassava
6 Cowpea
7 Groundnut
8 Cotton
9 Yam
10 Vegetables
11 Fruits
12 Other (specify): __

Codes C
0 Own storage
1 Agro-input dealer
2 Purchased from market
3 Exchange (farmer)
4 Private aggregator
5 FBO (cooperative)
11 Other (specify) ___________
6 Local seed producers
7 Extension officer (MoFA)
8 NGO
9 Gift
10 SARI/CSI

Codes D 0 Local 1 Improved

Codes E
1 Fertilizer: NPK (15-15-15)
2 Fertilizer: ammonium sulphate (SA)
3 Fertilizer 23-10-5 (Actyva)
4 Other compound fertilizer
5 Fertilizer: Other (specify)
6 Urea
7 Commercial organic fertilizer (including Fertisoil, Cocopeat)
8 Phosphorus
9 Sulfan
10 Inoculant
10 Other (specify) ___________

Codes F
0 None
1 Powder/Comdemn
2 Sarosate
3 Insecticide
4 Fungicide
5 Tintani
6 Other (specify)________

Section G: Labour and credit

Please I will like to ask about your labour use in farming during the 2015/2016 farming season

Crop Codes	G1 Family						G2 Hired — Did you use hired labour? 0=No 1=Yes						G3 Communal — Did you use communal labour? 0=No 1=Yes			
	Males		**Females**		**Children**		**Males**			**Females**			**Males**		**Females**	
	Num.	Days	Num.	Days	Num.	Days	Num.	Days	Rate(GHS)/ **Codes A**	Num.	Days	Rate(GHS)/ **Codes A**	Num.	Days	Num.	Days
Soybean:																
Other crops:																

Please I will now like to ask about your credit needs and access during the 2015/2016 cropping season

G4	During the cropping season, did you have liquidity constraints in financing production (inputs)? 0=No 1=Yes	**G10**	If no, how much were you given? ____________(GHS)
G5	If yes, did you apply/ask for any loan to finance production? 0=No >> **H** 1=Yes	**G11**	Was collateral required in getting the loan facility? 0=No 1=Yes
G6	If yes, were you granted? 0=No 1=Yes	**G12**	What did you use as collateral? **Codes C**
G7	Where did you access the credit? **Codes D**	**G13**	What was the interest you paid on the credit facility? __________GHS
G8	How much did you apply for? ______(GHS)		
G9	Were you given all you applied for? 0=No 1=Yes		

Codes A
1 Day
2 Acre

Activity codes:
1 Clearing
2 Ploughing
3 Planting
4 Chemical application
5 Weeding
6 Harvesting

Codes D
1 Friends or relatives
2 Local moneylenders
3 Banks
4 NGOs (specify) ________
5 Nonbank financial institution (including MFI)
6 Private aggregator
7 Input dealer
8 Outgrower
9 FBO
10 Others (specify)_________

Codes C
1 Land
2 Livestock
3 Farm produce
4 Building
5 Household asset
6 Other (specify)

Section H: Harvest, storage and marketing

Crop Codes	H1 What quantity of crop was harvested from plot over the 2015/2016 farming season?	H2 Was any crop lost during harvesting on field? 0=No 1=Yes	H3 How much of crop did you lose in total? (%)	For soybean H4 How was it harvested? **Codes E**	H5 How was it threshed? **Codes F**	H6 On what was it threshed? **Codes G**	H7 Was any crop lost during threshing? 0=No 1=Yes	H8 How much of crop did you lose in total? (%)	H9 How did you store crop? **Codes H**	H10 Do you treat harvest under storage with chemicals? 0=No 1=Yes
Soybean:										
Other crops:										

Code A
1 Jenguma
2 Quarshie
3 Afayak
4 Suong-Pungun
5 Anidaso
6 Salintuya-I (medium)
7 Salintuya-II (late)
8 Songda
9 Local variety
10 Other (specify) ____

Codes B
1 Rice
2 Maize
3 Millet
4 Sorghum
5 Cassava
6 Cowpea
7 Groundnut
8 Cotton
9 Yam
10 Vegetables
11 Fruits
12 Other (specify): __

Codes E
0 Hand
1 Combine harvester
2 Other(specify) ___

Codes F
0 Manual with sticks
1 Tractor
2 Thresher
3 Other (specify) _____

Codes G
0 On the floor
1 Fertilizer sacks
2 Tapolin

Codes H
0 Not stored
1 Local silo at home/farm
2 In bags at home/farm
3 With private aggregator
4 Cooperative/FBO facility
5 Communal storage unit
6 Other (specify)

Crop Codes	H11	H12	H13	H14	H15	H16	H17	H18	H19	H20	H21	H22	H23
	Did you sell crop? 0=No >>crop 1=Yes	Did you find out about market conditions before sale? 0=No 1=Yes	If yes, what was the infor. source? **Codes A**	Quantity sold during and since harvest(s) in 2015/16?	What unit price did you sell most of crop?	Where did you sell most of the crop? **Codes B**	Distance to market for crops transported to the market for sale? (Km)	What was the transport cost to the market? GHS	What other marketing costs did you incur? **Codes C**	Who did you sell most of your harvest to? **Codes E**	What proportion was sold to this buyer? (Kg)	Did buyer provide you with any services? 0=No 1=Yes	If yes, which services were you provided with? **Codes F**
Soy:													
Other:													

Crop code	H24	H25	H26	H27						
				Did you buy any crop for household consumption? 0=No >> next crop 1=Yes						
				H28	H29	H30	H31	H32	H33	H34
	When did you sell most of the harvest? **Codes G**	What was the principal reason for these sales? **Codes H**	Is the crop considered primarily as a cash or staple food crop? **Codes D**	If yes, quantity of crop purchased in 2015/16?	What unit price did you sell most of crop? (GHS)	Did you find out about market before buying? 0=No 1=Yes	If yes, what was the source of infor.? **Codes A**	Where did you buy most of these? **Codes B**	If in the market, distance to purchase point? (Km)	Transport cost from the market? GHS
Soy:										
Other:										

Codes A
1 Telephone/cell phone
2 Friends or relatives
3 Radio/TV
4 Traders
5 Newspaper
6 Extension officer
7 GOs/NGOs
8 Farmer based organisation (FBO)
9 ICT platform (ESOKO, e AGRI)
10 Other (specify) ________________

Codes B
1 On the farm
2 Market in the community
3 Market outside the com'ty

Codes C
1 Market toll
2 Loading/offloading
3 Other (specify) ____________

D
ple food crop
h crop

Codes E
1 Consumer within c'ty
2 Consumer elsewhere
3 Market traders
4 Private aggregator
5 =Cooperative/FBO
6 Outgrower
7 Pre harvest contractors
8 Input dealer
9 Other,specify_______

Codes F
1 Plough/tractor
2 Seeds
3 Weedicides/herbicides
4 Post-harvest chemicals
5 Post-harvest processing
6 Fertilizers/chemical
7 Organic fertilizer
8 Extension
9 Transportation
10 Other, specify _____

Codes G
1 Immediately after harvest or before cultivation
2 When household is cash constraint
3 When I noticed I had enough food for consumption
4 Noticed output price increases/anticipate a decrease in the near future

Codes H
1 Meeting household basic needs/necessities
2 Had some surplus left
3 Profit or take advantage of favorable market conditions

H35	Do you have a mobile phone in the household? 0=No 1=Yes	**H43**	If yes, how many agricultural associations are you involved in?
H36	Is there a mobile phone reception at the location of the household? 0=No 1=Yes	**H44**	Do you attend association meetings? 0=No 1=Yes
H37	Have you ever used mobile phone (either yours/someone's) to call for market information? 0=No >> H39 1=Yes	**H45**	How many times did you attend meetings during the 2015/16 season?
H38	If yes, how many times in the 2015/16 copping season?	**H46**	Have you ever had contract with an entity/individual in your farming in the past 5 years prior to the 2015-2016 farming season? 0=No >> Section I 1=Yes
H39	When you sold most output, did you negotiate and/or bargain with buyer(s)? 0=No 1=Yes	**H47**	If yes, which crops, quantity and unit price did you sell to contractors?
H40	Did you sell crop to any official source? 0=No 1=Yes		
H41	Did you purchase crop from an official source? 0=No 1=Yes	**H48**	When were prices determined between you and the contractor(s)? 0 =Before cultivation 1 =After harvest
H42	Do you belong to an agricultural association? 0=No 1=Yes	**H49**	Which services did the contractor provide you? **Codes A**

H47:

Crop code	Quantity (Kg)	Unit price (GHS)

Section I: Income, financing and expenditure

Please indicate the annual income you earn from the following sources:

	Source of income	**Amount/GHS**
I1	Annual income from sale of farm produce/crops	
I2	Annual income from sale of livestock	
I3	Annual income from non-farm activities	
I4	Gifts and remittances	
I5	Aid (from NGO/Gov't)	
I6	Other not classified	

Please indicate which of the following apply to you:

	Finance	**Response**
I7	Does the household often save food for household consumption in the next year? 0=No 1=Yes	
I8	Does the household head regularly save money? 0=No 1=Yes	
I9	Do you hold a bank account? 0=No 1=Yes	
I10	Do you hold other financial assets? 0=No 1=Yes	
I11	Do you often borrow money to meet regular expenditure requirements? 0=No 1=Yes	

Codes A
0 None
1 Plough/tractor
2 Fertilizer/other chemicals
3 Seeds In bags at home/farm
6 Extension
3 Harvest and post-harvest services
5 Transportation
6 Other (specify) __________

Please indicate the household expenditure on the under listed items:

I12	**Expenditure item**	**Expenditure (GHS)**
I13	How much did you spend on food in a regular month? [GHS]	
I14	How much did you spend on other regular non-food items (e.g.) in a regular month? [GHS]	
I15	Other expenditures (e.g. funerals, remittance, gifts, weddings e.t.c) over the past year? [GHS]	

Section J: Household food and nutritional status

Please answer the following questions in your capacity as the person responsible for food provision/preparation in the household in the past 4 weeks/one month.

J1. Could you please tell me **how many days** in the last 7 days your household has eaten the following foods?

	Food item	**Days eaten in last week (0-7 days)**
1	Maize	|____________|
2	Millet/Sorghum	|____________|
3	Rice	|____________|
4	Bread/Wheat	|____________|
5	Tubers (yam, cassava, plantain, other)	|____________|
6	Groundnuts and Pulses (beans, other nuts)	|____________|
7	Fish (eating as a main food)	|____________|
8	Fish powder, small fish (used for flavor only, Maggi)	|____________|
9	Red meat (sheep/goat/beef/etc)	|____________|
10	White meat (poultry)	|____________|
11	Vegetable oil, butter, shea butter, fats	|____________|
12	Eggs	|____________|
13	Milk and dairy products (main food)	|____________|
14	Milk in tea in small amounts	|____________|
15	Vegetables (including green leaves)	|____________|
16	Fruits	|____________|
17	Sweets, sugar, honey	|____________|

J2. In the last 7 days, how many hot meals did you have on average per day? ____________ (number of meals)

J3. In the last 3months, was there an instance where the household took less preferred food? 0=No 1=Yes

I will like to ask about your household food situation for the last 12 months

J4	**J5**	**J6**	**J7**	**J8**	**J9**	**J10**	**J11**	**J12**	**J13**
In the last 12 months, since (current month) of last year, did you ever reduce the quantity or quality of (entire household) meals because there wasn't enough money for food? **Codes A**	How many months did you experience this situation?	In the last 12 months, since (current month) of last year, did you ever reduce the quantity or quality of (your child's/any of the children's) meals because there wasn't enough money for food **Codes A**	How many months did you experience this situation?	In the last 12 months, **was there ever no food to eat** of any kind in your household because of lack of resources to get food? 0=No 1=Yes	How many months did you experience this situation?	In the past 12 months, did you or any household member go to **sleep at night hungry** because there was not enough food? 0=No 1=Yes	How many months did you experience this situation?	Do you currently receive food aid from government or an NGO? 0=No 1=Yes	If yes, how many years have you been receiving the aid?

Codes A: 1=Yes quantity was reduced 2=Yes quality was reduced 3=Yes both quantity and quality was reduced 4= No

Section K: Livestock and other assets

Please I will like to ask about your livestock and other assets of the household.

		Cattle	**Sheep**	**Goat**	**Pigs**	**Poultry**	**Others_____**	**Others_____**
K1	Do you own any of these animals in the household?	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes	0=No 1=Yes
K2	If yes, how many does the household own?							
K3	How many did you sell in the 2015/16 season?							
K4	At what price did you sell most of this? (GHS)							
K5	How many did you buy in the 2015/16 season?							
K6	At what price did you buy most of this? (GHS)							
K7	Do you seek for veterinary services for them? 0=No 1=Yes							
K8	If yes, how much did it cost you to vaccinate them in the last 12 months? GHS							

Please complete the table below on the asset owned by your household

#	**Asset/Item**	**Do you have item? 0=No 1=Yes**	**If yes, how many in all?**	**If yes, how many as at the beginning of 2015?**	**How much did you purchase the most current item? GHS**	**Price if you were to sell it now GHS**
1	Cutlass					
2	Hoe					
3	Knapsack					
4	Irrigation pump/kit					
5	Radio					
6	Television					
7	Bicycle					
8	Motorcycle					
9	Car/Moto-King/kia					
10	Bullock/ Donkey					
11	Thresher					
12	Tractor					
13	Mechanized sheller					
14	House					
15	Other (specify)……					
16	Other (specify)……					

End of interview and thank you for participating

Appendix 2: Focus group interview guide

Christian-Albrechts University of Kiel, Germany

Institute of Food Economics and Consumption Studies

Main ethnicity and religion

1. What is/are the main languages spoken in the community?

Codes		
1. Likpakpaln (Konkomba)	7. Hausa	13. Nankan
2. Chekosi	8. Bimoba	14. Kusaal
3. Mampruli	9. Dagaare/Wali	15. Twi
4. Dagbali (Dagbani)	10. Sissali	16. Ewe
5. Nanunli	11. Gruni	17. Ga
6. Gonja	12. Kasem	18. Other (specify) ________

2. Which ethnic group is the dominant?

Codes		
1. Konkombas	7. Hausas	13. Nankan
2. Chekosi	8. Bimobas	14. Kusasi
3. Mamprusi	9. Dagaabas/Walas	15. Akans
4. Dagombas	10. Sissalas	16. Ewes
5. Nanumbas	11. Grunsi	17. Gas
6. Gonjas	12. Kassenas	18. Other (specify)________

3. Which religion is the dominant?

Codes C	
0 No religion	
1 Muslim	3 Traditional
2 Christian	6 Other (specify) __________________

Farm labour wage rate

4. What was the wage rate per day during 2015/2016 season? _____________ GHS

5. Was the wage rate same for male and female? 0=No 1=Yes

6. If no, what was the wage rate for a female worker during 2015/2016 growing season? ___________ GHS

Transactions costs

7. What is the distance to the nearest tared road? ______________ Km

8. What is the most used means of transport to the nearest road?

Codes			
0 Foot	2 Bicycle	4 Motor King	6 Truck
1 Animal	3 Motor bike	5 Tractor	7 Other (specify) ______________

9. I... road using this most common means? ____________________Mins

10. What is the distance to the district capital? _______________ Km

11. What is the distance to the nearest agriculture office? _______________ Km

12. What is the distance to the nearest agriculture extension officer? _______________ Km

13. What is the distance to the nearest NGO or Research organization? _________________Km

Market

14. Do you have at least periodic market in the community? 0=No 1=Yes

15. What was the average soybean price in the community last year ____ GHS

16. What is the distance to the nearest market center? _______________ Km

17. What is the distance to the nearest financial institution? __________________Km

18. How many days per week a car/vehicle plies the community? _______________Days

19. Does the entire community has mobile phone service? 0=No 1=Yes

20. If no to 19, do you have mobile phone service in some sections of the community?

    0=No 1=Yes

21. If yes to 19, how many of such spots do you know of in the community?

    ____