The Institute of Food Economics and Consumption Studies

of the Christian-Albrechts-Universität zu Kiel

The Role of Communication Channels on Food Production and Household Welfare: Empirical Evidence from Northern Ghana

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural Nutrition Sciences

of the

Christian-Albrechts-Universität zu Kiel

Submitted by

M.Sc. Sadick Mohammed

Born in Ghana

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Dedication

I dedicate this thesis to my entire family for their constant support and prayers throughout the study.

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Kiel, November, 2021 Sadick Mohammed

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Abstract

Lack of information on innovative agricultural technologies continue to be a major constrain and the jinx to low technology adoption among smallholder farmers in developing countries, in particular SSA. The low technology adoption among farmers has been identified as one of the root causes of low productivity and consequently, inadequate food supply to feed the growing population, as well as high incidence of poverty in the developing countries. The lack of information is attributed to weakened and ineffective extension services, due to resource constraints to employ and equip extension agents to serve the needs of the widely dispersed smallholder farmers, who constitute majority of the farming population of the developing countries. The emergence of new communication channels such as ICTs offer some prospects to boost agricultural extension delivery and lower the barriers to information diffusion among farmers. However, not much is known about the impact of the new communication channels on food production and welfare via its role in improving farmers' technology adoption. Much of the empirical literature on ICTs' information diffusion potential tend to focus on impact outcomes such as market prices, searching behavior, weather information, crop planning, and transaction costs, with very little attention on yields, net returns and knowledge improvement. This study contributes to literature by employing the robust copula recursive bivariate probit and mixed-copula endogenous switching regression models, to examine the impact of participation in ICT-based extension channels on improved technology adoption, specifically the new *Rhizobia* inoculant technology, and its impact on farmers' technical knowledge, yields and farm net returns.

Moreover, adoption of improved technologies is central to productivity enhancement and poverty reduction, yet low technology adoption persist among poor smallholder farmers in developing countries, which has puzzled researchers and policymakers for decades. This has been attributed to lack of understanding about the adoption decision-making behavior of smallholder farmers,

leading to inability of policymakers to develop appropriate extension policies that can enhance technology adoption. For far too long, empirical researchers have modelled farmers' technology adoption decisions as a binary decision problem. Consequently, important information on farmers' adoption behavior relevant to policy formulation is lost and their adoption decision is misconstrued. This study contributes to knowledge on technology adoption by employing a dynamic treatment effect model to analyze farmers' adoption decision-making as a dynamic process, one that comprises a series of multiple decisions made over several stages or periods. Thus, bringing out the heterogeneities across different population of farmers and returns to technology adoption at each adoption stage that can inform appropriate tailor-made extension policies to facilitate technology adoption.

Furthermore, another important issue that compounds the lack of understanding of the farmers' adoption decision-making and the inability to design appropriate extension policies is the disconnection between empirical studies that examine adoption of technological packages and studies that analyze management practices of those packages. The absence of empirical studies that combine the two in a single study, to empirically analyze their interaction effect has been identified as a major shortcoming in the technology adoption literature. This knowledge gap has led to the neglect of important questions raised in empirical studies about the role of the information channels that were used to disseminate information about those technological packages to the potential adopters. This study attempts to bridge the knowledge gap by employing the stochastic frontier treatment effect with endogenous mediator model, which jointly estimate the impact of technology adoption and extension participation, and decompose their interaction into direct and indirect effects. The joint analysis of such important inter-related components of the technology adoption process could provide further information to guide extension delivery policies aim at enhancing technology diffusion and adoption among farmers.

Finally, notwithstanding the voluminous literature on the impact of *egocentric* information networks on technology diffusion and adoption among farmers in developing countries, its influence on the technical efficiency of farmers appears to be over looked in the literature. This study contributes to literature by employing spatial stochastic frontier analysis to investigate the impact of *egocentric* information networks on farmers' technical efficiency, productivity and its distributive mechanisms among farmers in the network.

The findings reveal that ICT-based extension channels are equally effective as the conventional extension channels, and in some instances, outperform them. Similarly, the findings also reveal that ICT-based channels lead to higher yields, farm net returns, and knowledge gained, relative to conventional extension channels and non-participation in extension programs. These findings suggest that investing in ICTs can help in accelerating progress towards the attainment of the SDGs, in particular, goals two and five, which seek to achieve zero hunger and provide equal access to extension services by all for enhance agricultural productivity.

Additionally, the results show that farmers who are at advanced stages of technology adoption tend to benefit more, compared to farmers at lower stages of adoption. The findings further reveal the existence of significant impact heterogeneities across different adoption stages, with the long-term benefits of adoption outweighing the short-term benefits. The heterogeneities reveal the existence of unrealized potential gains at some stages in the adoption process, in particular, at knowledge acquisition and trial stages, which extension policy-makers can target in order to maximize adoption impacts and save resources to expand extension outreach to benefit more farmers.

Furthermore, the results show that the direct impact of technology adoption alone contributes 72 percent to farm productivity and 73 percent indirectly due to improvement in farmers' efficiency, leading to overall welfare improvement of 77 percent. Similarly, the direct impact of extension participation alone contributes 28 percent to farm productivity and 27 percent indirectly due to improvement in farmers' efficiency, resulting in 23 percent improvement in farmers' welfare. These findings underscore the importance of not only investing resources in extension service provision to farmers, but also accompanying it with investment in research development aimed at developing new agricultural technologies that are affordable and appropriate to farmers' conditions.

Lastly, the empirical results show that 19 percent of farmers' technical inefficiency depend on the inefficiency of the farmers from whom they seek farming advice. Similarly, the results show that inefficient farmers tend to depend on efficient farmers in their *egocentric* information networks to improve their level of efficiency. The results further show that the level of influence on the efficiency of farmers is network specific and differ according to the nature of the social ties between farmers in the network. Finally, the findings reveal that failure to account for spatial heterogeneity can lead to underestimating technical efficiency of high efficient farmers, while overestimating that of medium and low efficient farmers. These findings suggest that identifying central farmers' in *egocentric* information networks and improving their technical knowledge in a farmer-to-farmer extension organization, can contribute to improving the productivity of many farmers.

Zusammenfassung

Der Mangel an Informationen über innovative Agrartechnologien ist nach wie vor eine der meist bedeutendsten Problematiken und Gründe dafür, dass Kleinbauern in den Entwicklungsländern, insbesondere in Sub-Sahara Afrika (SSA), derartige Technologien nur begrenzt nutzen und implementieren. Das niedrige Level der Aneignung derartiger Technologien durch die Landwirte wurde als eine der Hauptursachen für die geringe Produktivität und folglich für die unzureichende Versorgung mit Nahrungsmitteln zur Ernährung der wachsenden Bevölkerung sowie für die große Armut in den Entwicklungsländern identifiziert. Der Informationsmangel wird auf schwache und ineffektive Beratungsdienste, sogenannte *Extension Services*, zurückgeführt, da die Ressourcen für die Einstellung und Ausstattung von Beratern, den sogenannten *Extension Agents*, nicht ausreichen, um die Bedürfnisse der oftmals weit verstreut angesiedelten Kleinbauern zu erfüllen, die die Mehrheit der landwirtschaftlichen Bevölkerung in den Entwicklungsländern ausmachen.

Das Angebot an neuen Kommunikationskanälen wie den *Information and Communication Technologies*, den ICTs, bietet Möglichkeiten, die landwirtschaftliche Beratung zu verbessern und die Hürden einer effizienten Verbreitung von Informationen unter den Landwirten abzubauen. Über die Auswirkungen die diese neuen Kommunikationskanäle aufgrund ihrer zentralen Rolle bei der Verbesserung von Wissensverbreitung und somit der Verbreitung neuer Technologien auf die Lebensmittelproduktion und die Wohlfahrt der Landwirte haben, ist jedoch derzeit nicht viel bekannt. Ein Großteil der empirischen Literatur über das Informationsverbreitungspotenzial der ICTs stellt Auswirkungen wie Marktpreise, Suchverhalten, Wetterinformationen, Anbauplanung und Transaktionskosten in den Mittelpunkt der Forschung, während auf Erträge, Nettorenditen und Wissensverbesserung bisher ein geringerer Fokus gelegt worden ist. Diese Studie trägt zur wissenschaftlichen Forschungsliteratur bei, indem sogenannte *robust copula recursive bivariate probit* sowie *mixed-copula endogenous switching regression Modelle* eingesetzt werden, um die

Auswirkungen der Nutzung von ICT-basierten Beratungskanälen auf die Implementierung verbesserter Technologien, insbesondere der neuen *Rhizobia* Impfstofftechnologie, sowie das technische Wissen der Landwirte, die Erträge und die Nettorenditen der Betriebe zu untersuchen. Darüber hinaus ist die Nutzung verbesserter Technologien von zentraler Bedeutung für die Produktivitätssteigerung und die Armutsbekämpfung. Dennoch findet sie unter armen Kleinbauern in Entwicklungsländern nach wie vor wenig Anwendung, was Forscher und politische Entscheidungsträger seit Jahrzehnten vor ein Rätsel stellt. Diese Problematik wird unter anderem auf das mangelnde Verständnis über das Entscheidungsverhalten von Kleinbauern zurückgeführt, was dazu führt, dass die politischen Entscheidungsträger nicht in der Lage sind, geeignete Beratungsstrategien zu entwickeln, die die Akzeptanz von Technologien verbessern könnten. Lange Zeit hat die empirische Forschung die Entscheidungen von Landwirten über die Implementierung von Technologien als ein binäres Entscheidungsproblem modelliert. Die Folge einer solchen Modellierungsstrategie sind Informationslücken, die entstehen können, sodass wichtige Informationen, welche für die Formulierung politischer Maßnahmen relevant sind, verloren gehen können und Adoptionsentscheidungen von Landwirten so falsch interpretiert werden. Diese Studie trägt zum Wissensstand über die Adoption von Technologien bei, indem sie ein sogenanntes *dynamic treatment effect Modell* nutzt, um die Entscheidungsprozesse der Landwirte bezüglich der Nutzung von neuen Technologien als einen dynamischen Prozess zu analysieren. Dieser dynamische Prozess ist dabei charakterisiert durch eine Reihe von Mehrfachentscheidungen, die über mehrere Phasen oder Zeiträume getroffen werden.

Ein weiterer wichtiger Punkt, der das mangelnde Verständnis von den Entscheidungsprozessen der Landwirte und die Unfähigkeit, geeignete Beratungsstrategien zu entwerfen, noch verstärkt, ist die fehlende Verbindung zwischen empirischen Studien, die die Nutzung von Technologiepaketen untersuchen, und Studien, die die Managementpraktiken für diese Pakete analysieren. Das Fehlen von empirischen Studien, die die beiden genannten Aspekte kombinieren, um ihre Wechselwirkung empirisch zu analysieren, ist in der Fachliteratur bisher in einem geringen Umfang vertreten. Diese Wissenslücke hat dazu geführt, dass wichtige Fragen, die in empirischen Studien über die Rolle der Informationskanäle zur Verbreitung von Informationen über Technologiepakete aufgeworfen wurden, vernachlässigt worden sind. Die vorliegende Studie versucht, diese Wissenslücke zu schließen, indem sie ein sogenanntes *stochastic frontier treatment effect Modell* mit *endogenous mediator* nutzt, das die Auswirkungen der Adoption neuer Technologien und der Teilnahme an Extension Services gemeinsam schätzt und ihre Interaktion in direkte und indirekte Effekte aufschlüsselt. Die gemeinsame Analyse dieser wichtigen, miteinander verknüpften Komponenten könnte weitere Informationen für die Ausrichtung von Extension Services, die darauf abzielen, die Technologieverbreitung und-übernahme unter Landwirten zu fördern, liefern.

Abschließend ist festzustellen, dass trotz der umfangreichen Literatur über die Auswirkungen *egozentrischer* Informationsnetzwerke auf die Verbreitung und Übernahme von Technologien durch Landwirte in Entwicklungsländern ihr Einfluss auf die technische Effizienz der Landwirte in der Literatur offenbar übersehen wird. Diese Studie leistet einen Beitrag zur Literatur, indem sie die Auswirkungen *egozentrischer* Informationsnetzwerke auf die technische Effizienz der Landwirte, die Produktivität und die Verteilungsmechanismen unter den Landwirten im Netzwerk mit Hilfe einer sogenannten *spatial stochastic frontier Analyse* untersucht. Die Ergebnisse zeigen, dass ICT-basierte Beratungskanäle genauso effektiv sind wie die konventionellen Beratungskanäle, und in einigen Fällen sogar besser als diese. Ebenso zeigen die Ergebnisse, dass ICT-gestützte Kanäle im Vergleich zu konventionellen Beratungskanälen und der Nichtteilnahme an Beratungsprogrammen zu höheren Erträgen, netto Farmeinkommen und Wissenszuwachs führen. Diese Ergebnisse deuten darauf hin, dass Investitionen in ICTs dazu beitragen können, die Verwirklichung der SDGs zu beschleunigen, insbesondere der Ziele zwei und fünf, die darauf abzielen, den Hunger zu beseitigen und allen Menschen gleichen Zugang zu Extension Services zu gewähren welche das Potenzial haben die landwirtschaftliche Produktivität zu steigern. Darüber hinaus zeigen die Ergebnisse, dass Landwirte, die sich in einem fortgeschrittenen Stadium der Technologieeinführung befinden, tendenziell mehr profitieren als Landwirte in einem niedrigeren Stadium. Die Forschungsergebnisse zeigen weiter, dass die Auswirkungen in den verschiedenen Phasen der Technologieeinführung sehr unterschiedlich sind, wobei die langfristigen Vorteile die kurzfristigen Vorteile überwiegen. Die Heterogenität zwischen den Landwirten zeigt, dass in einigen Phasen des Adoptionsprozesses, insbesondere in der Phase des Wissenserwerbs und der Erprobung, nicht realisierte potenzielle Gewinne existieren, auf die die Entscheidungsträger in der Beratung abzielen könnten, um die Auswirkungen der Adoption zu maximieren und Ressourcen für eine Ausweitung der Beratungstätigkeiten zu sparen, sodass mehr Landwirte profitieren könnten. Darüber hinaus zeigen die Ergebnisse, dass die direkte Auswirkung der Technologieanwendung allein 72 Prozent zur landwirtschaftlichen Produktivität beiträgt und 73 Prozent indirekt durch die Verbesserung der Effizienz der Landwirte, was zu einer Gesamtwohlfahrtssteigerung von 77 Prozent führt. In ähnlicher Weise trägt die direkte Auswirkung von Extension Services allein 28 Prozent zur landwirtschaftlichen Produktivität bei und 27 Prozent indirekt durch die Verbesserung der Effizienz der Landwirte, was zu einer Verbesserung des Wohlstands der Landwirte um 23 Prozent führt. Diese Ergebnisse unterstreichen, wie wichtig es ist, nicht nur in die Beratung der Landwirte zu investieren, sondern auch in die Forschung, um neue landwirtschaftliche Technologien zu entwickeln, die erschwinglich und vor allem geeignet für, und angepasst an die Lebensbedingungen der Landwirte sind.

Abschließend zeigen die empirischen Ergebnisse, dass 19 Prozent der technischen Ineffizienz der Landwirte von der Ineffizienz der Landwirte abhängt, von denen sie landwirtschaftliche Beratung suchen. Des Weiteren offenbaren die Ergebnisse, dass ineffiziente Landwirte dazu neigen, sich auf

Informationen von effizienten Landwirten in ihren *egozentrischen* Informationsnetzwerken zu verlassen, um ihr eigenes Effizienzniveau zu steigern. Die Ergebnisse deuten außerdem darauf hin, dass der Einfluss auf die Effizienz der Landwirte netzwerkspezifisch ist und sich je nach Art der sozialen Beziehungen zwischen den Landwirten im Netzwerk unterscheidet. Schlussendlich zeigen die Ergebnisse, dass eine Nichtberücksichtigung von räumlicher Heterogenität dazu führen kann, dass die technische Effizienz hocheffizienter Landwirte unterschätzt und die der mittel- und wenig effizienten Landwirte überschätzt wird. Diese Ergebnisse lassen den Schluss zu, dass die Identifizierung zentraler Landwirte in *egozentrischen* Informationsnetzwerken und die Verbesserung ihres Fachwissens über ein Landwirt-zu-Landwirt-Beratungssystem dazu beitragen kann, die Produktivität vieler Landwirte zu steigern.

Chapter 1

General Introduction

1.1 Background

Agriculture contribution to economic growth and development cannot be over emphasized. The contribution spanned from supply of food, fiber, timber, to biofuel, which both man and industry thrive. With the global population estimated to reach almost 10 billion by 2050 (FAO, 2017), more is expected from agriculture to meet the growing needs of the population. To meet this challenge, public investment in the agriculture sector is necessary in order to improve agricultural productivity and sustainable growth (Timmer, 2014).

Sadly, public expenditure on agriculture appeared to have dwindled for the past two decades. In particular, sub-Saharan Africa (SSA) where public expenditure on agriculture slumped from 5.6 percent in 1960 – 1970 to 4.0 percent in 2000 – 2009 (FAO, 2017). The underinvestment has led to smallholder farmers lacking access to productive resources such as improved seeds, fertilizers, pesticides, credit and farm machinery to enhance productivity. Agricultural research and extension service delivery also suffered the same fate, resulting in inadequate funding to generate improved technologies as well as disseminate information about the improved technologies to farmers. However, adequate information and knowledge on improved technologies are necessary preconditions for technology adoption, even if it is insufficient (Foster and Rosenzweig, 2010; De Janvry *et al*., 2017). Consequently, farmers in the developing countries and SSA in particular have gained a well-documented notoriety for low or non-adoption of improved technologies in the literature (e.g., Foster and Rosenzweig, 2010; Duflo *et al*., 2008; Conley and Udry, 2010; Suri, 2011) over the years. The lack of adequate extension services have led to farmers using suboptimal or low productive technologies resulting in low productivity (Foster and Rosenzweig, 2010), exacerbating food and nutrition insecurity situation in the developing countries.

Fortunately, recent advancements in information communication technologies (ICTs), present an opportunity for more pluralistic and niche-based communication channels that can deliver lower-cost extension and advisory services to smallholder farmers to enhance technology adoption (Norton and Alwang, 2020). The ICTs employ digital tools (such as internet, GPS, drones, radio, television, video, mobile phone, virtual networks, etc.) to facilitate the collection, storage, analysis and sharing of data, information and knowledge (Deichmann *et al*., 2016; World Bank, 2016). This development has led to what is known in the literature as precision agriculture. Due to the potential of ICT based communication channels to combine both public and private financing mechanisms (Norton and Alwang, 2020), policy makers in developing countries are currently exploring the possibilities of using these tools to facilitate agricultural extension delivery to smallholder farmers. However, the current research efforts in this area tend to focus on the role of the new communication channels on market prices, weather and input sources information (e.g., Camacho and Conover, 2019; Tadesse and Bahiigwa, 2015; Zanello, 2012), to the neglect of its contribution to farmers' technical knowledge, technology adoption, and production activities as well as household welfare. Few studies in the literature have considered these areas of interest but the results are mixed. While some studies find positive or marginal results, others fail to find any statistical significant impact on the studies' outcomes. Several weaknesses have been attributed to the mixed findings, however, the one that stands out is that empirical studies failed to clearly delineate information effect from the technology effect (Aker *et al*., 2016; Bullock *et al*., 2009). The information effect focus the analysis on the channels used to deliver the information, quality of the information, timeliness as well as appropriateness and type of information disseminated.

Whereas the technology effect tend to focus the analysis on a particular targeted agricultural technology, whose outcome is specific and directed at particular group of individuals.

The present study attempts to address this weakness by examining the new communication channels impact on food production and welfare of farm households via its role in the dissemination of a specific agricultural technology, the new *Rhizobia* inoculant among smallholder soybean farmers in northern Ghana. Recently, a number of institutions employed a combination of the new communication and conventional channels to disseminate information about the new *Rhizobia* inoculant technology to smallholder soybean farmers in northern Ghana. The study considered the inoculant dissemination program as appropriate, since it provides the opportunity to delineate the information effect from the technology effect for proper identification. Notable institutions that were involved in the *Rhizobia* inoculant technology dissemination program are Centre for Scientific and Industrial Research – Savannah Agricultural Research Institute (CSIR-SARI), International Institute of Tropical Agriculture (IITA) and the United States Agency for International Development (USAID) through the ADANCE Project.

1.2 Problem statement

The adoption of improved agricultural technologies is often associated with increased productivity and welfare of farm households. This led to the notion that improving smallholder farmers' adoption of improved agricultural technologies will increase productivity and contribute to breaking the vicious cycle of poverty as well as food insecurity that engulf developing countries. Despite this potential, literature suggest that adoption of improved agricultural technologies is low among smallholder farmers in developing countries and in particular SSA, an observation that puzzled many researchers for decades (Suri, 2011; Sheahan and Barrett, 2017; Macours, 2019).

The technology adoption literature attribute myriads of reasons to this puzzling observation. Some of the reasons include procrastination and time-inconsistent preference dependence (Duflo, *et al.*, 2011), poor infrastructure in rural areas leading to exorbitant transaction cost (Suri, 2011), absence of formal agricultural insurance institutions (Karlan *et al.*, 2014), and inappropriate technologies that are not well suited to farmers' local conditions (Emerick *et al.*, 2016). Takahashi *et al.* (2020), note that even if appropriate and profitable technologies exist, they may not be widely diffused among farmers, partly, due to ineffective information dissemination systems, as a result of weak agricultural extension delivery systems.

The emergence of new communication channels such as ICTs have significantly revolutionized agricultural extension delivery programs for the past four decades (Norton and Alwang, 2020). The new communication channels plays significant role in lowering previously existing barriers to information diffusion to farmers (World Bank, 2017). However, the empirical studies on the impact of the new communication channels tend to focus on outcomes such as market prices, searching behavior, weather information, crop planning, and transaction costs, with very little work on technology adoption, yields, net returns and knowledge (Nakasone *et al.* 2014). Few studies that considered these outcomes in the literature report mixed findings. For example, while Dzanku *et al*. (2020) found positive results of video documentary on farmers' technology adoption in Ghana, Maredia *et al*. (2018) found no results of animated-videos on farmers' technology adoption in Burkina Faso. Given the significance of technology adoption, and yields as well as net returns to the farm household welfare, it is important that the impact of the new communication channels on these farm outcomes be thoroughly investigated to inform further policy decisions on investing in these channels.

Another grey area of concern is the inadequacy in understanding the behavior of farmers and their adoption decisions of new agricultural technologies (Pannell and Claassen, 2020). For years, economist have modelled farmers' technology adoption decisions as a binary decision, which is assumed to be instantaneous (Panell and Zilberman, 2020). In the process, important information on farmers' adoption behavior relevant to policy formulation is lost and their decisions are misinterpreted, and in the worst case, misunderstood as being irrational or counter intuitive (Besley and Case, 1993). Weersink and Fulton (2020) argued that farmers' adoption decisions should be understood as a process with multiple stages in which the final decision to use a new technology occurs only after the previous stages are completed. They further argued that current econometric models that seek to analyze farmers' adoption decisions should consider timing of the decisions and employ techniques that condition later-stage adoption decisions on previous adoption outcomes of the technology. The failure of previous studies to employ this approach have been a major contributory factor to the lack of convergence between previous adoption studies, because the heterogeneity among farmers at different stages of adoption and different socioeconomic as well as biophysical realities that face potential adopters remain hidden in the binary case (Pannell and Zilberman, 2020). It is therefore important that the dynamic patterns in farmers' technology adoption decisions be analyzed to shed light on the heterogeneity and stage dependent adoption policies to facilitate technology adoption.

Furthermore, the literature also note disconnection between studies that examine the adoption of improved technological packages and studies that analyze management practices of those packages. The absence of empirical studies that combine the two in a single study, to empirically analyze their interaction effect is a major shortcoming in the technology adoption literature (Takahashi *et al*., 2020). They argued that, this lacuna has led to the neglect of important questions raised in empirical studies about the role of the information channels that were used to disseminate those technological packages to the potential adopters. It is therefore argued that these two important and inter-related components of the technology adoption process be jointly evaluated to guide extension delivery policies for enhanced technology diffusion and adoption among farmers.

The literature identified resource constraints as the major reason for weak extension service delivery systems in developing countries (Blum and Szonyi, 2011). In order to optimize the limited resources available for extension delivery programs, farmers' *egocentric* information networks have been identified as an important and least-cost communication channel that can be leverage upon to enhance improved technologies diffusion and adoption among smallholder farmers. The potential of *egocentric* information networks to diffuse information about new technologies leading to farmers' adoption have been extensively explored in the literature (e.g., Beaman and Dillon, 2018; Di Falco *et al*. 2018; Fafchamps *et al*. 2021). However, the weakness of the network channel is lack of motivation and dedication, as well as individual willingness to share the right information, resulting in low quality information leading to informational imbalance between receiving farmers and disseminating farmers (Fafchamps *et al*. 2021; Kondylis *et al*. 2017). Recent studies attempt to address this weakness by exploring ways to improve the effectiveness of network communication channels, through incentivization and training, in order to fully incorporate its operations into extension service delivery system, known in the literature as farmer-to-farmer extension services (Takahashi et al., 2019; Shikuku and Melesse, 2020). However, the findings are mixed, with some finding the use of incentives to have positive impact of the effectiveness and quality of information shared (Shikuku *et al*., 2019), while some studies did not find any relationship between incentivization and effectiveness (e.g., Takahashi *et al*., 2019). One issue that is clear in these studies is that, the quality of information shared by the network is a major source of concern. Despite this shortcoming, the potential impact of the *egocentric* network information channels on farmers' productivity, in terms of its influence on the technical efficiency of farmers, appears to be over looked in the literature. Therefore, it is imperative that the role of *egocentric* information networks on farmers' technical efficiency be investigated, to guide extension policies that leverage on network channel to maximize productivity.

This dissertation attempts to fill these research gaps, using recent survey data of 600 farm households conducted between June to August 2018 in northern Ghana. The northern region was chosen because it is considered as one of the major food baskets of Ghana. Yet, in terms of extreme poverty incidence, it is the second poorest 30.7 percent region in the country (GSS, 2018). Hence, could provide the appropriate setting to examine the potential contribution of the new communication channels to food productivity and household welfare improvement via its role in technology dissemination and adoption.

1.3 Objectives of the study

The main objective of this study is to investigate the role of communication channels on food production and welfare of farm households in the northern region of Ghana. The specific objectives are as follows;

1. To examine the impact of ICT-based extension channels on improved technology adoption and welfare of farm households.
2. To analyze the impact heterogeneity in returns to adoption of improved agricultural technologies by farm households.
3. To evaluate the joint impact of extension program participation and improved technology adoption on productivity, efficiency and welfare of farm households.
4. To investigate the impact of *egocentric* information networks on the technical efficiency of farm households.

1.4 Significance of the study

The significance of the study is enormous and aimed to provide empirical evidence to inform effective extension service delivery policy, towards attainment of the Sustainable Development Goals (SDGs), in particular goal two and five, which seek to achieve zero hunger and equal access to extension services by all for enhance agricultural productivity. First, by examining the impact of ICT-based channels on technology adoption and welfare of farm households, a compelling evidence is provided for policymakers to invest in ICT infrastructure in rural farming areas. This will enable state agencies and other stakeholders to minimize cost by employing limited but specialized staff to transmit agricultural extension information to farmers from centralized locations, in order to facilitate productivity and economic growth in the developing countries.

Moreover, to the extent that ICT-based extension services remove direct person-to-person contact from extension service delivery, religious and cultural barriers could be overcomed to promote equitable access to extension by all farm households, particularly female farmers living in conservative farming communities. This could facilitate the realization of goal five of the SDGs, which seeks to empower women through enabled environment for information and communication, equal access to appropriate new technology, and timely access to extension services for enhance agricultural productivity.

Also, analysing the dynamic patterns of technology adoption could revealed heterogeneities among different population of farmers at various stages of technology adoption, who required special attention to facilitate their adoption process. This could provide empirical evidence to support extension targeting policies that address specific extension needs to achieve specific adoption targets, instead of one fit all extension policies. The policy relevance of extension targeting could be enormous, as more resources could be saved and used to expand extension services outreach to benefit more farmers. The study of the joint interaction of communication channels used in dissemination of technological packages and the adoption of the technological packages could provide further compelling evidence in support of stakeholders' investment in research and development as well as extension services provision. Finally, an investigation into the role of egocentric information network could provide valuable empirical evidence to inform the new farmer-to-farmer extension delivery organization policy, currently being considered some developing countries.

1.5 Agriculture sector in Ghana

The agriculture sector is a major contributor to the Ghanaian economy, employing 38.3% of the population, second only to the services sector 43.5% and remains the largest employer of the rural population 65.2%, compared to urban 11.8% (GSS, 2019). It is also the third highest contributor 22.2% to the gross national product (GDP) of Ghana, only marginal to the second position the industrial sector 22.3% (GSS, 2018). Majority of the farming population 90% are smallholder subsistent farmers, who cultivate less than two hectares of land and contribute 80% to the total agricultural output of the country (MoFA 2017). The agriculture sector in Ghana is very informal and as such, depends heavily on traditional farming method and rain fed agriculture.

The sector has the potential to expand, given that about 57% of the total land mass of Ghana consist of arable lands. However, the sector's growth has been lagging behind, falling from 6.1% growth rate in 2017 to 4.8% in 2018 below its projected growth target of 6.9% in 2019 (MOFA, 2020). The agriculture sector in Ghana is divided into four subsectors, which include crop subsector (including cocoa), livestock, forestry and logging as well as the fishing subsectors. The key agricultural commodities include cocoa, yam, cassava, plantain, maize, groundnuts, cocoyam, rice, oil palm, tomatoes, pepper, oranges, onions, sorghum and pineapples. The crops subsector alone lead by cocoa contributes 75% to agriculture GDP of the country, while the rest of the sectors contribute 35%.

The major challenge facing the agricultural sector in Ghana is low over reliance on rainfall agriculture due lack of investment in irrigation facilities and modern innovative agricultural production technologies. In addition to low investment, poor extension services, aging farmers as well as poor soils have led the low productivity of the sector. The extension officer to farmer ratio stands at 1:1500, compared to Food and Agricultural Organization (FAO) standard of 1:500 (FAO, 2018). The inadequate extension services is a major contributory factor to lack of adoption of innovative technologies that can enhance the sector's growth. As a result, majority of the rural folks who depend on the sector for their livelihoods continued to live in extreme poverty (GSS, 2018).

1.6 Agriculture Extension Defined

The term extension as used in modern days is believed to pre-dates back from 1850 through to 1867, during the educational development in England to refer to serving the educational needs of the growing populates near their homes (Jones and Garforth, 1997). Though, no formally agreed definition exists in literature for the term extension, it has been classified based on the functions it play in the development process. These classifications include; university extension (or continuing education), agricultural extension, rural development extension, health extension services as well as industrial extension (Rivera, *et al*., 2001).

Agricultural extension obtained its current usage refers to 'advice given to crop farmers (on pest control, watering, flood control, etc.) for mitigating potential loss in taxable revenues from farmers'. Similar to the modern ancestral usage of extension, there is no exact agreement in literature as to the definitive meaning of agriculture extension and therefore means different things to different people (Purcell and Anderson, 1997). Several authors discussing the concept derived its meaning based on the goal and purpose they perceive extension to achieve in the agricultural sector. Van den Ban and Hawkins (1996) arrived at five such derived definitions as: (1) transferring knowledge from researchers to farmers; (2) advising farmers in their decision-making; (3) educating farmers to be able to make similar decisions in future; (4) enabling farmers to clarify their own goals and possibilities and to realize them; and (5) stimulating desirable agricultural developments (through what they called rural guidance). However, Feder, *et al*. (1999) noted that, it is helpful to define agriculture extension as a system with a set of functions design to induce voluntary change among rural people. They suggested a range of activities in agriculture whose meaning can be defined as agricultural extension to include; (1) transferring technology in multiple directions for sustainable agricultural production, transformation and marketing; (2) transferring management to mobilize and organize farming, rural groups and communities; and (3) transferring capacity to educate, build human resources, and enhance local capacity in areas such as integrated pest management, market intelligent, farm management, input, market services and financial negotiations. Among all the definitions of agriculture extension that exist in literature, the most amenable to empirical analysis, in the view of this study and which the study adopted, is the recent definition offered by Anderson and Feder (2007), who defined agriculture extension as the delivery of information inputs to farmers.

It is argued in the literature (e.g., Rivera and Gustafson, 1991; Jones and Garforth, 1999) certain factors act as potential forces that derive changes in the mode and channels that agriculture extension delivery can occur. These potential forces are changes in economic and policy climate, social context in rural areas, systems knowledge and information technology. With the recent advancements in information and communication technology development, this present study empirically examined the impact of these new communication channels can influence food production and farm household welfare, through its applications in agriculture extension delivery.

1.7 Information and Communication Technology (ICT) Defined

The term information and communication technology (ICT) is very generic in its usage, therefore to clarify the term one will have to examine its component terms as it evolves into one concept. The root word *information* colloquially referred to news (that is something new to someone) or intelligence. However, its modern usage and application to different fields can be traced back to Shannon (1948) and Wiener (1948) both writing in statistical probability at the time. Shannon (1948) defines what has now been accepted as the formal definition of information as, “A thing used to eliminate the uncertainty of a random thing”. In the spirit of Shannon’s definition and its colloquial usage, information can be interpreted to mean any news or intelligence that can assist a decision maker to eliminate uncertainties in an uncertain situation (i.e. a stochastic process). However, Kullback (1968) notes that, Shannon’s definition of information tends to provide a formal description to what Fisher (1925b) earlier refer to as a measure of the knowledge a data (i.e. information) discloses or conveys (i.e. communication) about an unknown parameter to a statistician. This to information being defined as a processed data use to assist users (i.e. decision-makers) in making decisions (Chen, 2016).

The modern usage of information as applied to communication is the reflection of the role information plays in communication theory, which formulates a communication system as a stochastic or random process (Kullback, 1968). To this extent, communication theorists view the art and science of the communication system or process to be the ultimate amount of data compressed and transmitted (Cover and Thomas, 2006). Giving rise to the present concept of information communication.

However, for data to be compressed and transmitted (i.e. information communication) either as an analog or digital form, there must be a channel available to match the form of the data and its output. As the human society develop, new scientific discoveries and advancements led to the evolution of different means (i.e. technologies) of conveying or transferring data (i.e. information communication). This evolution made it possible for transferring data from merely as an oral message or letters to telegraph, to the telephone and to visuals or audio-visuals electronically with minimum or without human intervention (Chen, 2016). The overall effect is what has culminated into the concept of information and communication technology (ICT). The development of the ICT industry has made it possible for large volumes of information transfer through communication networks and the internet, at higher speed, larger scope, more diversified content and intensified directivity of message (Chen, 2016).

ICT tools be viewed as a set of smart tools consisting of both hardware and software. This set of tools functions as a competent team of highly disciplined, self-governing artificial agents that control, manage and execute commands strictly. ICT tools transmit symbolic objects of text, picture/photo, audio, video/audio-visual materials are describe as information objects. ICT tools also differ in the quantum and combination of the information objects they can store and convey as a signal. The quantum combination of the information objects therefore defines the signal strength of an ICT tool and the speed at which it is convey depends on the medium (i.e. either in fluids or solids as sound waves or in vacuum as electromagnetic waves) of conveyance. Prominent in this category are the ICT tools that convey electromagnetic signals as either visible light signals (suitable for conveying picture/photo and video images), radio signals (RF-radio frequency) or an integration of both signals. The most important signal in this category that has revolutionarize the ICT industry today and continue to do so is the radio signal. Specific tools in this domain include frequency for AM, FM, TV, cellular and satellite transmissions. The broad classification ICT products that operate using these ICT tools are what experts refer to as digital information resources. ICT digital tools that serve as information resources in the daily life of man are enormous and variant. Examples are telephone line for voice messaging and faxing, mobile phones for voice messaging, texting, video, etc, computers, TV, radio, GPS, Satellite, modem, among others (Semenov et al. 2005).

Generically, therefore, any electronic tool or device that is capable of processing, packaging and storing data for transmission and retrieval of the data can be described as ICT. This study therefore investigated how agricultural production innovations born out of research and transmitted through new ICT channels impact farmers technology adoption, knowledge about the technology and farm productivity.

1.8 ICT Applications in Agriculture and Extension Delivery

ICT since its development has revolutionized the industrial world and improved factor productivity in all fields. Empirical studies report successful applications of ICT digital tools in agriculture. Most of these studies are based on satellite and telecommunication receiving ICT digital tools and with few other tools. This is understandable due to ubiquitous nature of telecommunication receiving devices such as mobile phones and satellite receiving devices such as global positioning system (GPS) and many more. For instance, GPS-based ICT tools are employ by farmers at field level to monitor soil and climatic variables. This data enables farmers to forecast rainfall, synchronize land preparation and planting time. Farmers are also able to monitor and quantify soil nutrient level such as amount of nitrogen, phosphorus and potassium required for optimum plan growth in their fields. This practice has come to be known as precision farming in agriculture or precision agriculture. Bullock *et al*. (2009) studied the use of ICT in providing specific farm level data in variable rate technology (VRT) in the Illinois Cornfields of US. The VRT equipment is able to reveal major soil nutrients content and amount (e.g. nitrogen application rate) need by the farmer to apply on that field as well as forecast weather factors to assist farmers in making decisions. Saravanan and Bhattacharjee (2014) studied mobile applications for agricultural extension in India and report different applications of ICT in agriculture initiated by both public and private sector.

For instance, they reported a mobile phone based remote control system called Nano Ganesh, use for controlling irrigation water pumps by farmers in India to save time, water, energy and increase crop yields. It is estimated that between 2000 and 2013 close to forty-three different mobile base extension service were operating in India using ICT tools such as SMS (short messaging system), IVRS (integrated voice recorded system), pictures, videos, web interfaces and software/mobile apps to provide general crop information, weather and market place (Saravanan and Bhattacharjee, 2014). Also in Ghana, several studies report the use of ICT in agriculture. However, almost all evidence of ICT applications in agriculture in Ghana is limited to using radio or mobile phone services to obtain market information services (e.g., Nyarko *et al*. 2013; Zanello *et a*l. 2013; etc.)

1.9 Study area, data collection

The study area is Northern Ghana. Prior to this study, the Northern Ghana constitutes three regions namely Northern, Upper East and Upper West regions. However, following the creation of new regions by the Government of Ghana in 2019, the Northern Ghana currently constitutes five regions, which includes Northern, North-East, Savanna, Upper East and Upper West regions.

Specifically, the study area was in the former Northern region. The region covers an area of about 70,384 square kilometers and is considered the largest region in Ghana in terms of land mass. The Northern region shares boundaries with the Upper East and the Upper West regions to the north, the Brong-Ahafo and the Volta regions to the south, Togo to the east, and Cote d'Ivoire to the west. The land is mostly low lying except in the north-eastern corner with the Gambaga escarpment and along the western corridor. The region is drained by the Black and White Volta Rivers and their tributaries such as the Nasia and Daka rivers (GSS, 2013).

The climate of the region is relatively dry, with a single rainy season that begins in May and ends in October. The amount of rainfall recorded annually varies between 750 millimeters and 1,050 millimeters. The dry season starts in November and ends in March/April with maximum temperatures occurring towards the end of the dry season (March - April) and minimum temperatures in December and January. The harmattan winds, which occur from December to early February, have a considerable effect on temperatures in the region, making them vary between 14^0C at night and 40^0C during the day. Humidity is very low, aggravating the effect of the daytime heat. The rather harsh climatic conditions adversely affect economic activity in the region and in the health sector, enable cerebrospinal meningitis to thrive, almost to endemic proportions. The region also falls in the onchocerciasis zone. Even though the disease is currently under control, a vast area is still underpopulated and under-cultivated due to past ravages of river blindness. The main vegetation is grassland, interspersed with guinea savannah woodland, characterized by drought-resistant trees (GSS, 2013).

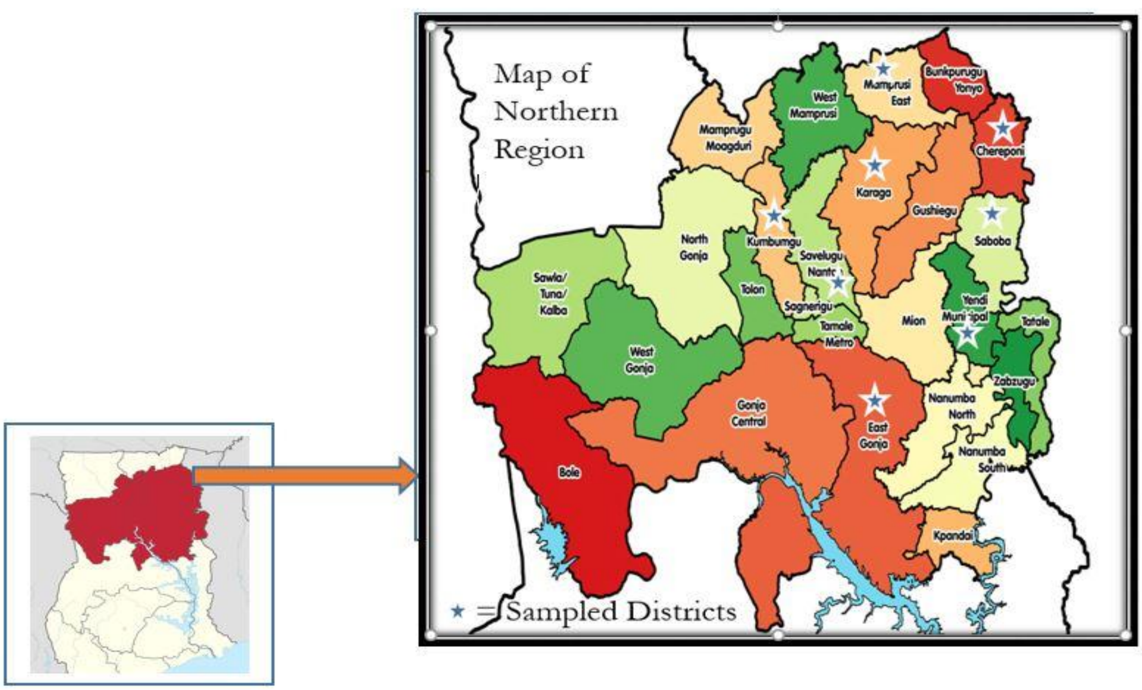

Figure 1. 1 Map of study area

Source: Wikipedia (2011; 2017) and Modified by the Author.

The three regions of the north (i.e., Northern, Upper East, and Upper West Regions) are among the poorest in the country and consistently ranked, in terms of poverty incidence, higher 10% higher than the national average. In particular, the Northern region is rated as the second poorest region in Ghana with the poverty rate of 61.1% (GSS 2018). The main occupation of the people in the region is agriculture (70.6%), who live in predominantly rural areas. In terms of ICT usage, 48.9% owns a mobile phone in the region and 55.8% people use mobile phones. However, the region has the least ownership of all types of computer in Ghana (GSS 2019).

The northern region comprises twenty-six (26) districts, of which the study sampled eight districts, in order to conduct a survey for this study (see Figure 1.1). The survey was conducted from June to August, 2018 (see Appendix 3 for the questionnaire). A random sample of 600 smallholder farm households was drawn. The sample was drawn using a multi-stage sampling technique. Based on the proportion of beneficiary communities (78%) in the inoculant dissemination program and intensity of soybean production in Ghana, northern region was purposively selected. Cluster sampling technique was used to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on dissemination program participation status of districts and intensity of soybean production at the district level within the clusters, eight (8) districts, comprising four (4) from each cluster were purposively sampled. From the ECZ: Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ: East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, 5-7 communities were proportionally sampled, based on the extension channel received, dissemination program participation, and farmer population. One farmer-based organization (FBO) was randomly selected from a list of FBOs that were exposed to the inoculant technology and another randomly selected from a list of unexposed FBOs for each community. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer assisted personal interview (CAPI), a list of the farmers' information network members (INMs) was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs and interviewed in a face-to-face session.

1.10 Structure of thesis

The dissertation contains six chapters. Chapter one presents the general introduction to the study, while chapters two to five contain journal articles. Specifically, chapter two employed copula recursive bivariate probit and mixed-copula endogenous switching regression analysis to examine the impact of participation in ICT-based extension channels on improved technology adoption (e.g., the new *Rhizobia* inoculant) and its impact on farmers' technical knowledge, soybean yields and farm net returns. Chapter three employed dynamic treatment effect to analyze heterogeneity in returns to farmers' adoption of agricultural technologies with incomplete diffusion, conceptualizing technology adoption as a multi-stage decision-making problem, instead of one time binary decision. Chapter four employed the stochastic frontier treatment effect with endogenous mediator model to simultaneously examine the impact of technology adoption and extension participation and decompose the impact into direct and indirect effects. Chapter five used spatial stochastic frontier analysis to investigate the impact of *egocentric* information networks on farmers' technical efficiency, productivity and its distributive mechanisms among farmers in the network. Chapter six presents the general summary, conclusions and policy implications of the study.

References

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

Anderson, J.R., and Feder, G. (2007). Handbook of agricultural economics. Agricultural Extension 3, 2343 – 2378.

Beaman, L. and Dillon, D. (2018). Diffusion of agricultural information within social networks: evidence on gender inequalities from Mali. *Journal of Development Economics, 133:147-161*.

Besley, T. & Case, A. (1993). New developments in development: Modelling technology adoption in developing countries. *American Economic Review, 396 – 402*.

Blum, M. L., and Szonyi, J. (2011). Investment requirements in extension to achieve zero hunger and adapt to climate change. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Bullock, D. S., Ruffo, M. L., Bullock, D. G., and Bollero, G. N. A. (2009). The Value of Variable Rate Technology: An Information-Theoretic Approach. *American Journal of Agricultural Economics*, 91(1):209–223.

Camacho, A. and Conover, E. (2019). The impact of receiving SMS price and weather information on small scale farmers in Colombia. *World Development, 123:104596.*

Chen, S. (2016). Characteristics and Development of Information Industry and Its Impact on the Economy. In M. Li et al. (eds.), Proceedings of 2015 2nd International Conference on Industrial Economics System and Industrial Security Engineering, Springer Science and Business Media Singapore. DOI 10.1007/978-981-287-655-3_2.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review*, 100(1):35–69.

Cover, T. M. and Thomas, J. A. (2006). Elements of Information Theory, 2nd Edition. John Wiley & Sons, Inc.

De Janvry, A., Macours, K. and Sadoulet, E. (eds) (2017). *Learning for Adopting: Technology Adoption in Developing Country Agriculture*: FERDI, France: Clermont-Ferrand.

Deichmann, U., Goyal, A., and Mishra, D. (2016). Will Digital Technologies Transform Agriculture in Developing Countries? *Agricultural Economics*, 47:21 – 33.

Di Falco S., Feri, F., Pin, P., and Vollenweider, X. (2018). Ties that bind: Network redistributive pressure and economic decisions in village economies. *Journal of Development Economics, 131:123 – 131*.

Duflo, E., Kremer, M., and Robinson. J. (2008). Psychology and Development: Theory and Experimental Evidence. How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya. *American Economic Review*, 98(2):482–488.

Duflo, *et al.*, 2011; Duflo, E., Kremer, M., and Robinson, J. (2011). Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *American Economic Review 101 (6): 2350–90.*

Dzanku, F. M., Osei, R. D., Nkegbe, P. K., and Isaac Osei-Akoto, I. (2020). Information Delivery Channels and Agricultural Technology Uptake: Experimental Evidence from Ghana. *European Review of Agricultural Economics, 00(00):1 – 39*.

Emerick, K., de Janvry, A., Sadoulet, E., and Dar, M. H. (2016). Technological innovations, downside risk and the modernization of agriculture. *American Economic Review, 106(6): 1537-1561*.

Fafchamps, M., Islam, A., Malek, A., and Pakrashi, D. (2021). Mobilizing P2P Diffusion for New Agricultural Practices: Experimental Evidence from Bangladesh. *The World Bank Economic Review, 00(0):1 – 26.*

Feder, G., Willet, A., and Zijp, W. (1999). Agricultural extension: Generic challenges and some ingredients for solutions. Agricultural Extension: Generic Challenges and Some Ingredients for Solutions. The International Bank for Reconstruction and Development / The World Bank. https://doi.org/10.1596/1813-9450-2129.

Fisher, R. A. (1925b). Theory of Statistical Estimation. *Mathematical Proceedings of the Cambridge Philosophical Society*, 22:700 – 725.

Food and Agriculture Organization (FAO) (2017). The future of food and agriculture – trends and challenges, Rome.

Foster, A. and Rosenzweig, M. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, 2:395–424.

Ghana Statistical Service (GSS). (2013). 2010 Population and Housing Census. Regional Analytical Report. Northern Region. Ghana Statistical Service. Accra, Ghana.

Ghana Statistical Services (GSS) (2018). Ghana living standards survey round 7: Poverty trends in Ghana 2005 – 2017. Ghana Statistical Services. Accra, Ghana.

Ghana Statistical Services (GSS) (2019). Ghana living standards survey round 7: Main report. Ghana Statistical Services. Accra, Ghana.

Jones, G. E., and Garforth, C. (1997). The history, development, and future of agricultural extension. In: Swanson, B. E., Bentz, R. P., and Sofranko, A. J. (eds). Improving agricultural extension: a reference manual. FAO, Rome.

Karlan, D., Osei, R. D., Osei-Akoto, I., and Udry, C. (2014). Agricultural decisions after relaxing Credit and Risk Constraints. *Quarterly Journal of Economics 129 (2): 597–652.*

Kondylis, F., Mueller, V., and Zhu, S. (2017). Seeing is believing? Evidence from an extension network experiment. *Journal of Development Economics*, 125:1 – 20.

Kullback, S. (1968). Information Theory and Statistics. Dover Publications, Inc.

Macours, K. (2019). Farmers' demand and the traits and diffusion of agricultural innovations in developing countries. *Annual Review of Resource Economics, 11, 483–499.*

Maredia, M. K., Reyes, B., N Ba, N. M., Dabire, L. C., Pittendrigh, B., and Bello-Bravo, J. (2018). Can Mobile Phone-Based Animated Videos Induce Learning and Technology Adoption among Low-Literate Farmers? A Field Experiment in Burkina Faso. *Information Technology for Development 24: 429–60.*

Ministry of Food and Agriculture (MoFA) (2017). Planting for food and jobs: Strategic plan for implementation (2017 – 2020). MoFA, Accra Ghana.

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

Ministry of Food and Agriculture (MoFA) (2020). Medium term expenditure framework (MTEF) for 2020-2023: Programme Based Budget Estimates. MoFA, Accra Ghana.

Nakasone, E., Torero, M. and Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics*, 6:533 – 550.

Norton, G. W., and Alwang, J. (2020). Changes in Agricultural Extension and Implications for Farmer Adoption of New Practices. *Applied Economics Perspectives and Policy, 42(1): 8 – 20.*

Nyarko, Y., Hildebrandt, N., Romagnoli, G., Soldani, E., (2013). Market Information Systems for Rural Farmers Evaluation Of Esoko MIS—Year 1 Results. New York University. Accessed September 24, 2013, available at http://www.nyucted.org/archives/1108.

Pannell, D., and Zilberman, D. (2020). Understanding Adoption of Innovations and Behavior Change to Improve Agricultural Policy. *Applied Economic Perspectives and Policy, 42(1): 3 – 7*.

Pannell, D.J., and Claassen, R. (2020). The Roles of Adoption and Behavior Change in Agricultural Policy. *Applied Economic Perspectives and Policy, 42(1): 31– 41.*

Purcell, D. L. and Anderson, J. R. (1997). Agricultural Extension and Research: Achievements and Problems in National Systems. World Bank Operations Evaluation Study. Washington, D.C., World Bank.

Rivera, W. M., and Gustafson, D. J. (Eds.). (1991). Agricultural extension: Worldwide institutional evolution and forces for change. Amsterdam and New York: Elsevier.

Rivera, W. M., Qamar, M. K., and Crowder, L.V. (2001). Agricultural and rural extension worldwide: Options for institutional reform in the developing countries. FAO, Rome.

Saravanan, R., and Bhattacharjee, S. (2014). Mobile phone applications for agricultural extension in India, In: Saravanan, R (Ed.). Mobile phones for agricultural extension: Worldwide mAgri Innovations and Promise for Future, New India Publishing Agency, New Delhi. pp. 1-75.

Shannon, C. E. (1948). A Mathematical Theory of Communication. *The Bell System Technical Journal*, 27:379 – 423, 623 – 656.

Sheahan, M., & Barrett, C. B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy, 67, 12–25.*

Shikuku, K. M., and Melesse, M. B. (2020). Networks, incentives and technology adoption: evidence from a randomized experiment in Uganda. *European Review of Agricultural Economics, 47(5):1740 – 1775.*

Shikuku, K. M., Pieters, J., Bulte, E., and Läderach, P. (2019). Incentives and the diffusion of agricultural knowledge: Experimental evidence from Northern Uganda. *American Journal of Agriculture Economics, 101(4):1164 – 1180*.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1):159–209.

Tadesse, G. and Bahiigwa, G. (2015). Mobile Phones and Farmers' Marketing Decisions in Ethiopia. *World Development, 68: 296 – 307*.

Takahashi, K., and Muraoka, R., and Otsuka, K. (2020). Technology Adoption, Impact, and Extension in Developing Countries: A Review of Recent Literature. *Agricultural Economics, 51:31 – 45.*

Takahashi, K., Mano, Y., and Otsuka, K. (2019). Learning from experts and peer farmers about rice production: Experimental evidence from Cote d'Ivoire. *World Development*, 122: 157 – 169.

Timmer, C.P. (2014). Managing structural transformation: a political economy approach. WIDER Annual Lecture 18. Helsinki, The United Nations University World Institute for Development Economics Research (UNU-WIDER).

Van den Ban, A.W., and Hawkins. H. S. (1996). Agricultural Extension. Second edition. Oxford: Blackwell Science.

Weersink, A. and Fulton, M. (2020). Limits to Profit Maximization as a Guide to Behavior Change. *Applied Economic Perspectives and Policy 42(1): 67 – 79*.

Wiener, N. (1948). Cybernetics. John Wiley and Sons, New York.

Wikipedia (2011). Ghana – Northern. https://de.m.wikipedia.org/wiki/Datei:Districts_of_the_Northern_Region_(2012).svg. (Access on August 8, 2021).

Wikipedia (2017). Districts of the Northern Region 2012. https://en.m.wikipedia.org/wiki/File:Ghana_-_Northern.svg. (Access on August 8, 2021).

World Bank, (2016). World development Report 2016: digital dividends, World Bank Washington D.C.

World Bank. (2017). ICT in Agriculture: Connecting Smallholders to Knowledge, Networks, and Institutions. Updated Edition), Washington, DC. https://openknowledge.worldbank.org/handle/10986/27526 (Accessed on August 13, 2021).

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

Chapter 2
Do ICT Based Extension Services Improve Technology Adoption and Welfare? Evidence from Ghana

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Abstract

This paper examines the impact of ICT-based extension channels on farmers' adoption of a new agricultural technology (*Bradyrhizobium* inoculant), knowledge gain on the new technology, yields and farm net returns. Using recent survey data of 600 smallholder soybean farmers from Ghana, we employ copula functions to account for potential selection bias and endogeneity. Standard selectivity correction models often employed in the literature rely on multivariate normality (MVN) assumption, which is easily violated, especially, when there is tail dependence in the distribution of the observed data, thus making the distribution non-normal. The copula functions approach allows the modelling of selectivity based on multivariate non-normality to account for this deficit in the data, but retaining the MVN as a special case. Our empirical findings reveal that ICT-based extension channels are equally effective as the conventional extension channels, and in some instances, outperform them. We also find that ICT-based channels lead to higher yields, farm net returns, and knowledge gained, relative to conventional extension channels and non-participation in extension programs. The current study provides compelling evidence that investing in ICTs can help in accelerating progress towards attainment of the Sustainable Development Goals, in particular goal two, which seeks to achieve zero hunger.

Keywords: ICT-based Extension, Inoculant adoption, Welfare, Copulas Functions and Selection Bias.

JEL: C31, C34, O33, Q16, Q55

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2.1 Introduction

Adoption of improved technologies depends on farmers' access to good and timely information, as well as learning opportunities for those technologies (Hanna *et al.*, 2014; Ashraf *et al.*, 2009). Limitations of improved technologies couple with lack of learning opportunities and factors such as poverty, poor prices due to high transaction cost and market failure are seen as major determinants for non-adoption of otherwise profitable agricultural technologies (Suri, 2011). Lack of access to information by farmers is partly attributed to inadequate supply of agricultural extension services, stemming from insufficient funding of public extension programs. The reason being that, public extension programs have struggled in the past to justify their effectiveness and outcomes to warrant continuous provision of public funds (Blum and Szonyi, 2011; Anderson and Feder, 2004).

The development of information and communication technology (ICT) such as internet and proliferation of mobile phones among farmers, even in the remotest areas of developing countries, can be an important source of information dissemination channels to farmers at a reasonable cost (Deichmann *et al.*, 2016). In particular, ICTs can help in accelerating progress towards the attainment of the Sustainable Development Goal (SDGs) of zero hunger, by helping farmers to increase crop yields and incomes, and improving food and nutrition security while reducing their use of energy (Camacho and Conover 2019). Over the last two decades, the literature (e.g., Camacho and Conover 2019; Tadesse and Bahiigwa 2015; Tack and Aker 2014; Zanello 2012; Jensen 2007) has been inundated with reports of positive and mixed impacts of various forms of ICT tools (e.g. videos, radio, SMS text via mobile phone) on farm operations of smallholder farmers in developing countries. For instance, Jensen's (2007) seminal work on India found that mobile phone adoption improved welfare of both fish producers and consumers through the elimination of price dispersions and reduction in fish wastage that could have resulted due to lack of sales. In a recent study, Camacho and Conover (2019) studied the use of mobile phone SMS text to disseminate price and weather information to farmers in rural Colombia, and found that farmers who received SMS text on price and weather information improved their planting and selling decisions, compared to farmers who did not. Also in a study of mobile phone-based price information on Ethiopian farmers, Tadesse and Bahiigwa (2015) reported little or no searching behavior among farmers who participated in the program. By contrast, Aker and Mbiti (2010) and Tack and Aker (2014) in their studies on Niger, found mobile phone usage to be associated with gains in price dispersion and increased searching behavior among the traders who used mobile phones. Similarly, Zanello (2012) found that radio and mobile phone used to disseminate price information to farmers resulted in reduction of transaction cost, market participation and food crop quantity traded in Ghana.

Basically, the observation from the empirical literature on ICT deployment in agricultural extension services delivery are limited to mobile phones, perhaps, due to its portability and convenience to use. Equally important ICT tools such as video, radio, and TV that are at the disposal of farmers in rural remote areas receive less attention. Moreover, the empirical studies on the impact of ICT-based technology tend to focus on outcomes such as market prices, searching behavior, weather information, crop planning, and transaction costs, with very little work on technology adoption, yields, net returns and knowledge (Nakasone *et al.* 2014). Recent studies that have examined the impacts of alternative ICT-based extension channels such as video documentaries, mediated-videos, animated-videos, and audios (i.e. listening clubs) on the adoption of new technologies and farm performance include Dzanku *et al.* (2020), and Maredia *et al.* (2018). In their study on Ghana, Dzanku *et al.* (2020) found video documentary to be effective in inducing technology adoption and increasing crop yield. However, they did not investigate the impact on farmer technical knowledge gain on the new technology, which they admit as a shortcoming in their study.

The present study seeks to contribute to the literature on the impact of ICT-based agricultural extension services, by using cross-sectional data of 600 soybean farmers from northern Ghana, to examine the impact of farmers' participation in ICT-based extension services on technical knowledge, yields, farm net returns and adoption of a newly introduced agricultural technology (*Bradyrhizobium* inoculant). This technology is important because, the inoculant is an organic agricultural input, identified as a cost-effective alternative for resource-poor farmers in developing countries to rehabilitate their depleted soils, by enhancing the build-up of biological nitrogen fixation (BNF) organisms in the soil (Giller, 2001). The inoculant has the potential to increase crop yields between 20 – 29 percent (Ulzen *et al.*, 2016), which is substantial for resource-poor farmers in developing countries. To the extent that we analyze the impact of ICT-based extension services on yields and farm net returns, which directly influence farmers' food security status, the study contributes to the literature on measures to enhance the food and nutritional status of farm households.

Our study differs from the previous studies because of the empirical strategy employed and the outcomes considered. In particular, we analyze participation in ICT-based extension service as a selection process, whereby the expected benefits from participation drive farmers' participation decision. Specifically, we employ the copula functions to account for selection bias, and to capture the differential impact of participation on participants and non-participants. Standard selectivity correction models used in some studies often rely on the strong multivariate normality (MVN) assumption, which is easily violated, especially, when there is tail dependence, and the distribution becomes non-normal (Zimmer 2012). In such cases, the copula function approach, which is robust to non-normality, is preferable to traditional selectivity correction models such as Heckman selection, endogenous switching regression, and double selection models, which are based on the strong MVN assumption (Smith 2003).

The rest of the article is organized as follows. Section 2 presents the conceptual framework underpinning the study, while sections 3 and 4 present the empirical framework as well as the estimation strategy, respectively. In sections 5 and 6, we present the data and the empirical results, respectively. We then discuss the policy implications of our findings and conclusions in section 7.

2.2 Conceptual Framework

To ascertain the significance of ICT-based agricultural extension for smallholder farmers' technology adoption behavior and farm performance, we need to understand the drivers of technology adoption and farm performance and how information affects these decisions and general performance (Deichmann *et al*. 2016). A farmer's adoption decision at any point in time depends on the information that the farmer receives from extension agents or peers (Abdulai *et al.*, 2008; Genius *et al.*, 2013; Camacho and Conover, 2019). The information may concern expected net benefits obtainable from the given technology (i.e. strategic information), or the recommended procedure for using the technology (i.e. technical knowledge). To the extent that farmers mostly obtain strategic information through own learning and from their peers, we assume the extension channel delivers technical knowledge to farmers. Intuitively, an effective information channel for disseminating agricultural innovations to farmers, therefore, is the one that can deliver information with high *recall* probability such that farmers can efficiently apply the technology at the farm level with precision. Let $\mathbb{C}$ represent an information channel's capacity, $\boldsymbol{K}$ be vector of technical information for dissemination to farmers, and $\boldsymbol{Y}$ be the vector of outcomes (such as knowledge, adoption, yields, and net returns) that farmers can obtain, conditional on using the information channel. We assume that the information channel mimics the behavior of a discrete, noiseless and symmetrical memoryless information channel. In line with Cover and Thomas (2006), we specify the farmer's expected net benefits from participation in the channel as below;

$$\mathbb{C} = (\mathbf{K}, \rho(y|k), \boldsymbol{Y}) \quad \text{and} \quad \rho \geq 0 \tag{1}$$

where $\rho(y|k)$ is the probability transition matrix that governs the conditional distribution of the observed outcome y, conditional on receiving a discrete unit of information k. An effective information channel is, therefore, the one that maximizes farmers' conditional outcomes as follows;

$$\mathbb{C} = \max_{\rho(y|k)} \boldsymbol{I}(\mathbf{K}; \boldsymbol{Y}) \tag{2}$$

where $\boldsymbol{I}(.)$ is an indicator function of dependence between the information channel and the conditional outcomes (such as knowledge, adoption, yields and net returns). Empirically, the mean conditional outcomes of a farmer using any randomly selected extension channel can be estimated from the outcomes' observed probability distribution $\rho(\text{y})$ as;

$$\rho(\text{y}) = \rho(\text{k})\rho(y|k) \tag{3}$$

where $\rho(\text{k})$ is the probability distribution of the farmer's decision to use any randomly available extension service channel and all others remain as defined earlier.

2.3 Econometric Specification and Identification Strategy

2.3.1 Outcome Specification

The econometric specification of the individual farmer's conditional mean outcome Y, (in our case yields, farm net returns, inoculant knowledge, and inoculant adoption) based on equation (3), can be expressed as follows;

$$Y_i = \alpha_0 + X_i\beta + K_{\mathbb{C}}\gamma + \varepsilon_i \tag{4}$$

where X, is a vector of observed farmers' characteristics, $K_{\mathbb{C}}$ is an indicator of the information channel from which the farmer received his information about a new technology (the new technology in our case is the *Bradyrhizobium* inoculant technology), α_0 is a constant, β and γ are parameters of interest and ε is the error term.

However, when using observational data, a number of econometric issues arise, if we are to estimate equation (4) above using ordinary least squares. In particular, the choice of an information channel from which the farmer obtains his information from, $K_{\mathbb{C}}$. As argued in the empirical literature (see Foster and Rosenzweig 2010), the choice of information channel by farmers matters in the adoption of new technologies, as it relates to raising farmers' awareness and interest in the technology, and their readiness to invest in these technologies. Additionally, due to differences in the mode of information delivery by a chosen channel, farmers' outcome levels may also differ, resulting in farmers self-selecting into channels that they perceive will offer the highest benefits, resulting in selectivity bias and inconsistent estimation (Heckman, 1979). Another problem is that when the conditional outcome involved is binary, the issue of reverse causality may arise due to simultaneity problem (Heckman, 1978). To consistently estimate equation (4), we address these problems in the sections that follows.

2.3.2 Identification Strategy

This section presents the procedure we employ to account for selection bias and potential endogeneity in our outcome variables that are continuous, such as yields, farm net returns and inoculant knowledge. We consider two available information channels, which include ICT-based extension channel (ICT) and Conventional extension channel (CE). We let j represent the channel indicator, such that an individual farmer's conditional benefits for choosing a given channel can be denoted as Y_{ij}, so that $\{Y_{ICT}, Y_{CE}\}\forall Y_{ij}$; where Y_{ICT} and Y_{CE} are farmers' conditional benefits for choosing to participate in either ICT-based or Conventional extension channels, respectively. We can re-specify the conditional outcome equation (4) in terms of the information channel chosen as follows;

$$Y_{ij} = \alpha_0 + X_i\beta + D_j\gamma + \varepsilon_{ij} \quad (5)$$

where X, is a vector of observed farmers' characteristics, D_j is a binary participation decision indicator, which is equal to 1, if the farmer choose to participate in a given channel and 0 otherwise, α_0 is a constant, β and γ are parameters of interest and ε_j is a channel-specific error term. But the participation decision may be potentially endogenous as unobserved factors (such as age, gender, education, distance to the nearest extension office, availability of electricity, etc) that determine a farmer's participation decision in a given information channel may correlate with that of the conditional benefits from participation. Intuitively, a farmer will participate if the conditional net benefits for participation is greater than that of non-participation. Let D_j^* be a latent indicator of the net benefits for participation observed by the econometrician as D_j, a binary indicator which equals 1, if $D_j^* > 0$, the farmer will participate, and 0 otherwise. We can then express the farmer's participation decision in terms of observable characteristics as follows;

$$D_j = Z_i\delta + \epsilon_{ij}, \quad D_j = 1[D_j^* > 0] \quad \text{and } D_j = 0[D_j^* < 0] \quad (6)$$

where Z is a vector of observed characteristics that directly affect D_j but not Y_j (variables excluded from the model of Y_j, i.e., the instruments for identifying D_j, the participation decision), δ is a vector of parameters and ϵ_j is the error term. Therefore, for any information channel that is chosen, two regimes of conditional outcomes can be observed, which can be expressed as below;

For ICT-Based Extension Channel:

Regime 1: $Y_{ICT1} = X_i\beta + \mu_1$, if $D_j = 1[D_j^* > 0]$

Regime 0: $Y_{ICT0} = X_i\beta + \mu_0$, if $D_j = 0[D_j^* < 0]$ (7)

For Conventional Extension Channel:

$$\textit{Regime } 1: Y_{CE1} = X_i\beta + \mu_1, \text{ if } D_j = 1[D_j^* > 0]$$
$$\textit{Regime } 0: Y_{CE0} = X_i\beta + \mu_0, \text{ if } D_j = 0[D_j^* < 0] \quad (8)$$

where Y_{ICT1}, and Y_{CE1}, are the conditional benefits from participation in ICT-based and Conventional channels respectively, Y_{ICT0}, and Y_{CE0} are the counterfactual cases for non-participation, respectively, μ is the error term and all others remain as defined earlier.

Also, our interest in this study is to compare the impact of the two information channels. To enable us do such comparison, we specify the inter-channel comparison conditional outcomes model as follows;

For ICT-Based versus Conventional Extension Channel:

$$\textit{Regime } ICT: Y_{ICT} = X_i\beta + \mu_{ICT}, \text{ if } D_j = 1[D_j^* > 0]$$
$$\textit{Regime } CE: Y_{CE} = X_i\beta + \mu_{CE}, \text{ if } D_j = 0[D_j^* < 0] \quad (9)$$

where Y_{ICT}, is the conditional benefits for participating in ICT-based and Y_{CE}, is the counterfactual case, if the farmer chooses to participate in the Conventional channel instead of ICT-Based, μ_{ICT} and μ_{CE} are the error terms, respectively, and all others remain as defined before.

2.3.3 Simultaneity Bias Correction and Participation Decision on Binary Outcomes

On the other hand, when the conditional outcome Y_j is binary, as in this case (where inoculant adoption equals 1 if the farmer adopts and 0 otherwise) and the observed potential endogenous participation decision D_j is also binary, then, the conditional benefits in terms of information channel chosen can be expressed as (Han and Vytlacil 2017 and Han and Lee 2019) below;

For ICT-Based Extension Channel:

$$Y_{ICT} = \mathbf{1}\left[X_i\beta + D_j\gamma - \varepsilon_{ij} \geq 0\right], \text{ and } Y_{ICT} = 0, \text{ Otherwise}$$
$$D_{ICT} = \mathbf{1}\left[X_i\beta + Z_i\delta - \epsilon_{ij} \geq 0\right], \text{ and } D_{ICT} = 0, \text{ Otherwise} \quad (10)$$

For Conventional Extension Channel:

$$Y_{CE} = \mathbf{1}\left[X_i\beta + D_j\gamma - \varepsilon_{ij} \geq 0\right], \text{ and } Y_{CE} = 0, \text{ Otherwise}$$
$$D_{CE} = \mathbf{1}\left[X_i\beta + Z_i\delta - \epsilon_{ij} \geq 0\right], \text{ and } D_{CE} = 0, \text{ Otherwise} \quad (11)$$

where Y_{ICT} and Y_{CE} are the binary conditional outcomes from participation (i.e., Y_{ICT} = 1, if the farmer adopts the inoculant, conditional on participating in ICT-based extension channel and $Y_{ICT} = 0$, otherwise; and same goes for Y_{CE}), D_{ICT} and D_{CE} are the indicators for the farmer's decision to participate in ICT-based and Conventional extension channels respectively, all other variables remain as defined earlier. We follow similar approach as in equation (9) to estimate the inter-channel impact for comparison.

2.4 Estimation Strategy

Standard selectivity models estimation often rely on multivariate normality (MVN) assumption, whereby μ in the outcome equation and ϵ in the participation equation are assumed to be normally distributed and uncorrelated (i.e., $corr(\mu, \epsilon) = \rho$). But the MVN assumption may break down, especially when there is tail dependence, and the distribution becomes non-normal (Zimmer 2012). When this happens, traditional selectivity models such as Heckman selection, endogenous switching regression, and double selection models, which are based on the strong MVN assumption becomes less helpful and unsuitable (Smith 2003). The weakness of the MVN statistical assumption on which most selectivity models are based, is well documented in the econometrics literature, resulting in many employing generalized parametric procedures (e.g., Lee 1984), semi-parametric and non-parametric approaches (e.g., Härdle and Manski 1993) to relax the assumption. In the context of these difficulties, using alternative multivariate distribution, such as the copula approach, that allows for non-normality becomes useful (Smith 2003). In line with Smith (2003; 2005), we employ the copula function approach in this study. The copula approach allows the modelling of selectivity based on multivariate non-normality, but retaining the MVN as a special case. The copula approach induces a joint distribution by specifying the marginal distribution and the function that binds them together (i.e. the copula). Thus, parameterizing the dependence structure to capture all the joint behavior (i.e., both observable and unobservable), which then frees the location and the scale structures, enabling them to take different distributions (Smith 2003). Our estimation strategy in this study is as follows; first, we estimate the impact of the extension channels on the continuous outcomes (i.e., yields, farm net returns and inoculant knowledge) using the mix-copula[2] endogenous switching regression approach (Hasebe 2013). Second, we analyze the impact of the extension channels on the binary outcome (i.e., inoculant adoption) using the mix-copula recursive bivariate probit approach of Mara *et al.* (2020). Both approaches are estimated using full information maximum likelihood approach (FIML). Using mixture of copulas in the specifications of the marginal and the joint distributions result in better model fit (Zimmer 2012). For parsimonious reasons, we assume a bivariate copula distribution for both the binary and continuous outcomes.

2.4.1 Mixed-Copula Endogenous Switching Regression Specification (MCESR)

In line with Hasebe (2013), we let *F* and *f* represent the *cdf* and *pdf* respectively, $F_{ICT}(Y_{ICT})$ and $F_{CE}(Y_{CE})$ denote marginal *cdfs*, respectively, and $F_{ICT,CE}(Y_{ICT},Y_{CE})$ be a bivariate joint *cdf* of the outcomes, which are assumed to have continuous support throughout. The copula function can be specified as follows;

$$\begin{aligned} F_{ICT,CE}(Y_{ICT},Y_{CE}) = \mathrm{C}\{F_{ICT}(Y_{ICT}), F_{CE}(Y_{CE}); \theta_{ICT/CE}\} &= \mathrm{C}(\mu_{ICT}, \mu_{CE}; \theta) \\ &= \mathrm{C}(\mu_{ICT}, \epsilon; \theta) \\ &= \mathrm{C}(\mu_{CE}, \epsilon; \theta) \qquad (12) \end{aligned}$$

[2] Mixed-copula as used here refers to the combination of different copulas either from the same family or from different families of copulas, such as combining different Archimedean and/or Elliptical family of copulas to avoid misspecification and improve model fit.

where θ is a dependence parameter, $\mathrm{C}(.;.)$ is a bivariate copula function and all other variables remain as defined earlier. With the *cdf* and *pdf* established, a parsimonious log-likelihood function for the bivariate copula for the endogenous switching regression model can be specified as (Hasebe 2013);

$$LL = \prod_{i=1}^{N}\{\frac{\partial}{\partial \mu_j}\mathrm{C}\left(\mu_j, \epsilon_j; \theta_j\right) \mathrm{x} f_j\left(\epsilon_j\right)\}^{D_j=1}[\{1 - \frac{\partial}{\partial \mu_j}\mathrm{C}\left(\mu_j, \epsilon_j; \theta_j\right) \mathrm{x} f_j\left(\epsilon_j\right)\}]^{D_j=0} \qquad (13)$$

where f_j is the marginal *pdf* of the participation equation and all other variables remain as defined. In the impact evaluation literature, interest lies in the average treatment effect on the treated (ATT). That is, the effect of farmer's participation on the conditional outcomes. In line with Hasebe (2013), we compute the ATT as follows;

$$ATT = E\left(Y_{j_1} - Y_{j_0} \middle| X, D_j = 1\right) = X'\beta_{j_1} - X'\beta_{j_0} + E\left(\mu_{j_1} - \mu_{j_0} \middle| \epsilon_j > -Z'\delta\right)$$

$$= ATE + E\left(\mu_{j_1} \middle| \epsilon_j > -Z'\delta\right) - E\left(\mu_{j_0} \middle| \epsilon_j > -Z'\delta\right) \qquad (14)$$

where ATE is the average treatment effect, measured as $ATE = E\left(Y_{j_1} - Y_{j_0} \middle| X'\beta_{j_1}, X'\beta_{j_0}\right) = (X'\beta_{j_1} - X'\beta_{j_0})$, and all other variables remain as defined earlier.

2.4.2 Mixed-Copula Recursive Bivariate Probit Specification (MCRBP)

Conversely, we let F and f represent the *cdf* and *pmf (i.e., the probability mass function)* respectively, $F_{Y_j}\left(Y_j\right)$ and $F_{D_j}\left(D_j\right)$ denote marginal *cdfs*, respectively, and $F_{Y_j,D_j}(Y_j,D_j)$ be a bivariate joint *cdf* of the outcomes. Following Trivedi and Zimmer (2017) and Mara *et al.* (2020), the recursive bivariate probit copula can then be expressed as;

$$F_{Y_j,D_j}(Y_j,D_j;\theta) = \mathrm{C}\left(F_{Y_j}\left(Y_j\right), F_{D_j}\left(D_j\right);\theta\right) - \mathrm{C}\left(F_{Y_j}\left(Y_j - 1\right), F_{D_j}\left(D_j\right);\theta\right)$$

$$- \mathrm{C}\left(F_{Y_j}\left(Y_j\right), F_{D_j}\left(D_j - 1\right);\theta\right) + \mathrm{C}\left(F_{Y_j}\left(Y_j - 1\right), F_{D_j}\left(D_j - 1\right);\theta\right) \qquad (15)$$

The log-likelihood (LL) is obtained by taking the natural logarithm of the specification in equation (15) and summing over all observations (Trivedi and Zimmer 2017). In line with this, we specify the log-likelihood function as follows;

$$LL = \sum_{i=1}^{N} log\,[\mathrm{C}\left(F_{Y_j}(Y_j), F_{D_j}(D_j); \theta\right) - \mathrm{C}\left(F_{Y_j}(Y_j - 1), F_{D_j}(D_j); \theta\right) - \mathrm{C}\left(F_{Y_j}(Y_j), F_{D_j}(D_j - 1); \theta\right) + \mathrm{C}\left(F_{Y_j}(Y_j - 1), F_{D_j}(D_j - 1); \theta\right)] \tag{16}$$

Following Han and Lee (2019), the average treatment effect on the treated (ATT), which measures a well identified impact of participation on the conditional binary outcome (i.e. inoculant adoption) can be obtained as follows;

$$ATT = E\left(Y_{j_1} - Y_{j_0} \middle| X, D = 1\right) = \Pr\left[Y_{j_1} = 1, D_j = 1 \middle| X, Z\right] - \Pr\left[Y_{j_1} = 0, D_j = 1 \middle| X, Z\right] = F_{\varepsilon_j}\left(X'\beta_{j_1} + \delta_1\right) - F_{\varepsilon_j}\left(X'\beta_{j_1}\right) \tag{17}$$

The ATT as expressed in equation (17) is much preferred to the ATT, usually computed in classical recursive bivariate estimations of this nature in the literature (e.g. Ma and Abdulai 2017), without the inclusion of an instrument for identification. As argued by Han and Lee (2019), without an instrument, even if all the predicted probabilities are used to derive the ATT, the bias and lack of identification that the ATT suffers can still not be rectified.

2.5 Data

2.5.1 Sampling Procedure

The study employs data from a recent survey of farm households in the northern region of Ghana. The survey was conducted from June to August, 2018. The sample was drawn using a multistage sampling technique. Based on the proportion of beneficiary communities (78%) in the inoculant dissemination extension program and intensity of soybean production in Ghana, northern region was purposively selected. Cluster sampling technique was employed to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on participation status of districts in the extension program and intensity of soybean production at the districts level within the clusters, eight (8) districts, comprising of four (4) from each cluster were purposively sampled. From the ECZ, Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ, East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, 5-7 communities were proportionately sampled, based on the extension channel received, extension program participation, and farmer population. One farmer-based organization (FBO) was randomly selected from a list of FBOs that participated in the extension dissemination program and another randomly selected from a list of FBOs that did not participate in the program. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer assisted personal interview (CAPI), a list of the farmers' information network members (INMs) was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs for interview. A total of 600 farm households, consisting of 325 farmers who participated in the inoculant dissemination program and 275 who did not participate in the program were interviewed in a face-to-face session.

2.5.2 Measuring the Farmer Inoculant Knowledge

The inoculant is a knowledge intensive technology, which requires that farmers understand and follow the right procedures of application in order to obtain its full benefits. To measure farmers' knowledge on inoculant application, first, we obtained samples of extension dissemination materials (e.g. video documentaries and audio clips, scientific guide on inoculant application and instructions on the labels of the inoculant packaging materials) from the frontline organizations that were directly involved in the dissemination exercise. Due to space constraints, we present detailed description on the structure of the test in Table A1 in the appendix. We synthesized the entire procedure[3] into four key thematic sections and examined farmers on it during the survey. The four sections are; (1) confirmatory test: where we tested farmers' ability to physically identify at least one brand[4] of full packaged inoculant and a placebo and then, raw inoculant sample and a placebo. As part of the confirmatory test, we also tested farmers' ability to identify crops that inoculants can be applied on, in order to assess farmers' knowledge on choosing the appropriate inoculant type for the right crop[5]. (2)Technical recommendation test section, which we further divide into two sub-measures. The first sub-measure tested farmers' ability to identify standard quantities and measurements, as well as materials that are required for proper inoculation to start. In the second sub-measure, we employed both objective and subjective test procedures to test farmers' knowledge on the correct inoculation process. In the objective test, farmers' ability to demonstrate the inoculation process through recall from memory was tested (i.e., 'know by memory'), while in the subjectivity test, an enumerator mentioned each step in the application process and the farmer identified it as either true or false (Kondylis et al. 2015). (3) Precautionary measures test: we divide this section into general precautions and specific precautions. The general precautions tested farmers' ability to identify the right and wrong procedures as were contained in the extension materials, while the specific precaution test focused on farmers' inoculant storage knowledge. The final section (4) tested farmers' understanding of the reasoning behind certain critical stages in the inoculation process, such as the need to air-dry inoculated seeds instead of sun drying. We allocate one point score to each correct answer provided by a farmer to a question in each section, except section four, which we score three points, for tasking the cognitive ability of

[3] We validated our inoculant knowledge test questions with the frontline organization that carry out the dissemination intervention.
[4] Specific inoculant brands we used for farmer identification are *Sarifix*, *Legumfix*, *Biofix* and *Nodumax*, the placebo was cow dunk, and a well-known dairy product packaged similarly as the inoculant for the raw and packaged inoculants respectively.
[5] Different types of the inoculant are made for different leguminous crops such as soya bean, groundnuts, cowpea etc.

the farmer. This gives a total score of fifty points, which we convert to a continuous variable on 1 – 100 point scale.

2.5.3 Descriptive Statistics and Mean Differences

The descriptive statistics of our data is presented in Table 1. The table shows that the average soy yield of a farmer is 798kg/ha, and on average 780GHC/ha as farm net returns. Average knowledge test score of a farmer is 40%, while on average 51% of farmers adopted the inoculant technology. The ICT-based extension channels considered in this study is video documentary and radio listening clubs. Due to the smaller number of farmers who used the individual channels, we combined both the video and the listening club users as one sample for the ICT-based channel, in order to generate enough sample power for statistical comparison. Table 1 shows that 30% of our total sample of farmers participated in the ICT-based channel. The Conventional channels considered are farmer field days and field demonstrations also combined as one channel to obtain good sample power for statistical analysis. Table 2.1 shows that 24% of the sample population of farmers participated in the Conventional channel. As shown in Table 1, the pool sample of farmers (i.e., the AES-Pooled Channel) who participated in either of the extension channels constitute 54%, while the remaining 46% did not participate in any of the extension channels, forming the basis for the analysis in this study.

Table 2. 1 Descriptive Statistics and Variable Definitions

Variable	Definition	Mean	SD	Min	Max
Outcomes					
Yields	Soybean yield per hectare (Kg/ha)	798.06	781.51	32.41	5509.42
Farm Net Returns	Gross revenue less variable cost (GHC/ha)	779.82	665.85	75.11	4205.40
Knowledge Test Score	Inoculant knowledge test score (%)	40.105	34.733	0	98
Adopt-Inoculant	1 If farmer adopts inoculant, Otherwise=0	0.510	0.500	0	1
Information Channels					
AES-Pooled-Channel	1 If farmer participates in any of the extension channels, Otherwise=0	0.542	0.499	0	1
ICT-Based-Channel	1 If farmer participates in only ICT-based extension Channel, Otherwise=0	0.305	0.461	0	1
CE-Channel	1 If farmer participates in only Conventional extension Channel, Otherwise=0	0.237	0.425	0	1
Control Variables					
Age	Age of farmer (years)	41.56	13.32	18	87
Gender	1 If farmer is male, 0 for female	0.708	0.455	0	1
Edu	Number of years of schooling (years)	2.792	4.687	0	21
HHize	Number of people	5.785	3.045	1	27
Farmsize	Area of land planted with soybean (ha)	5.045	4.371	5.045	4.371
Labor	Total labor used in soy cultivation (Worker-days/ha)	7.808	24.23	0.198	274.73
Laborcost	Total cost of person's day worked per hectare (GHC)	102.062	155.360	23.373	1542.618
Agrochem	Total amount of active ingredient in chemical used (kg/ha)	4	7.186	0	87.22
Chemcost	Total cost of agrochemicals used per hectare (GHC)	57.671	81.830	0	1688.850
Credit	Credit constrain = 0; Otherwise = 1	0.828	0.377	0	1
FBOmem	1 If farmer is a member of FBO, Otherwise=0				
Resemtech	1 If inoculant usage resembles existing inputs usage, Otherwise=0	34.933	35.22	0	100
Techdiff	1 If inoculant application process is considered difficult, Otherwise=0	0.278	0.267	0	1
Location					
WCZ	1 If farmer is in Western Corridor Zone, Eastern Corridor Zone = 0	0.567	0.496	0	1
Soilqual	Soil quality (scale 0 -1)	0.508	0.500	0	1
Rainfall	Amount of rainfall in (%)	61.63	16.24	20	100
Instruments for Exclusion Restriction					
Distextoff	Distance to nearest extension office in (km)	18.90	25.10	0.016	160.93
Electgrid	1 If community is connected to the national grid for electricity supply, Otherwise = 0	0.512	0.500	0	1
Ethnicity	1 If dissemination language is in farmer's mother tongue, Otherwise=0	0.695	0.461	0	1
Comextoff	1 if community has extension agent, Otherwise = 0	0.625	0.485	0	1

Note: SD is standard deviation; Min and Max are minimum and maximum values respectively.

Table 2.2 presents the mean difference comparison of the socio-economic characteristics of the AES-Pooled sample of farmers (i.e., the AES-Participants) against the characteristics of farmers who did not participate in any extension channel at all (i.e., the Non-Participants). Table 2.2 shows that the AES-participants have higher yields and farm net returns, compared to Non-Participants, although the differences are not statistically significant. Average inoculant knowledge score as well as adoption for AES-Participants are statistically higher, compared to that of Non-Participants. On average, AES-Participants appear to be predominantly male older farmers living in smaller households with little education, compared to Non-Participants. AES-Participants also cultivate significantly smaller farms and face low labor demand as well as credit constraints, compared to Non-Participants. AES-Participants significantly experience more rainfall shocks but cultivate lands with higher soil quality, compared to Non-Participants. On average, AES-Participants live closer to the nearest extension office and in communities that are connected to the national electricity grid.

We also compare the mean differences between farmers who participated in ICT-based extension to Conventional extension participants (CE-Participants) presented in Table 2.3. There appears to be significant differences between the two groups of farmers. Table 2.3 shows that ICT-based participants earned significantly higher soy yields and farm net returns from soy production, compared to CE-Participants.

Table 2. 2 Mean Difference Comparison between AES-Participants and Non-Participants

Variables	AES-Participants (S.E)	Non-Participants (S.E)	Mean Diff. (S.E)
Yields	805.538	789.231	16.307
	(44.556)	(45.612)	(64.083)
Farm Net Returns	792.251	765.131	27.120
	(39.020)	(37.534)	(54.591)
Knowledge Score	69.698	5.131	64.568***
	(0.786)	(0.696)	(1.068)
Adopt-Inoculant	0.618	0.382	0.237***
	(0.027)	(0.029)	(0.040)
Gender	0.738	0.673	0.066*
	(0.024)	(0.028)	(0.037)
Age	42.557	40.389	2.168**
	(0.794)	(0.722)	(1.089)
HHSize	5.566	6.044	-0.477**
	(0.166)	(0.187)	(0.249)
Edu	2.754	2.836	-0.083
	(0.260)	(0.283)	(0.384)
Farmsize	4.774	5.365	-0.592*
	(0.221)	(0.288)	(0.358)
Agrochem	3.666	4.395	-0.729
	(0.327)	(0.510)	(0.589)
Chemcost	56.064	59.570	-3.506
	(2.721)	(6.547)	(6.709)
Labor	6.253	9.645	-3.392*
	(0.925)	(1.857)	(1.982)
Laborcos	93.708	111.935	-18.228
	(6.955)	(11.118)	(12.718)
Credit	0.778	0.887	-0.109***
	(0.023)	(0.019)	(0.031)
FBOmem	0.960	0.956	0.004
	(0.011)	(0.012)	(0.016)
Resemtech	49.292	17.964	31.329***
	(1.840)	(1.786)	(2.588)
Techdiff	0.265	0.343	-0.078
	(0.025)	(0.047)	(0.051)
WCZ	0.545	0.593	-0.048
	(0.028)	(0.030)	(0.041)
Rainfall	60.431	63.055	-2.624**
	(0.924)	(0.943)	(1.327)
Soilqual	0.645	0.598	0.046***
	(0.010)	(0.013)	(0.016)
Comextoff	0.600	0.655	-0.055
	(0.027)	(0.029)	(0.040)
Distextoff	16.836	21.257	-4.421**
	(1.274)	(1.645)	(2.052)
Electgrid	0.618	0.385	0.233***
	(0.027)	(0.029)	(0.040)
Ethnicity	0.723	0.662	0.061
	(0.025)	(0.029)	(0.038)
No. of Observ.	**325**	**275**	

Note: *** , ** and * are 1%, 5% and 10% significance level respectively and values in brackets are standard errors. The table contains mean difference comparison of the characteristics between farmers who participated in agriculture extension services (AES) and farmers who did not participate. The column, Participant, represents farmers who participated in AES, while the column, Non-Participant, represents farmers who did not participate in AES at all.

Table 2. 3 Mean Difference Comparison between ICT-Based and CE Participants

Variables	ICT-Based-Participants (S.E)	CE-Participants (S.E)	Mean Diff (S.E)
Yields	887.126	700.393	186.734**
	(67.392)	(52.408)	(89.367)
Farm Net Returns	866.251	696.884	169.367**
	(55.813)	(52.067)	(78.224)
Knowledge Score	66.667	73.606	-6.939***
	(1.090)	(1.040)	(1.540)
Adopt-Inoculant	0.607	0.634	-0.027
	(0.036)	(0.041)	(0.054)
Gender	0.754	0.718	0.036
	(0.032)	(0.038)	(0.049)
Age	42.891	42.127	0.764
	(1.014)	(1.265)	(1.602)
HHSize	5.667	5.437	0.230
	(0.197)	(0.282)	(0.334)
Edu	2.770	2.732	0.038
	(0.347)	(0.394)	(0.525)
Farmsize	5.249	4.162	1.087***
	(0.319)	(0.287)	(0.441)
Agrochem	4.511	2.578	1.933***
	(0.514)	(0.327)	(0.651)
Chemcost	63.575	46.384	17.192***
	(4.283)	(2.690)	(5.410)
Labor	7.938	4.082	3.857**
	(1.496)	(0.848)	(1.856)
Laborcos	106.392	77.361	29.031**
	(10.969)	(7.136)	(13.951)
Credit	0.770	0.789	-0.018
	(0.031)	(0.034)	(0.047)
FBOmem	0.967	0.951	0.017
	(0.013)	(0.018)	(0.022)
Resemtech	44.590	55.352	-10.762***
	(2.284)	(2.942)	(3.666)
Techdiff	0.286	0.239	0.046
	(0.034)	(0.036)	(0.050)
WCZ	0.448	0.669	-0.221***
	(0.037)	(0.040)	(0.054)
Rainfall	59.563	61.549	-1.986
	(1.200)	(1.442)	(1.863)
Soilqual	0.635	0.657	-0.021
	(0.014)	(0.15)	(0.021)
Comextoff	0.601	0.599	0.003
	(0.036)	(0.041)	(0.055)
Distextoff	20.697	11.859	8.838***
	(2.074)	(1.038)	(2.526)
Electgrid	0.623	0.613	0.010
	(0.036)	(0.041)	(0.054)
Ethnicity	0.656	0.810	-0.154***
	(0.035)	(0.033)	(0.049)
No. of Observ.	**183**	**142**	

Note: *** , ** and * are 1%, 5% and 10% significance level respectively and values in brackets are standard errors. The table contains mean difference comparison of the characteristics of farmers who participated in ICT-based extension against farmers who participated in Conventional extension. The column, ICT-based Channel, represents the mean characteristics of ICT-based extension participants, while the column, CE Channel, represents that of Conventional extension participants.

However, in terms of inoculant knowledge test scores, ICT-based participants perform significantly lower than CE-Participants. The difference in average inoculant adoption between the two extension channels is statistically insignificant. The table also shows that ICT-based participants significantly operate larger farms with higher usage of agrochemicals and labor, resulting in higher agrochemical and labor cost in production, compared to CE-Participants. Table 3 further reveals that ICT-based participants live further away from the nearest extension office, compared to CE-Participants.

Though, there appears to be significant differences in yields, farm net returns as well as inoculant knowledge scores and adoption between AES-Participants and Non-Participants, as well as ICT-based and CE extension participants, as discussed above, information on average differences alone is inadequate to explain the decisions farmers make, because the average differences do not account for other confounding factors that are heterogeneous among farmers in a given population. We therefore employ appropriate econometric techniques to further analyze the differences in farmers' extension participation and technology adoption decisions, as one based on a selection process taking into account the expected benefits from participation. We present and discuss the empirical results in the next section.

2.6 Empirical Results

First, we performed an exploratory analysis to choose the best performing copula, using the Akaike Information Criteria (AIC) for the binary outcome model and Vuong's (1989) test for the continuous outcome models. Based on the AIC, Student's-*t* distribution is chosen as the best copula for the marginals of both the ICT-based channel and the Conventional channel (CE). For the pooled channel (AES-Pooled) Clayton copula is chosen, while a rotated Gumbel (Gumbel-270^0) and unrotated Gumbel distributions are chosen for the channel choice and adoption decisions, respectively. Due to the binary nature of both the intervention (i.e. farmer's extension channel choice) and the expected outcome of interest (i.e. farmer's inoculant adoption decision), a probit link function with Bernoulli distribution is employed for the estimation. We report the copula(s) chosen at the top row and the selection criteria statistic at the bottom row of tables with the results.

2.6.1 Determinants of Extension Participation and Inoculant Adoption

In Table 2.4, we present estimates from the copula recursive bivariate probit (CRBP) model for the binary outcome variable, that is, inoculant adoption decision. The estimates represent the conditional probabilities of farmers' adoption of the inoculant technology conditional on participation in a given extension channel. Tables 2.5, 2.6 and 2.7 present estimates from the copula endogenous switching regression (CESR) model for the continuous outcome variables, that is, inoculant knowledge scores, yields and farm net returns, respectively. In the interest of brevity, we focus the discussion on Table 2.4, as it covers the determinants of the two decisions, that is, the extension channel choice and that of inoculant adoption decisions, respectively. We will, however, make reference to the continuous outcomes' Tables as the need arises for purposes of comparison. To begin with, we discuss identification of the recursive bivariate model, as using observational data to estimate a binary outcome resulting from a binary decision (such as adoption) is an arduous task, because of identification issues arising from endogeneity and selection bias. Marra *et al.* (2020) and Hans and Lee (2019) have demonstrated that this can be overcome in the copula framework, with the help of an instrument. In this regard, we use *Ethnicity*, which determines the native spoken language as instrument for identification. It is expected that, if a farmer's native language is used as the language of instruction in a particular extension channel during a dissemination program, it can influence the farmer's choice of participation in that channel, but should not correlate with his inoculant adoption decision. As shown in Table 2.4, the coefficient of *Ethnicity* is positive and statistically significant in both the ICT-based and the CE models. We observe similar results in the yields and net returns models in Tables 2.6 and 2.7, suggesting that, *Ethnicity* plays an important role in extension dissemination, particularly, when the extension channel involved is not based on person-to-person delivery (such as ICT-based channels) to generate farmers' interest to participate.

Table 2.4 also shows that the ρs are negative and statistically significant at 1% level in the ICT-based and CE models, suggesting that there is positive self-selection into both the extension channel choice and the inoculant adoption decisions. Similar pattern of statistical significance is observed in Tables 2.5, 2.6 and 2.7. However, whereas the signs of the coefficients indicate negative selection for participants, the signs for non-participants are positive in both ICT-based and CE channels. Generally, the ρ in the pooled model (i.e. Model 1) shows positive selection on participation in extension delivery, suggesting that farmers with below-average yields and net returns have a higher probability of participating in the extension delivery programs.

Identification of the recursive bivariate model also relies on first order stochastic dominance (FOSD), whereby the distribution of the correlations between the marginals either show an increasing or decreasing concordance (Trivedi and Zimmer 2017; Hans and Lee 2019; Mara *et al.*, 2020). The results in Table 2.4 show that the coefficient of the *Kendall's tau* (τ) is negative and statistically significant (at 1% level) for both the ICT-based and CE models. The signs of the confidence intervals (i.e. the lower and upper bounds) are all negative, suggesting concordance in the distributions of the correlations.

Table 2. 4 Copula Recursive Bivariate Probit Estimates – Inoculant Adoption (Discrete)

	Model 1: Clayton [p-b-b]		Model 2: Student-*t* [p-*b*-*b*]		Model 3: Student-*t* [p-*b*-*b*]		Model 4: Gumbel -270° Gumbel [p-*b*-*b*]	
Variable	**AES-Pool**	**Ino-Adoption**	**ICT-Base-Part**	**Ino-Adoption**	**CE-Part**	**Ino-Adoption**	**ICT-vs-CE-Part**	**Ino-Adoption**
	Coeff (S.E)	*Coeff (S.E)*	*Coeff (S.E)*	*Coeff (S.E)*	*Coeff (S.E)*	*Coeff (S.E)*	*Coeff (S.E)*	*Coeff (S.E)*
Const.	1.491**(0.646)	-3.658***(1.067)	-0.228(0.652)	-3.388***(0.965)	0.311(0.687)	-3.904***1.001)	-0.492(0.853)	-3.529**(1.780)
AESChannel	-	0.317*(0.179)	-	1.1202***(0.502)	-	1.586***(0.446)	-	-1.227*(0.668)
Age	-0.049**(0.024)	0.086**(0.037)	0.006(0.023)	0.065**(0.035)	-0.054**(0.024)	0.101***(0.037)	0.036(0.029)	0.139***(0.056)
Age^2	0.001***(3.0e-4)	-0.001**(4.0e-4)	-6.03e-4(2.42e-4)	-0.001*(4.0e-4)	0.001***(2.0e-4)	-0.001***(4.0e-4)	-3.5e-4(3.0e-4)	-1.4e-3***(5.7e-4)
Edu	-0.015(0.013)	-0.002(0.021)	-0.008(0.013)	0.002(0.019)	-0.005(0.014)	0.002(0.019)	4.7e-3(0.018)	0.038(0.037)
Farmsize	-0.012(0.023)	0.019(0.039)	-0.001(0.023)	0.013(0.036)	-0.005(0.031)	0.016(0.036)	-0.022(0.040)	-0.013(0.065)
HHSize	-0.034*(0.019)	-0.003(0.031)	-0.009(0.020)	0.001(0.029)	-0.028(0.020)	0.003(0.030)	0.026(0.027)	0.062(0.043)
Gender	0.178(0.128)	-0.456**(0.213)	0.131(0.134)	-0.415**(0.204)	0.091(0.142)	-0.472**(0.209)	0.060(0.182)	-0.407(0.343)
Soilqual	0.501*(0.279)	0.364(0.450)	0.025(0.292)	0.379(0.417)	0.578*(0.317)	0.112(0.443)	-0.264(0.421)	-0.447(0.748)
Rainfall	-0.006*(0.003)	-0.004(0.006)	-0.007*(0.004)	-0.003(0.005)	-2.2e-4(0.004)	-0.004(0.005)	-0.006(0.005)	-0.009(0.008)
Credit	-0.380***(0.147)	0.087(0.239)	-0.309**(0.142)	0.158(0.221)	0.091(0.151)	0.057(0.222)	-0.113(0.180)	-0.055(0.359)
WCZ	-0.107(0.113)	-0.132(0.188)	-0.395***(0.117)	0.018(0.192)	0.314***(0.130)	-0.244(0.175)	-0.599***(0.159)	-0.413(0.304)
Laborcos	1.3e-4(0.001)	0.002(0.002)	0.001(0.001)	0.001(0.002)	-0.001(0.001)	0.002(0.002)	2.9e-4(0.002)	-8.8e-5(0.003)
Agrochem	0.002(0.016)	-0.031(0.029)	0.004(0.014)	-0.027(0.025)	-0.008(0.032)	-0.015(0.025)	-0.013(0.041)	-0.033(0.052)
Labor	-0.003(0.007)	-0.008(0.012)	-0.005(0.007)	-0.005(0.011)	0.001(0.010)	-0.009(0.010)	0.010(0.014)	0.004(0.021)
Chemcost	-1.2e-4(0.001)	0.001(0.002)	0.001(0.001)	0.001(0.001)	-0.002(0.003)	0.001(0.001)	0.008**(0.004)	0.002(0.006)
Ethnicity	0.444**(0.206)	-	0.455***(0.190)	-	0.342*(0.188)	-	0.511(0.333)	-
Distkm	-0.004*(0.002)	-0.006(0.004)	0.002(0.002)	-0.006*(0.004)	-0.012***(0.004)	-0.001(0.004)	0.011***(0.004)	9.8e-4(0.006)
Comextoff	-0.140 (0.115)	-0.026(0.187)	-0.055(0.118)	-0.017(0.173)	-0.109(0.127)	0.003(0.179)	0.126(0.159)	0.170(0.290)
Electgrid	0.578***(0.109)	3.228***(0.189)	0.396***(0.114)	2.664***(0.408)	0.301***(0.121)	2.776***(0.307)	-0.026(0.155)	3.486***(0.581)
ρ	5.12e-8***[4.14e-8, 100]		-0.712***[-0.932, -0.165]		-0.698***[-0.925, -0.179]		1.57***[1.070, 8.100]	
τ	2.56e-8***[2.07e-8, 0.980]		-0.504***[-0.764, -0.105]		-0.492***[-0.752, -0.115]		0.363***[0.061, 0.877]	
LL	-500.693		-472.282		-422.974		-248.283	
No. of Observ.	600		600		600		325	
Joint Test	Prob = 0.904		0.935		0.983		0.997	
AIC	1079.386		1022.564		923.948		574.566	
BIC	1250.866		1194.044		1095.428		722.135	

Note: *** , ** and * are 1%, 5% and 10% significance level respectively and values in brackets are standard errors, '*na*' means not available because the parameter is no analytically computed, τ is the Kendall's concordance parameter. The alphabets in square brackets are the link functions and its distributions, where *p* indicates probit and *b* represents Bernoulli distribution. Each model represents participation in different extension channels. Model 1, represents a pool of all extension channels together for assessing general extension participation impact on outcomes, Models 2 and 3 represent participation in ICT-based and Conventional extension channels respectively, whereas Model 4 is the inter-channel comparison model, which compares participation in ICT-based extension against participation in Conventional extension as the base channel.

Table 2. 5 Copula Endogenous Switching Regression Estimates – Knowledge Test Score (%)

	Model 1: Frank-Clayton [*p-n-t*]			Model 2: Frank-Clayton [*p-n-t*]			Model 3: Frank-Clayton [*p-n-t*]			Model 4: Frank-Clayton [*p-n-t*]		
Variables	**Select**	**AES-Pool**	**Non-Part**	**Select**	**ICT-Part**	**Non-Part**	**Select**	**CE-Part**	**Non-Part**	**Select**	**ICT-Part**	**CE-Part**
	Coeff	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*	*Coeff*
Const.	1.316**	4.202***	2.262***	-0.690	4.522***	3.059***	0.294	4.592***	2.980***	-1.267***	4.590***	4.164***
	(0.653)	(0.018)	(0.569)	(0.679)	(0.070)	(0.604)	(0.219)	(0.322)	(0.411)	(0.096)	(0.194)	(0.195)
Gender	0.141	-0.022***	0.165	0.096*	-0.008	0.112	0.041	-0.009	0.175	0.058	-0.004	-0.025
	(0.179)	(0.009)	(0.230)	(0.055)	(0.044)	(0.250)	(0.107)	(0.010)	(0.157)	(0.036)	(0.029)	(0.024)
Age	-0.048***	-0.0002	-0.038***	0.026*	-0.002	-0.056***	-0.056***	0.002	-0.009	0.069***	-0.011**	-0.001
	(0.014)	(0.001)	(0.006)	(0.014)	(0.004)	(0.002)	(0.007)	(0.002)	(0.021)	(0.011)	(0.005)	(0.001)
Age^2	0.001***	1.0x10^{-5}	0.0006***	-0.0002	2.2x10^{-5}	0.001***	0.001***	-2.0x10^{-5***}	0.0002	-0.001***	0.0001***	3.0x10^{-5***}
	(0.0001)	(1.4x10^{-5})	(0.0001)	(0.0002)	(4.0x10^{-5})	(4.3x10^{-5})	(0.0001)	(4.3x10^{-6})	(0.0002)	(0.0002)	(4.4x10^{-5})	(3.4x10^{-6})
Edu	-0.117**	-0.020	-0.529***	0.013	-0.019	-0.263***	-0.132***	-0.008	-0.168**	0.093**	-0.026	-0.005
	(0.061)	(0.026)	(0.141)	(0.080)	(0.017)	(0.006)	(0.052)	(0.018)	(0.078)	(0.048)	(0.024)	(0.016)
Techdiff	-0.195***	-0.023	0.164	0.005	-0.026	0.249***	-0.190***	0.001	-0.090*	0.091	-0.037	0.042
	(0.051)	(0.014)	(0.108)	(0.080)	(0.034)	(0.045)	(0.037)	(0.005)	(0.051)	(0.129)	(0.042)	(0.044)
Resemtech	0.001	-0.0002	0.0001	-0.004***	0.0002	0.005***	0.005***	-0.001***	-0.003	-0.005***	0.001***	0.0001
	(0.003)	(0.0003)	(0.007)	(0.001)	(0.001)	(0.002)	(0.0001)	(0.0001)	(0.004)	(0.0005)	(0.0001)	(0.0001)
Ethnicity	0.365***	0.035***	0.392***	-0.252***	0.091**	0.729***	0.672***	-0.091***	0.013	-0.515***	0.142***	0.023*
	(0.131)	(0.008)	(0.090)	(0.067)	(0.045)	(0.090)	(0.052)	(0.004)	(0.049)	(0.103)	(0.002)	(0.014)
FBOmem	-1.133**	0.012	0.139	-0.063	-0.106*	0.188	-1.145***	-0.013	0.484	0.239	-0.120	0.087
	(0.584)	(0.018)	(0.385)	(0.066)	(0.058)	(0.319)	(0.345)	(0.210)	(0.516)	(0.192)	(0.093)	(0.193)
WCZ	0.011	0.049***	0.121*	-0.386***	0.105	0.309***	0.391***	-0.061	-0.184***	-0.508***	0.113***	0.009
	(0.072)	(0.003)	(0.071)	(0.050)	(0.066)	(0.031)	(0.010)	(0.045)	(0.021)	(0.054)	(0.039)	(0.009)
Comextoff	-0.418***			-0.111***			-0.364***			-0.016		
	(0.048)			(0.012)			(0.127)			(0.030)		
Electgrid	1.550***			0.546**			1.179**			0.388***		
	(0.244)			(0.261)			(0.542)			(0.086)		
Distextoff	-0.005			-0.001			-0.012***			0.003		
	(0.006)			(0.005)			(0.003)			(0.005)		
$ln\sigma_1/ln\sigma_0$		-1.645***	0.025		-1.308***	0.226***		-1.705***	0.194***		-1.361***	-1.774***
		(0.146)	(0.024)		(0.147)	(0.081)		(0.040)	(0.026)		(0.089)	(0.080)
ρ_1/ρ_0		-11.835***	1.363***		2.566***	-1.853***		1.231***	-2.331***		2.689***	-0.748***
		(0.013)	(0.185)		(0.188)	(0.044)		(0.482)	(0.451)		(0.184)	(0.245)
τ_1/τ_0		-4.0x10^{-6**}	-0.149		-0.867**	0.199		-0.631**	0.246		-0.880**	0.083
		(5.0x10^{-8})	(na)		(0.022)	(na)		(0.112)	(na)		(0.019)	(na)
Wald test ($\rho = 0$)	5315.64***			28.22***			4.30*			29.39***		
LL	-327.65			-647.68			-638.41			-125.67		
Sample(N)	600			600			600			600		
Wald chi2(12)	28.13***			28.34***			59.19***			43.65***		
Vuong's statistic	0.016***			-0.037***			0.006***			-0.004		
	(0.003)			(0.005)			(0.001)			(0.005)		

Note: *** , ** and * are 1%, 5% and 10% significance level respectively and values in brackets are standard errors, '*na*' means not available because the parameter is no analytically computed, τ is the Kendall's concordance parameter. The alphabets in square brackets are the link functions and its distributions, where *p* indicates probit and *n*, *l*, *t* represents normal, logistic and Student's *t* distributions, respectively. Each model represent participation in different extension channels. Model 1, represents a pool of all extension channels together for assessing general extension participation impact on outcomes, Models 2 and

3 represent participation in ICT-based and Conventional extension channels respectively, whereas Model 4 is the inter-channel comparison model, which compares participation in ICT-based extension against participation in Conventional extension as the base channel.

Table 2. 6 Copula Endogenous Switching Regression Estimates – Yield (lnKg/ha)

	Model 1: Frank-Gumbel [*p-n-l*]			Model 2: Frank-Frank [*p-n-t*]			Model 3: Frank-Frank [*p-n-t*]			Model 4: Frank-Gumbel [*p-l-l*]		
Variables	**Select**	**AES-Pool**	**Non-Part**	**Select**	**ICT-Part**	**Non-Part**	**Select**	**CE-Part**	**Non-Part**	**Select**	**ICT-Part**	**CE-Part**
	Coeff.	*Coff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*
Const.	1.779**	4.956***	4.964***	-1.143	6.117***	4.939***	0.199	5.117***	4.932***	-1.619***	5.240***	4.633***
	(0.911)	(0.359)	(0.494)	(0.830)	(0.178)	(0.225)	(0.361)	(0.922)	(0.58)	(0.286)	(0.076)	(0.836)
Gender	0.295	0.099***	-0.137***	0.152	0.079	-0.085***	0.267***	−0.162**	0.022	-0.019	0.228***	0.022
	(0.419)	(0.038)	(0.026)	(0.415)	(0.301)	(0.033)	(0.086)	(0.085)	(0.027)	(0.062)	(0.053)	(0.074)
Age	-.071***	0.009**	0.004	0.029	-0.014**	0.003	-0.069***	0.029**	0.011	0.080***	-0.0002	0.006
	(0.022)	(0.004)	(0.034)	(0.033)	(0.007)	(0.008)	(0.010)	(0.015)	(0.024)	(0.010)	(0.005)	(0.011)
Age^2	0.001***	-0.0001	1.2x10^{-4}	-0.0003	0.0001	-4.1x10^{-5}	0.001***	-0.0003**	-0.0002	-0.001***	-2.12x10^{-5***}	-4.31x10^{-5}
	(0.0003)	(0.0001)	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)	(2.1x10^{-6})	(0.0001)
HHSize	-0.016	0.007	-0.009***	0.017	0.007	-0.013***	-0.040	0.007	0.013	0.044	0.018	-0.005***
	(0.034)	(0.008)	(0.003)	(0.043)	(0.030)	(0.0003)	(0.031)	(0.017)	(0.010)	(0.078)	(0.020)	(0.002)
Edu	-0.232*	-0.092**	0.137	-0.033	-0.098	-0.040	-0.073	-0.086	0.010	0.140	-0.069***	-0.216***
	(0.137)	(0.047)	(0.339)	(0.078)	(0.142)	(0.192)	(0.070)	(0.077)	(0.227)	(0.200)	(0.022)	(0.083)
Farmsize	0.018	0.223***	0.218***	-0.006	0.261***	0.225***	0.061	0.299***	0.192***	-0.055	0.212***	0.304***
	(0.019)	(0.014)	(0.037)	(0.061)	(0.072)	(0.023)	(0.142)	(0.074)	(0.038)	(0.156)	(0.022)	(0.015)
Agrochem	-0.029	-0.030**	-0.059**	-0.021	-0.028	-0.061***	-0.068	-0.058***	-0.041***	0.002	-0.023***	-0.077
	(0.019)	(0.016)	(0.031)	(0.027)	(0.045)	(0.017)	(0.155)	(0.006)	(0.017)	(0.077)	(0.008)	(0.091)
Chemcost	0.003	0.003	0.006***	0.007***	0.001	0.006***	-0.001	0.005***	0.005***	0.008***	0.002	0.004
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.0001)	(0.008)	(0.002)	(0.001)	(0.002)	(0.002)	(0.007)
Labor	-0.006***	-0.021***	-0.017***	0.001	-0.022***	-0.017***	-0.014	-0.043***	-0.016***	0.027**	-0.019***	-0.044***
	(0.001)	(0.002)	(4.3x10^{-5})	(0.012)	(0.008)	(0.002)	(0.013)	(0.017)	(0.0003)	(0.013)	(0.001)	(0.005)
Laborcos	0.0004	0.002***	0.002***	0.001	0.001	0.002***	0.0002	0.002**	0.002***	-0.001	0.002***	0.003***
	(0.001)	(0.001)	(0.0004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.0001)
Credit	-0.563***	0.035	-0.105***	-0.315*	0.204	-0.049*	-0.309	0.151	-0.0002	-0.161	0.026	-0.007
	(0.054)	(0.107)	(0.007)	(0.171)	(0.142)	(0.030)	(0.261)	(0.135)	(0.126)	(0.433)	(0.099)	(0.027)
Rainfall	-0.004	0.001	0.0001	0.003	-0.002***	0.001	0.001	0.001	-0.002**	0.004	-0.002***	0.003
	(0.005)	(0.001)	(0.001)	(0.009)	(0.0005)	(0.002)	(0.008)	(0.008)	(0.001)	(0.006)	(0.0005)	(0.003)
Soilqual	0.403***	0.174***	0.287	0.062	0.037	0.336	0.543	-0.121	0.153	-0.251	0.153	0.210***
	(0.041)	(0.017)	(0.315)	(0.089)	(0.103)	(0.293)	(0.523)	(0.529)	(0.112)	(0.171)	(0.224)	(0.060)
WCZ	-0.293	0.005	0.114***	-0.678***	0.268	0.069***	0.506***	-0.169**	-0.013	-0.783***	0.086**	-0.057
	(0.187)	(0.013)	(0.026)	(0.193)	(0.165)	(0.026)	(0.059)	(0.076)	(0.039)	(0.138)	(0.041)	(0.062)
Comextoff	-0.241***			0.058			-0.217**			0.337**		
	(0.009)			(0.125)			(0.115)			(0.146)		
Distkm	-0.004			-0.004			-0.006***			0.009		
	(0.009)			(0.010)			(0.001)			(0.012)		
Electgrid	0.584***			0.234			0.415***			0.048*		
	(0.176)			(0.513)			(0.054)			(0.025)		
Ethnicity	0.091***			-0.407***			0.225			-0.636***		
	(0.033)			(0.159)			(0.292)			(0.141)		
$ln\sigma_1/ln\sigma_0$		-1.441***	-0.737***		-0.877***	-0.758***		-1.015***	-0.662***		-1.433***	-1.531***
		(0.032)	(0.096)		(0.091)	(0.015)		(0.248)	(0.022)		(0.025)	(0.188)
ρ_1/ρ_0		-16.125***	-3.115***		19.308***	-3.424**		20.343***	-5.077***		-16.117***	-3.092***
		(1.017)	(0.399)		(2.476)	(1.576)		(0.801)	(0.170)		(1.006)	(0.141)

τ_1/τ_0		-9.94x10^{-8}**	0.317		-0.810	0.343		-0.819	0.462		-1.0x10^{-7}**	0.315
		(1.01x10^{-7})	(na)		(na)	(na)		(na)	(na)		(-6.3x10^{-8})	(na)
Wald test ($\rho =$ 0)	61.059***			3.5x10^{7}***			2.9x10^{5}***			478.779***		
LL	-360.506			-345.433			-333.281			219.269		
Sample(N)	600			600			600			600		
Wald chi2(18)	30.42**			44.05***			38.41***			37.54***		
Vuong's statistic	0.038***			-0.006*			0.008***			0.006		
	(0.006)			(0.003)			(0.001)			(0.004)		

Note: *** , ** and * are 1%, 5% and 10% significance level respectively and values in brackets are standard errors, '*na*' means not available because the parameter is no analytically computed, τ is the Kendall's concordance parameter. The alphabets in square brackets are the link functions and its distributions, where p indicates probit and n, l, t represents normal, logistic and Student's t distributions, respectively. Each model represent participation in different extension channels. Model 1, represents a pool of all extension channels together for assessing general extension participation impact on outcomes, Models 2 and 3 represent participation in ICT-based and Conventional extension channels respectively, whereas Model 4 is the inter-channel comparison model, which compares participation in ICT-based extension against participation in Conventional extension as the base channel.

Table 2. 7 Copula Endogenous Switching Regression Estimates – Farm Net Returns (lnGHC/ha)

Variables	Model 1: Frank-Gumbel [*p-n-l*]			Model 2 : Clayton-Plackett [*p-n-l*]			Model 3: Frank-Clayton [*p-n-t*]			Model 4: Clayton-Plackett [*p-n-l*]		
	Select	**AES-Pool**	**Non-Part**	**Select**	**ICT-Part**	**Non-Part**	**Select**	**CE-Part**	**Non-Part**	**Select**	**ICT-Part**	**CE-Part**
	Coeff.	*Coff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*	*Coeff.*
Const.	1.536***	4.796***	4.460***	-1.056	5.390***	4.906***	0.478	4.827***	4.527***	-1.434	5.055***	4.725***
	(0.775)	(0.007)	(0.467)	(0.895)	(0.473)	(0.249)	(0.455)	(0.222)	(0.243)	(1.208)	(0.341)	(0.356)
Gender	0.283	0.004	-0.046	0.113	0.074	-0.031	0.241***	-0.080	-0.030	-0.002	0.014	-0.031
	(0.391)	(0.071)	(0.060)	(0.221)	(0.084)	(0.037)	(0.102)	(0.057)	(0.074)	(0.261)	(0.131)	(0.095)
Age	-0.0678**	0.007***	0.024*	0.044	0.004	0.004	-0.051**	0.018***	0.020***	0.089**	0.003	0.004
	(0.019)	(0.001)	(0.014)	(0.032)	(0.014)	(0.009)	(0.025)	(0.005)	(0.006)	(0.039)	(0.011)	(0.008)
Age^2	0.001***	-0.0001***	-0.0003**	-0.0004	-0.0001	-0.0001	0.001***	-0.0002***	-0.0002***	-0.001***	-0.00004	-0.0001
	(0.0002)	($9\text{x}10^{-6}$)	(0.0001)	(0.0003)	(0.0001)	(0.0001)	(0.0002)	(0.00004)	(0.0001)	(0.0004)	(0.0001)	(0.0001)
HHSize	-0.013	0.019***	0.001	0.017	0.005	0.004	-0.039	0.010***	0.017***	0.058	0.017*	0.014**
	(0.041)	(0.007)	(0.003)	(0.032)	(0.009)	(0.006)	(0.037)	(0.003)	(0.001)	(0.036)	(0.009)	(0.007)
Edu	-0.204*	-0.027**	0.184	0.066	0.029	0.056	-0.178**	0.032	0.115*	0.213	-0.001	-0.110
	(0.121)	(0.014)	(0.147)	(0.075)	(0.039)	(0.042)	(0.085)	(0.059)	(0.065)	(0.141)	(0.064)	(0.077)
Farmsize	0.025	0.318***	0.272***	0.004	0.295***	0.287***	0.059	0.416***	0.263***	0.008	0.299***	0.395***
	(0.024)	(0.022)	(0.006)	(0.063)	(0.030)	(0.036)	(0.103)	(0.053)	(0.030)	(0.086)	(0.043)	(0.029)
Agrochem	-0.042*	-0.062***	-0.090***	-0.017	-0.046***	-0.092***	-0.030	-0.115***	-0.069***	-0.020	-0.050***	-0.145***
	(0.024)	(0.005)	(0.011)	(0.029)	(0.011)	(0.023)	(0.075)	(0.022)	(0.019)	(0.032)	(0.010)	(0.056)
Chemcost	0.004	0.003***	0.007***	0.004	0.001	0.007***	-0.003	0.005***	0.006***	0.005*	0.002	0.006
	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)	(0.003)	(0.001)	(0.004)
Labor	-0.006***	-0.016***	-0.002	0.003	-0.016***	-0.004	-0.014*	-0.047***	-0.005***	0.011	-0.017***	-0.036***
	(0.001)	(0.001)	(0.003)	(0.004)	(0.002)	(0.002)	(0.008)	(0.012)	(0.0002)	(0.008)	(0.003)	(0.004)
Laborcos	0.001	-0.0003***	-0.001	-0.0002	-0.0002	-0.001*	-0.0002	0.0004	-0.001**	-0.001	-0.0002	-0.0002
	(0.001)	(0.0001)	(0.001)	(0.001)	(0.0003)	(0.0005)	(0.0001)	(0.001)	(0.0002)	(0.001)	(0.0004)	(0.001)
Credit	-0.554***	0.016	-0.095**	-0.265*	0.060	-0.026	-0.288	0.069	-0.0004	-0.091	-0.002	-0.017
	(0.052)	(0.072)	(0.041)	(0.158)	(0.055)	(0.053)	(0.488)	(0.137)	(0.128)	(0.170)	(0.051)	(0.035)
Rainfall	-0.004	-0.0002	-0.0001	-0.0003	0.0001	-0.0004	-0.001	0.001	-0.0003	0.002	0.0003	0.001
	(0.005)	(0.0001)	(0.0001)	(0.003)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)
Soilqual	0.478***	0.031	0.104	-0.103	-0.0003	0.175**	0.726***	-0.253**	0.059	-0.626**	0.119	-0.005
	(0.142)	(0.080)	(0.075)	(0.325)	(0.147)	(0.078)	(0.222)	(0.128)	(0.124)	(0.309)	(0.112)	(0.167)
WCZ	-0.268	-0.063***	0.010	-0.585***	0.166***	-0.016	0.408**	-0.123***	-0.100***	-0.688***	0.098*	-0.069
	(0.179)	(0.016)	(0.034)	(0.145)	(0.053)	(0.031)	(0.175)	(0.065)	(0.034)	(0.188)	(0.058)	(0.055)
Comextoff	-0.164***			-0.00004			-0.112			0.107		
	(0.063)			(0.107)			(0.269)			(0.103)		
Electgrid	0.556**			-0.043			-0.172			-0.041		
	(0.246)			(0.081)			(0.155)			(0.206)		
Ethnicity	0.045***			-0.143**			0.107*			-0.446***		
	(0.023)			(0.070)			(0.057)			(0.167)		
Distextof	-0.0001			-0.003***			-0.001			-0.005**		
	(0.007)			(0.001)			(0.004)			(0.002)		
$ln\sigma_1/ln\sigma_0$		-1.776***	-1.191***		-1.459***	-1.161***		-1.455***	-1.089***		-1.565***	-1.310***
		(0.123)	(0.010)		(0.206)	(0.070)		(0.212)	(0.044)		(0.221)	(0.050)
ρ_1/ρ_0		-15.669***	-3.280***		-10.718***	-3.156***		4.607	-2.344***		-9.718***	-8.895***
		(1.005)	(1.077)		(2.697)	(0.528)		(4.278)	(0.788)		(2.824)	(1.317)

τ_1/τ_0		-1.57x10^{-7}**	0.331		na	-0.021**		-0.980**	0.247		na	-0.0001**
		(1.58x10^{-7})	(na)		(na)	(0.011)		(0.082)	(na)		(na)	(0.0001)
Wald test($\rho = 0$)	9.274***			3.2x10^{8}***			4270.271***			4.6x10^{7}***		
LL	-245.845			-228.010			-209.999			-131.134		
Sample(N)	600			600			600			600		
Wald chi2(18)	29.12**			34.01***			37.78***			23.62***		
Vuong's statistic	0.059***			-0.038***			0.015***			-0.064***		
	(0.005)			(0.004)			(0.004)			(0.005)		

Note: *** , ** and * are 1%, 5% and 10% significance level respectively and values in brackets are standard errors, '*na*' means not available because the parameter is no analytically computed, τ is the Kendall's concordance parameter. The alphabets in square brackets are the link functions and its distributions, where p indicates probit and n, l, t represents normal, logistic and Student's t distributions, respectively. Each model represent participation in different extension channels. Model 1, represents a pool of all extension channels together for assessing general extension participation impact on outcomes, Models 2 and 3 represent participation in ICT-based and Conventional extension channels respectively, whereas Model 4 is the inter-channel comparison model, which compares participation in ICT-based extension against participation in Conventional extension as the base channel.

The estimates in Table 2.4 also reveal that, the coefficients of the variables representing extension channel choice (i.e. *AESChannel)* are positive and statistically significant in both the ICT-based and CE adoption models (at 1% levels respectively), suggesting that extension channel choice positively impact on farmers' inoculant technology adoption decision. In particular, the likelihood of inoculant adoption increases by 112% and 159% for ICT-based and CE participants, respectively. The magnitude of the changes is consistent with Oreopoulos and Petronijevic (2018) observation that person-to-person contact information channels have larger effects on outcomes, compared to technology mediated channels. The inter-channel comparison model (i.e. Model 4) also shows that farmers who participated in the CE channel are more likely (123%) to adopt the inoculant, compared to that of ICT-based. The implication of this finding is that, face-to-face communication channels tend to have greater influence on getting farmers to adopt a new technology, compared to technology-mediated channels, such as ICT-based extension channels. This is intuitive, given the fact that face-to-face channels afford farmers' the opportunity to learn the correct usage of the new technology at first hand and also improve acceptance of the technology (Foster and Rosenzweig 2010). In spite of this, the positive effect of the ICT-based channel on adoption is consistent with the literature on ICT deployment in agricultural extension delivery (e.g. Aker 2011; Dzanku *et al.,* 2020). However, considering that the effect size of the ICT-based channel (112%) and that of the inter-channel comparison model (123%) are close, suggests that in the presence of resource constraints to undertake face-to-face extension delivery, ICT-based channels could be an optimal choice.

Furthermore, Table 2.4 shows that, farmer's distance to the nearest extension office plays an important role in determining the type of extension channel to choose. For instance, in the ICT-based and the Inter-channel comparison model (i.e. Model 4), the coefficients are positive and significant (at 1% level), suggesting that as the distance of a farmer's location to the nearest extension office increases by a kilometer, the likelihood of the farmer choosing ICT-based extension channel increases by 1.1%. On the other hand, a decrease in distance, increases the likelihood of CE choice by same margin (1.2%). A similar observation is made in Tables 2.5, 2.6 and 2.7.

Quite interesting is the coefficient of the variable representing connection to national electricity grid which is positive and statistically significant (at 1% level) across all models, suggesting that availability of electricity increases the likelihood of both participation in ICT-based extension as well as inoculant adoption. The positive and significant coefficient on CE participation suggests that availability of electricity in rural communities could be a pull factor for extension staff to reside in the communities, which could increase farmer's extension contacts. We find a similar pattern in Tables 2.5, 2.6, and 2.7. The results show positive coefficient for farm size in all the outcome equations across all models, but only statistically significant for yields and net returns in Tables 2.5 and 2.6, respectively, indicating that larger farms obtain higher yields and net returns relative to smaller farms.

2.6.2 ICT Impact on Inoculant Adoption, Knowledge Score, Yield and Net Returns

In this section, we present the treatment effects, which measure the impact of participation in the extension channels on farmers' inoculant adoption, knowledge scores, as well as yields and farm net returns. The average treatment effect on the treated (ATT) estimates are presented in Table 2.8, consisting of four panels A, B, C and D, each containing estimates for knowledge scores, yields, net returns and inoculant adoption, respectively. For the binary outcome (i.e. inoculant adoption), the ATT represents the likelihood of inoculant adoption, conditional on participation.

In terms of knowledge score, the results in Panel A of Table 2.8 shows that, farmers who participated in the ICT-based channel have almost twice recall probability (205%) compared to CE participants (174%), suggesting that farmers who participated in ICT-based channel perform better in recalling the procedures of inoculant application than CE channel participants. The inter-channel comparison model confirms that ICT-based had 42% recall probability than CE farmers. This finding is consistent with Maredia *et al*. (2018) who found that, animated videos induced learning on a new technology as compared to conventional information channels, but did not lead to significant adoption among farmers in Burkina Faso.

Table 2. 8 Impact of Extension Channel on Farm Outcomes

Extension Channel Type	If Farmer Participate (S.E)	If Farmer did not Participate (S.E)	ATT
Panel A: Inoculant Knowledge Test Score			
AES-Pooled	4.237(0.002)	2.628(0.023)	1.609***
ICT-Based	4.822(0.007)	2.777(0.025)	2.046***
CE	4.690(0.005)	2.955(0.015)	1.735***
ICT-Based vs CE	4.656(0.009)	4.239(0.002)	0.417***
Panel B: Yield (lnKg/Ha)			
AES-Pooled	6.604 (0.032)	6.055(0.035)	0.549***
ICT-Based	7.777(0.036)	6.269(0.033)	1.508***
CE	7.696(0.041)	6.219(0.035)	1.477***
ICT-Based vs CE	6.614(0.032)	6.231(0.035)	0.383***
Panel C: Farm Net Returns (lnGHC/Ha)			
AES-Pooled	6.402(0.039)	6.070(0.036)	0.333***
ICT-Based	7.261(0.038)	6.384(0.037)	0.877***
CE	7.088(0.047)	6.231(0.036)	0.857***
ICT-Based vs CE	6.925(0.036)	6.262(0.042)	0.663***
Panel D: Inoculant Adoption			
AES-Pooled			3.650*** [0.600, 9.160]
ICT-Based			20.340*** [1.620, 44.300]
CE			26.400*** [8.500, 46.400]
ICT-Based vs CE			-13.140*** [-33.970, -0.850]

Note: *** , ** and * are 1%, 5% and 10% significance level respectively, values in brackets and square brackets are standard errors and 95% confidence intervals respectively.

Table 2.8, panels B and C show that, yields as well as net returns of farmers who participated in ICT-based channel increased by 151% and 88%, respectively, compared to 148% and 86% for CE channel participants. Again, the inter-channel comparison model shows that, ICT-based participants attain 38% and 66% yields and farm net returns, respectively, higher than their CE counterparts. Intuitively, these findings imply that, when ICT-based extension channels are able to generate acceptance by farmers and get farmers to adopt the technology, then, the impact of extension on yields and farm net returns may be equivalent (perhaps even higher) to that of person-to-person extension contacts can achieve.

Panel D in Table 2.8 shows that, generally, participation in the extension dissemination program lead to an increase in the likelihood of inoculant adoption by 3.7%. However, when we consider channel specific impact on adoption, the likelihood increases to 20% and 26% for ICT-based and CE channels respectively. Further comparison between the ICT-based and the CE in the inter-channel model shows that CE extension channel outperforms that of ICT-based channel by 13%, suggesting that person-to-person information channels are still better in getting farmers to adopt a new technology, compared to technology-mediated channels (Oreopoulos and Petronijevic 2018).

2.7 Conclusions and Policy Implications

This study analyzed the effectiveness of ICT-based extension channels in the dissemination of a new agricultural technology (*Bradyrhizobium* inoculant) and its impact on household welfare measures such as yields and farm net returns, using recent survey data of 600 farmers from northern Ghana. We employed the robust copula functions estimator to account for potential endogeneity and selection bias problems. Our empirical results revealed that farmers who chose the services of ICT-based extension channel, perform better, in terms of inoculant knowledge gain, yields and farm net returns than farmers who chose to participate in conventional extension, and much higher than those who did not participate in extension services. However, in terms of the likelihood of adoption of the inoculant technology, conventional extension participants achieved higher impacts than ICT-based participants. The channel comparison results, in relation to non-participation, show that both ICT-based and conventional extension channels are equally effective on their own accord and can be used independently to disseminate new technology information to farmers. However, evidence from inter-channel comparison suggests that farmers who reside far away from extension agents tend to substitute ICT-based extension for conventional extension services, which in their situation may be more beneficial in terms of knowledge gains, yields and farm net returns. Our findings further showed that every kilometer increase in distance away from farmers' location to the nearest extension office or the district capital, increases their preferences for ICT-based extension channels, compared to conventional extension.

Our findings offer several policy implications aimed at improving agricultural extension service delivery in developing countries. First, the fact that ICT-based extension channel comparatively outperformed conventional extension suggests that ICT-based extension services could be a viable alternative to conventional extension service provision. Hence, policy-makers could consider investing in expansion of ICT infrastructure such as installation of mobile communication masses across farming communities to improve the signal reception strength in these areas in order to scale-up the effectiveness of mobile phone, television and radio signals. This will enable state agencies and other stakeholders to minimize cost by employing limited but specialized staff to transmit agricultural extension information to farmers from centralized locations. Moreover, to the extent that ICT-based extension services remove direct person-to-person contact from extension service delivery, religious and cultural barriers could be overcomed so as to promote equitable access to extension by all farm households, particularly female farmers living in conservative farming communities. Furthermore, the finding that access to electricity exerts a positive effects on farmers' likelihood of participation in ICT-based extension and inoculant adoption suggests that government investment in rural electrification could complement the digitization of agricultural information or extension service delivery to enhance technology adoption, raise agricultural productivity, and improve farmers' incomes, as well as food and nutrition security.

References

Abdulai, A. and Huffman, W. (2014). The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Economics, 90(1): 26 – 43*.

Abdulai, A., Monnin, P., and Gerber, J. (2008). Joint estimation of information acquicition and adoption of new technologies under uncertainty. *Journal of International Development*, 20:437 – 451.

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

Aker, J.C. and Mbiti, I. S. (2010). Mobile phones and economic development in Africa. *Journal of Economic Perspectives*, 24(3):207–232.

Anderson, J. R., and Feder, G. (2004). Agricultural extension: Good intentions and hard realities. *World Bank Research Observer*, 19 (1):41–60.

Ashraf, N., Giné, X., and Karlan, D. (2009). Finding Missing Markets (and a Disturbing Epilogue): Evidence from an Export Crop Adoption and Marketing Intervention in Kenya. *American Journal of Agricultural Economics 91 (4): 973–90*.

Blum, M. L., and Szonyi, J. (2011). Investment requirements in extension to achieve zero hunger and adapt to climate change. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Camacho, A. and Conover, E. (2019). The impact of receiving SMS price and weather information on small scale farmers in Colombia. *World Development*, *123:104596*.

Cover, T. M. and Thomas, J. A. (2006). Elements of Information Theory, 2nd Edition. John Wiley and Sons, Inc.

Deichmann, U., Goyal, A., and Mishra, D. (2016). Will Digital Technologies Transform Agriculture in Developing Countries? *Agricultural Economics*, 47:21 – 33.

Dzanku, F. M., Osei, R. D., Nkegbe, P. K., and Isaac Osei-Akoto, I. (2020). Information Delivery Channels and Agricultural Technology Uptake: Experimental Evidence from Ghana. *European Review of Agricultural Economics, 00(00):1 – 39*.

Foster, A. and Rosenzweig, M. (2010). Microeconomics of technology adoption. *Annual Review of Economics*, *2:395–424*.

Genius, M., Koundouri, P., Nauges, C. and Tzouvelekas, V. (2013). Information transmission in irrigation technology adoption and diffusion: social learning, extension services and spatial effects. *American Journal of Agricultural Economics*, 96 (1):328-344.

Giller, K.E. (2001). Nitrogen Fixation in Tropical Cropping Systems. Second Edition. CAB International, Wallingford, UK.

Hanna, R., Mullainathan, S., and Schwartzstein, J. (2014). Learning through Noticing: Theory and Experimental Evidence from a Field Experiment. *Quarterly Journal of Economics, 129 (3):1311–53.*

Han, S. and Vytlacil, E. J. (2017). Identification in a generalization of bivariate probit models with dummy endogenous regressors. *Journal of Econometrics* 199(1):63 – 73.

Han, S., and Lee, S. (2019). Estimation in a generalization of bivariate probit models with dummy endogenous regressors. *Journal of Applied Econometrics* 34: 994 – 1015.

Härdle, W. and Manski, C.F. (1993). Nonparametric and semiparametric approaches to discrete response analysis. *Annals of the Journal of Econometrics 58, 1–274.*

Hasebe, T. (2013). Copula-based maximum-likelihood estimation of sample-selection models. *The Stata Journal, 13(3):547 – 573*.

Heckman, J. J. (1978). Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica* 46(4): 931 – 959.

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

Jensen, R., (2007). The Digital Provide: Information (Technology), Market Performance and Welfare in the South Indian Fisheries Sector. *Quarterly Journal of Economics,* CXXII(3), 879 – 924.

Kondylis, F., Mueller, V., and Zhu, S. (2015). Measuring agricultural knowledge and adoption. *Agricultural economics,* 46: 449 – 462.

Lee, L.-F. (1984). Tests for the bivariate normal distribution in econometric models with selectivity. *Econometrica 52: 843 – 863*.

Mara, G., Radice, R., and Zimmer, D. M. (2020). Estimating the binary endogenous effect of insurance on doctor visits by copula-based regression additive models. *Journal of the Royal Statistical Society C, 69(4):953 – 971*.

Maredia, M. K., Reyes, B., N Ba, N. M., Dabire, L. C., Pittendrigh, B., and Bello-Bravo, J. (2018). Can Mobile Phone-Based Animated Videos Induce Learning and Technology Adoption among Low-Literate Farmers? A Field Experiment in Burkina Faso. *Information Technology for Development 24: 429–60.*

Nakasone, E., Torero, M. and Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics*, 6:533 – 550.

Oreopoulos and Petronijevic, (2018). Student coaching: how far can technology go? *Journal of Human Resource, 53(2): 299 – 329*.

Smith, M. D. (2003). Modelling sample selection using Archimedean copulas. *Econometrics Journal, 6:99 – 123*.

Smith, M. D. (2005). Using Copulas to Model Switching Regimes with an Application to Child Labour. *The Economic Record, 81(255):S47 – S57*.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica 79(1):212 – 220.*

Tack, J. B. and Aker, J. C. (2014). Information and firms' Search Behaviour. Economics Department, Tufts University. Unpublished mimeo.

Tadesse, G. and Bahiigwa, G. (2015). Mobile Phones and Farmers' Marketing Decisions in Ethiopia. *World Development, 68: 296 – 307*.

Trivedi, P., and Zimmer, D. M. (2017). A Note on Identification of Bivariate Copulas for Discrete Count Data. *Econometrics* 5(10): 1 – 11.

Ulzen, J., Abaidoo, R. C., Mensah, N. E., Masso, C. and AbdelGadir, A. H. (2016). Bradyrhizobium inoculants enhance grain yields of soybean and cowpea in Northern Ghana. *Frontiers in Plant Science, 7: 1770*.

van Heerwaarden, J., Baijukya, F., Kyei-Boahen, S., Adjei-Nsiah, S., Ebanyat, P., Kamai, N., Wolde-meskel, E., Kanampiu, F., Vanlauwe, B. and Giller, K. (2018). Soyabean response to rhizobium inoculation across sub-Saharan Africa: Patterns of variation and the role of promiscuity. *Agriculture, Ecosystems and Environment, 261: 211 – 218*.

Vuong, Q.H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica, 57: 307 – 333*.

Zanello, Z. (2012). Mobile Phones and Radios: Effects on Transactions Costs and Market Participation for Households in Northern Ghana. *Journal of Agricultural Economics,* 63(3):694 – 714.

Zimmer, M. D. (2012). The Role of Copulas in the Housing Crisis. *Review of Economics and Statistics, 94(2): 607 – 620*.

Appendix

Table A 1. Construction of Farmer Inoculant Knowledge Measurement

No	Areas of Inoculant Knowledge Test (A)	Measurement (B)	Indicators (C)	Allocated Score (D)
1	*Confirmatory*			
		Subjective measure	Know by crop name	
		Objective measure	Know by physical identification	2
2	*Technical Recommendations*			
2.1	*Standard Recommended Measurement*	Subjective measure	Materials and Quantities	5
2.2	*Recommended Mode of Application*			
		Subjective measure	Farmer recall application procedure from memory	7
		Objective measure	Farmer re-orders application procedures list provided by enumerator	7
3	*Precautionary Measures*			
3.1	*Generic precautions*	Objective measure	Farmer identified Do's listed by enumerator as True/False	5
		Objective measure	Farmer identified Don'ts listed by enumerator as True/False	7
3.2	*Specific precautions*	Subjective measure	Recommended storage procedures	8
4	*Understanding*	Objective measure	Reasons for critical actions e.g. inoculation and drying.	3
Total				**50**

Note: The table contains detailed information on the construction of our inoculant knowledge outcome variable. Column **A** presents information on critical components of the inoculation procedure that we examined farmers on; Column **B** show the type of measurement criteria used in the test; Column **C** presents detailed description of the measurement indicators that were used to elicit information on the critical components of the inoculation procedure; while Column **D** presents marks allocated to each of the test components that farmers were examined on.

Chapter 3
Heterogeneity in Returns to Agricultural Technologies with Incomplete Diffusion: Evidence from Ghana

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Abstract

In this study, we employ a dynamic treatment effect approach to analyze heterogeneity in returns to farmers at different stages of adoption of a newly introduced inoculant technology, using a recent survey data of 600 soybean farmers from northern Ghana. Although farmers differ in their returns to adoption of new technologies, many empirical studies often fail to account for this heterogeneity. The empirical results reveal that farmers who are at advanced stages of adoption appear to, on average, more than double their yields and farm net returns, suggesting that the inoculant technology may be a game changer in the fight against extreme poverty in the region, where poverty is endemic and crop yields are persistently below the average potential yield target. Our findings further reveal that extension services as well as efficient input and output markets are key to the adoption process, by influencing knowledge acquisition, adoption and continued adoption. Our findings also show significant impact heterogeneity at each adoption stage with the long-term benefits of the inoculant technology outweighing its short-term benefits.

Keywords: Dynamic Treatment Effect, Multi-stage Decision-making, Impact Assessment, Heterogeneity, Inoculant Technology Adoption.

JEL: C32, D83, O33, Q10, Q16.

3.1 Introduction

Low agricultural productivity and perennial food insecurity are major global concerns facing low-income countries, particularly, countries in sub-Sahara Africa (SSA). Central to tackling the problem, is increasing crop yields and sustaining gains through adoption of improved agricultural technologies (Takahashi *et al.*, 2020). Yet, technology adoption rate among farmers in these countries appear to be very low (Suri, 2011; Sheahan and Barrett, 2017; Macours, 2019). While some analysts partly attribute the phenomenon to lack of information, low education, credit constraints, among other factors, others question the empirical and theoretical adoption models used to analyze farmers' adoption decisions (Feder *et al*., 1985; Lindner, 1982; Basley and Case, 1993). In particular, Besley and Case (1993) note that, technology adoption is a dynamic process in which farmers make series of decisions over multiple-stages or seasons. Lindner *et al.* (1982) succinctly summarized the adoption process into three broad categories as *discovery stage*, *evaluation stage* and *trial stage*. Each stage in the adoption process collects different sets of vital information for the farmer to update subsequent decisions. However, classical studies on technology adoption mostly consider farmers' adoption decisions as static, ignoring the dynamic processes embedded in farmers' decision-making. As a result, important information on farmers' adoption behavior relevant to policy formulation is lost and their decisions are misinterpreted. Thus, it is not uncommon for analysts to find farmers' adoption decisions at odds with rationality, and sometimes counter intuitive (Besley and Case, 1993).

This study departs from the classical approach and analyze farmers' adoption decisions in a dynamic framework. Previous studies that examined farmers' technology adoption decision-making in a dynamic framework mainly looked at adoption determinants, patterns of diffusion and intensity of adoption (e.g. Simtowe *et al.*, 2016; Lambrecht *et al.*, 2014; Abdulai and Huffman, 2005; Feder and Slade, 1984), while some studies employed it to explain farmers' learning behavior, risk preferences and uncertainties (Ghadim and Pannell, 1999). The missing link in the dynamic adoption literature is the impact of adoption on output levels and other welfare indicators such as yields and farm net returns, which underlie farmers' adoption and continued adoption decisions. These indicators also drive adoption patterns and clarify risks and uncertainties that may surround a given technology (Besley and Case, 1993; Feder *et al.*, 1985). We contribute to the literature by analyzing farmers' adoption decision-making process as a multi-stage decision problem in an impact evaluation framework. One, in which each stage of adoption is characterized by different margins of payoffs or gains that accrue to farmers at that stage. We apply this approach to analyze farmers' adoption decisions of a new *Rhizobia* inoculant technology among 600 soybean farmers in northern Ghana, taking into account that farmers' returns from adoption may be heterogeneous and stage dependent.

Few studies in the technology adoption literature have analyzed heterogeneity in returns to adoption of agricultural technologies (Shahzad and Abdulai, 2020; Abdul Mumin and Abdulai 2021). However, adoption at different stages were not considered. As argued by Heckman *et al.* (2018), individuals differ in their returns to treatment, and failure to account for this heterogeneity can lead to confusion in interpreting the estimated effects of treatment, particularly when the individuals may be at different stages of treatment. In this study, we employ a dynamic treatment effect model to account for heterogeneity in returns to adoption for farmers at different stages of adoption. Thus, we analyze the relationship between the farmers' state of adoption and the final outcomes (which in our case, yields and farm net returns) obtained from adoption. The adoption stages considered in this study include awareness and knowledge acquisition about the inoculant technology, trying the technology, adopting and continuous adoption of the technology. The inoculant technology is a recently developed agricultural input by research scientists to improve productivity of grain legumes in SSA. The technology exploits the symbiotic relationship of an elite strain of bacteria known as *Bradyrhizobium japonica*, as an inoculant to enhance nitrogen fixation in legumes. One crop that has received much attention in this process is soybean (see van Heerwaarden *et al.,* 2018; Chibeba *et al.,* 2018). Field experiments of the inoculant show promising results with a potential to increase average soy grain yield by 20 – 29 percent in African soils (Chibeba *et al.*, 2018). The technology was recently introduced to smallholder farmers in northern Ghana by a number of organizations[6] and their partners working together to improve soybean production in the region. As a newly introduced technology with incomplete diffusion, it is imperative to investigate what factors drive the adoption of the inoculant technology and to what extent can information from one stage of adoption decision influence further adoption decisions in the process, as well as the impact of adoption on yields and farm net returns.

Our findings reveal that farmers who are at advanced stages of adoption appear to, on average, more than double their yields and farm net returns, suggesting that the new inoculant technology have the potential to contribute to poverty reduction in the region, where poverty is endemic and crop yields are below the potential yields target. Our findings further reveal that the long-term effects are much stronger than the short-term effects, conditional on the markets being able to absorb the excess supply that may result from higher yields. Finally, we also found that extension services as well as efficient input and output markets are key to the inoculant adoption process, by influencing knowledge acquisition, adoption and continued adoption.

The rest of the paper is organized as follows. Sections 2 and 3 present the theoretical framework and empirical specification, while sections 4 and 5 present the identification and estimation strategy and the study context, respectively. Section 6 presents the data used in the study, while section 7 contains our empirical results. The final section presents conclusions and policy implications of the study.

[6] Notable organizations farmers identified include CSIR- SARI, IITA and USAID-ADVANCE Project.

3.2 Theoretical Framework

We assume that farmers are risk-neutral and their technology adoption decisions are guided by expected net benefits from adoption (Kleemann and Abdulai 2013). Farmers' adoption decisions of a new technology is conceptualized as a decision tree consisting of five decision-making nodes along adoption path T (see Figure 1A). Let N represent a finite adoption decision-making nodes along the entire adoption path with a finite decision horizon ($\underline{s}, \overline{s}$), where $\underline{s}$ is the lowest adoption state and $\overline{s}$ is the highest attainable adoption state; $A_n(s)$ be the choice indicator for adoption state s for a farmer at adoption decision-making node n and $W_n(s)$ be the expected net benefits for a farmer in adoption state s.

In line with Heckman *et al.* (2016), the farmer's current adoption state s net benefits can be expressed as follows;

$$W(s) = \sum_{n=1}^{N} A_n(s) W_n(s) \quad (1)$$

where $W(s)$ is the current net benefits for a farmer in adoption state s, and all other notations remain as defined earlier.

Under autonomy, when the discrete choices made by a decision-maker at the decision-making node is known to the econometrician, the dynamic discrete choice model can be employed to understand the decision-maker's intertemporal behavior and its consequences (Heckman *et al.* 2016). We assume that the farmer's adoption state decision at any decision-making node is autonomous. A farmer may decide to stop at any adoption state or continue to the next state, if the expected net benefits for continuing to the next adoption state is lower than the current adoption state's net benefits. Let $\mathcal{H}(s)$ be the individual farmer's perceived state value of the net benefits for continuing to the next adoption state. The individual farmer's perceived value function for continuing to any adoption state s along the adoption path t can be represented as (Heckman *et al.* 2016);

$$V(\mathcal{H}(s), s) = \max_{A_n(t)\in Å(s)} E\left[\sum_{t=s}^{\bar{s}} \delta^{t-s} \sum_{n=1}^{N} A_n(t) W_n(t) | \mathcal{H}(s)\right] \quad (2)$$

where $Å(s)$ is the set of feasible current and future adoption state choices available to the farmer at the decision-making node, δ is farmer's assumed discount factor for valuing the perceived net benefits across the decision horizon[7] and all other notations remain as defined earlier. The farmer's valuation of state net benefits from adoption at any adoption decision-making node consists of the current state s benefits and that of the future adoption state $s+1$ benefits, if they continue to the next adoption state[8]. To reflect this relationship in the farmer's value function at each decision-making node n, we follow Heckman *et al.* (2016) and express the state-specific value function in terms of equations 1 and 2 as follows;

$$V_n(\mathcal{H}(s), s) = W_n(\mathcal{H}(s), s) + \delta E[V(\mathcal{H}(s+1), s+1) | \mathcal{H}(s), A_n(s) = 1] \quad (3)$$

where $W_n(.,.)$ is the farmer's current adoption state s value function and $\delta E[V(.)]$ is the farmer's expected value function, if the farmer continue to the next adoption state $s+1$.

However, expected net benefits from adoption at any state is latent and cannot be observed, but the actual adoption choices made by the farmer can be observed. We let the adoption choice indicator $A_n(s)$ equal to 1, if a farmer at decision node n choses to be in adoption state s and 0, otherwise. Based on the state-specific perceived net benefits value function, the farmer's adoption state choice[9] at any decision-making node n, can be represented as (Heckman *et al.* 2016);

$$A_n(s) = 1 \; if \; [n = \underset{j\in\{1,.....,N\}}{\text{argmax}}\{V_j(\mathcal{H}(s), s)\}\,] \text{ for } \; s < \bar{s};$$

$$A_n(s) = 0, \text{ Otherwise} \quad (4)$$

---

[7] In our calculation of the continuation value we used the *Weisbrod's* procedure, which uses the transitional probability as the discount factor. This takes away the discretion of assuming any arbitrary discount factor which is hard to observe in reality compounded by the difficulty in assessing its heterogeneity among any group of decision makers Fagereng *et al.* (2020).

[8] This implies that the farmer at each stage of adoption is able to forecast the net benefits of the next stage.

[9] This specification doe not assume any choice decision rules, as such, it neither imposes rational expectation assumption nor forward-looking behavior on agents as in traditional discrete choice literature. Hence, agents may be myopic, time inconsistent and may be subjected to surprises (Heckman *et al*., 2016; 2018).

As noted by Heckman et al. (2016; 2018), the specification of the decision rule in equation 4 differs from conventional decision-making rules in the dynamic discrete choice literature. In the sense that, no specific choice rule is assumed, as such it neither imposes rational expectation assumption nor forward-looking behavior on agents at any decision node. Hence, agents may be myopic, time inconsistent and may be subjected to surprises. For instance, it is possible under a myopic decision rule as inherent in the Bellman's decision rules for a farmer who obtains negative returns at early stages of adoption to abandon the technology. Likewise, under a forward-looking behavior as inherent in the Euler decision rule for a farmer to continue to adopt the technology with the expectation of getting higher returns in the long term, despite obtaining negative returns at the early stages of adoption[10].

3.3 Empirical Specifications

Let Y_i denote the individual farmer's net benefits from soybeans production and A_i be the indicator for the farmer's inoculant adoption choice decision. Empirically, equation 4 can be expressed as the farmer's expected outcomes from the inoculant adoption choice decision as follows;

$$Y_i = \alpha_i + \rho_i A_i + \gamma_i X_i + U_i \qquad (5)$$

where X_i is a vector of observed characteristics (farm and household level characteristics); ρ_i and γ_i are vectors of parameter of interest, α_i is a constant and U_i is an error term.

Conventional static adoption decision analysis often treats A_i to be a single binary decision (e.g., Kleemann and Abdulai 2013). However, farmers tend to evaluate the performance of the technology over many seasons before making final adoption decision. As such, the adoption decision indicator A_i may not be a onetime binary decision, but several binary decisions across many seasons or transitions. In this setting, we assume that the farmer's adoption decision follows

[10] We thank an anonymous reviewer for making this suggestion on the theoretical explanation of the decision-making mechanisms.

a dynamic process. One in which the farmer is assumed to make finite adoption decisions in an irreversible sequential order over multiple-stages.

Let $\mathcal{J} = \{1, \ldots, \bar{s} - 1\} \forall N$ be a set of all possible terminal adoption states, and $S = \{1, \ldots, \bar{s}\}$ denote an ordered set of all stopping states (i.e. all states that a farmer is observed to make a stop during the process) with $\bar{s}$ as the highest attainable state. A farmer at each node makes a binary decision, either to remain at node j $(j \neq 0)$ or transit to the next node $j + 1 (j \neq j + 1)$ and $j \in \mathcal{J}$. We assume the farmer operates in a time stationary decision environment and past choices reveal the farmer's transition decisions. Let D represent a finite set of all possible transition decisions that a farmer can make over the decision horizon $D_j \in$ D, D_s is the farmer's stopping state decision for all $s \in S$, and Q_j is history of all states the farmer visited and assumed to be binary (i.e. $Q_j = 1$ if the farmer visits a state, otherwise $Q_j = 0$). We fixed $D_j = 0$ $(D_s \neq 1)$, if a farmer at j does not stop but moves to $j + 1$ and $D_j = 1$ $(D_s = 1)$, if the farmer stops at state j (Heckman *et al.* 2016; 2018).

The farmer must make a transition decision, either to remain at j or move from j to $j + 1$. We assume that net benefits differ from state to state, and the farmer compares the current state benefits to the net benefits of moving to the next state, before making a transition decision. We specify the farmer's transition decision (D_j) as follows;

$$D_j = \left\{ \begin{matrix} 0, \ if \ \boldsymbol{I_j} \geq 0, \ j \in \mathcal{J} = \{1, \ldots, \bar{s} - 1\} \\ 1, \ otherwise \end{matrix} \right\} \text{for } Q_j = 1, \quad j \in \mathcal{J} = \{1, \ldots, \bar{s} - 1\} \qquad (6)$$

where $\boldsymbol{I_j}$ is the indicator of the farmer's perceived state-specific value function for a farmer considering a move from $j (j \neq 0)$ to $j + 1$.

At each adoption state, the perceived value function $\boldsymbol{I_j}$ is assumed to cross a threshold value for the farmer to move from one state to another. To understand the farmer's choice decision at each adoption state, we specify the empirical state-specific value function $\boldsymbol{I_j}$ in a separable model as (Heckman *et al.,* 2016; 2018);

$$\boldsymbol{I_j} = \emptyset_j(\boldsymbol{Z}) - \eta_j, \quad j \in \mathcal{J} = \{1, \dots, \bar{s} - 1\} \tag{7}$$

where $\boldsymbol{Z}$ is a vector of observed characteristics that includes an instrument for identification not included in X_i, and η_j is the unobserved factors that affect the farmer's transitional ability.

Due to observed and unobserved factors that characterize different adoption transitions, each transition decision that the farmer makes has a range of potential outcomes. By indexing the state-specific potential outcomes as k (where $k \in \boldsymbol{K_s}$ and $\boldsymbol{K_s}$ is a set of all possible outcomes), a farmer at adoption state s potential outcomes from inoculant adoption can be denoted as Y_s^k. The individual farmer's state-specific potential outcomes equation for any adoption state can then be expressed in a separable model as (Heckman *et al.* 2016; 2018);

$$Y_s^k = \tau_s^k(\boldsymbol{X}) + U_s^k, \ \ k \in \boldsymbol{K_s}, \ \ \mathrm{s} \in S_s \tag{8}$$

where Y_s^k is the state-specific potential outcome, $\boldsymbol{X}$ is a vector of observed characteristics that determine the outcome at a particular state; τ_s^k is a parameter of interest and U_s^k is state-specific unobserved factors. Conditional on the number of adoption states that a farmer visits during the transitional process, the observed potential outcome common across all adoption states (Y^k) visited, can be expressed in a switching regression framework (Quant, 1972) as follows;

$$Y^k = \left(\textstyle\sum_{S\backslash\{\bar{s}\}} D_s Y_s^k\right)(1 - D_0) + \left(Y_0^k\right) D_0 \tag{9}$$

where D_s is the stopping decision indicator, D_0(i.e., for $D_s \neq 1$) is the transition decision indicator; Y_s^k is as defined earlier and Y_0^k is the counterfactual outcome, if the farmer decides to remain at the current adoption state.

3.4 Impact Identification and Estimation Strategy

The identification of dynamic technology adoption decisions must take into consideration heterogeneity in observed and unobserved farmer characteristics (Fagereng *et al.,* 2020; Benhabib *et al.,* 2019; Gabaix *et al.,* 2016). In particular, farmers' differ in wealth endowment, which is potentially endogenous to their transitional ability. Let $\boldsymbol{\theta}$ denote finite dimensional vector of farmer's unobserved wealth endowments (e.g. financial ability for farm investment) that can be proxied by observables (e.g. household assets, livestock holding, and non-farm income sources) in a measurement equation. Intuitively, the financial ability of a farmer determines the scale of farm operations and investment in production inputs. Thus, generating a potential correlation between the farmer's transition decision and the potential outcomes[11]. We re-specify both the state-specific value function and the potential outcome equations (7 and 8, respectively) controlling for unobserved wealth endowment as below;

$$\boldsymbol{I_j} = \emptyset_j(\boldsymbol{Z}) + \boldsymbol{\theta}'\lambda_j - v_j, \qquad j \in \mathcal{J} = \{1, \dots, \bar{s} - 1\} \tag{10}$$

$$Y_s^k = \tau_s^k(\boldsymbol{X}) + \boldsymbol{\theta}'\psi_s^k + \omega_s^k, \quad k \in \boldsymbol{K_s}, \ \mathrm{s} \in S_s \tag{11}$$

where λ_j and ψ_s^k are vectors of parameters of interest, respectively; v_j and ω_s^k are the error terms, respectively, $\boldsymbol{Z}$ and $\boldsymbol{X}$ are as defined previously.

We assume there could be problems with measurement errors, because $\boldsymbol{\theta}$ is not directly observed, but proxied with observable indicators. Let **M** be a system of measurement equations that link a vector of N_M measurement indicators of $\boldsymbol{\theta}$ to equations (10 and 11). Parsimoniously, the measurement equation **M** can be specified as below (Heckman *et al.,* 2016; 2018);

11 First, $\boldsymbol{\theta}$ correlates with the unobservable factors in the outcome equation as a result of heterogeneities in returns to farmers' wealth endowment, due to differences in levels of investment in their scale of production and intensity of input use. We approximate this correlated effect in a linear-in-parameter factor model as ($U_s^k = \theta'\psi_s^k + \omega_s^k$). Second, $\boldsymbol{\theta}$ also correlates with the unobservable factors in the transitional choice decision, due to inadequate financial ability to undertake further investment in the production cycle. This correlated effect is also approximated in a linear-in-parameter factor model as ($\eta_j = -(\theta'\lambda_j - v_j)$) (see Heckman *et al*., 2016; 2018) for more details.

$$\mathbf{M} = \phi(\boldsymbol{X}, \boldsymbol{\theta}, \boldsymbol{e}) = \begin{pmatrix} M_1 \\ \vdots \\ M_{N_M} \end{pmatrix} = \begin{pmatrix} \Phi_1(X, \theta, e_1) \\ \vdots \\ \Phi_{N_M}(X, \theta, e_{N_M}) \end{pmatrix} \tag{12}$$

where $\boldsymbol{X}$**,** is a vector of observed variables, $\boldsymbol{\theta}$ is a vector of endowment factors and $\boldsymbol{e}$ is a vector of error terms that ensure orthogonality ($\boldsymbol{e} \perp\!\!\!\perp X, Z, \theta, v, \omega$) with the error terms in equations (10) and (11) (Heckman *et al.,* 2016;2018).

By conditioning on ($\boldsymbol{D_i}$**,** $\boldsymbol{M_i}, \boldsymbol{X_i}$, $\boldsymbol{Z_i}$), a parsimonious maximum likelihood function ($\mathcal{L}$)[12] for an individual farmer can be specified as follows;

$$\mathcal{L} = \prod_i f(\boldsymbol{Y_i}, \boldsymbol{D_i}, \boldsymbol{M_i} | \boldsymbol{X_i}, \boldsymbol{Z_i})$$

$$= \prod_i \int f_Y(\boldsymbol{Y_i} | D_i, X_i, Z_i, \theta) f_D(\boldsymbol{D_i}, \boldsymbol{M_i} | X_i, Z_i, \theta) f_M(\boldsymbol{\theta}) d\boldsymbol{\theta} \tag{13}$$

where $f_Y(.)$, $f_D(.)$, and $f_M(.)$ are the probability density functions for the potential outcomes, adoption decision and the measurement equations, respectively and all other notations remain as earlier defined.

Equation 13 consists of three components, which are estimated simultaneously in a factor structural discrete choice model. The factor model $f_M(.)$ is estimated in the first-stage and in the second-stage, the adoption decision model $f_D(.)$ is estimated with the inclusion of an instrument (Z) to account for selection bias and a factor score (θ) predicted from the measurement model in the first-stage to account for unobserved ability or wealth endowment effect on the farmer's adoption decision. In the final stage, the potential outcomes (i.e., both the treated case and the counterfactual case) model $f_Y(.)$ is estimated conditional on the first two stages.

[12] We do not intend to reproduce the full likelihood equation as captured in Heckman *et al. (2016; 2018)*, so interested readers can please see Heckman *et al.* (2016; 2018) for the full specification of the likelihood function as well as the measurement equation.

3.4.1 Estimation of Treatment Effects

In this section, we provide the econometric relationship between the treatment and the outcomes. The treatment refers to the various transitional states, while the outcomes are the state-specific benefits[13]. Let T_j^k denote farmer-specific treatment effect for being at state *j*. The T_j^k of an individual farmer selected at random from the population of $Q_j = 1$ with characteristics; $\boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}$, making a decision whether to transit from j to $j+1$ or remain at j can be represented as;

$$T_j^k = \left(Y^k | \boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}, Q_j = 1,\ Fix\ D_j = 0\right) - \left(Y^k | \boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}, Q_j = 1,\ Fix\ D_j = 1\right) \qquad (14)$$

The population-level average treatment effect (ATE) for farmers at state j, conditional on ($Q_j = 1$) and integrating over the vector of $\boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}$, is obtained as below;

$$ATE_j^k \coloneqq \int \cdots \int E(T_j^k [Y^k | \boldsymbol{X} = \boldsymbol{x}, \boldsymbol{Z} = \boldsymbol{z}, \boldsymbol{\theta} = \bar{\boldsymbol{\theta}}])\, dF_{X,Z,\theta}(\boldsymbol{x}, \boldsymbol{z}, \bar{\theta}\ | Q_j = 1) \qquad (15)$$

The same procedure is followed to obtain the treatment effect for both treated (ATT) and untreated (ATUT) farmers at each transition state.

Unlike the classical treatment effect models, the total effect at the individual-level can be decomposed into two components. First, is the direct effect of making a transition from j to $j+1$ and second, is the continuation effect for going beyond $j+1$ to l (where l is the subsequent states after $j+1$), which evaluates the long-term impact informing farmer's transition decisions (Heckman *et al.*, 2016; 2018). The continuation effect (C_{j+1}^k) component of the treatment effect is

13 Note that fixing is different from conditioning. Its use here is to make it possible to derive the counterfactual outcome of not making a transition, which is necessary because the farmer has made a transition and is therefore not available at the counterfactual state to make the decision (see Heckman *et al., 2016; 2018).*

derived by conditioning on ($Q_j = 1$), of the population of farmers at $j + 1$, using the law of iterated expectations as follows[14];

$$E_{X,Z,\theta}\left(C_{j+1}^{k}\right) = E_{X,Z,\theta}[\textstyle\sum_{l=j+1}^{\bar{s}-1}\{E(Y_{l+1}^{k} - Y_{l}^{k}\big|\boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}, Q_{l+1} = 1,\ Fix\ Q_{j+1} = 1\big)$$

$$.\,Pr(Q_{l+1} = 1\big|\boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}, Q_j = 1,\ Fix\ Q_{j+1} = 1\big)\}|Q_j = 1] \qquad (16)$$

where Pr is the transitional probability of moving beyond $j + 1$ to l (where l is the subsequent states after $j + 1$). The average marginal treatment effect (AMTE), which offers more in-depth into the decision-making behavior of a decision-maker is also obtained as below;

$$AMTE_j^k \coloneqq \iiint E\left[T_j^k(Y^k\big|\boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta})\right]dF_{X,Z,\theta}(x, z, \bar{\theta}\ |Q_j = 1, |I_j| \leq \varepsilon) \qquad (17)$$

The economic intuition of the AMTE is that, it represents a fair measurement of the *ex post* gross marginal benefits of moving from one adoption state to the next state for a population of farmers at a decision-making node, who may be indifferent in their transition decision ($|I_j| \leq \varepsilon$) (Heckman *et al.,* 2016; 2018). Thus, the AMTE represents an empirically well identified marginal benefits from adoption that an indifferent farmer considers before making an adoption transition decision[15].

3.5 Context of Study

Soil fertility constitutes a critical production input in agriculture and plays an important role in the welfare of poor subsistent agricultural societies (Kim and Bevis 2019; Kleemann and Abdulai 2013). With about 90 percent of the farming population in Ghana being subsistent and cultivating less than two hectares of land (MoFA 2017), degradable soil conditions present a major challenge to food productivity and farm livelihoods. In particular, when 80 percent of Ghana's total

[14] The *direct effect* is the expected net benefits that accrues to a farmer for transiting to the next adjacent adoption decision node such as (from *j* to *j+1*). Whereas the *continuation effect* is the expected net benefits that accrues to a farmer for transiting beyond the next adjacent adoption decision node such as (transiting from *j* to *j+1*, to *j+2*, to *j+3*, …to *j+l*) and so on.
15 The AMTE is different from local average treatment effect (LATE), in the sense that, LATE is not define for any specific margin of choice and also depends on the population of instrument compliers to measure treatment effect.

agricultural output depends on this category of farmers (MoFA 2017). To maintain the productive capacity of soils in Ghana, scientific research organizations such as the International Institute of Tropical Agriculture (IITA) and the Council for Scientific and Industrial Research-Savannah Agricultural Research Institute (CSIR-SARI) and their partner organizations introduced the *Rhizobia* inoculant technology to smallholder grain legume farmers. One key crop that is targeted among other crops is soybean. The crop is targeted due to its potential to undergo sustainable intensification and ability to provide high amount of protein and other essential amino acids useful for consumption by humans, animals and for biofuel (Heerwaarden *et al.*, 2018; Chibeba *et al.*, 2018; Foyer *et al.* 2018). The inoculant technology is an organic input containing isolates of an elite strain of bacterial (*Bradyrhizobium japonicum*) and an organic carrier material (Lupwayi, *et al.*, 2000). The inoculant technology is seen as a cost-effective alternative to rehabilitating poor soils by enhancing the build-up of biological nitrogen fixation (BNF) organisms in the soil (Giller, 2001).

The inoculant technology is expected to cost-effectively improve smallholder farmers' welfare by sustainably increasing productivity, while minimizing cost of production, compared to inorganic inputs such as mineral fertilizers, which is sometimes priced out of reach for most smallholder farmers. The inoculant dissemination program was centered in the three regions (Northern, Upper East and Upper West) of northern Ghana, due to their soybean production potential in the country as well as the high incidence of extreme poverty situation in these parts of the country. The northern region where this study is focus on is second poorest (30.7%) region in the country in terms of extreme poverty incidence followed by the Upper East region (27.7%) with the Upper West region (45.2%) ranking first in the country (GSS, 2018). With soybean being a cash crop, it is expected that increase in productivity will lead to increase in the household income, which can contribute to poverty reduction for the poor households who depend on agriculture for income as well as food and nutrition security.

3.6 Survey Procedure and Data Source

We use primary data from a recent survey of farm households in the northern region of Ghana, which was conducted from June to August 2018. The sample was drawn using a multi-stage sampling technique. The northern region was purposively selected because it is a major soybean growing hub in the country and also happens to be the largest beneficiary of the agricultural extension program that disseminated the novel inoculant technology. Cluster sampling technique was employed to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on the districts participation in the dissemination program and intensity of soybean production in the districts within the clusters, eight (8) districts, comprising four (4) from each cluster were purposively sampled. From the ECZ, Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ, East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, five to seven communities were proportionally sampled, based on the dissemination channel received, program participation and farmer population. Because the dissemination program was implemented through farmer-based organization (FBO), one FBO was randomly selected from a list of treated FBOs for each treated community and another randomly selected FBO from a list of untreated FBOs for each untreated community. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer assisted personal interview (CAPI), a list of the farmers' information network members (INMs) in the community was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs for interview. A total of 600 farm households, consisting of 325 participants and 275 non-participants, were interviewed in a face-to-face session.

We also collected detailed data on the farm household inoculant usage, capital assets, participation in nonfarm income generation activities and livestock value, in addition to socio-demographic and farm characteristics. Table 3.1 presents definition and descriptive statistics of the variables used in the analysis.

Table 3. 1 Descriptive Statistics

Variables	Definition and Measurement	Mean(SD)
Outcome variables		
Yield	Soybean yield per hectare (kg/ha)	829.64 (888.24)
Farm Net Returns	Gross revenue less variable cost (GHC/ha)	840.26 (762.11)
Decision variables		
Aware	Farmer is aware of inoculant = 1; Otherwise = 0	0.84 (0.37)
Acknow	Farmer acquire knowledge on inoculant = 1; Otherwise = 0	0.66 (0.47)
Tryout	Farmer first use of inoculant = 1; Otherwise = 0	0.32 (0.47)
Adopt	Farmer second use of inoculant = 1; Otherwise = 0	0.265 (0.44)
Cont-Adopt	Farmer use inoculant at least for the third time = 1; Otherwise = 0	0.26 (0.44)
Control variables		
Gender	Male = 1; Female = 0	0.71 (0.46)
Age	Number of years	41.56 (13.32)
HHize	Number of people	5.78 (3.05)
Edu	Years of schooling	2.79 (4.69)
Farmsize	Number of hectares	5.05 (4.37)
Agrochem	Amount of active ingredient in gram used per hectare	4.00 (7.19)
Agrochemcost	Total cost of agrochemicals used per hectare (GHC)	57.67 (81.83)
Labor	Person's day worked per hectare	7.81 (24.23)
Laborcost	Total cost of person's day worked per hectare (GHC)	102.06 (155.36)
Extcont	At least one prior extension visit before inoculant = 1; Otherwise = 0	0.54 (0.50)
Credit	Credit constrain = 0; Otherwise = 1	0.83

Variables	Definition and Measurement	Mean(SD)
		(0.38)
District fixed effects		
WCZ	District is in the Western Corridor Zone = 1; Eastern Corridor Zone = 0	0.57 (0.50)
Measurement variables		
lnendwt	*Log* monetary value of household capital asset endowment in (GHC)	7.27 (1.79)
Asset_index	Household physical assets index	82.93 (122.59)
Nonfarminco	Farmer engaged in non-farm work = 1; Otherwise = 0	0.63 (0.48)
Livestock	Household livestock value (TLU)	1.18 (2.44)
Plot level fixed effects		
Rainfall	Amount of rainfall in (%)	61.63 (16.24)
Soil	Soil quality (scale 0 -1)	0.623 (0.20)
Instruments		
Elradsig	Electricity and radio signal are in farmer's community = 1, Otherwise = 0	0.95 (0.23)
Comextoff	Presence of extension agent in farmer's community = 1; Otherwise = 0	0.63 (0.49)
Distexttof	Distance to nearest extension office/district capital in (km)	18.86 (23.53)
Minac	Mode of inoculant acquisition: Purchase = -1; Gift = 1 and Not Available = 0	0.26 (0.67)
Unculand	Household have at least 1ha of uncultivated land = 1; Otherwise = 0	0.67 (0.47)
Commarkt	Presence of local market in farmer's community = 1; Otherwise = 0	0.19 (0.39)
Observations (N)		**600**

(Continued from above)

Notes: The table shows the definition, measurement and descriptive statistics of the farm households. With the inoculant technology being new to farmers, we employed a hybrid coding structure of Cooper's et al. (2011) to give it direction for policy relevance. Therefore, farmers who acquire the technology without paying anything is coded as positive (+1), while those who purchased it are coded negative (-1), and none availability as zero (0).

A mean difference comparison in Table 3.A1 in the Appendix, reveals significant differences in socio-economic characteristics between the dissemination program participants and non-participants. In particular, program participants significantly differ in gender, age, previous extension contacts, soil quality conditions, and mode of inoculant acquisition, compared to non-participants. Program participants also appear to have shorter distances to the nearest extension office and have amenities such as electricity and radio signals in their communities. However, it appears program participants operate smaller farms, use less labor, experience lower level of rainfall and live in smaller households, compared to non-participants.

Using recall information from our cross-sectional survey, we constructed a dynamic multi-stage adoption data, which is used for this analysis. In the absence of a longitudinal data, farmers' recall information may be used to approximate the dynamic pattern of the adoption process (Besley and Case, 1993). We asked farmers the year they first heard of the inoculant technology and the year they first used the technology on their own farms. We also conducted an inoculant knowledge test and obtained farmers' inoculant knowledge test scores, a threshold of which we use to proxy for passive information acquisition (i.e. knowledge acquisition) in the adoption process. We took information on farmers' active participation in any field trial/demonstration on the use of the inoculant technology. Farmers who participated in field trial/demonstration are deemed to have tried the technology[16] and, therefore said to have acquired active information. Past studies that looked at adoption as a dynamic process failed to distinguish between the role play by active information acquisition and passive information acquisition. Intuitively, each of these modes of information acquisition may generate different learning outcomes and impacts on the adoption process (Feder and Slade, 1984). Exploiting farmers' repeated inoculant usage history and time differentials among farmers in our data, we constructed five (5) ordered nodes of farmers' sequential adoption decisions[17], based on the synthetic cohort assumption (SCA)[18].

Table 3.2 shows the sub-samples and characteristics of farmers at each cohort across the various stages of inoculant adoption. About 84% farmers are at awareness stage, 66% at knowledge acquisition stage, 32% at the trial stage, 27% and 26% at adoption and continued adoption stages, respectively.

16 Farmers who use the inoculant only once is also considered as trial even without participation in field demonstration exercise.
17 See the farmers' adoption decision tree in Appendix A.1.
18 The SCA is a standard practice in the dynamic discrete-choice literature (Heckman *et al*., 2016; 2018).

Table 3. 2 Comparison of Farmer Characteristics by Adoption Stages

Variables	Aware Mean(SE)	Acknow Mean(SE)	Tryout Mean(SE)	Adopt Mean(SE)	Cont-Adopt Mean(SE)
Yield	0.33***	0.04	0.17**	0.30***	0.40***
	(0.11)	(0.08)	(0.09)	(0.09)	(0.09)
Farm Net Return	0.12	-0.05	-0.14*	-0.15*	0.04
	(0.01)	(0.08)	(0.08)	(0.08)	(0.08)
Gender (Male=1)	-0.03	0.10	0.06	0.06	-0.10**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Age	2.33	3.05***	1.19	1.28	3.51***
	(1.48)	(1.14)	(1.17)	7(1.23)	(1.24)
HHSize	-0.38	-0.16	-0.46*	-0.19	0.58*
	(0.34)	(0.26)	(0.27)	(0.28)	*(0.28)
Edu	-0.01	0.03	0.05	0.08*	-0.03
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
Farmsize	0.004	-0.42	-0.66*	-0.61	0.04
	(0.49)	(0.38)	(0.38)	(0.40)	(0.41)
Agrochem	0.07	-0.57	-0.75	-0.87	-0.16
	(0.80)	(0.62)	(0.63)	(0.66)	(0.67)
Agrochemcost	-8.14	-5.33	-3.75	-7.49	-1.03
	(9.11)	(7.06)	(7.20)	(7.57)	(7.65)
Labor	-1.81	-3.12	1.00	1.92	-0.88
	(2.70)	(2.09)	(2.13)	(2.24)	(2.27)
Laborcost	-6.03	-22.72*	8.79	12.34	-3.57
	(17.31)	(13.38)	(13.66)	(14.36)	(14.53)
Extcont	0.62***	0.80***	0.18***	0.08*	0.19***
	(0.05)	(0.03)	(0.04)	(0.05)	(0.05)
Credit	-0.07	-0.08***	-0.02	-0.02	-0.04
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Rainfall	-3.26*	-2.45*	0.40	0.52	-1.50
	(1.81)	(1.40)	(1.43)	(1.50)	(1.52)
Soil	0.02	0.02	0.03	0.03	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
WCZ	-0.09*	-0.02	0.06	0.04	0.03
	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)
Comextoff	-0.12**	-0.02	0.06	0.06	-0.002
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Distextoff	-6.46**	-4.38**	-6.82***	-8.16***	-5.24**
	(2.79)	(2.16)	(2.19)	(2.30)	(2.34)
Elradsig	-0.02	0.01	-0.01	-0.01	0.004
	(0.03)	(0.00)	(0.02)	(0.02)	(0.02)
Commarkt	-0.01	-0.02	-0.08***	-0.08**	0.05
	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)
Minac	0.31***	0.14***	0.46***	0.58***	-0.32***
	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)
Unculand	-0.07	-0.04	-0.08*	-0.08*	-0.06
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Asset_index	15.46	-2.87	6.14	4.89	7.46
	(13.65)	(10.59)	(10.78)	(11.35)	(11.46)
Nonfarminco	-0.03	0.01	0.03	0.07	0.04
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
Livestock	0.18	0.19	0.11	0.06	0.14
	(0.27)	(0.21)	(0.21)	(0.23)	(0.23)
Endwt	318.74	369.43	89.70	196.64	2145.04
	(1425.30)	(1104.36)	(1124.92)	(1183.99)	(1193.10)
Sub-Samples	**504**	**397**	**189**	**159**	**154**

*Notes: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. The table shows the differences in mean comparison of farmers at various binary decision nodes (e.g. Aware vs Unaware, Acquire knowledge vs No-Knowledge, Tryout vs No-Tryout, Adopt vs Non-Adopt, Continued-Adoption vs Discontinued-Adoption).*

Farmers at each cohort also appear to differ significantly in their observed characteristics.

Figure 3.1 shows the diffusion and adoption curves of the inoculant from 2014 to 2018, the self-reporting period covered in the survey. As seen in Figure 3.1, no farmer in our sample either heard or used the inoculant technology in 2014. It appears the dissemination program intensified in 2015 and peaked in 2016, when many farmers became aware of the technology. Within this period, adoption was slow until 2017, when most farmers begun using the inoculant, an indication that diffusion of the inoculant technology may still be incomplete and farmers may be at different stages in the adoption process, justifying our argument to depart from the classical approach.

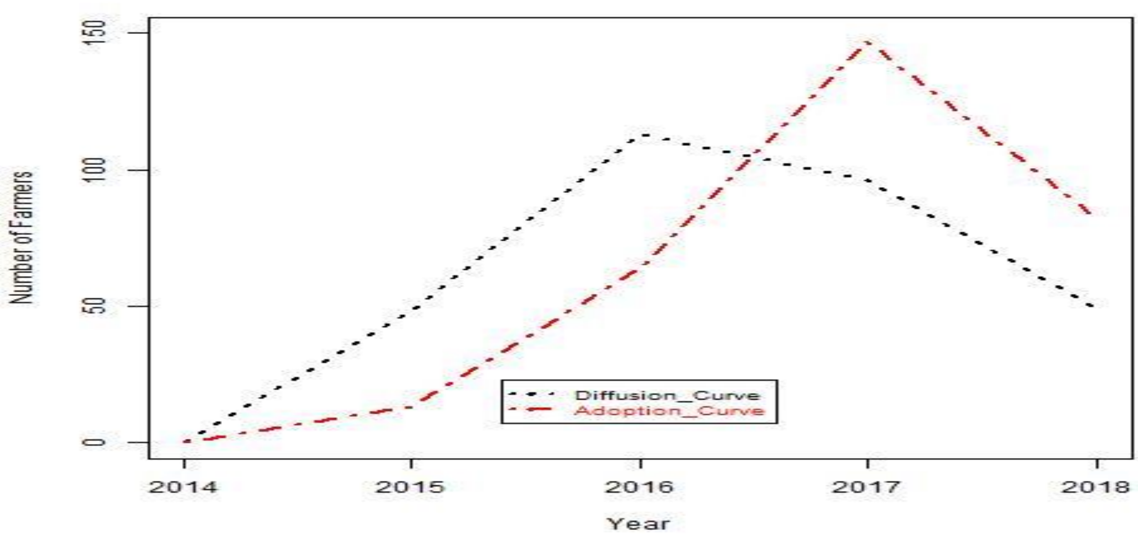


Figure 3. 1 Inoculant Technology Diffusion and Adoption in Northern region, 2014 – 2018.

3.7 Empirical Results

3.7.1 Determinants of Adoption Transition Decisions

Table 3.3 presents the results on factors that determine farmers' decision to transit from one adoption state to the other. The table contains estimates from two generalized continuation ratio models with a probit link (Model 1 and 2). Note that the continuation ratio model, unlike proportional odd models, estimates the conditional probability of being above a particular adoption state given that a farmer has attained that particular adoption state (Liu and Bai, 2019; Bauldry *et al.*, 2018; Fullerton and Xu, 2016). Model 1 assumes that farmers and adoption states are homogenous in characteristics and in benefits across states, respectively (implying the parallel line/proportional-odd assumption). As such, model 1 constraint coefficients across all transitions to be equal. In model 2, we relax the parallel line assumption and allow farmer characteristics and adoption states to differ due to heterogeneity that exist in farmer characteristics and benefits accruing to farmers at different adoption states. The specification in model 2 is important because when farmers make sequential adoption decision, but is misspecified as a dichotomous decision, this can lead to serious statistical bias and inconsistent estimates (Buis, 2017; Williams, 2016). A log-likelihood ratio test (reported below in the last row of table 3) between the two models shows that model 2 is a better specification of the farmers' adoption decision-making process, compared to model 1. We therefore restrict the discussion of our results to model 2 estimates, since that is more consistently estimated.

Before delving into a discussion of the individual predictors, we first comment on the threshold-crossing index describing the adoption transition behavior of farmers, as captured in equation (6) of the empirical specification and the average transitional probability. We report estimates of the threshold indices and the average transitional probabilities in the lower part of Table 3.3. As shown in the Table, the threshold estimates in model 1 are positive and significantly different from zero (at 5% and 1% level, respectively) across all the adoption states, suggesting that adoption states are heterogeneous and farmers move from lower benefits adoption states to higher benefits states.

Table 3. 3 Determinants of Adoption States Transition Decision

Variables	All States	Acknow	Tryout	Adopt	Cont-Adopt
	Model 1	**Model 2**	**Model 2**	**Model 2**	**Model 2**
	Coeffs. (S.E)	**Coeffs. (S.E)**	**Coeffs. (S.E)**	**Coeffs. (S.E)**	**Coeffs. (S.E)**
Gender (Male=1)	-0.14	-0.37	-0.16	0.08	-0.60**
	(0.10)	(0.23)	(0.17)	(0.18)	(0.22)
Age	0.04**	0.09**	0.06**	0.03	-0.05
	(0.02)	(0.04)	(0.03)	(0.03)	(0.04)
Age^2	-3-e4*	-0.001	-0.001**	-3-e4	0.001
	(2-e4)	(0.001)	(3-e4)	(3-e4)	(0.001)
HHSize	0.01	-0.01	0.03	0.002	-0.05
	(0.01)	(0.03)	(0.02)	(0.03)	(0.05)
Edu	0.11	0.39*	0.30*	-0.04	-0.53**
	(0.09)	(0.2)	(0.17)	(0.17)	(0.28)
Farmsize	-0.01	-0.02	-0.03	-0.02	0.03
	(0.02)	(0.04)	(0.03)	(0.04)	(0.05)
Agrochem	0.002	0.01	0.01	0.003	-0.09
	(0.01)	(0.02)	(0.03)	(0.03)	(0.06)
Agrochemcost	-0.001	-0.001	-0.003	7-e6	0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.01)
Labor	0.01	0.02**	0.01	0.01	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Laborcost	-0.001	-0.003*	-0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Extcont	0.98***	2.53***	0.54***	0.94***	1.35***
	(0.09)	(0.29)	(0.15)	(0.17)	(0.38)
Credit	-0.078	-0.191	-0.001	-0.106	-0.107
	(0.097)	(0.324)	(0.177)	(0.183)	(0.253)
Rainfall	0.001	-0.004	0.01	0.002	-0.01*
	(0.002)	(0.01)	(0.004)	(0.01)	(0.01)
Soil	0.44**	0.78*	0.19	0.24	0.17
	(0.20)	(0.45)	(0.37)	(0.30)	(0.64)
WCZ	0.19**	0.42**	0.09	0.04	0.67***
	(0.08)	(0.22)	(0.15)	(0.16)	(0.23)
Distextof	-0.01***	-0.01	-0.01***	0.01	-0.01
	(0.002)	(0.003)	(0.003)	(0.004)	(0.01)
Comextoff	0.08	0.08	0.11	0.03	-0.32
	(0.08)	(0.20)	(0.14)	(0.16)	(0.25)
Elradsig	0.07	-0.35	0.23	0.01	5.93***
	(0.14)	(0.35)	(0.28)	(0.33)	(0.62)
Minac	0.11*	0.66***	0.42***	-0.07	-0.50***
	(0.06)	(0.13)	(0.08)	(0.08)	(0.12)
Unculand	-0.23***	-0.25	-0.17	-0.22	0.10
	(0.09)	(0.21)	(0.14)	(0.15)	(0.22)
Commarkt	0.05	0.23	0.25	-0.23	0.24
	(0.10)	(0.25)	(0.18)	(0.19)	(0.30)
Thre-index (I)	0.33	1.340	1.68**	1.38	5.35***
	(0.48)	(1.21)	(0.83)	(0.97)	(1.35)
LL	-733.399	-651.463			
Wald Chi^2	182.31***	676.60***			
LR Test $\chi^2(2)$	163.87***				
Trans. Prob.		0.895	0.672	0.916	0.774
		[0.191]	[0.156]	[0.140]	[0.314]
Observ. (N)	536	536			

*Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are robust standard errors, while values in square brackets are standard deviations. The table shows estimates from the generalized continuation-ratio probit model as represented by equation (6) in the empirical specification, which measures the conditional probability* $[Pr(\boldsymbol{I_j} < \boldsymbol{I_{j+1}} | \boldsymbol{X} = x, \boldsymbol{Z} = z, \boldsymbol{\theta} = \bar{\theta}, Q_j = 1)]$ *of a farmer moving from adoption state j to j+1.*

Compared to model 2, the threshold estimates of model 1 are generally downward bias, indicating that agents make sequential adoption decisions. All the threshold indices across the two models are positive. Specifically, the threshold for farmers at the knowledge acquisition state to move to trial state is 1.3, and 1.7 for farmers at trial state to move to adoption state, 1.4 for farmers at adoption state to move to continued adoption. Interestingly, the threshold for farmers at the continued adoption state increases sharply to 5.3, suggesting that farmers' may have high expectations of benefits in order to continue their adoption of the inoculant after field and own trials. Lambrecht *et al.* (2014) in their study of mineral fertilizer adoption in Eastern Congo made similar observation that farmers' expectations of potential returns increase after trials, arguing that such expectations may have negative influence on continued adoption. Intuitively, what this means is that, farmers' perception of gaining an additional unit benefit is very high in arriving at an adoption decision. A finding which is consistent with optimizing behavior of farmers in adoption of new agricultural technologies in the literature (see Abdulai and Huffman, 2005). Again the fact that, the threshold index is monotonic across adoption states indicates heterogeneity in state-specific marginal benefits, a phenomenon that is also consistent with sorting behavior among agents (Bui, 2017; Lindeboom and van Doorslaer, 2004). To the extent that agents sort on gains, implies that farmers' adoption decision is sequential, as captured in our dynamic specification, rather than dichotomous, as often assumed in classical adoption models (see Buis, 2017; Mare, 2006; 2011).

Table 3.3 also reports the average transition probability at each adoption state. The transition probability measures the chances of agents passing through a particular transition. Intuitively, it implies that, the more agents pass through a particular transition indicates that the differences in benefits are higher between those that pass and those who fail to pass (Buis, 2017). The results show that, on average 90% of farmers at awareness state pass through to knowledge acquisition state and 67% of farmers at knowledge acquisition state pass through to the trial state, meaning that more farmers are exposed to the inoculant technology. The table further reveals that 92% of trial farmers pass to adoption state, and 77% of the farmers at adoption state pass to continued adoption state. Also, because benefits differ between farmers who attain a particular adoption state and those who did not, means, at each stage farmers can learn more about average benefits of the new technology from other farmers. In this way, the probability of more farmers adopting the new technology increases due to learning, as information acquisition and adoption decisions of new agricultural technologies are often jointly determined (Abdulai *et al.,* 2008). The high average transition probabilities at the knowledge acquisition and trial states underscore the importance of extension information provision and promotion campaigns in the diffusion and adoption process of new agricultural technologies, as echoed in the literature (Takahashi *et al.,* 2020; Anderson and Feder, 2007).

We now turn our attention to the individual predictors. In Table 3.3, a positive coefficient of a predictor is interpreted as the conditional probability of being at a particular adoption state and moving beyond to a higher state where margins of benefits are perceived to be greater, while the reverse is true for a negative coefficient (Liu and Bai, 2019; Bauldry *et al.,* 2018; Buis, 2017). The results in Table 3.3 show that the coefficient of prior extension contact (*Extcont*) is positive in all adoption states (significant at 1% level), suggesting that farmers who have access to adequate extension services are more likely to be aware and knowledgeable in the inoculant technology, compared to farmers with less previous extension contacts. A finding that is consistent with the argument that knowledge-intensive agricultural technologies require skilled extension staff to facilitate the adoption process (Takahashi *et al.,* 2020; Issahaku and Abdulai, 2019).

Table 3.3 shows that mode of inoculant acquisition (*Minac*) plays a role in farmers' adoption decisions. The results reveal that farmers who acquire the inoculant as a free gift are more likely to move from awareness state through to trial state but are less likely to get to adoption and continued adoption states. Indicating that, free distribution of new divisible technologies to farmers during dissemination programs have high probability in creating awareness, getting farmers to acquire knowledge and trying the technology, but may not lead to adoption and continued adoption. Conversely, farmers whose mode of acquisition is by purchase have high probability of getting to continued adoption, compared to farmers who had free inoculant or have no access to inoculant supply, indicating that input markets to ensure constant supply of the inoculant to farmers may be indispensable in getting farmers into adoption and continued adoption states. This finding agrees with Shiferaw *et al.* (2015), who found input supply constraints to be responsible for non-adoption of improved groundnut variety among adoption-willing farmers in Uganda.

Table 3.3 shows that farmer location has positive effects across adoption transition states. The results reveal that farmers located in the western corridor zone (*WCZ*), which is closer to the regional capital, have high probability of moving beyond knowledge acquisition state to continued adoption state, compared to farmers in the eastern corridor zone (the base category). The results further show that decrease in distance (*Distextof*) to the nearest extension office, increases the likelihood of farmers moving beyond trial and adoption states to continued adoption state. This suggests that farmers who are close to the district or the regional capital may have better infrastructure and access to information, compared to their counterparts who may be remotely located. A finding that is in line with Suri's (2011) suggestion that removing supply and infrastructure constraints may be cost-effective way to facilitate adoption of improved agricultural technologies among farmers.

Table 3.3 also shows that soil quality plays an important role in farmers' adoption decisions. Because the inoculant technology is an organic product with huge potential of maintaining good soil structure and fertility (van Heerwaarden *et al.*, 2018), farmers who perceived the quality of soil in their farm plots to be fertile or good are more likely (significant at 1% level) to move beyond inoculant knowledge acquisition state to adoption and continued adoption states[19]. The coefficient of rainfall at the continued adoption state is negative (significant at 10% level), indicating that inadequate rainfall may negatively influence farmers' continued adoption decision, a finding similar to that of Shahzad and Abdulai (2020), who found average daily rainfall to have negative influence on farmers' adoption decision of climate-smart farm practices in Pakistan.

The results in Table 3.3 also highlight the importance of farmers' socioeconomic characteristics on their adoption decisions. The results show that the coefficient representing age is positive and significant in all adoption states, except at the continued adoption state, while the squared term have negative and statistically significant coefficient across all adoption states, but positive at the continued adoption state. This finding suggests that at younger ages, an increase in age increases the probability of adoption, with the maximum effect occurring at approximately 46 years, while at older ages, the probability of adoption decreases with increasing age. However, once adoption takes place, older farmers who are more experienced are likely to benefit from the new technology more than younger farmers and therefore more likely to sustain their adoption. This finding corroborates Lambrecht *et al.* (2014), who found older and more experienced farmers to be more efficient and better judges of expected returns than less experienced younger farmers, resulting in higher continued adoption rates of mineral fertilizer among older farmers in Eastern Congo. Table 3.3 also shows that education is positive in the transition decision of farmers from awareness to knowledge acquisition and trial states (significant at 10% level respectively), but negative at adoption and continued adoption states (significant at 1% level), suggesting that increasing levels of education increases the probability of learning about the new technology at the early stages in the technology adoption or diffusion process, and declines at later stages after farmers have learnt

[19] Majority of the farmers in our sample were the indigenous land owners and not renters, hence, this observation is consistent with economic theory of owner-operated lands as farmers have the obligation to maintain productivity of their lands into the future.

more about the new technology. The results in Table 3 also reveal that access to at least one hectare of uncultivated (*Unculand*) land is important in the adoption of newly introduced technologies. Farmers without extra land are less likely to try a new technology or adopt immediately, but are more likely to be in continued adoption state once the technology is well diffused and farmers learn from the trials of others. Intuitively, this makes sense as risk averse farmers may be reluctant to commit their only productive lands to the new technology, compared to farmers who have access to extra land available.

3.7.2 Impact on Returns to Inoculant Adoption

In this section, we present results of the estimates of the transition stages on the outcome variables. The impact of inoculant adoption on yields and farm net returns are presented in Tables 3.4 and 3.5, respectively. These results are obtained from the third-stage estimates of equation (13) (i.e., $f_Y(.)$) of our factor structural model[20]. The estimated impacts represent the observed cases that the farmer makes a transition to a particular stage and the counterfactual case that the farmer did not make the transition. Hence, the results are the average effects on yields and farm net returns at each adoption state that the farmer attained. For brevity, we focus the discussion on the impact on yields (Table 3.4) and extend it to the farm net returns (Table 3.5). Both Tables 3.4 and 3.5 show positive and statistically significant impact of inoculant adoption on yields and farm net returns, respectively, across all adoption states. The results in Table 3.4 reveal that, on average, the yields for farmers who used the inoculant for the first season (i.e. at the trial state) was 108kg/ha of soybeans, with the yields increasing to 151kg/ha and 191kg/ha for farmers who used it for at least two seasons (i.e. at the adoption state) and farmers who used it for at least three seasons (i.e. at the continued adoption state), respectively. We observe a pattern of marginal incremental benefits as

[20] We report the first-stage, the second-stage and the third-stage estimates in the appendix (see Tables 3A.1&3A.2 in Appendix A.2&A.3), they do not contribute much to the current discussion. Note that the outcome variables are log values.

farmers move from one adoption state to the other, suggesting that farmers may still be learning about the inoculant technology and the benefits are heterogeneous, depending on the adoption state of the farmer.

Table 3. 4 Impact on Yield (kg/ha)

Treatment Effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE†	0.66***	0.94***	1.35***	1.73***
	(0.29)	(0.03)	(0.04)	(0.07)
ATE	0.73***	1.08***	1.51***	1.91***
	(0.03)	(0.03)	(0.05)	(0.08)
ATT	0.75***	1.06***	1.45***	2.08***
	(0.03)	(0.04)	(0.06)	(0.11)
ATUT	0.34***	1.11***	2.06***	1.70***
	(0.13)	(0.06)	(0.13)	(0.13)
AMTE†	1.58***	1.60***	1.57***	1.69***
	(0.07)	(0.08)	(0.08)	(0.09)
AMTE	1.96***	1.87***	1.77***	2.09***
	(0.07)	(0.09)	(0.10)	(0.13)

*Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. The Table show the estimates of the treatment effects (without continuation values) of the adoption process on soybeans net returns. ATE is the average treatment effects for farmers at each adoption state;* $ATE^{\dagger}$ *is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting to a higher level adoption state or not.* $AMTE^{\dagger}$ *is the average marginal effects for the full population of farmers who are indifferent between transiting to a higher level adoption state or not.*

Table 3. 5 Impact on Farm Net Returns (GHC/ha)

Treatment Effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE†	0.43***	0.46***	0.48***	0.51***
	(0.03)	(0.03)	(0.04)	(0.05)
ATE	0.50***	0.56***	0.51***	0.49***
	(0.02)	(0.03)	(0.04)	(0.04)
ATT	0.54***	0.51***	0.47***	0.62***
	(0.02)	(0.03)	(0.04)	(0.06)
ATUT	0.02	0.67***	0.85***	0.34***
	(0.05)	(0.04)	(0.13)	(0.06)
AMTE†	0.48***	0.49***	0.49***	0.58***
	(0.05)	(0.06)	(0.06)	(0.07)
AMTE	0.60***	0.50***	0.45***	0.67***
	(0.04)	(0.05)	(0.05)	(0.07)

*Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. The Table show the estimates of the treatment effects (without continuation values) of the adoption process on soybeans net returns. ATE is the average treatment effects for farmers at each adoption state;* $ATE^{\dagger}$ *is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting to a higher level adoption state or not.* $AMTE^{\dagger}$ *is the average marginal effects for the full population of farmers who are indifferent between transiting to a higher level adoption state or not.*

This finding is consistent with van Heerwaarden *et al.* (2018) who found average yields to be in the range of 102 – 180kg/ha in an on-farm experimental trials of the inoculant across ten countries in sub-Sahara Africa (with Ghana included). On the other hand, average farm net returns for farmers at the trials state is 56GHC/ha, 51GHC/ha at the adoption state and 49GHC/ha at the continued adoption state (see Table 3.5), suggesting that early adopters of the inoculant benefit more in terms of revenue due to marginal increase in their yields in those seasons. This observation is consistent with the literature on diffusion and adoption of new technologies, where early adopters tend to get the greatest returns, thereby triggering the race to high order adoption (e.g. Karshenas and Stoneman, 1993).

Table 3.4 further shows that the average marginal treatment effect (AMTE) for farmers at various margins of indifference deciding whether to make the next transition or remain where they are, in terms of yields, is 187kg/ha for farmers at the trial state, 177kg/ha at the adoption and 209kg/ha at the continued adoption state. It can be observed in Table 3.5 that, with farm net returns, the AMTE is 50GHC/ha for farmers at the trial state, 45GHC at the adoption state and 67GHC/ha at the continued adoption state. The AMTE estimates for both outcome measures are positive across all adoption states and significant at the 1% level, suggesting that farmers with unobserved factors (such as wealth endowment) that increase their ability to make further adoption transitions stand to gain more from such transitions. In other words, farmers who tried the inoculant technology and have the financial ability to continue to use the inoculant stand to benefit more from their continued adoption. We also observe from the results in Tables 3.4 and 3.5 that the impact gap is wider for yields compared to that of farm net returns, which can be attributed to differences in prices faced by farmers (both input and output prices), timing and place of sales.

Figures 3.2 and 3.3 present the distributions of impacts at the sub-population level of farmers at each adoption state. We find that farmers who are observed to make a transition at each adoption state (that is, the treated case – TT) obtain higher yields and farm net returns, compared to if the same farmers did not make the transition (that is, the untreated case –TUT). The results reveal that the impact distributions at the sub-population means for both outcomes are positive and above the sub-population means at zero. Examining the pattern of the impact distributions at the sub-population means reveal an interesting finding. In particular, we observe positive pattern of selection on gains (i.e. TT>ATE>TUT) at the knowledge and continued adoption states, and negative or reverse pattern of selection (i.e. TUT>ATE>TT) at the trial and adoption states[21]. These findings suggest two heterogeneous group of farmers. One group that would have benefited more from further investment in the inoculant adoption, but, due to low levels of unobserved factors (such as wealth endowment) are unable to make transitions beyond trial and adoption states (i.e.

[21] *Selection on gains* in this literature refers to a case where farmers who have higher or lower values of unobserved ability (i.e., unobserved factors such as wealth endowment that poses a resistance to a farmer to make a transition) to transit obtain higher than average (positive selection on gain) or lower than average (negative or reserve selection on gain) net benefits from making an adoption transition.

the negative selection on gains group). The second group (i.e. the positive selection on gains group) with high level of unobserved factors, and low benefits from the inoculant adoption which suggests that the inoculant technology may be more beneficial to poor farmers. These findings imply that, there are still unrealized potential gains to be made from the inoculant dissemination program, suggesting that policies aimed at promoting trial and adoption of the technology among farmers may still be necessary to achieve the desired impact.

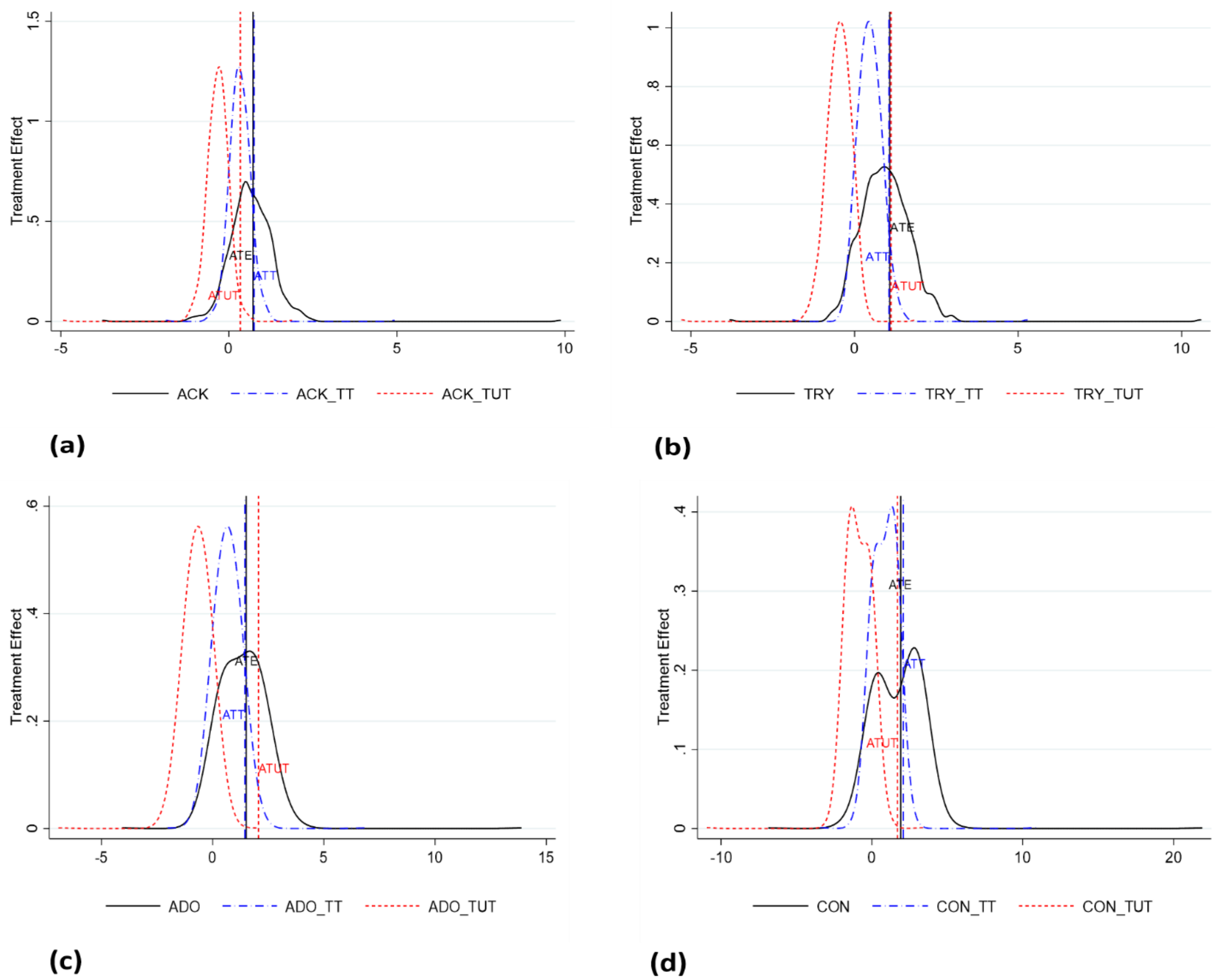


Figure 3. 2 Treatment Effect Distributions at each Adoption Transition (Sub-population Level) – Yield (Kg/ha)

Note: **ACK**=Knowledge Acquisition State; **TRY**=Trial State; **ADO**=Adoption State; **CON**=Continued Adoption State; **TT** represents Treated State; **TUT** represents Untreated State. **ATE**=Average Treatment Effect Curve; **ATT**=Average Treatment Effect on the Treated Curve; **ATUT**=Average Treatment Effect on the Untreated Curve.

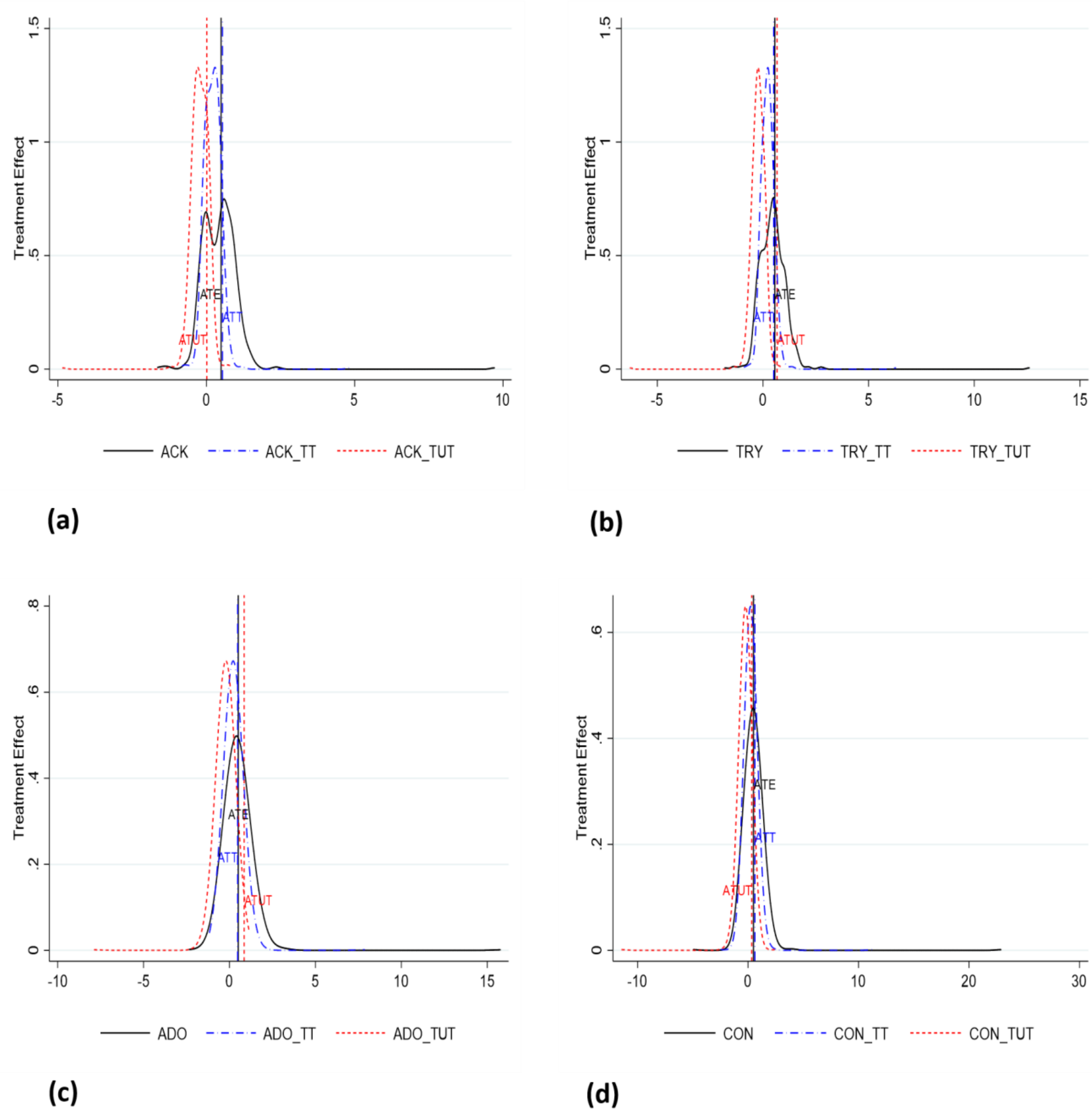


Figure 3. 3 Treatment Effect Distributions at each Adoption Transition (Sub-population Level) – Net Returns (GHC/ha).

Note: ACK=Knowledge Acquisition State; **TRY**=Trial State; **ADO**=Adoption State; **CON**=Continued Adoption State; **TT** represents Treated State; **TUT** represents Untreated State. **ATE**=Average Treatment Effect Curve; **ATT**=Average Treatment Effect on the Treated Curve; **ATUT**=Average Treatment Effect on the Untreated Curve.

3.7.3 Long-term Impact of Returns to Inoculant Adoption

In this section, we present results derived from the estimates of equation (16) in the empirical specification in Tables 3.6 and 3.7 for yields and farm net returns respectively. The results represent the long-term impact of technology adoption, which approximate *ex-post* valuation of opportunities that farmers' current adoption decisions open up for them. As noted by Besley and Case (1993), current adoption choices have future consequences and have to be taken into consideration when analyzing farmers' adoption choices. Intuitively, farmers who try a technology are more likely to adopt, and those who adopt conditional on the benefits, are more likely to sustain their adoption. This valuation of the dynamic impact of opportunities constitutes the long-term forecast of benefits informing farmers' adoption decisions, but is often overlooked in traditional technology adoption impact studies.

The results in Tables 3.6 and 3.7 show similar patterns in the distribution of benefits, similar to those computed without the inclusion of the continuation values presented in Tables 3.4 and 3.5. All the estimated coefficients are positive and statistically significant at 1% level, indicating that farmers' valuation of expected long-term benefits at each adoption state is important in the adoption decisions they make. The estimates of ATE presented in row 2 of Table 3.6, suggest that the average total effect on yields for farmers at the trial state is 204kg/ha. Similarly, the effects for farmers at the adoption and continued adoption states are 298kg/ha and 329kg/ha, respectively. In terms of farm net returns, presented in Table 3.7, we find average total effect to be 91GHC/ha for farmers at the trial state, 85GH/ha at adoption state and 78GHC/ha at continued adoption state.

Table 3. 6 Impact on Yield Estimates with Continuation Values (kg/ha)

Treatment Effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
$ATE^{\dagger}$	1.09^{***}	1.76^{***}	2.55^{***}	2.93^{***}
	(0.04)	(0.07)	(0.10)	(0.13)
ATE	1.14^{***}	2.04^{***}	2.98^{***}	3.29^{***}
	(0.04)	(0.06)	(0.11)	(0.14)
ATT	1.17^{***}	2.02^{***}	2.83^{***}	3.57^{***}
	(0.04)	(0.07)	(0.11)	(0.19)
ATUT	0.78^{***}	2.09^{***}	4.33^{***}	2.95^{***}
	(0.19)	(0.10)	(0.20)	(0.13)
$AMTE^{\dagger}$	6.64^{***}	7.65^{***}	7.68^{***}	7.55^{***}
	(0.40)	(0.36)	(0.39)	(0.40)
AMTE	8.19^{***}	9.01^{***}	8.61^{***}	8.80^{***}
	(0.35)	(0.36)	(0.39)	(0.64)

*Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. The Table show the estimates of the total dynamic treatment effects (Including continuation values) of the adoption process on soybean yields. ATE is the average treatment effects for farmers at each adoption state;* $ATE^{\dagger}$ *is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting to a higher level adoption state or not.* $AMTE^{\dagger}$ *is the average marginal effects for the full population of farmers who are indifferent between transiting to a higher level adoption state or not.*

Table 3. 7 Impact on Farm Net Returns Estimates with Continuation Values (GHC/ha)

Treatment Effects	Acknow (1)	Tryout (2)	Adopt (3)	Cont-Adopt (4)
ATE*	0.66***	0.71***	0.76***	0.79***
	(0.05)	(0.06)	(0.08)	(0.10)
ATE	0.77***	0.91***	0.85***	0.78***
	(0.04)	(0.04)	(0.07)	(0.08)
ATT	0.86***	0.82***	0.76***	0.99***
	(0.04)	(0.05)	(0.07)	(0.01)
ATUT	-0.14	1.09***	1.67***	0.52***
	(0.19)	(0.07)	(0.21)	(0.11)
AMTE*	2.70***	2.71***	2.66***	3.16***
	(0.32)	(0.35)	(0.35)	(0.40)
AMTE	3.56***	2.98***	2.59***	3.95***
	(0.22)	(0.27)	(0.27)	(0.39)

*Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. The Table show the estimates of the total dynamic treatment effects (Including continuation values) of the adoption process on soybeans net returns. ATE is the average treatment effects for farmers at each adoption state;* $ATE^{\dagger}$ *is the average treatment effects for the full population of farmers; ATT is the average treatment effects for farmers who chose to transit to a higher adoption state; ATUT is the average treatment effects for farmers who chose not to transit to a higher adoption state. The average marginal treatment effect (AMTE) is the average effects for farmers at an adoption transition state who are indifferent between transiting to a higher level adoption state or not.* $AMTE^{\dagger}$ *is the average marginal effects for the full population of farmers who are indifferent between transiting to a higher level adoption state or not.*

Tables 3.6 and 3.7 also show that the total AMTE estimates at all adoption states are positive and statistically significant at 1% level. In particular, the results reveal that total AMTE for farmers at the margin of trial is 901kg/ha, 861kg/ha for farmers at the margins of adoption and 880kg/ha for farmers at the margins of continued adoption. These estimates are close to the experimental results of van Heerwaarden *et al.* (2018), who found average total yield of 1343kg/ha obtained by inoculant users in an on-farm experiment in ten countries of sub-Sahara Africa (with Ghana included). A plot of the full distributions of the total treatment effects at both population and sub-population levels reveal similar distributions of impacts[22] and selection on gains pattern among the farmers. The implication of this finding is that, there exists potential long-term benefits from adoption of inoculant technology, as farmers' yields and farm net returns appear to more than

22 See Appendix A.5, A.6 and A.7 for population level and sub-population level distributions, respectively.

double, compared to the short-term benefits. This observation resonates with the benefits stream of organic agricultural inputs that have long-term impacts on improving soil fertility[23].

3.7.4 Robustness Check

The validity of our treatment effects hang on proper identification of the unobserved wealth endowment effect on farmers' transitional ability, as expressed in the factor model in equation (12) of the empirical specification. In the interest of brevity, we discuss the distributions of the unobserved factors as well as the heterogeneity of the factors across each adoption state, but present the results in the appendix, by way of robustness check. Figure 3A.6 presents the mixture of two normal distributions of the unobserved wealth endowment for farmers at each of the adoption state (see Appendix A.8). The results show evidence of sorting into adoption states by unobserved wealth endowment, with this endowment having significant impact on the distributions of farm outcomes. The distributions around the zero mean confirm our findings of the existence of two heterogeneous group of farmers based on selection on gains. That is, the negative and positive selection on gains groups of farmers.

Figure 3A.7 in Appendix A.9 presents the distributions of the unobserved wealth endowments for farmers at each adoption state. We observe that the distributions of the endowment is heterogeneous across each adoption state, indicating that farmers' wealth endowment may play an important role in moving them from one adoption state to the next adoption state.

Finally, Table 3A.3 presents results of exogeneity test for the instrumental variables (IVs) employed as the exclusion restriction variables for identification of farmers' adoption choice decisions at each adoption state as expressed in equation (7) of the empirical specifications. In line with Heckman *et al.* (2018), we employed state dependent instrumental variables to identify each

23 See Appendix A.4 for mean plot of AMTE and ATE compared for both outcomes.

autonomous adoption decision, while controlling for farmer's wealth endowment at each adoption state. We assume that different adoption states are identified by different instruments that are important to that state. As seen in Table 3A.3, the Anderson-Rubin (AR) test statistic of the IVs in both the yields and the farm net returns models are not statistically significant at any conventional level, indicating that the IVs use for the exclusion restriction satisfy the exogeneity requirement and that the instruments do not have direct influence on yields and farm net returns, except through the different states of adoption that they identify.

3.8 Conclusions and Implications

In this study, we address the question of what drives the dynamic pattern of farmers' technology adoption and its diffusion over time or space. Using farm level data of soybean farmers in Ghana, we analyzed technology adoption as a multi-stage dynamic decision problem in an impact evaluation framework. We employed dynamic treatment effects model, a novel procedure, to examine heterogeneity in returns to adoption of newly introduced technologies, focusing on the newly introduced inoculant technology. Our findings reveal new insights into the role of information in farmers' adoption decisions, the distribution of returns in the entire chain of the adoption process, and factors that influence continued adoption, or otherwise, of new agricultural technologies. Consistent with Besley and Case (1993), we find substantial impact heterogeneity at each adoption state, which we contend drive the adoption process. Our results showed that contact to extension agents is key to the adoption process, by influencing knowledge acquisition, adoption and continued adoption. We also found that although free distribution of newly developed divisible agricultural technologies to farmers during dissemination programs increases farmer awareness, knowledge acquisition, trial and take up, it does not guarantee continued adoption as argued by Lambrecht *et al.* (2014). In contrast, we found that the existence of efficient input markets tend to drive the probability of continued adoption. We also observed that farmers who live closer to the distribution centers, had higher probability of continuous adoption of the new technology, a finding that confirms the significance of improving agricultural markets to ensure that farmers gain access to improved varieties. Our impact analysis revealed that the long-term effects are much stronger than the short-term effects, conditional on the markets being able to absorb the excess supply that may result from higher yields. We therefore conclude that the diffusion and continued adoption of the new inoculant technology is contingent on gains from adoption, as well as efficient input and output markets. Finally, the fact that our findings reveal the existence of untapped potential gains from some stages of adoption, implies that our approach can enable policy-makers identify different sub-population of farmers, who require special attention during extension program implementation, to be targeted in order to maximize the impact. The extension policy targeting approach will save resources and expand the outreach to benefit more farmers, thus increasing productivity at least cost.

References

Abadi Ghadim, A. K., and Pannell, D. J. (1999). A conceptual framework of adoption of an agricultural innovation. *Agricultural Economics, 21(2), 145–154.*

Abdulai, A., and Huffman, W. E. (2005). The diffusion of new agricultural technologies: the case of crossbred-cow technology in Tanzania. *American Journal of Agricultural Economics, 87(3), 645 – 659.*

Abdulai, A., Monnin, P., and Gerber, J. (2008). Joint estimation of information acquisition and adoption of new technologies under uncertainty. *Journal of International Development, 20, 437 – 451.*

Abdul Mumin, Y., and Abdulai, A. (2021). Social networks, adoption of improved variety and household welfare: Evidence from Ghana. *European Review of Agricultural Economics, 00(00):1 – 32.*

Anderson, J. R., and Feder, G. (2007). Agricultural extension. In R. Evenson & P. Pingali (Eds.), Handbook of agricultural economics (Vol. 3, pp. 2343–2378). Amsterdam: Elsevier.

Bauldry, S. Xu, J., and Fullerton, A. S. (2018). gencrm: A new command for generalized continuation-ratio models. *Stata Journal, 18(4), 924 – 936.*

Benhabib, J., Bisin, A., and Luo, M. (2019). Wealth distribution and social mobility in the US: A quantitative approach. *American Economic Review, 109 (5), 1623–1647.*

Besley, T., and Case, A. (1993). New developments in development: Modelling technology adoption in developing countries. *American Economic Review, 396 – 402.*

Buis, M. (2017). Not all transitions are equal: The relationship between effects on passing steps in a sequential process and effects on the final outcome. *Sociological Methods and Research, 46(3), 649 – 680.*

Chibeba, M.A., Kyei-Boahen, S., Guimarães, d-F.M., Nogueira, A.M. and Hungria, M. (2018). Feasibility of transference of inoculation-related technologies: A case study of evaluation of soybean rhizobial strains under the agro-climatic conditions of Brazil and Mozambique. *Agriculture, Ecosystems and Environment, 261, 230 – 240.*

Cooper, B., Rose, J., and Crase, L. (2011). Does anybody like water restrictions? Some observations in australian urban communities. *Australian Journal of Agricultural and Resource Economics, 56, 61-81.*

Cornelissen, T., Dustmann, C., Raute, A., and Schonberg, U. (2018). Who benefits from universal child care? Estimating marginal returns to early child care attendance. *Journal of Political Economy, 126(6), 2356 – 2409.*

Fagereng, A., Guiso, L., Malacrino, D., and Pistaferri, L. (2020). Heterogeneity and persistence in returns to wealth. *Econometrica, 88(1), 115 – 170.*

Feder G., and Slade, R. (1984). The acquisition of information and the adoption of new technology. *American Journal of Agricultural Economics, 66(2), 312–320.*

Feder, G., Just, R. E., and Zilberman, D. (1985). Adoption of agricultural innovations in developing-countries – A survey. *Economic Development and Cultural Change, 33(2), 255–298.*

Foyer, C. H., Siddique, K. H. M., Tai, A. P. K., Anders, S., Fodor, N., Wong, F-L., Ludidi, N., Chapman, M. A., Ferguson, B. J., Considine, M. J., Zabel, F., Prasad, V. P. V., Varshney, R. K., Nguyen, H. T., and Lam, H-M. (2018). Modelling Predicts that Soybean is Poised to Dominate Crop Production across Africa. *Plant Cell Environment, 42:373–385*.

Fullerton, A. S., and Xu, J. (2016). Ordered regression models: Parallel, partial, and non-parallel alternatives. Boca Raton, FL: Chapman and Hall/CRC.

Gabaix, X., Lasry, J.-M., Lions, P.-L., and Moll, B. (2016). The dynamics of inequality. *Econometrica, 84(6), 2071–2111.*

Ghana Statistical Service. (2018). *Ghana living standards survey round 7: Poverty trends in Ghana 2005 – 2017*. Ghana Statistical Service, Accra, Ghana.

Giller, K.E. (2001). Nitrogen fixation in tropical cropping systems. Second edition. CAB International, Wallingford, UK.

Heckman, J. J., Humphries, J. E., and Veramendi, G. (2018). Returns to education: The causal effects of education on earnings, health and smoking. *Journal of Political Economy, 126(S1), S197 – S246.*

Heckman, J. J., Humphries, J. E., and Veramendi, G. (2016). Dynamic treatment effects. *Journal of Econometrics, 191, 276 – 292.*

Issahaku, G. and Abdulai, A. (2019). Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. *Australian Journal of agricultural and Resource Economics, 64, 396 – 420.*

Karshenas, M. and Stoneman, P. L. (1993). Rank, stock, order and epidemic effects in the diffusion of new process technologies: An empirical model. *RAND Journal of Economics, 24(4), 503 – 528.*

Kleemann, L., and Abdulai, A. (2013). Organic certification, agro-ecological practices and return on investment: Evidence from Pineapple producers in Ghana. *Ecological economics*, *93:330 – 341*.

Kim, K., and Bevis, L. (2019). Soil fertility and poverty in developing countries. *Choices, 34(2), 1– 8*.

Lambrecht, I., Vanlauwe, B., Merckx, R., and Maertens, M. (2014). Understanding the process of agricultural technology adoption: Mineral fertilizer in Eastern DR Congo. *World Development, 59, 132–146.*

Lindeboom, M., and van Doorslaer, E. (2004). Cut-point shift and index shift in self-reported health. *Journal of Health Economics, 23(6), 1083–1099.*

Lindner, R. K., Pardey, P. G., and Jarrett, F. G. (1982). Distance to information source and the time lag to early adoption of trace element fertilizers. *Australian Journal of Agricultural Economics, 26(2), 98–113.*

Liu, X., and Bai, H. (2019). Forward and backward continuation ratio models for ordinal response variables. *Journal Modern Applied Statistical Methods, 18(2), eP3043. DOI: 10.22237/jmasm/1604190180.*

Lupwayi, N.Z., Olsen, P.E., Sande, E.S., Keyser, H.H., Collins, M.M., Singleton, P.W., and Rice, W.A. (2000). Inoculant Quality and its Evaluation. *Field Crops Research 65:259-270.*

Macours, K. (2019). Farmers' demand and the traits and diffusion of agricultural innovations in developing countries. *Annual Review of Resource Economics, 11, 483–499.*

Mare, R. D. (2006). Response: Statistical models of educational stratification – Hauser and Andrew's Models for school transitions. *Sociological Methodology, 36, 27 - 37.*

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

Mare, R. D. (2011). Introduction to symposium on unmeasured heterogeneity in school transition models. *Research in Social Stratification and Mobility, 29, 239-45.*

Quandt, R. E. (1972). A new approach to estimating switching regressions. *Journal of the American Statistical Association 67, 306–310.*

Shahzad, M. F., and Abdulai, A. (2020). The heterogeneous effects of adoption of climate-smart agriculture on household welfare in Pakistan. *Applied Economics, 53, 1013 - 1038.*

Sheahan, M., and Barrett, C. B. (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy, 67, 12–25.*

Shiferaw, B., Kebede, T., Kassie, M., and Fisher, M. (2015). Market imperfections, access to information and technology adoption in Uganda: challenges of overcoming multiple constraints. *Agricultural Economics, 46(4), 475–488.*

Simtowe, F., Asfaw, S., and Abate, T. (2016).Determinants of agricultural technology adoption under partial population awareness: The case of pigeonpea in Malawi. *Agricultural and Food Economics, 4(7), 1 – 21.*

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica, 79(1), 159–209.*

Takahashi, K., Muraoka, R., and Otsuka, K. (2020). Technology adoption, impact, and extension in developing countries: A Review of Recent Literature. *Agricultural Economics, 51, 31 – 45.*

Teklewold, H., Kassie, M., Shiferaw, B., and Köhlin, G. (2013). Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: Impacts on household income, agrochemical use and demand for labor. *Ecological Economics 93, 85–93.*

van Heerwaarden, J., Baijukya, F., Kyei-Boahen, S., Adjei-Nsiah, S., Ebanyat, P., Kamai, N., Wolde-meskel, E., Kanampiu, F., Vanlauwe, B., and Giller, K. (2018). Soyabean response to rhizobium inoculation across sub-Saharan Africa: Patterns of variation and role of promiscuity. *Agriculture, Ecosystems and Environment, 261, 211 – 218.*

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal, 6, 58–82.*

Williams, R. (2016). Understanding and Interpreting Generalized Ordered Logit Models. *Journal of Mathematical Sociology, 40:7−20.*

Appendix

Table 3A. 1 Comparison of Program Participants and Non-Participants

Variables	**Participants Mean(SE)**	**Non- Participants Mean(SE)**	**Mean Diff (SE)**
Yield	6.28	6.24	0.03
	(0.05)	(0.06)	(0.08)
Farm Net Return	6.313	6.42	-0.10
	(0.05)	(0.05)	(0.07)
Gender	0.74	0.67	0.066^{*}
	(0.02)	(0.03)	(0.04)
Age	42.56	40.39	2.17^{**}
	(0.79)	(0.72)	(1.09)
HHSize	5.57	6.04	-0.47^{**}
	(0.17)	(0.19)	(0.25)
Edu	0.35	0.36	-0.01
	(0.03)	(0.03)	(0.04)
Farmsize	4.77	5.37	-0.59^{*}
	(0.22)	(0.29)	(0.36)
Agrochem	3.67	4.40	-0.72
	(0.33)	(0.51)	(0.59)
Agrochemcost	56.06	59.57	-3.51
	(2.72)	(6.55)	(6.71)
Labor	6.25	9.65	-3.39^{*}
	(0.93)	(1.86)	(1.98)
Laborcos	93.71	111.94	-18.23
	(6.96)	(11.12)	(12.72)
Extcont	1.94	0.70	1.25^{***}
	(0.06)	(0.07)	(0.09)
Credit	0.78	0.89	-0.11^{***}
	(0.02)	(0.02)	(0.03)
Rain	60.43	63.06	-2.62^{**}
	(0.92)	(0.94)	(1.33)
Newsoil	0.65	0.60	0.05^{***}
	(0.01)	(0.01)	(0.02)
WCZ	0.55	0.59	-0.05
	(0.03)	(0.03)	(0.04)
Comextoff	0.60	0.66	-0.06
	(0.03)	(0.03)	(0.04)
Distextoff	16.84	21.26	-4.42^{**}
	(1.27)	(1.65)	(2.05)
Elradsig	0.96	0.92	0.04^{**}
	(0.01)	(0.02)	(0.02)
Commarkt	0.17	0.21	-0.04
	(0.02)	(0.03)	(0.03)
Minac	0.31	0.21	0.10^{*}
	(0.04)	(0.04)	(0.05)
Unculand	0.66	0.68	-0.03
	(0.03)	(0.03)	(0.04)
Asset_index	85.91	79.42	6.49
	(6.09)	(8.22)	(10.05)
Nonfarminco	0.63	0.64	-0.01
	(0.03)	(0.03)	(0.04)
Livestock	1.3	1.04	0.27
	1(0.15)	(0.13)	(0.20)
Endwt	5963.89	5325.29	638.60
	(768.67)	(688.29)	(1048.41)

No. of Observations	**325**	**275**

*Notes: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. The table shows the differences in mean comparison of farmers who participated in the inoculant dissemination program against farmers who did not participate.*

Appendix A.1

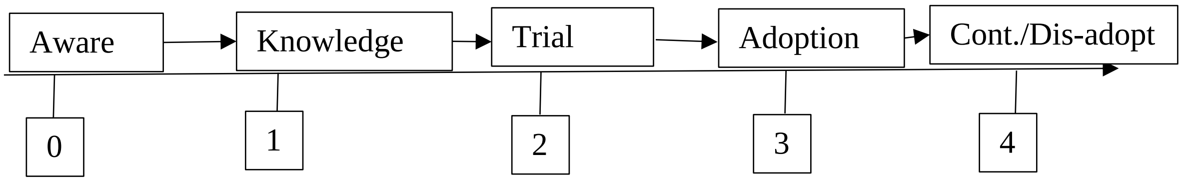


Figure 3A. 1 Farmers' Adoption Decision Tree. The figure illustrates a conceptualized farmers' sequential adoption decision problem analyze in this study.

In the first stage, farmers normally become aware of the technology and begin searching for information on it. The second stage is where farmers collect further information on expected gains and technical information on how to use the technology, thus, becoming knowledgeable in the technology. In the third stage, farmers tryout the technology and/or observe trials of other farmers to evaluate the technology's performance. The fourth stage is where farmers make the decision to adopt or not to adopt, while the final stage describe farmers' continued adoption or dis-adoption decision of the technology (see Simtowe *et al.,* 2016; Lambrecht *et al.*, 2014).

Appendix A.2

Table 3A. 2 Estimates of Choice Decisions and Yield (*ln*Kg/ha).

	Acknow			Tryout			Adopt			Cont-Adopt		
Variables	**Choice**	**Acknow**	**No-Acknow**	**Choice**	**Trial**	**No-Trial**	**Choice**	**Adopt**	**No-Adopt**	**Choice**	**Cont-Adopt**	**Dis-Adopt**
Const.	-1.302	4.551^{***}	4.050^{***}	-1.153	3.994^{***}	4.371^{***}	-1.995^{***}	4.328^{***}	4.412^{***}	-2.729^{***}	4.250^{***}	4.321^{***}
	(1.105)	(0.389)	(0.558)	(0.742)	(0.478)	(0.383)	(0.805)	(0.450)	(0.366)	(0.769)	(0.559)	(0.346)
Gender	-0.184	0.010	-0.037	0.166	0.072	-0.040	0.220	0.049	-0.059	-0.345^{***}	0.070	0.032
	(0.192)	(0.073)	(0.010)	(0.142)	(0.089)	(0.074)	(0.150)	(0.080)	(0.072)	(0.140)	(0.097)	(0.069)
Age	0.063	0.027^{**}	0.035^{*}	0.013	0.027^{*}	0.031^{***}	0.049^{*}	0.013	0.031^{***}	0.084^{***}	0.024	0.025^{**}
	(0.040)	(0.012)	(0.020)	(0.024)	(0.015)	(0.013)	(0.026)	(0.015)	(0.012)	(0.026)	(0.018)	(0.012)
Age^2	-0.001	$-3.0\text{x}10^{-4**}$	$-4.0\text{x}10^{-4*}$	$-1.0\text{x}10^{-4}$	$-2.0\text{x}10^{-4}$	$-3.0\text{x}10^{-4***}$	$-4.0\text{x}10^{-4}$	$-1.0\text{x}10^{-4}$	$-3.0\text{x}10^{-4***}$	-0.001^{***}	$-2.0\text{x}10^{-4}$	$-3.0\text{x}10^{-4**}$
	$(4\text{x}10^{-4})$	$(1.0\text{x}10^{-4})$	$(3.0\text{x}10^{-4})$	$(2\text{x}10^{-4})$	$(2.0\text{x}10^{-4})$	$(1.0\text{x}10^{-4})$	$(3.0\text{x}10^{-4})$	$(2.0\text{x}10^{-4})$	$(1.0\text{x}10^{-4})$	$(3\text{x}10^{-4})$	$(2.0\text{x}10^{-4})$	$(1.0\text{x}10^{-4})$
HHSize	0.020	-0.003	-0.004	-0.024	0.018	-0.006	-0.005	0.017	-0.005	0.021	0.001	-0.008
	(0.028)	(0.010)	(0.014)	(0.020)	(0.014)	(0.010)	(0.021)	(0.011)	(0.010)	(0.019)	(0.012)	(0.010)
Edu	0.109	-0.045	0.112	0.220	0.026	-0.043	0.330^{***}	-0.019	-0.042	0.175	-0.127	-0.011
	(0.190)	(0.072)	(0.093)	(0.134)	(0.085)	(0.074)	(0.141)	(0.076)	(0.070)	(0.140)	(0.097)	(0.066)
Farmsize	0.012	0.207^{***}	0.204^{***}	-0.054^{**}	0.221^{***}	0.195^{***}	-0.063^{**}	0.214^{***}	0.199^{***}	0.020	0.193^{***}	0.208^{***}
	(0.030)	(0.014)	(0.016)	(0.027)	(0.019)	(0.012)	(0.030)	(0.017)	(0.012)	(0.025)	(0.020)	(0.012)
Agrochem	-0.002	-0.041^{***}	-0.013	0.007	-0.020	-0.009	0.010	-0.029^{*}	-0.011	-0.008	-0.077^{***}	-0.013^{*}
	(0.019)	(0.014)	(0.009)	(0.018)	(0.019)	(0.008)	(0.021)	(0.015)	(0.008)	(0.019)	(0.023)	(0.007)
Agrochcost	$-3.0\text{x}10^{-4}$	0.004^{***}	0.001	$2.0\text{x}10^{-4}$	0.001	0.001	$-2.0\text{x}10^{-4}$	0.003^{*}	0.001	$4\text{x}10^{-4}$	0.007^{***}	0.001
	(0.002)	(0.001)	$(4.0\text{x}10^{-4})$	(0.001)	(0.002)	$(4.0\text{x}0^{-4})$	(0.001)	(0.002)	$(4.0\text{x}10^{-4})$	(0.001)	(0.002)	$(4.0\text{x}10^{-4})$
Labor	0.017^{*}	-0.023^{***}	-0.018^{***}	0.009	-0.017^{***}	-0.027^{***}	0.014^{*}	-0.015^{***}	-0.028^{***}	-0.005	-0.012^{**}	-0.024^{***}
	(0.010)	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.007)	(0.003)	(0.004)	(0.007)	(0.005)	(0.004)
Laborcost	-0.003^{**}	0.003^{***}	0.002^{***}	$-3.0\text{x}10^{-4}$	0.002^{***}	0.004^{***}	-0.001	0.002^{***}	0.004^{***}	0.001	0.003^{***}	0.003^{***}
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Extcont	3.087^{***}	-0.550^{*}	-0.081	0.152	0.265	-0.056	-0.087	0.448^{*}	-0.112	0.386	0.825^{***}	-0.238
	(0.496)	(0.304)	(0.489)	(0.431)	(0.292)	(0.210)	(0.443)	(0.238)	(0.211)	(0.424)	(0.306)	(0.189)
Credit	0.025	-0.110	0.088	0.117	-0.108	-0.110	0.096	-0.080	-0.124	-0.104	0.106	-0.161^{**}
	(0.257)	(0.075)	(0.133)	(0.151)	(0.095)	(0.084)	(0.160)	(0.084)	(0.082)	(0.155)	(0.099)	(0.078)
Rainfall	0.002	0.004^{**}	-0.005^{*}	$2.0\text{x}10^{-4}$	0.006^{***}	$2.0\text{x}10^{-4}$	-0.001	0.005^{**}	$4.0\text{x}10^{-4}$	-0.003	-0.003	0.004^{**}
	(0.005)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Soil	-0.358	0.121	0.642^{***}	0.230	0.213	0.286^{*}	0.231	0.285^{*}	0.217	0.188	0.339	0.303^{**}
	(0.419)	(0.163)	(0.204)	(0.296)	(0.179)	(0.168)	(0.315)	(0.162)	(0.159)	(0.311)	(0.211)	(0.148)
WCZ	-0.020	-0.041	0.074	0.190	-0.088	0.046	0.078	0.017	-0.012	0.029	-0.036	0.005
	(0.179)	(0.063)	(0.088)	(0.124)	(0.078)	(0.065)	(0.135)	(0.070)	(0.063)	(0.129)	(0.088)	(0.059)
Endwt ($\boldsymbol{\theta}$)	-0.042	-0.082^{**}	0.015	-0.033	0.053	-0.026	-0.019	0.057^{*}	-0.026	-0.021	0.094^{***}	-0.036
	(0.048)	(0.039)	(0.025)	(0.053)	(0.037)	(0.025)	(0.054)	(0.030)	(0.025)	(0.052)	(0.038)	(0.023)
Distextof	-0.001			-0.008^{***}			-0.013^{***}			-0.005^{*}		
	(0.003)			(0.003)			(0.004)			(0.003)		
Comextoff	0.097											
	(0.174)											
Elradsig	-0.607^{**}											
	(0.006)											
Minac				0.636^{***}			0.816^{***}			-0.417^{***}		
				(0.086)			(0.092)			(0.084)		
Unculand				-0.216^{*}								
				(0.121)								
Commarkt										0.308^{**}		

				(0.170)
LL	-4698.88	-4847.53	-4786.02	-4809.42
Obs (N)	600	600	600	600
Wald chi2(17-18)	47.05***	78.28***	101.97***	55.53***

*Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. In this table, the first column at each stage contains coefficients and standard errors of the individual binary choice decision of the sequential adoption model, the second and third columns at each stage contain coefficients and standard errors of the effect of making choice on farmer yield and its counterfactual, respectively. We included instrumental variables at each stage to control for selection bias. The instrumental variables are distance to nearest extension office (Distextof), presence of an extension agent in the community (Comexttoff), availability of electricity or radio signal in the community (Elradsig), availability of inoculant (Minac), availability of uncultivated land to the farmer. (Unculand) and presence of local market in the community (Commarkt).*

Appendix A.3

Table 3A. 3 Estimates of Choice Decisions and Farm Net Revenue (*ln*GHC/ha).

	Acknow			Tryout			Adopt			Cont-Adopt		
Variables	Select	Acknow	No-Acknow	Select	Trial	No-Trial	Select	Adopt	No-Adopt	Select	Cont-Adopt	Dis-Adopt
Const.	-1.306	5.022***	4.783***	-1.169	4.980***	4.968***	-2.009***	4.791***	5.002***	-2.768***	5.063***	4.970***
	(1.105)	(0.226)	(0.336)	(0.740)	(0.287)	(0.231)	(0.803)	(0.332)	(0.216)	(0.778)	(0.390)	(0.208)
Gender	-0.184	0.005	-0.010	0.166	0.071	0.042	0.220	-0.034	0.022	-0.344***	0.118*	-0.035
	(0.192)	(0.042)	(0.060)	(0.141)	(0.054)	(0.045)	(0.150)	(0.059)	(0.043)	(0.140)	(0.067)	(0.041)
Age	0.063	0.004	0.019	0.013	0.004	0.012	0.049*	0.007	0.012	0.084***	-0.005	0.013*
	(0.040)	(0.007)	(0.012)	(0.024)	(0.009)	(0.008)	(0.026)	(0.011)	(0.007)	(0.026)	(0.012)	(0.007)
Age^2	-0.001	-4.0x10^{-5}	-2.0x10^{-4*}	-1.0x10^{-4}	-1.0x10^{-4}	-1.0x10^{-4}	-4.0x10^{-4}	-1.0x10^{-4}	-1.0x10^{-4*}	-0.001***	1.0x10^{-5}	-1.0x10^{-4*}
	(4.0x10^{-4})	(1.0x10^{-4})	(1.0x10^{-4})	(2x10^{-4})	(1.0x10^{-4})	(1.0x10^{-4})	(3.0x10^{-4})	(1.0x10^{-4})	(1.0x10^{-4})	(3.0x10^{-4})	(1.0x10^{-4})	(1.0x10^{-4})
HHSize	0.020	0.004	0.005	-0.024	0.009	0.001	-0.005	0.013	-2.0x10^{-4}	0.021	0.013	-0.002
	(0.028)	(0.006)	(0.008)	(0.020)	(0.008)	(0.006)	(0.021)	(0.008)	(0.006)	(0.019)	(0.009)	(0.006)
Edu	0.109	-0.023	0.068	0.221	0.056	-0.038	0.331***	0.093*	-0.042	0.174	-0.045	-0.009
	(0.109)	(0.042)	(0.056)	(0.134)	(0.051)	(0.045)	(0.141)	(0.056)	(0.042)	(0.140)	(0.067)	(0.039)
Farmsize	0.012	0.266***	0.229***	-0.054**	0.282***	0.234***	-0.063**	0.283***	0.235***	0.020	0.265***	0.247***
	(0.030)	(0.008)	(0.010)	(0.027)	(0.027)	(0.007)	(0.030)	(0.012)	(0.007)	(0.025)	(0.014)	(0.007)
Agrochem	-0.002	-0.068***	-0.028***	0.007	-0.055***	-0.031***	0.010	-0.056***	-0.031***	-0.008	-0.094***	-0.033***
	(0.019)	(0.008)	(0.005)	(0.018)	(0.011)	(0.005)	(0.021)	(0.011)	(0.005)	(0.019)	(0.016)	(0.004)
Agrochcost	-3.0x10^{-4}	0.005***	0.001***	2.0x10^{-4}	0.004***	0.001***	-2.0x10^{-4}	0.004***	0.002***	4.0x10^{-4}	0.007***	0.002***
	(0.002)	(0.001)	(3.0x10^{-4})	(0.001)	(0.001)	(3.0x10^{-4})	(0.001)	(0.001)	(3.0x10^{-4})	(0.001)	(0.001)	(3.0x10^{-4})
Labor	0.017*	-0.012***	-0.009***	0.009	-0.008***	-0.013***	0.014**	-0.006***	-0.013***	-0.005	-0.002	-0.012***
	(0.010)	(0.003)	(0.003)	(0.007)	(0.002)	(0.003)	(0.007)	(0.003)	(0.003)	(0.007)	(0.004)	(0.002)
Laborcost	-0.003**	3.0x10^{-4}	2.0x10^{-4}	-3.0x10^{-4}	0.004	0.001*	-0.001	-0.001*	0.001**	0.001	-4.0x10^{-4}	4.0x10^{-4}
	(0.002)	(3.0x10^{-4})	(4.0x10^{-4})	(0.001)	(0.001)	(4.0x10^{-4})	(0.001)	(4.0x10^{-4})	(3.0x10^{-4})	(0.001)	(0.001)	(3.0x10^{-4})
Extcont	3.090***	-0.021	-0.406	0.176	-0.066	-0.027	-0.059	0.047	-0.021	0.458	0.118	-0.043
	(0.496)	(0.177)	(0.295)	(0.424)	(0.170)	(0.125)	(0.435)	(0.169)	(0.123)	(0.431)	(0.211)	(0.115)
Credit	0.025	-0.009	0.070	0.117	-0.037	0.025	0.096	-0.055	0.017	-0.103	0.091	-0.046
	(0.257)	(0.044)	(0.080)	(0.151)	(0.057)	(0.051)	(0.160)	(0.062)	(0.048)	(0.155)	(0.068)	(0.047)
Rainfall	0.002	-3.0x10^{-4}	-0.001	2.0x10^{-4}	0.001	1.0x10^{-4}	-0.001	2.0x10^{-4}	3.0x10^{-4}	-0.003	-0.001	4.0x10^{-4}
	(0.005)	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
Soil	-0.358	0.031	0.188	0.230	0.126	0.029	0.230	0.203*	0.012	0.187	0.070	0.075
	(0.419)	(0.094)	(0.123)	(0.296)	(0.108)	(0.101)	(0.315)	(0.120)	(0.094)	(0.311)	(0.146)	(0.088)
WCZ	-0.020	-0.064*	-0.025	0.191	-0.063	-0.025	0.079	-0.019	-0.042	0.031	-0.134**	-0.024
	(0.179)	(0.037)	(0.053)	(0.124)	(0.047)	(0.039)	(0.135)	(0.052)	(0.037)	(0.129)	(0.061)	(0.035)
Endwt (***θ***)	-0.041	0.005	-0.008	-0.030	-0.0002	-0.005	-0.015	0.006	-0.003	-0.012	0.013	-0.002
	(0.048)	(0.03)	(0.015)	(0.052)	(0.022)	(0.015)	(0.052)	(0.021)	(0.015)	(0.053)	(0.026)	(0.014)
Distextof	-0.001			-0.008***			-0.013***			-0.005*		
	(0.003)			(0.003)			(0.004)			(0.003)		
Comextoff	0.097											
	(0.174)											
Elradsig	-0.607**											
	(0.303)											
Minac				0.636***			0.817***			-0.416***		
				(0.086)			(0.092)			(0.084)		
Unculand				-0.216*								
				(0.121)								

Commarkt				0.308**
				(0.152)
LL	-4380.24	-4539.54	-4504.98	-4524.94
Obs.(N)	600	600	600	600
Wald chi2(17-18)	47.12***	78.31***	101.95***	55.65***

Note: *** , ** and * are 1% , 5% and 10% significance levels respectively; values in brackets are standard errors. In this table, the first column at each stage contains coefficients and standard errors of the individual binary choice decision of the sequential adoption model, the second and third columns at each stage contain coefficients and standard errors of the effect of making choice on farmer yield and its counterfactual, respectively. We included instrumental variables at each stage to control for selection bias. The instrumental variables are distance to nearest extension office (*Distextof*), presence of an extension agent in the community (*Comexttoff*), availability of electricity or radio signal in the community (*Elradsig*), availability of inoculant (*Minac*), availability of uncultivated land to the farmer. (*Unculand*) and presence of local market in the community (*Commarkt*).

Appendix A.4: Average Marginal Treatment Effect (AMTE) and Average Treatment Effect (ATE) Compared.

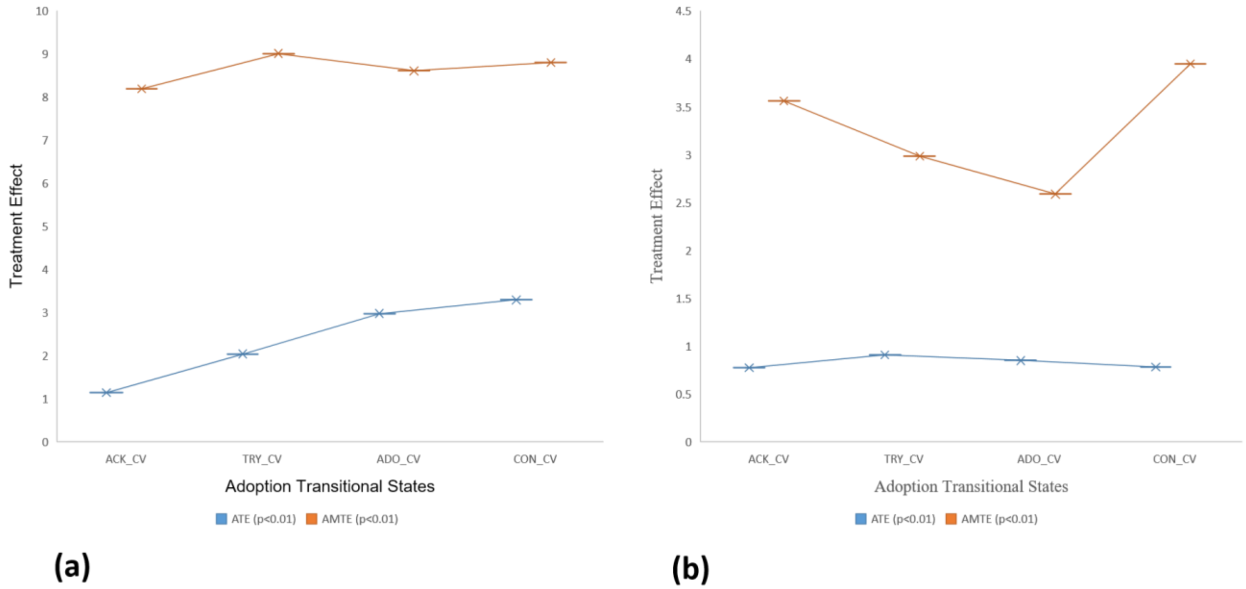
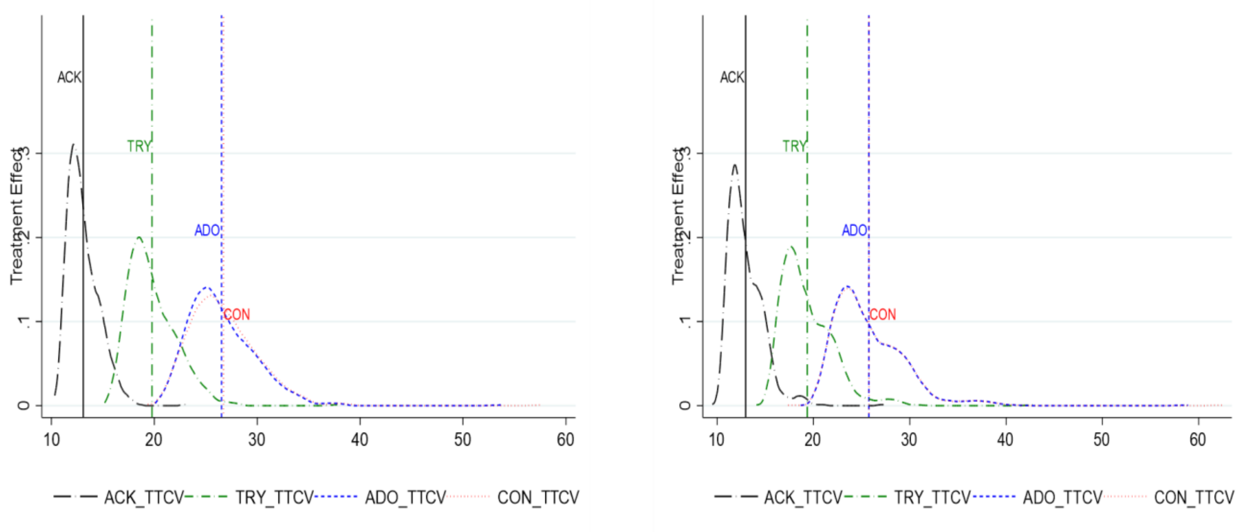


Figure 3A. 2 Mean Plot of Average Marginal Treatment Effect across Adoption Transitional States (panel (a) and (b) represent distributions of yield (Kg/ha) and farm net returns (GHC/ha), respectively.

***Note**: We see in figure 3A.2 that the AMTE, which is treatment effect conditional on individual unobserved essential heterogeneities (such as wealth endowment) outweighs the average treatment effect (ATE), suggesting that farmers sort on gains and benefitted from their individual heterogeneities.*

Appendix A.5: Population Level Treatment Effect Distribution with Continuation Values.



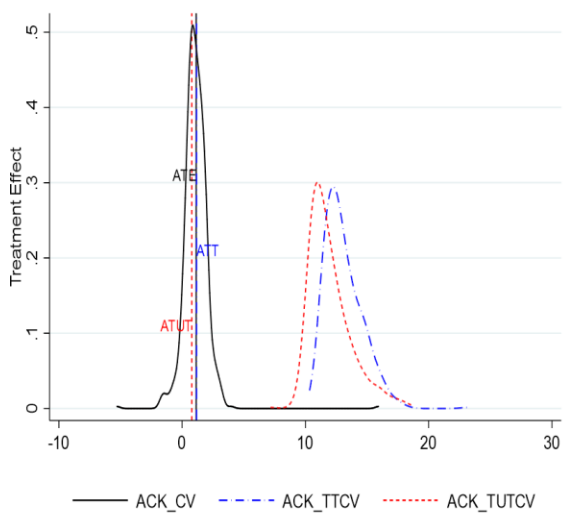
(a) **(b)**

Figure 3A. 3 Treatment Distribution across Adoption Transitional States (panel (a) and (b) represent distributions of yield (Kg/ha) and farm net returns (GHC/ha), respectively.

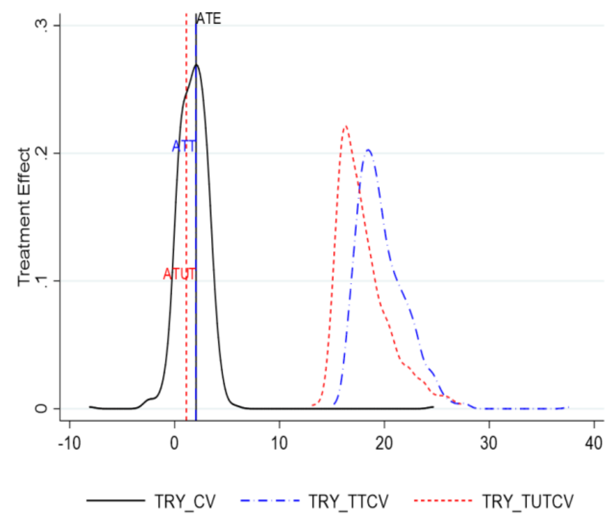
Note: ACK=Knowledge Acquisition State; **TRY**=Trial State; **ADO**=Adoption State; **CON**=Continued Adoption State; **TTCV** represents Treated State Continuation Values.

Note*: Figure 3A.3 shows the long-term impact distribution around its own mean at each adoption state at the population level without conditioning on making a transition. It can be seen, that the long term impact of farmer at adoption and continued adoption states are marginally distributed around the same mean but visibly ahead of that of knowledge and trial states.*

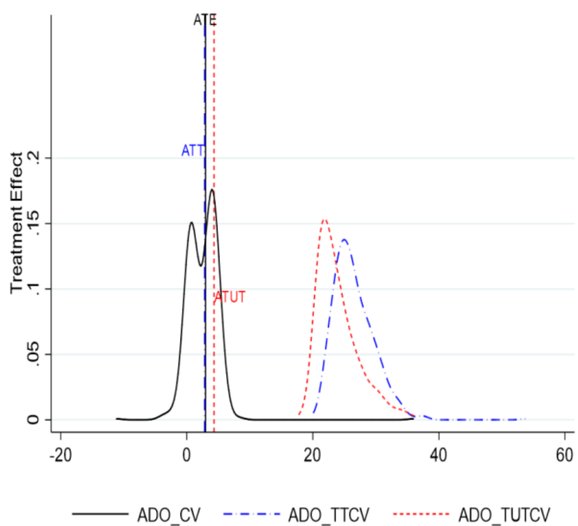
Appendix A.6: Sub-Population Level Treatment Effect Distribution with Continuation Values.



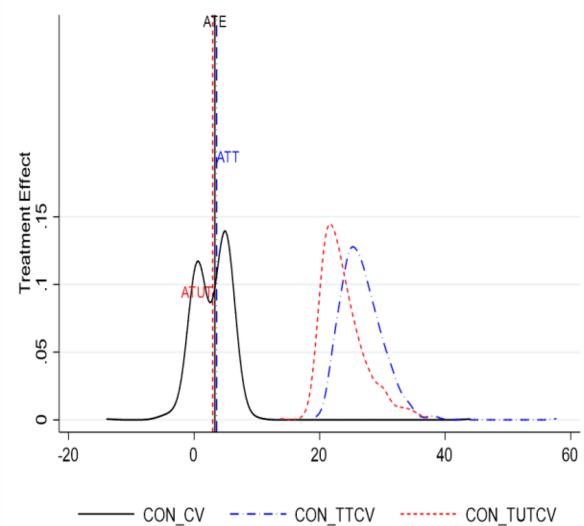
(a)



(b)



(c)



(d)

Figure 3A. 4 Treatment Effect Distributions with Continuation Values at each Adoption Transition (Sub-population Level) – Yield (Kg/ha)

Note: ACK=Knowledge Acquisition State; **TRY**=Trial State; **ADO**=Adoption State; **CON**=Continued Adoption State; **TTCV** represents Treated State Continuation Values; **TUTCV** represents Untreated State Continuation Values. **ATE**=Average Treatment Effect Curve; **ATT**=Average Treatment Effect on the Treated Curve; **ATUT**=Average Treatment Effect on the Untreated Curve.

***Note**: Figure 3A.4, presents long-term impact distribution of inoculant adoption on yield at the sub-population level. The distribution at each adoption state is marginally above the sub-population mean of zero. However, the treatment effect on the untreated visibly dominates that of the treated but both distributions are towards the right of the mean, indicate positive long term impact of the inoculant adoption.*

Appendix A.7: Sub-Population Level Treatment Effect Distribution with Continuation Values.

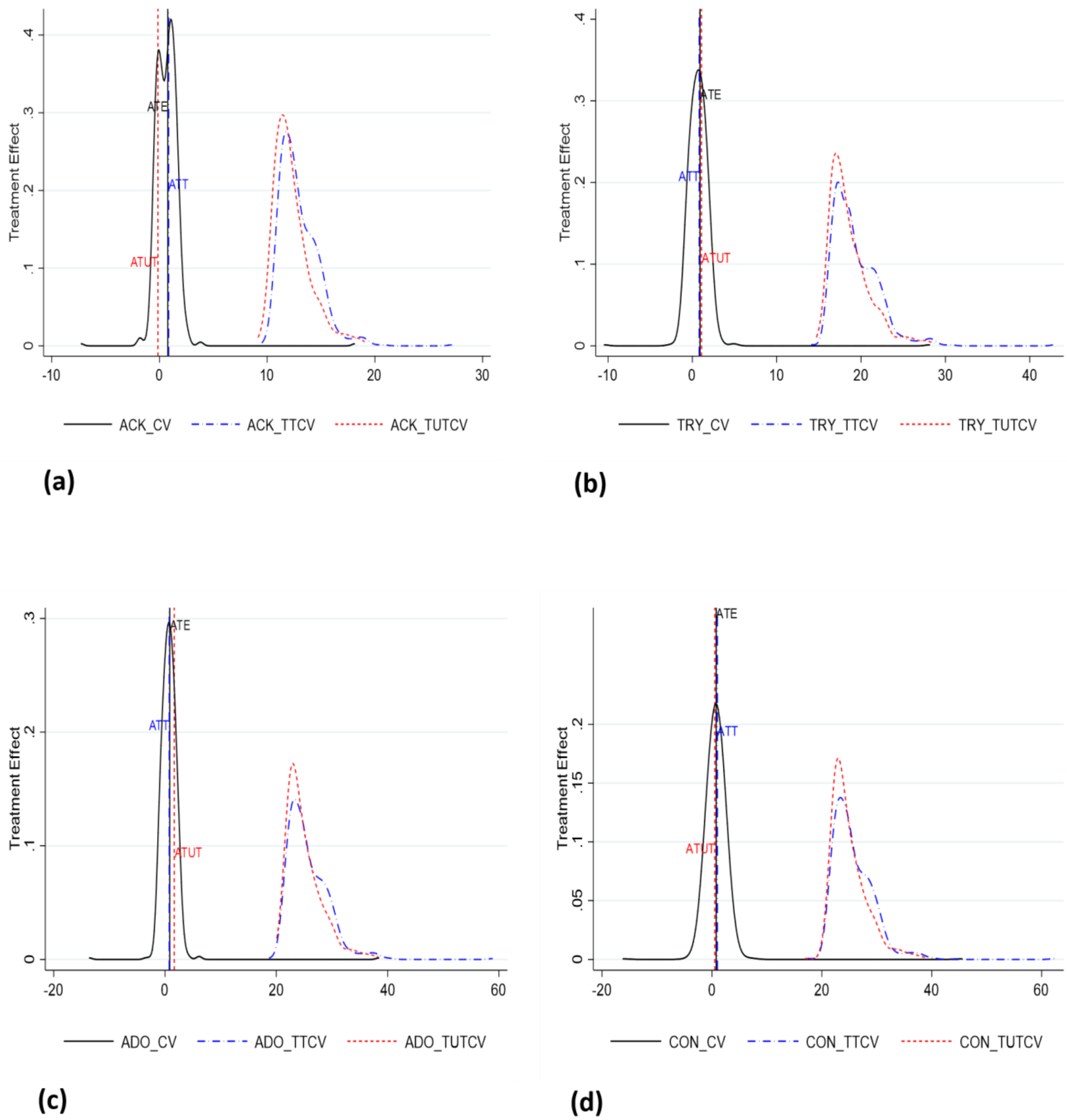


Figure 3A. 5 Treatment Effect Distributions with Continuation Values at each Adoption Transition (Sub-population Level) – Farm Net Returns (GHC/ha).

Note: **ACK**=Knowledge Acquisition State; **TRY**=Trial State; **ADO**=Adoption State; **CON**=Continued Adoption State; **TTCV** represents Treated State Continuation Values; **TUTCV** represents Untreated State Continuation Values. **ATE**=Average Treatment Effect Curve; **ATT**=Average Treatment Effect on the Treated Curve; **ATUT**=Average Treatment Effect on the Untreated Curve.
Note*: Figure 3A.5 presents long-term impact distributions of inoculant adoption on farm net returns at the sub-population level. We see a similar pattern of distribution as that of the yield in the figure above.*

Appendix A.8: Robustness Checks for Sorting on Gains

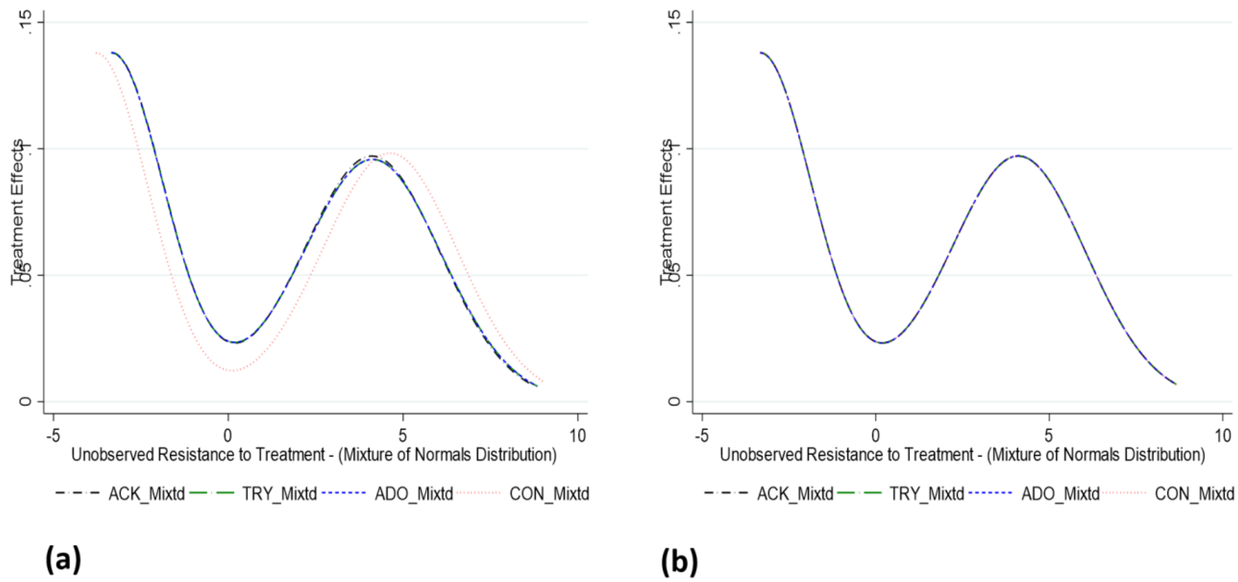


Figure 3A. 6 Mixture of Two Normals Distributions of the Unobserved Wealth Endowment (panel (a) and (b) represent distributions of yield (Kg/ha) and farm net returns (GHC/ha), respectively.

Note*: Figure 3A.6 presents the distribution of the observed resistance to treatment across each adoption state. Cornelissen et al. (2018) note that the selection on gains pattern (i.e. evidence of sorting) have a known relationship between the distributions of the unobserved resistance to treatment and the treatment effects, when plotted. As seen in figure A6, we observe that as the unobserved resistance to treatment decreases, gains (or treatment effect) from adoption increases and as the unobserved resistance to treatment increases, gains from adoption decreases, indicating a negative selection on gains (i.e. TUT>ATE>TT).*

Appendix A.9: Identification

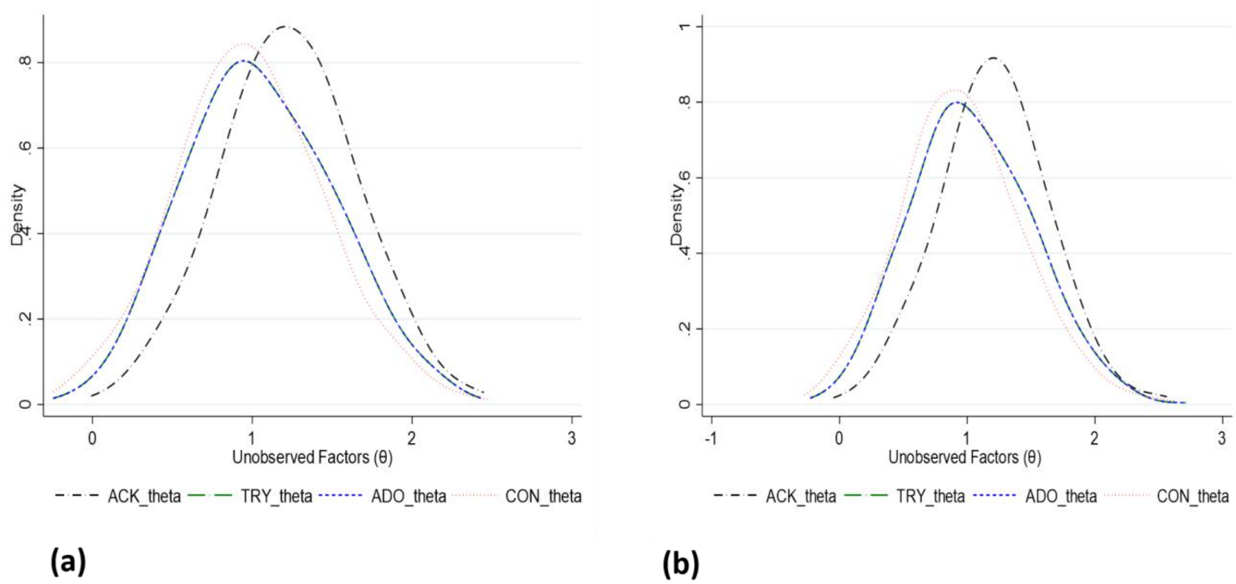


Figure 3A. 7 Distribution of Unobserved Factors across States (panel (a) and (b)) represent distributions of yield (Kg/ha) and farm net returns (GHC/ha), respectively.

***Note**: The Figure shows the distribution of wealth endowments across each adoption transition state. As can be seen all factors differ across each state, indicating that the factor models that we estimate for each of the adoption state is well identified.*

Appendix A.10: Instrumental Variables (IVs) Exogeneity Test for Exclusion Restriction

Table 3A.3 presents the results of exogeneity test for the instrumental variables (IVs) employed as the exclusion restriction variables for identification of farmers' adoption choice decisions at each adoption state as expressed in equation 7 of the empirical specifications. In line with Heckman *et al.* (2018), we employed state dependent instrumental variables to identify each autonomous adoption decision, while controlling for farmer's wealth endowment at each adoption state. We assume that different adoption states are identified by different instruments that are important to that state.

In the awareness state, we employed both district and community level instruments to identify this critical state of adoption. The district level instrument, distance to the nearest extension office *Distextof* and the community level instrument, presence of extension agent in the community *Comexttoff* are the instruments used for the exclusion restriction. It is expected that supply and diffusion of information as reflected by intensity of information campaigns and extension activities both district wide and at the individual community level will increase the probability of farmers' awareness (Lambrecht *et al*. 2014), but should have no direct effect on yields and farm net returns except through awareness. As seen in Table 3A.3, the Anderson-Rubin (AR) test statistic of the IVs in both the yields and farm net returns models are statistically insignificant at any conventional level, indicating that the IVs use for the exclusion restriction satisfy the exogeneity requirement and that the instruments do not have direct influence on yields and farm net returns, except through awareness.

At the knowledge acquisition state *Acknow*, cost of searching for information is expected to increase the probability of knowledge acquisition (Lambrecht *et al*. 2014 and Abdulai *et al.* 2008; Feder and Slade 1984), but should have no direct influence on yields or farm net returns except through knowledge acquired. Since ICT channels were included in the inoculant dissemination program, the presence of electricity as well as good signals for wire communication increase the likelihood of the farmer's community being targeted by program implementers, thereby increasing the farmer's probability to cheaply acquire knowledge. Therefore, in addition to distance and presence of extension agent, we included the presence of electricity and good signals for wire communication *Elradsig* as the exclusion restriction instrument for knowledge acquisition state. The results in Table 3A.3 show that the AR test statistic is statistically insignificant in both the yields and farm net returns models, suggesting that IVs satisfy the minimum exogeneity requirement for exclusion restriction.

In the Trial state, we employed farm household's ownership of uncultivated land *Unculand* and mode of inoculant acquisition *Minac* in addition to distance to the nearest extension office *Distextof* as instruments for exclusion restriction. It is expected that smallholder farmers who have no access to additional land will not cultivate their only productive land to a newly introduced technology, due to the risk of failure. However, access to additional land increases farmer's probability to try new technologies (Feder *et al.*, 1985). Also farmers whose mode of obtaining the new technology is through gift as part of promotion campaigns increases their probability of trial. Furthermore, farmers who live in close proximity to extension are more likely to be targeted for either on-farm or off-farm extension activities, hence increasing their propensity to try the new technology. We assume that these instruments have no direct influence on yields and farm net returns except through increase in farmer's propensity to try the technology. The AR test statistic in Table 3A.3 is not statistically significant at any conventional level for both yields and farm net returns models, suggesting that the instruments satisfy the exogeneity requirement for exclusion restriction.

At the adoption and continuous adoption states, distance to nearest extension office *Distextof*, mode of inoculant acquisition *Minac* and the presence of local market in the community *Commarkt* are employed as the exclusion instruments. It is expected that in addition to proximity to extension and mode of acquisition of the inoculant technology, the presence of a community market in the farmer's locality increase farmer's continuous access to information, inoculant and complimentary inputs supply as well as market for farm outputs due to increase yield from adoption. Thus, increasing the farmer's probability to adopt and continue to adopt. The AR test statistic in Table 3A.3 show that the test statistic is statistically insignificant at any conventional level of confidence, suggesting that except through increasing the farmer's propensity to adopt and continue use of the technology the instruments have no direct influence on farmer's yields and farm net returns.

Table 3A. 4 Anderson – Rubin (AR) IV Exogeneity Test for Exclusion Restriction

Outcome	Adoption State	AR Test Statistic	P-Value
Panel A			
Yield	*Awareness*	8.349	0.331
	Acknow	8.450	0.399
	Trial	11.823	0.334
	Adopt	10.825	0.293
	Cont-Adopt	22.754	0.204
Panel B			
Farm Net Returns	*Awareness*	0.007	0.997
	Acknow	0.135	0.990
	Trial	2.313	0.707
	Adopt	0.722	0.779
	Cont-Adopt	5.369	0.497
No. of observation(N)		*600*	

Note: 100,000 bootstrap replications were used in estimation of the AR-test statistic.

References

Abdulai, A., Monnin, P., and Gerber, J. (2008). Joint estimation of information acquisition and adoption of new technologies under uncertainty. *Journal of International Development, 20, 437 – 451*.

Cornelissen, T., Dustmann, C., Raute, A., and Schonberg, U. (2018). Who Benefits from Universal Child Care? Estimating Marginal Returns to Early Child Care Attendance. *Journal of Political Economy*, *126(6):2356 – 2409.*

Feder, G., Just, R. E., and Zilberman, D. (1985). Adoption of agricultural innovations in developing-countries – A survey. *Economic Development and Cultural Change, 33(2), 255–298.*

Lambrecht, I., Vanlauwe, B., Merckx, R., and Maertens, M. (2014). Understanding the Process of Agricultural Technology Adoption: Mineral Fertilizer in Eastern DR Congo. *World Development*, *59:132–146.*

Simtowe, F., Asfaw, S. and Abate, T. (2016).Determinants of Agricultural Technology Adoption under Partial Population Awareness: The Case of Pigeonpea in Malawi. *Agricultural and Food Economics, 4(7):1 – 21*.

Chapter 4
The Impact of Extension Dissemination and Technology Adoption on Farmers Efficiency and Welfare in Ghana

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Abstract

Examining the welfare impact of agricultural development interventions that incorporate diffusion of improved production technologies to farmers within extension delivery programs can be challenging, because of the difficulty in ascertaining the individual impacts of the production technology and the extension delivery program. Using recent farm level data from extension dissemination program of legume inoculant technology in Ghana, we employ a novel approach to investigate, simultaneously, the impact of the inoculant technology adoption and the extension program participation on farmers' productivity, efficiency and welfare. We decompose each of these impact measures into subcomponents whose causal paths can be traced to both the adoption of the production technology and the extension delivery program. We find that improved technology adoption alone contributes 72% directly to farm productivity and 73% indirectly due to improved farmer efficiency, leading to 77% improvement in farmers' welfare. On the other hand, extension delivery program participation alone contributes 28% directly to farm productivity and 27% indirectly due to improved farmer efficiency, resulting in 23% improvement in farmers' welfare.

Keywords: Stochastic Frontier Analysis, Mediation Analysis, Treatment Effect, Impact Assessment, Inoculant Technology Adoption.

JEL: C26, D24, O13, Q16, Q18.

4.1 Introduction

The increasing global food demand calls for adoption of new agricultural technologies to increase food production. Similar concerns in the past led to the introduction of the green revolution, a policy that advocated for intensifying the use of high yielding varieties, mineral fertilizers and tractors among smallholder farmers in developing countries (Pingali, 2012). Although the policy led to an increase in agricultural productivity and food supply, it also contributed to environmental impacts such as degraded lands, impoverish soils and adverse climatic conditions due to reactive nitrogen released from agriculture production activities (Pingali 2012; Zhang *et al.*, 2015). Increase in food production cannot be achieved without sufficient nitrogen supply, as nitrogen allows farmers to increase crop production per unit area of land (Zhang *et al.*, 2015). To mitigate the effect of pollution from reactive nitrogen while ensuring sufficient food production, a new paradigm shift is required (Mutuma *et al.*, 2014; Zhang *et al.*, 2015).

The Integrated Soil Fertility Management (ISFM) is one of such new approaches employed to promote soil fertility enhancing technologies for resource-poor farmers in developing countries (Crowley and Carter, 2000). A technology promoted under the program among smallholder soybean farmers in northern Ghana is the legume inoculant technology. The soybean is targeted due to its potential to undergo sustainable intensification, its industrial value and nutritional quality (Heerwaarden *et al.*, 2018; Foyer *et al.* 2018). The inoculant technology is an organic input containing isolates of an elite strain of bacterial (*Bradyrhizobium japonicum*) and organic carrier material (Lupwayi, *et al.*, 2000). The inoculant technology is seen as cost-effective alternative to rehabilitating poor soils by enhancing the build-up of biological nitrogen fixation (BNF) organisms in the soil (Giller, 2001). Empirical evidence of potential productivity gains from inoculant is reported in the literature (see Rurangwa *et al.*, 2018; Heerwaarden *et al.*, 2018; Chibeba *et al.*, 2018). Notably, grain yield of soybean increased by 20 – 29 percent in Mozambique (Chibeba *et* *al.*, 2018) and 12 – 19 percent in the northern region of Ghana (Ulzen *et al.*, 2016), relative to uninoculated fields. Yield response to inoculant significantly varies across agro-ecological zones in Africa and depend on agronomic practices and varietal promiscuity to the strain of the *Rhizobia* in the inoculant (Heerwaarden *et al.*, 2018). To improve efficiency, organizations involved in the dissemination of the inoculant technology employ several innovative extension methods[24] to school farmers on good agronomic and crop management practices on the inoculant technology.

Our goal in this study is to simultaneously assess the impact of the inoculant technology adoption and the extension participation on farmers' productivity and efficiency. Usually, agricultural development programs such as the inoculant dissemination program often have a dual goal of inducing an upward shift in the production frontier and promoting better management, which incorporates two potentially endogenous treatments in a single program (Bravo-Ureta, 2014). The treatment of a new superior technology and that of building human capital, each having the potential to influence both the technology frontier function and the inefficiency function independently (Huang and Liu, 1994; Kumbhakar *et al.*, 2009). However, empirical studies often overlook the double treatment endogeneity, most often addressing one of them, and subsuming the other into distributional assumptions of the model. For instance, in Dinar *et al.* (2007) study on the impact of extension service in Greece, extension participation is analyzed as performing a dual role, an input in the production function and a factor narrowing the technology gap, exerting direct and indirect effects in the production process. Their approach implicitly assumed homogeneous technology and fail to account for selection bias in the extension participation. In the event that farmers self-select into an extension program or adopt superior production technology, the direct and indirect effects due to heterogeneity in technology or enhanced farmer capacity will be

[24] The extension channels employ are video documentaries, radio listening clubs, on-farm and off-farm trials, field days, brochures, use of community volunteers.

unaccounted for and the impact will be incomplete. Other studies following the seminal work of Dinar *et al*. (2007) employ a mixed multi-stage approach to address the issue of selectivity and technology heterogeneity (e.g. Bravo-Ureta, *et al*., 2012; Villano *et al*., 2015; Abdulai and Abdulai, 2016; De los Santos-Montero and Bravo-Ureta, 2017; Abdul-Rahaman and Abdulai, 2018; Bravo-Ureta, *et al*., 2020). Even though the mixed multi-stage approach accounts for selection bias, it fails to account for the direct and indirect impacts that heterogeneous production technologies may have on both the production frontier and the efficiency function. The mixed multi-stage approach also attempts to address technology heterogeneity among production units by estimating group-specific frontiers for different groups of production units and further use the group frontiers to obtain the meta-frontier for comparison. However, because the maximum likelihood estimates of the predicted group-specific frontier is neither known *a prior* nor estimated relative to the same frontier, some degree of biasness in this approach is unavoidable and difficult to ascertain (Huang *et al.,* 2014). Moreover, as indicated by Triebs and Kumbhakar (2018), the approach subsumes observed variables like extension service with the potential to augment the farmer's managerial ability in the inefficiency parameter of the model. On the contrary, the managerial ability does not only influence the inefficiency function but also the technology frontier, resulting in non-neutrality of the production function (Huang and Liu, 1994; Triebs and Kumbhakar 2018). Also, the endogeneity issues address in the mixed multi-stage approach center mainly on the feedback between the technology choice and the production model residuals, but not on accounting for endogeneity, which could separately and simultaneously affect the technology frontier and the production inefficiency function (Chen *et al.,* 2020).

The present study attempts to fill the gap and contribute to the above literature on impact assessment and technical efficiency, using survey data of 600 farm households from northern Ghana. Specifically, we employ the stochastic frontier model with endogenous treatment and mediator effect (Chen *et al.,* 2020), to estimate the impact of dual purpose development interventions, and to decompose the impact into direct and indirect effects. This novel approach brings together mediation analysis[25], treatment effect and that of the stochastic frontier models in a single framework. Using this approach, we are able to disentangle the dual purpose development interventions' impact into four components. That is, the direct effects on the technology frontier, the indirect effects on the technology frontier that go through the mediator, the direct effects on the technical inefficiency, and the indirect effects on the technical inefficiency that go through the mediator. Our approach departs from the conventional approaches in the literature (e.g. Bravo-Ureta, *et al*., 2012; Villano *et al*., 2015; Abdulai and Abdulai, 2016; De los Santos-Montero and Bravo-Ureta, 2017; Bravo-Ureta *et al.,* 2020), in which a conventional SPF model that corrects for sample selection bias is estimated. In particular, we estimate a treatment effect model using the stochastic frontier regression framework, while addressing endogeneity from selection bias, endogenous treatment and mediator variables. We also account for treatment heterogeneities among production units.

The rest of the paper is organized as follows: In sections 2 and 3, we present the conceptual and empirical framework and empirical identification of causal impact respectively, section 4 discusses the empirical specification and the estimation procedure, while section 5 describes the data and descriptive Statistics. The empirical results are presented in section 6, while section 7 contains the conclusion and policy implications.

4.2 Conceptual and Empirical Framework

In agriculture, new production technologies such as high yielding varieties, complementary inputs like fertilizer, or as in our case, the inoculant technology have the potential to shift the production

[25] The mediation analysis is also known as the Baron-Kenny models in the statistics literature.

frontier upwards. Also farmers who receive extension services or technical training on the new technology may experience further shift in the production frontier upwards by reducing production inefficiencies. The two shifts envisage two potentially endogenous treatments in a single agricultural development intervention that incorporates dissemination of new production technologies and training of farmers. First, adoption of a new superior technology that affects both the production frontier function and the inefficiency function (Kumbhakar *et al.,* 2009), and extension training that builds human capital with the potential to influence both the production frontier function and the inefficiency function (Huang and Liu, 1994; Triebs and Kumbhakar, 2018).

To represent both frontiers, let Y denote individual farmer i observed output under a given technology and X be a vector of observed covariates. We express the farmer's observed output in a conventional stochastic frontier form (Kumbhakar and Lovell, 2000) as;

$$Y = Y^{*} - u, \quad u \geq 0 \qquad (1)$$

where Y^{*}, is the unobserved stochastic frontier that may be influenced directly by the new technology and indirectly by extension training and $u \geq 0$, is the unobserved production inefficiency assumed to be randomly distributed, which may be influenced directly by extension training and indirectly by the new technology. The expression in equation 1 indicates that Y^{*} and u are two distinct unobserved random components, which can be separately identified. In line with Chen *et al.* (2020), we stochastically express each unobserved function in terms of observed covariates in a system of equations as follows;

$$Y = \begin{cases} Y^{*} = h(X, \beta^{h}) + v \\ u = g(X, \beta^{g}) + \tilde{u} \end{cases} \quad \text{and} \qquad (2)$$

$E[Y^{*}|X] = h(X, \beta^{h})$, and $E[u|X] = h(X, \beta^{g})$, $E[v|X] = 0$, $E[\tilde{u}|X] = 0$

where X is a vector of covariates, $h(.)$ is the frontier function with parameter vector β^h and $g(.)$ is a non-negative inefficiency function with parameter vector β^g, while v and $\tilde{u}$ are error terms assumed to be independently and identically distributed. $E[.]$ is the expectation operator which identifies the conditional mean expectations of the equations in the system. To relate the effect of the production frontier and the inefficiency to observed farmer-specific potential outcome, given his observed characteristics and inputs, we express equation 1 in terms of its conditional mean representation as follows;

$$E[Y|X] = h(X, \beta^h) - g(X, \beta^g) \tag{3}$$

By letting Y_1 to be the potential outcome of a farmer who adopts the technology (i.e. the inoculant technology) and Y_0 be the potential outcome, if the same farmer did not adopt, then, the average treatment effect on the treated (ATT) for adopters can be specified as;

$$ATT = E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \tag{4}$$

where D is a binary adoption indicator, with $D = 1$ if the farmer adopts and 0 otherwise.

4.3 Impact Identification Strategy

In observational data situation like ours, evaluating the impact of the inoculant dissemination program on farmers' welfare and the shifts in the production technology and inefficiency functions may suffer serious identification problems, resulting in biased estimates. However, with good and valid instruments, it is possible to categorize the whole population into a well identified mutually disjoint sub-population of adopters who are compliers of the instrument (Imbens and Angrist, 1994; Angrist et al., 1996).

In our setting, we use rural electrification as the most likely exogenous instrument that can identify various sub-population of inoculant adopters. Given that the rhizobia in the inoculant survive within a temperature limit of about 25^0C, it requires a controlled temperature storage facility.

Hence, it is expected that farmers who live in communities connected to the national grid of electricity supply may have access to the technology, compared to their counterparts who live in communities without electricity supply. If we let Z_1 represent an instrumental variable (IV) that takes a value of 1, if the farmer's village is connected to national electricity grid, and 0 otherwise, the propensity of a farmer adopting the technology can be specified in the following latent variable (i.e., D^*) discrete choice model;

$$D^* = \gamma_{z_1} Z_1 + \gamma_x X + U_D, \text{ with } D = \begin{cases} 1, & if\ D^* \geq 0 \\ 0, & otherwise \end{cases} \quad \text{and}$$

$$D = 1(\gamma_{z_1} Z_1 + X\gamma_x + U_D \geq 0) \tag{5}$$

where D is a discrete adoption decision indicator, with $D = 1$ if the farmer adopts inoculant and 0 otherwise, X is a vector of covariates, γ is the parameter of interest and U is the error term.

Naturally, it is expected that the effect of extension service participation (i.e. the managerial skills) is mainly observed after the farmer adopts the technology on which the extension training is based on. That is, when the farmer uses or adopts the inoculant technology. As such, the extension functions as a post-adoption mediator and can be modelled as a function of adoption. With a potentially endogenous binary mediator, such as the extension service participation in this case, the mediation effect can be identified with a continuous exogenous variable with known distribution and whose level differs with adoption status (Frölich and Huber, 2017; Chen *et al.*, 2020). In this circumstance, we rely on farmer's distance to the nearest extension office as a possible exogenous continuous instrument. We expect that farmer's propensity to participate in extension service programs increases as the distance decrease and decreases as the distance increase. If we let Z_2 be a continuous instrumental variable (IV) whose distribution[26] and level decrease as mediation takes

26 See Figure A1 in the appendix for the plot of the distribution of the continuous IV Z_2, showing both properties of increasing and decreasing propensities, as a necessary condition for identification.

the value of 1, and increase as mediation goes to 0, then, the propensity of a farmer who adopts the technology to also participate in the extension program can be expressed in a latent variable (i.e., M^*) model as follows;

$$M^* = \alpha_d D + \alpha_{z_2} Z_2 + X\alpha_x + U_M, \text{ with } M_i = \begin{cases} 1, & if\ M^* \geq 0 \\ 0, & otherwise \end{cases} \quad \text{and}$$

$$M = 1(\alpha_d D + \alpha_{z_2} Z_2 + X\alpha_x + U_M \geq 0) \tag{6}$$

where M is a binary mediation indicator, with $M = 1$ if the farmer participates in extension program and 0 otherwise, D is the adoption status indicator, X is a vector of covariates, α is the parameter of interest and U is the error term. Considering altogether equations 5 and 6, (which identify both the potentially endogenous adoption and extension decisions), suggest that the post-mediation potential outcome Y is a function of D and M, pre-supposing that, the post-mediation potential outcome can be represented as $Y(D, M(D))$. Where $M(D)$ is the mediator function whose effect depends on the adoption status of the farmer.

Given a binary adoption indicator (i.e., D(1), D(0)) and a binary IV ($Z_1 \in \{0,1\}$), four potential outcomes representing four mutually disjoint sub-population of farmers can be identified as follows (Angrist *et al.*, 1996; Imbens and Angrist, 1994);

$$(D(1), D(0)) = \begin{cases} (1,1), & always\ takers, \\ (1,0), & compliers\ (\boldsymbol{C}), \\ (0,1), & defiers, \\ (0,0), & never\ takers. \end{cases} \tag{7}$$

where $\boldsymbol{C}$ is an indicator of instrument compliers, who are induced to adopt the technology based on the instrument. This sub-population of farmers, no matter the circumstance, does not change adoption status with the assigned status by the instrument (Angrist *et al.* 1996). Due to this known behavior, their potential impact better approximates that of causal estimates from a full compliance experimentation. Therefore, by conditioning on the observed covariates of farmers X and their complier status $\boldsymbol{C}$, the average treatment effect on the treated as expressed in equation 4 can be identified (Chen *et al*., 2020) as follows;

$$CLATE = E\big[Y\big(1, M(1)\big)\big|X = x, \boldsymbol{C}\big] - E[Y(0, M(0))|X = x, \boldsymbol{C}] \qquad (8)$$

where $CLATE$ is the conditional local average treatment effect. Also, because the levels of the continuous instrumental variable for identifying the mediation effect varies with adoptions status, it is possible to decompose the unconditional local average treatment effect into direct and indirect effects as in Chen *et al.* (2020);

$$CDLATE = E\big[Y\big(1, M(1)\big)\big|X = x, \boldsymbol{C}\big] - E[Y(0, M(1))|X = x, \boldsymbol{C}] \qquad (9)$$

$$CILATE = E\big[Y\big(0, M(1)\big)\big|X = x, \boldsymbol{C}\big] - E[Y(0, M(0))|X = x, \boldsymbol{C}] \qquad (13)$$

where $CDLATE$ is the conditional direct local average treatment effect and the $CILATE$ is the conditional indirect local average treatment effect. Conversely, the unconditional average treatment effect can also be derived from the conditional local average treatment effects, by conditioning on only the sub-population of farmers who are compliers as follows;

$$LATE = E[CLATE(X)|\boldsymbol{C}] = E\big[Y\big(1, M(1)\big)\big|\boldsymbol{C}\big] - E[Y(0, M(0))|\boldsymbol{C}] \qquad (11)$$

$$DLATE = E\big[Y\big(1, M(1)\big)\big|\boldsymbol{C}\big] - E[Y(0, M(1))|\boldsymbol{C}] \qquad (12)$$

$$ILATE = E\big[Y\big(0, M(1)\big)\big|\boldsymbol{C}\big] - E[Y(0, M(0))|\boldsymbol{C}] \qquad (13)$$

where LATE is the local average treatment effect which captures the total effect, while DLATE and ILATE are direct and indirect local average treatment effects respectively, that capture the impact due to technology adoption and mediation.

4.4 Empirical Specification and Estimation

A farmer's propensity to participate in extension services (i.e. the potential mediation model) may correlate with his inoculant adoption decision (i.e. the potential treatment model) either due to observed or unobserved factors. We assume that the error terms are independently and identically distributed and follow a bivariate normal distribution. In line with Chen *et al*. (2020), we specify the joint extension participation and inoculant adoption decisions as a bivariate probit, with a bivariate normal distribution and CDF $F_{U_{M,D}}(.,.,\rho_{md})$ as follows;

$$P(M, D|Z_1, Z_2, X, \eta), \text{ and } \qquad \begin{bmatrix} U_M \\ U_D \end{bmatrix} |(Z_1, Z_2, X) \sim N\left(\begin{bmatrix} U_M \\ U_D \end{bmatrix}, \begin{bmatrix} 1 & \rho_{md} \\ \rho_{md} & 1 \end{bmatrix}\right) \qquad (14)$$

where $\eta \equiv (\alpha_d, \alpha_{z_2}, \alpha_x, \gamma_{z_1}, \gamma_x, \rho_{md})$ is a maximum likelihood estimator of a vector of parameters. In a first-stage estimation, a bivariate probit model is estimated to control for selection bias from both observables and unobservables. To unify the impact assessment and mediation analysis within the stochastic frontier analysis framework, we represent the frontier function of Aigner *et al*. (1977) and Meeusen and van den Broeck (1977) in the form of Chen *et al.* (2020), for $d, d' \in \{0,1\}$[27], as follows;

$$Y\big(d, M(d')\big) = \breve{h}\big(d, M(d'), X, \beta_{dj}^{h}\big) - \breve{g}\Big(d, M(d'), X, \beta_{dj}^{g}\Big) + U_Y(v\big(d, M(d')\big) + \tilde{u}\big(d, M(d')\big)) \quad (15)$$

where $\breve{h}(d, M(d'), X)$ and $\breve{g}(d, M(d'), X)$ are potential frontier and non-negative potential inefficiency functions, respectively; X is a vector of covariates; β is a parameter of interest; while $v\big(d, M(d')\big)$ and $\tilde{u}\big(d, M(d')\big)$ are potential random error terms. The binary adoption indicator is $D = d, d' \in \{0,1\}$ and $j = M(d')$ is the mediator function whose distribution varies with adoption

27 The observed binary adoption decision indicator d varies as d', taking the value of 1, if a farmer adopts the inoculant technology and 0, otherwise.

status. The conditional mean expectation of equation (15) combines the potential output model and the potential mediator model as;

$$E\left[Y(d, M(d'))|X, \boldsymbol{C}\right] = h_{d'}\left(X, \alpha_m, \beta_{dj}^h\right) - g_{d'}\left(X, \alpha_m, \beta_{dj}^g\right) \qquad \text{and} \qquad (16)$$

$E\left[v\left(d, M(d')\right)\middle|X, \boldsymbol{C}\right] = 0$, $E\left[\tilde{u}\left(d, M(d')\right)\middle|X, \boldsymbol{C}\right] = 0$, and $E[M(d')|X, \boldsymbol{C}] = m_{d'}(X, \alpha_m)$

where $m_{d'}(.)$ is a non-negative function of the potential mediator model in {0,1} with a parameter vector α_m. To reflect variations in the distribution of the non-negative potential mediator model as the adoption indicator takes the value within {0,1} in the estimated parameters of interest, we rewrite equation 16 as;

$$E\left[Y(d, M(d'))|X, \boldsymbol{C}\right] = h_{d'}\left(X, \alpha_m, \beta_{d1}^h, \beta_{d0}^h\right) - g_{d'}\left(X, \alpha_m, \beta_{d1}^g, \beta_{d0}^g\right) \qquad (17)$$

We estimated the parameters in equation (17) using a two-stage weighted nonlinear least squares (WNLS) method. Let the individual farmer's observed outcome (Y), extension service participation (M), inoculant adoption (D) and covariates (X) be a weighted random vector $W \equiv (Y, M, D, X)$ with sample size N, and $\beta_d \equiv (\beta_{d1}^h, \beta_{d0}^h, \beta_{d1}^g, \beta_{d0}^g)$ be an arbitrary vector space of a weighted nonlinear least squares estimator (WNLSE) observed as $b_d \equiv (b_{d1}^h, b_{d0}^h, b_{d1}^g, b_{d0}^g)$. The parameter space can be expressed as the minimizer of the weighted mean square error (MSE) of the observed outcomes of interest (Frölich and Huber, 2014; Chen *et al.*, 2020) as follows;

$$\beta_d \equiv \underset{b_{d\in\beta_d}}{\operatorname{argmin}} \sum\nolimits_{d'=0,1} E[w(d, d', \alpha_w)(Y - h_{d'}\left(X, \alpha_m, b_{d1}^h, b_{d0}^h\right) + g_{d'}(X, \alpha_m, b_{d1}^g, b_{d0}^g)^2] \quad (18)$$

where $w(d, d', \alpha_w) \equiv w(1{,}1, \alpha_w)$, $w(1{,}0, \alpha_w)$, $w(0{,}1, \alpha_w)$, and $w(0{,}0, \alpha_w)$ is a weighted function of (D, Z_1, Z_2, X), with a parameter vector α_w obtained from the first-stage estimation. The weighting function $w(d, d', \alpha_w)$ accounts for heterogeneities within the production units that may be due to observed and unobserved firm-specific factors influencing production (or outcomes, which in our case is yield and farm net returns). The WNLS is estimated using the generalized method of moment (GMM) approach. The generalized moment-based approach overcomes the restrictiveness in forcing the traditional parametric family of production functions (such the Cobb-Douglas, Translog, and others) in assuming specific distributions, which is sometimes inappropriate leading to modelling bias and misleading conclusions (Giannakas et al., 2003; Vidoli and Ferrara 2015; Ferrara and Vidoli 2017; Ferrara 2020).

4.5 Data and Descriptive Statistics

The present study uses farm level data obtained from a recent survey conducted in the northern region of Ghana from June to August 2018. The sample was drawn using a multi-stage sampling technique. Based on the proportion of beneficiary communities (78%) in the inoculant dissemination program and intensity of soybean production in Ghana, northern region was purposively selected. Cluster sampling technique was used to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on dissemination program participation status of districts and intensity of soybean production at the district level within the clusters, eight (8) districts, comprising four (4) from each cluster were purposively sampled. From the ECZ: Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ: East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, 5-7 communities were proportionally sampled, based on the extension channel received, dissemination program participation, and farmer population. One farmer-based organization (FBO) was randomly selected from a list of FBOs that were exposed to the inoculant technology and another randomly selected from a list of unexposed FBOs for each community. Using a lottery approach, we randomly drew five farmers from each FBO. After a preliminary interview session with each of the selected farmers, using a computer assisted personal interview (CAPI), a list of the farmers' information network members (INMs) was compiled. The CAPI random number generator then used farmers' unique identification numbers to randomly sample three network members from each farmer's INMs for interview. A total of 600 farm households, consisting of 325 inoculant exposed farmers and 275 unexposed farmers, were interviewed in a face-to-face session. The data collected include inoculant adoption status, dissemination program participation status, household demographic characteristics, location characteristics, input used, crop yield and farm net returns, plot level precipitation and soil quality.

Definitions and summary statistics of the variables used in the empirical analysis are presented in Table 4.1. It shows that 54% of our sampled farmers participated in the inoculant extension program. Table 4.1 also shows that 51% of farmers adopted the inoculant with an average yield of 830kg/ha soybeans and net returns of 840GHC/ha. The population of farmers in our sample are quite young with an average age of 42 years and predominantly male farmers 71%, with very low level of education, averaging 3 years of schooling.

As shown in Table 4.1, average land cultivated to soybeans is 5ha, using an average total labor supply of 8persons hours per day/ha and 4kg/ha of agrochemicals in the process. It further shows that 57% of the farmers are located in the western corridor zone. Table 4.1 again, shows that 51% of the farmers live in communities that are connected to the national grid of electricity supply, and located at an average distance of 19km to the nearest extension office and 2km to the nearest market. In terms of inoculant knowledge test score, Table 4.1 reveals that farmers obtain an average of 56% inoculant knowledge score from participating in the dissemination program.

Table 4. 1 Definition and Summary Statistics

Variable	Definition	Mean	SD	Min	Max
Outcomes					
Yield	Soybean yield per hectare (lnKg/ha)	829.64	888.24	32.41	5703.87
Farm Net Return	Gross revenue less variable cost (lnGHC/ha)	840.26	762.11	75.11	4229.89
Treatment Variable					
Adopt-Inoculant	1 If farmer adopts inoculant, Otherwise=0	0.510	0.500	0	1
Mediator Variable					
AES-Part	1 If farmer participated in dissemination program, Otherwise=0	0.542	0.499	0	1
Production Inputs					
Land	Area of land planted with soybean (ha)	5.045	4.371	5.045	4.371
Labor	Total labor used in soy cultivation (Worker-days/ha)	7.808	24.23	0.198	274.73
Agrochem	Total amount of active ingredient in chemical used (kg/ha)	4	7.186	0	87.22
Chemdumy	1 If farmer uses agrochemical, Otherwise=0	0.025	0.156	0	1
Improvar	1 If farmer uses improve seed variety, Otherwise=0	0.700	0.459	0	1
Creditconst	1 If farmer is not credit constrained, Otherwise=0	0.828	0.377	0	1
Farmer-Specific Characteristics					
Age	Age of farmer (years)	41.56	13.32	18	87
Gender	1 If farmer is male, 0 for female	0.708	0.455	0	1
Edu	Years of schooling	2.792	4.687	0	21
Location					
WCZ	1 If farmer is in Western Corridor Zone, Eastern Corridor Zone = 0	0.567	0.496	0	1
Distmarket	Distance to nearest market (km)	2.362	4.137	0.100	50.10
Soilqual	1 If soil quality is good, Poor soil quality=0	0.508	0.500	0	1
Rainfall	Amount of rainfall in (%)	61.63	16.24	20	100
Instrumental Variables					
Distextoff (Z_2)	Distance to nearest extension office in (km)	18.90	25.10	0.016	160.93
Electgrid (Z_1)	1 If community is connected to the national grid for electricity supply, Otherwise = 0	0.512	0.500	0	1
Other Control Variables					
Testscore	Inoculant knowledge test score (%)	56.091	23.75	2	98
Resemtech	1 If inoculant usage resembles existing inputs usage, Otherwise=0	34.933	35.22	0	100
Techdiff	1 If inoculant application process is considered difficult, Otherwise=0	0.278	0.267	0	1
Dislang	1 If dissemination language is in farmer's mother tongue, Otherwise=0	0.695	0.461	0	1
Comextoff	1 if community has extension agent, Otherwise = 0	0.625	0.485	0	1

Note: SD is standard deviation; Min and Max are minimum and maximum values respectively.

4.6 Empirical Results

First, we present the results of the first-stage bivariate probit estimates, as the identification of the model hinges on it and present the estimates in the appendix due to space limitation[28]. Next, we present and discuss estimates of the weighted nonlinear least-squares, estimated via the generalized method moments procedure.

4.6.1 First-Stage Bivariate Probit Estimates

Table 4A.2 presents estimates from the bivariate probit model. The model is used to account for selection bias and for identification of the instrumental variable (IV) regression. Table 4A.2 shows that, both the extension participation model (i.e. the mediation model) and the adoption model are highly correlated due to unobserved heterogeneities. The *p*-value for the null hypothesis shows that ρ_{md} is significantly different from zero (at 1% level), indicating that farmers' extension participation and inoculant adoption decisions may be correlated due to unobserved heterogeneities. However, the sign for ρ_{md} is negative, suggesting that farmers are likely to substitute adoption of new technologies (such as the inoculant) with knowledge acquisition from extension participation (Huth and Allee 2002). This observation is intuitive, because extension services and adoption of improved technologies tend to enhance farmers' production efficiency (Huang and Liu, 1994; Kumbhakar *et al.*, 2009; Triebs and Kumbhakar, 2018). The significance of ρ_{md} also suggests that farmers may have self-selected into the extension program or adoption of the inoculant technology.

Table 4A.2 also shows that, the two instrumental variables are both significantly different from zero (at 1 % level). In particular, distance to the nearest extension office (Z_2), which is used to identify extension program participation, is negative and significant at 1% level. More importantly,

28 Although the covariates in the bivariate probit model can be considered as determinants of inoculant adoption and extension participation, we focus on its identification properties, because the primary interest in this study is for proper model identification, and not to model determinants of participation and adoption decisions.

farmer's community connection to the national electricity grid (Z_1), which we used to identify the inoculant adoption model, is positive and highly significant at 1% level. This implies that one percent increase in rural electrification of communities, increases the likelihood of inoculant adoption by 320%. Intuitively, this makes sense, because the rhizobia used in formulating the inoculant survive in a particular temperature range (25^0C), which stands to reason that, communities with access to constant electricity supply could well operate cold storage facilities. As a result, farmers in such communities may have access to the inoculant, hence, are more likely to adopt, compared to farmers living in communities without constant electricity supply (Dzanku *et al.,* 2020). Our finding of positive effect of community electricity connectivity on farm households' production activities is consistent with existing literature on rural electrification impact on households' economic activities (see Thomas *et al.*, 2020; IEG-World Bank, 2008; Cabraal *et al.,* 2005; Martins, 2005). It is, however, unique by linking rural electrification to agricultural technology adoption.

The validity of the instrument for identification of local average treatment effect in our IV regression estimation strategy requires that the instrument be monotonic increasing function of the level of the instrumental variable (Z_1), and the level of the treatment (*D*) (see Chen *et al.,* 2020). As shown in Table 4A.2, both the instrument in the treatment model and the treatment indicator *D* in the mediation model have positive signs and highly significant (at 1% conventional level), suggesting that our instrument is valid and strong. Intuitively, what it means is that, inoculant adoption increases with increasing extension participation and community electricity connectivity.

4.6.2 Determinants of Technology and Inefficiency Frontiers

Tables 4.2 and 4.3 present factors that affect the production technology and inefficiency frontiers with respect to yield (lnKg/ha), for the case scenario that farmers' adopt the inoculant technology with mediation and the counterfactual scenario of non-adoption nor mediation, respectively (see Tables 4.4 and 4.5, for that of farm net returns). The factors explain the observed yield and net returns variabilities in each scenario among farmers with different adoption and mediation conditions in our sample. For the sake of brevity, we focus the discussion on the yield, which can be extended to that of the net returns.

The model estimated is a weighted nonlinear least-squares regression using generalized method of moment. As such, it does not represent any specific conventional production function model, and as such does not depend on any functional form distribution assumptions. Though we estimate a nonlinear regression model with most of the covariates being log and log-squares, the parameter estimates can be interpreted as in a linear regression estimates (Chen *et al.,* 2020). Our approach of estimating the stochastic production frontier is akin to that of the generalized additive models (GAMs) approach that fits a response variable on a sum of smooth functions of explanatory variables in a regression context with normal distribution (Ferrara, 2020; Ferrara and Vidoli 2017). This specification is preferred to the conventional functional form specifications, due to its flexibility in relaxing the need to impose perfect linearity condition on the underlying stochastic frontier function between the explanatory variables and the outcomes of interest (Ferrara, 2020).

Each Table contains two columns corresponding to two different adoption scenarios. In Table 4.2, column one contains estimates for the case of adoption with mediation (i.e. Adopters^{M}), henceforth, mediated-adopters (MA).

Table 4. 2 Adoption with Mediation – (Weighted Nonlinear Least-Squares) – Yield (lnKg/Ha)

Variables	Adopters^{M} ***(d, M(d'))=(1,1)***	Non-Adopters^{N} ***(d, M(d'))=(0,0)***
	Coeff.(S.E)	*Coeff.(S.E)*
Age	0.009*(0.005)	0.021(0.016)
Gender	0.096(0.128)	0.350(0.379)
Edu	0.017(0.046)	0.204**(0.095)
Edusq	-0.003(0.003)	-0.016***(0.006)
lnland	0.717***(0.101)	0.098(0.332)
lnlaborsq	0.037***(0.012)	-0.042(0.045)
lnagrochem	-0.031(0.023)	0.328***(0.113)
Chemdumy	-0.440(1.487)	1.244(1.497)
Improvar	-0.168(0.158)	-0.516(0.408)
WCZ	-0.073(0.138)	-1.384***(0.336)
Distmarket	-0.005(0.017)	-0.008(0.041)
Soilqual	0.341***(0.115)	0.506(0.378)
Rainfall	-0.008***(0.003)	-0.007(0.012)
Creditconts	-0.194(0.123)	-0.006(0.542)
Tsresid	-0.652***(0.179)	-4.271***(0.936)
Const.	5.604***(0.458)	264.037***(54.392)
Inefficiency		
$\beta^{g}_{(ts)}$	-10.281***(4.284)	-0.015***(0.006)
$\beta^{g}_{(0)}$	0.457***(0.171)	5.786***(0.207)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who participate in the extension program and adopt the inoculant (i.e. Adopters^{M} = Mediated-Adopters, abbreviated as (MA)) and farmers who neither participate nor adopt the inoculant (i.e. Non-Adopters^{N} = Non-Mediated-Non-Adopters, abbreviated as (NM-NA)), respectively.*

Table 4. 3 Adoption without Mediation – (Weighted Nonlinear Least-Squares) – Yield (lnKg/Ha)

Variables	Adopters^{N} (d, M(d'))=(1,0)	Non-Adopters^{M} (d, M(d'))=(0,1)
	Coeff.(S.E)	*Coeff.(S.E)*
Age	-0.0003(0.020)	0.019(0.015)
Gender	0.490*(0.280)	1.050**(0.524)
Edu	-0.051(0.107)	-0.593***(0.208)
Edusq	0.004(0.006)	0.046***(0.017)
lnland	0.958***(0.291)	0.862***(0.363)
lnlaborsq	-0.021(0.032)	-0.067(0.066)
lnagrochem	0.100*(0.060)	-0.246**(0.126)
Chemdumy	-0.156(13.989)	-12.237(7.661)
Improvar	0.411(0.449)	-0.211(0.536)
WCZ	0.441(0.477)	-1.510***(0.474)
Distmarket	-0.003(0.025)	-0.065(0.055)
Soilqual	0.635***(0.267)	1.201***(0.496)
Rainfall	0.002(0.011)	-3.3-e5(0.014)
Creditconts	-0.518(0.374)	0.810(0.697)
Tsresid	-0.223***(0.077)	-3.403***(0.933)
Const.	5.595***(1.227)	102.035***(2.270)
Inefficiency		
$\beta^{g}_{(ts)}$	-7.980***(2.112)	-0.016**(0.008)
$\beta^{g}_{(0)}$	0.080(0.247)	4.862***(0.025)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who did not participate in the extension program but adopt the inoculant (i.e. Adopters^{N} = Non-Mediated-Adopters, abbreviated as (NM-A)) and farmers who participate in the extension program but did not adopt the inoculant (i.e. Non-Adopters^{M}, abbreviated as M-NA)), respectively.*

Table 4. 4 Adoption with Mediation – (Weighted Nonlinear Least-Squares) – Farm Net Returns (lnGHC/Ha)

Variables	Adopters^{M} ***(d, M(d'))=(1,1)***	Non-Adopters^{N} ***(d, M(d'))=(0,0)***
	Coeff.(S.E)	*Coeff.(S.E)*
Age	0.002(0.002)	-0.065*(0.037)
Gender	-0.157***(0.062)	-0.635(0.754)
Edu	-0.005(0.019)	0.231(0.205)
Edusq	0.0002(0.001)	-0.009(0.014)
lnland	1.108***(0.042)	1.185*(0.674)
lnlaborsq	-0.009(0.006)	0.154*(0.091)
lnagrochem	-0.016(0.010)	-0.094(0.141)
Chemdumy	-0.366(0.464)	-3.434(3.090)
Improvar	-0.094(0.066)	1.078(0.921)
WCZ	-0.103*(0.057)	0.001(0.674)
Distmarket	-0.006(0.006)	0.028(0.074)
Soilqual	0.007(0.051)	0.373(0.761)
Rainfall	-0.006***(0.002)	-0.013(0.022)
Creditconts	-0.013(0.053)	6.478***(1.315)
Tsresid	0.014(0.071)	-15.578***(3.401)
Const.	5.699***(0.236)	254.477***(53.500)
Inefficiency		
$\beta^{g}_{(ts)}$	-8.430**(3.616)	-0.007***(0.001)
$\beta^{g}_{(0)}$	-0.538***(0.091)	5.730***(0.209)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who participate in the extension program and adopt the inoculant (i.e. Adopters^{M} = Mediated-Adopters, abbreviated as (MA)) and farmers who neither participate nor adopt the inoculant (i.e. Non-Adopters^{N} = Non-Mediated-Non-Adopters, abbreviated as (NM-NA)), respectively.*

Table 4. 5 Adoption without Mediation – (Weighted Nonlinear Least-Squares) – Farm Net Returns (lnGHC/Ha)

Variables	Adopters^{N} *(d, M(d'))=(1,0)*	Non-Adopters^{M} *(d, M(d'))=(0,1)*
	Coeff.(S.E)	*Coeff.(S.E)*
Age	-0.009(0.007)	-0.085***(0.030)
Gender	0.202**(0.088)	-5.664***(1.270)
Edu	-0.003(0.034)	0.161(0.325)
Edusq	0.0001(0.004)	0.006(0.027)
lnland	1.136***(0.104)	1.962***(0.649)
lnlaborsq	-0.024**(0.010)	-0.029(0.137)
lnagrochem	0.012(0.019)	-0.362*(0.195)
Chemdumy	-0.193(4.158)	-11.631(16.412)
Improvar	0.095(0.148)	-5.725***(1.211)
WCZ	0.238*(0.139)	-0.531(0.935)
Distmarket	0.001(0.008)	0.011(0.095)
Soilqual	0.146*(0.088)	-2.129**(0.920)
Rainfall	-0.001(0.003)	0.011(0.029)
Creditconts	-0.336***(0.129)	-6.223***(1.693)
Tsresid	-0.493**(0.232)	-2.509(2.121)
Const.	5.557***(0.480)	96.343***(30.533)
Inefficiency		
$\beta^{g}_{(ts)}$	-15.551*(8.707)	-0.040***(0.008)
$\beta^{g}_{(0)}$	-1.720***(0.647)	4.441***(0.426)
Observ. (N)	*306*	*294*

*Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors. Columns one and two represents farmers who did not participate in the extension program but adopt the inoculant (i.e. Adopters^{N} = Non-Mediated-Adopters, abbreviated as (NM-A)) and farmers who participate in the extension program but did not adopt the inoculant (i.e. Non-Adopters^{M}, abbreviated as M-NA)), respectively.*

This category represent the scenario that farmers participated in the extension program and also adopted the inoculant technology, while column two represents the counterfactual case scenario for farmers who neither participated in the extension program nor adopted the inoculant technology, henceforth refer to as non-mediated-non-adopters (NM-NA). In Table 4.3, column one represents the case scenario of farmers, who did not participate in the extension program but adopted the inoculant technology (i.e. Adopters^{N}), hereafter, non-mediated-adopters (NM-A), whereas column two represents the counterfactual case of farmers who participated in the extension program but did not adopt the inoculant technology (i.e. Non-Adopters^{M}), hereafter refer to as mediated-non-adopters (M-NA).

The estimates for the constant term in Table 4.2 captures the effect of unobserved farmer-specific characteristics on the production function, are all positive and statistically significant across all farmers. These results suggest that farmers may have certain unobserved characteristics that enhance or limit their ability to push the production frontier upward, irrespective of the superiority of the production technology being employed. Similar trend is observed in Table 4.3. The results also show that observed farmer-specific characteristics such as education, gender and age have significant impact in shifting the production frontier of farmers. In particular, for NM-NA farmers, education is positive and significant at 5% level, while education square is negative and significant 1% level, suggesting that an increase in education pushes the production frontier of this category of farmers upwards, with the maximum effect occurring at 2 years of schooling. On the other hand, education is negative and significant at 1% level for M-NA farmers, while that of the squared term is positive, suggesting that this category of farmers require more years of schooling, in order for education to have positive impact on their production frontier.

Also in Table 4.2, gender (i.e. being a male farmer) has positive coefficient across all farmers, but statistically significant (at 10% and 5% levels) for only NM-A and M-NA farmers respectively, suggesting that being a male farmer within our study area generally improve ones' productivity. This observation may be due to the fact that male farmers in most parts of developing countries have better access to family labor, quality land and other resources than female farmers, a finding that is in line with Gebre *et al.* (2019) in their study of gender differences in agricultural productivity among maize farmers in Ethiopia. However, the reverse is observed for the net returns in Tables 4.4 and 4.5, suggesting that in terms of net returns, female farmers' are able to push their net returns frontier upwards, compared to their male counterparts. This observation is intuitive as female farmers are more likely to have good marketing skills, compared to their male counterparts, as such are more likely to bargain for good prices.

Table 4.2 also shows that among the conventional inputs (land, labor, agrochemicals and improved seed variety), land has the highest effect on the production frontier. Land is positive and statistically significant at 1% level across all category of adopters (except NM-NA which is not statistically significant), suggesting that a unit increase in land cultivated to soybean under the inoculant technology leads to increase in yields ranging between 72kg/ha to 96kg/ha across various category of farmers. Similar but greater effect is observed in terms of net returns per hectare of land (see Tables 4.4 and 4.5). The results further reveal that the effect of labor on the production frontier is positive and statistically significant at 1% level for MA farmers, suggesting that this group of farmers benefited from labor availability.

Also in Tables 4.2 and 4.3, the quantity of agrochemicals used is positive and significant at 1% and 10% for NM-NA and NM-A farmers respectively, indicating that the quantity of agrochemicals applied to control weeds shifts the production frontier of this category of farmers upwards. It is possible that some farmers may not have used agrochemicals, which if not accounted for could bias the results. Following Battese (1997), we included a dummy variable for chemical usage and did not find any statistical significant effect at any conventional level.

In addition to the conventional and farmer-specific characteristics, we also controlled for environmental and geographical factors using zonal dummies, plot level soil quality and precipitation. The results reveal that the zonal dummy which indicates whether the farmer is located in the western corridor zone (WCZ) or eastern corridor zone (base category) is negative across all category of adopters but statistically significant for NM-NA and M-NA farmers only, suggesting that the eastern corridor zone has high potential for soybean production, compared to the WCZ, since being in that zone shifts the production frontier upwards relative to being in WCZ. Tables

4.2 and 4.3 also reveal that soil quality at the farm level plays significant (at 1% level of statistical significance) role in shifting the production frontiers upwards across all category of adopters. The results further show that insufficient precipitation at the plot level significantly shifts the production frontier downwards. In particular, that of MA (at 1% level of significance), a finding which is consistent with adverse effects of rainfall on productivity in the literature.

In the last two rows of Tables 4.2 and 4.3, we present estimates of post-mediation factor(s) that influence farmers' level of (in)efficiency in the usage of the inoculant technology that could have great impact on yields obtained from adoption. We conducted an inoculant technical knowledge quiz and use the test scores to proxy the post-mediation factors in the inefficiency frontier function. As shown in the Tables, the coefficient of a constant only inefficiency frontier model (represented as $\beta^{g}_{(0)}$) is positive and statistically significant at 1% level across all adopters, suggesting that adopting the inoculant technology without sufficient technical knowledge on its usage makes farmers highly inefficient and less beneficial. On the other hand, the coefficient of the inefficiency model, with inoculant knowledge test score (represented as $\beta^{g}_{(ts)}$) is negative and statistically significant at 1% level across all adopters, indicating that adopting the technology with sufficient technical knowledge increases farmers' production efficiency (i.e. reduces farmers' inefficiency). Similar results pattern is obtained for net returns in Tables 4.4 and 4.5. This finding learns credence to Dzanku *et al.* (2020), who argued that effective application of the inoculant technology requires knowledge on proper storage and inoculation procedures in order to replicate the effective experimental results of the inoculant technology by farmers.

4.6.3 Impact of Mediation and Inoculant Adoption on Productivity, Efficiency and Welfare

In this section, we report estimates of the treatment effects derived in equations 11 – 13. The results for yields and farm net returns are presented in Tables 4.6 and 4.7, respectively. Focusing on Table

4.6, the first column contains total impact of program participation on the farm household's welfare, decomposed into welfare contribution coming directly from adoption of new technology and indirectly from participation in the extension program. The second column contains total impact of inoculant adoption on the production frontier of inoculant adopters' relative to non-adopters, decomposed into the portion due directly to technological change which shifts the observed production frontier closer to the ideal production frontier (i.e. the potential yield frontier), and indirectly due to improvement in adopters' technical knowledge in shifting the production frontier. The estimates in the third column represent the total impact on the production efficiency of inoculant adopters relative to non-adopters, decomposed into efficiency gained due to technological change and indirectly due to improvement on inoculant adopters' technical knowledge.

The results in column one of Table 4.6 show that, the total treatment effect (measured as the local average treatment effect (LATE)) on yields is positive and statistically significant at the 1% level. Specifically, the impact on yield is 52kg/ha (and 46GHC/ha for net returns), suggesting that farmers who participate in the extension program and adopt the inoculant technology increased their yields (and net returns), compared to if they had neither participate in the extension program nor adopt the inoculant technology.

Table 4. 6 Productivity, Efficiency and Welfare Estimates on Soybean Yield - (lnKg/ha)

Impact on: Welfare	Technology Frontier	Inefficiency Frontier
LATE	$LATE_h$	$LATE_g$
52.296***(0.496)	-203.283***(1.987)	-256.086***(2.333)
DLATE	$DLATE_h$	$DLATE_g$
40.218***(0.427)	-145.942***(1.633)	-186.199***(2.010)
ILATE	$ILATE_h$	$ILATE_g$
12.071***(0.281)	-57.884***(1.337)	-69.915***(1.579)

*Note: *** indicates 1% level of significance; Values in brackets are bootstrapped standard errors from 1,000 re-samples. LATE is local average treatment effect, representing the total effect of participation in the extension dissemination program and inoculant adoption; DLATE is direct local average treatment effect, representing the component of the total effect that comes from inoculant adoption; ILATE is indirect local average treatment effect, representing the component of the total effect that comes from extension participation.*

Table 4. 7 Productivity, Efficiency and Welfare Estimates on Net Returns – (lnGHC/ha)

Impact on: Welfare	Technology Frontier	Inefficiency Frontier
LATE	$LATE_h$	$LATE_g$
46.026***(0.573)	-185.568***(2.333)	-231.511***(2.245)
DLATE	$DLATE_h$	$DLATE_g$
26.478***(0.492)	-124.835***(1.998)	-151.354***(2.402)
ILATE	$ILATE_h$	$ILATE_g$
19.543***(0.466)	-60.683***(1.418)	-80.189***(1.805)

*Note: *** indicates 1% level of significance; Values in brackets are bootstrapped standard errors from 1,000 re-samples. LATE is local average treatment effect, representing the total effect of participation in the extension dissemination program and inoculant adoption; DLATE is direct local average treatment effect, representing the component of the total effect that comes from inoculant adoption; ILATE is indirect local average treatment effect, representing the component of the total effect that comes from extension participation.*

This finding implies that farmers who have access to constant electricity supply and extension information achieve higher welfare benefits, compared to farmers who do not have access to both electricity and extension information.

A decomposition of the welfare benefits due to mediation indicate that 77% (i.e. DLATE = 40kg/ha) of the welfare benefits, in terms of marginal gains in yield, can be attributed to the farm household's adoption of improved technology (i.e. the inoculant), while 23% (ILATE = 12kg/ha) is due to the farm household's participation in inoculant extension dissemination program.

The total treatment effect on the production frontier in column two of Table 4.6 shows that, the technological change led to a reduction in the yield gap between the production frontier of adopters and that of the best production frontier by 203kg/ha. In order words, farmers who participate in the extension program and adopt the inoculant technology increased their yields by 203kg/ha, which agrees with Ulzen *et al.* (2018) who reported that farmers' soybean yield increased by 200kg/ha with inoculant application in northern Ghana. Further decomposition of the impact on the shift of the production frontier shows that 72% (i.e. $DLATE_h$ =146kg/ha) is due to adoption of the improved technology, while 28% ($ILATE_h$ = 58kg/ha) of the shift is due to enhancement in farmers' technical knowledge on the improved technology usage. Intuitively, the total effect is an interaction of adoption of the improved technology and technical knowledge in the management of the new technology that leads to realization of the full potential of the technology. This finding is in line with Takahashi *et al.* (2020), who in a recent review of the literature on technology adoption and extension, highlight the need to collaborate the two in a single study.

In column three of Table 4.6, the total effect on the technical efficiency shows that improvement in technical efficiency of farmers led to an increase in yield of about 256kg/ha. This indicates that farmers who participate in the extension program and adopt the inoculant technology are able to cut down their inefficiency up to 256kg/ha (i.e. yield that would have been lost due to inefficiency) by adopting improved technology with technical knowledge. The marginal gain due to technical efficiency appears to outweighs that of yield at the production frontier (i.e. 203kg/ha). This finding is consistent with the argument by Huang and Liu (1994) that farmers who acquire technical knowledge on a new technology prior to adoption of the technology tend to benefit more. A decomposition of the total effect of technical efficiency shows that 73% (i.e. $DLATE_g$ =186kg/ha) of the improvement comes from the farmer's adoption of improved technology, while 27% ($ILATE_g$ = 70kg/ha) comes from technical knowledge on the technology, implying that the synergic effect of better technology and technical knowledge is required for farmers to be fully technically efficient. However, greater proportion of technical efficiency is achieved by adopting improved technology, which is consistent with Kumbhakar *et al.* (2009) argument that some technologies inherently make the farmer efficient or inefficient. We find similar patterns of impact on the production technology frontier and the technical efficiency frontier in the net returns model presented in Table 4.7.

4.6.4 Production and Technology Gap Profiles

In Figures 4.1 and 4.2, we present the conditional (i.e. condition on being a complier) mean yield estimates in deciles across various sub-population of adopters at the production technology and technical inefficiency frontiers, respectively (see Figures 4A.2 and 4A.3 in the appendix for farm net returns). This is important in characterizing the production and technology gap between the sub-population of adopters and non-adopters, since adoption of an improved technology may induce inequalities in the production structures of farmers, due to heterogeneity in production technology and technical efficiency of farmers at the respective frontiers. Recent literature in the stochastic frontier analysis employ quantile regression to profile the production and technology gap among firms for structural analysis (e.g. Lai *et al.,* 2020; Huang *et al.,* 2017). However, the quantile regression approach is somehow restrictive as it allows for characterization of firms only at the quantile means and not at the individual firm level means, as in the case of standard regression (Fortin *et al.* 2011), the approach employed in this paper.

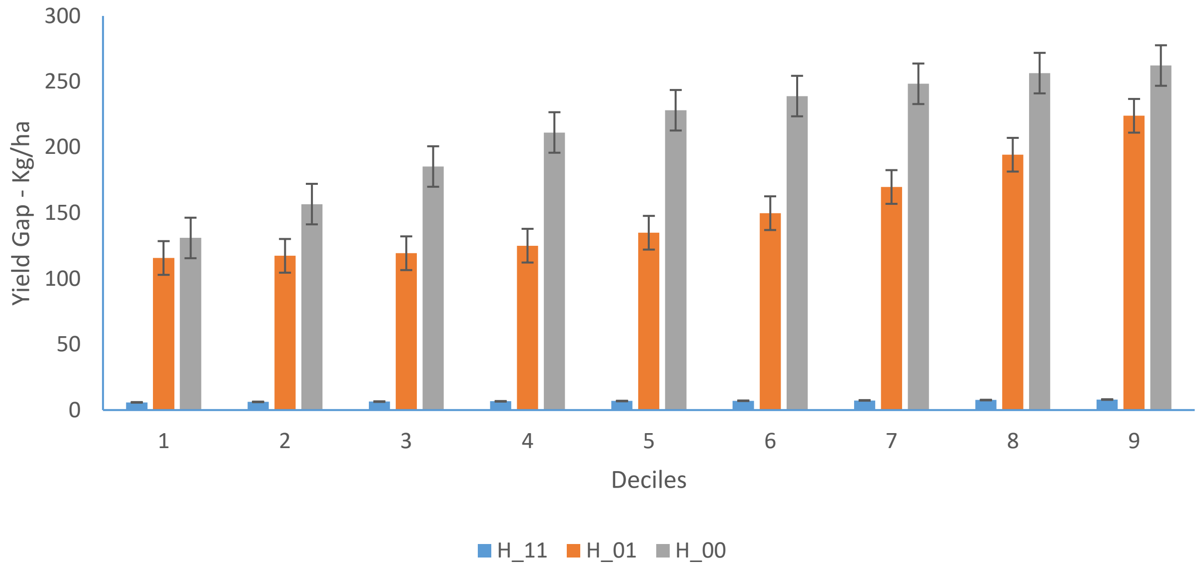


Figure 4. 1 Yield Gap Profile at the Production Technology Frontier (Kg/Ha).

Where H-11, H-00 and H-01 01 indicates mediated-adopters, non-mediated-non-adopters and mediated-non-adopters, respectively at the production technology frontier function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different production technology frontiers, compared to farmers at the best production frontier operating at zero technological inefficiency.

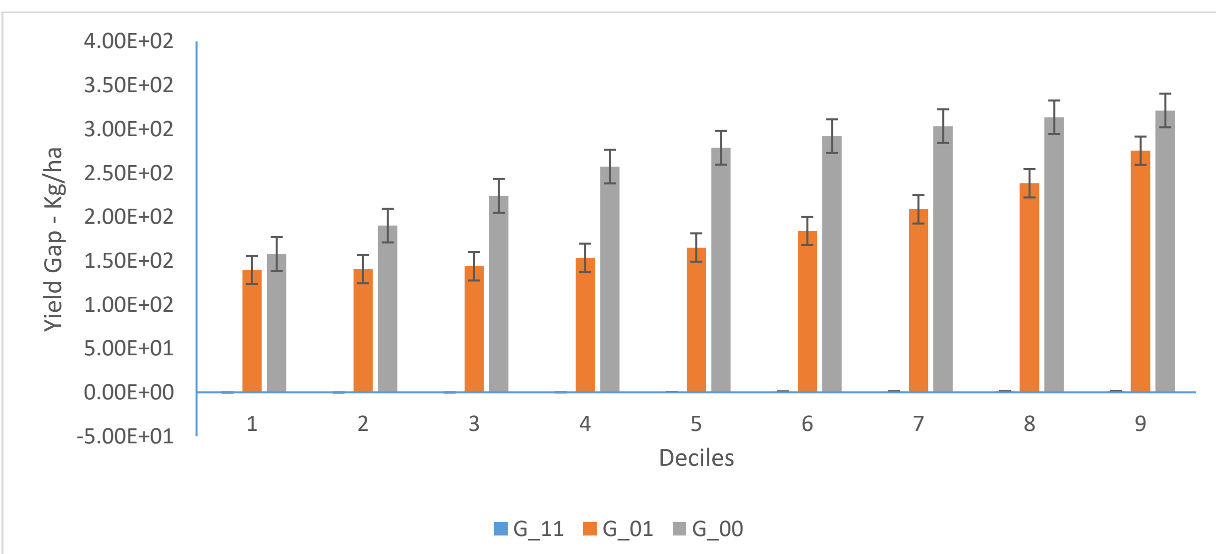


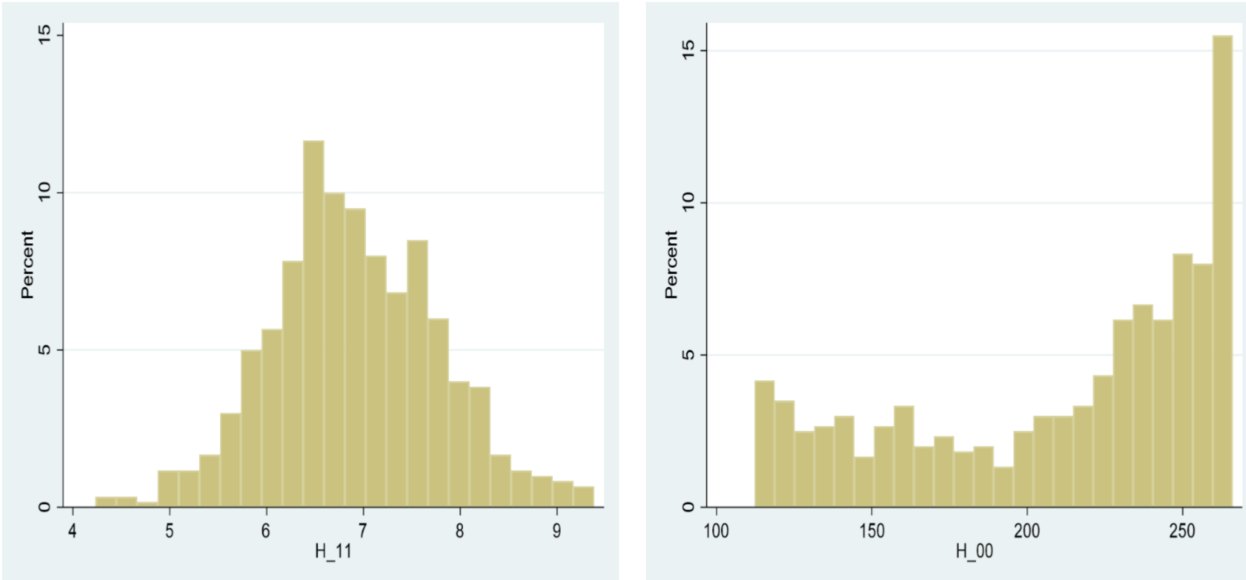
Figure 4. 2 Yield Gap Profile at the Inefficiency Frontier (Kg/Ha).

Where G-11, G-00 and G-01 indicates mediated-adopters, non-mediated-non-adopters and mediated-non-adopters, respectively at the technical inefficiency function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different levels of technical inefficiency, compared to farmers operating at zero technical inefficiency.

Figure 1shows that, the yield distance of farmers who participate in the extension program and adopt the inoculant technology – (i.e. the MA farmers (H-11)) at every decile is more closer to zero, compared to farmers who neither participate in the extension program nor adopt the technology (i.e. the NM-NA farmers (H-00)). Similarly, the MA farmers yield gap is also narrower, compared to farmers who participate in the extension program but did not adopt inoculant (i.e. the M-NA farmers (H-01)), suggesting that the yield gap of farmers who participate and adopt the inoculant technology is more closer to farmers producing soybeans at the best production technology frontier.

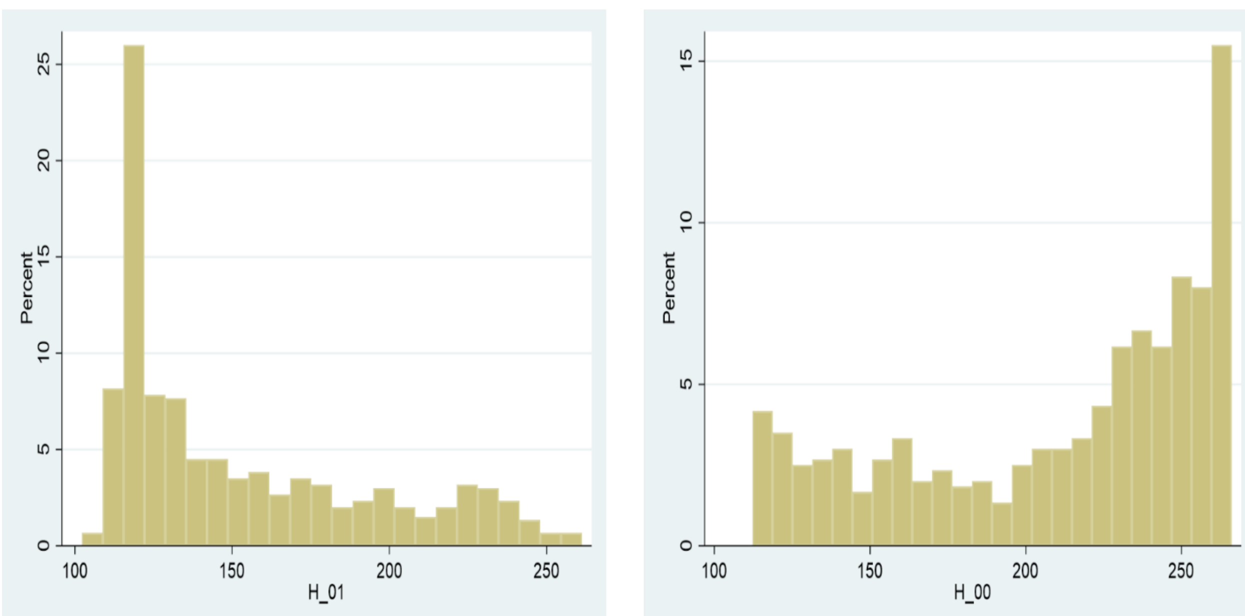
Also in Figure 4.2, the conditional mean plot of the yield at the technical efficiency frontier shows that, the average yield distance of MA farmers (G-11) at every decile is almost on the zero line, as compared to that of NM-NA (G-00) and M-NA (G-01) farmers respectively, indicating that farmers who participate in the extension dissemination program and adopt the inoculant are technically more efficient than farmers who neither adopt nor participate in the dissemination program. However, a comparison of the yield distance at both the production frontier and the technical efficiency frontier between farmers who participated in the extension dissemination program but did not adopt the inoculant (i.e. the M-NA farmers – (H-01 and G-01)) is also lower, when compared to that of NM-NA farmers (i.e. H-00 and G-00), suggesting that, extension participation even without adoption of a new technology may still be effective in improving farmers' efficiency. We find similar production and technical efficiency profile patterns in the net returns estimates presented in Figures 4A.2 and 4A.3.

Figures 4.3 and 4.4 show the full conditional mean yield distributions for MA farmers (H-11) in panel (a), compared to NM-NA farmers (H-00) in panel (b) and also that of M-NA (H-01) farmers in panel (a), compared to NM-NA (H-00) farmers in panel (b), respectively.



(a) Mediated-Adopters (b) Non-Mediated-Non-Adopters

Figure 4. 3 Comparison of Yield (Kg/Ha) Distributions at the Technology Frontier – Direct Effect

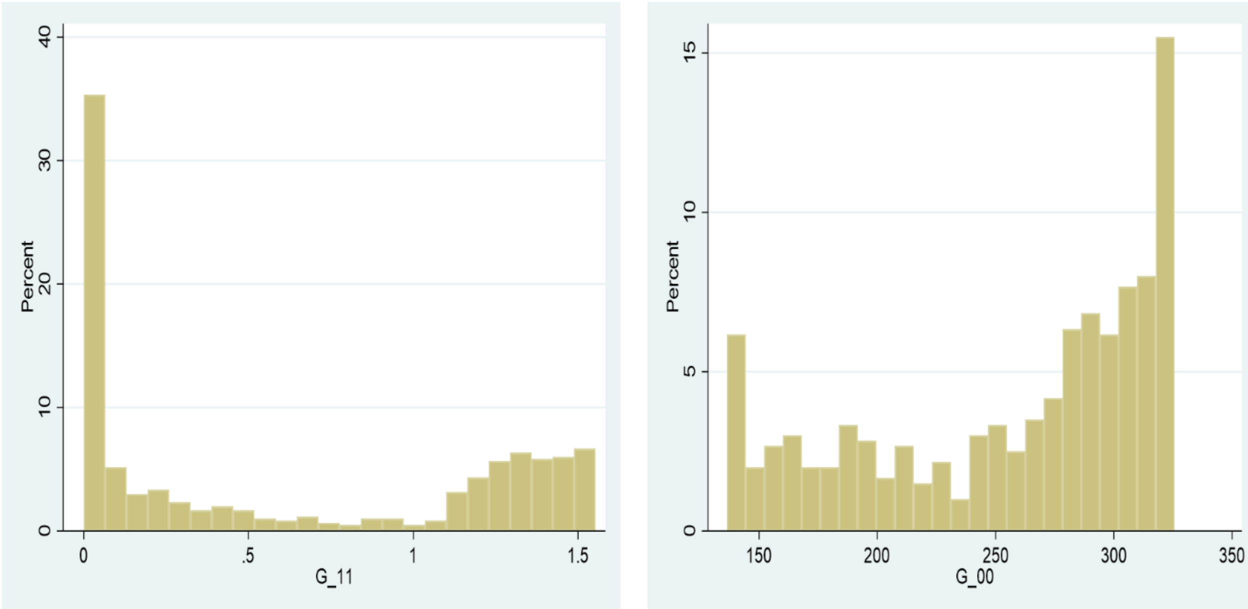


(a) Mediated- Non-Adopters (b) Non-Mediated-Non-Adopters

Figure 4. 4 Comparison of Yield (Kg/Ha) Distributions at the Technology Frontier – Indirect Effect

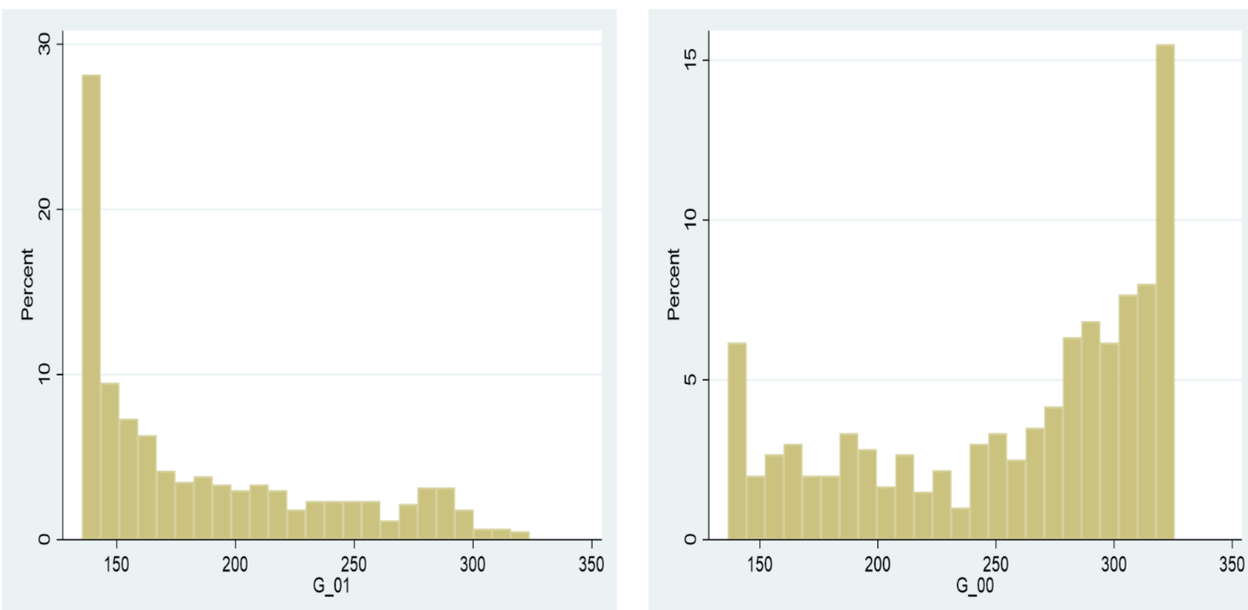
The mean yield distribution at the production technology frontier of MA farmers is much lower, and appears to be densely skewed to the left (i.e. towards zero), compared to that of the distributions of NM-NA and M-NA farmers. This finding in an indication that a greater percentage of the yield variability among the farmers may be attributed to technology heterogeneity, which greatly minimizes the yield distance between farmers who participate in the extension program and adopt the technology and those who did not. Similar pattern of distribution is observed in respect of the farm net returns in Figures 4A.4 and 4A.5 in the appendix.

Conversely, the mean yield distribution at the technical efficiency frontier in Figures 4.5 and 4.6 show that the distribution for MA farmers (i.e. G-11) is also densely skewed to the left (i.e. towards zero), compared to that of NM-NA (i.e. G-00) and M-NA (G-01) farmers, respectively. These results indicate that conditional on participating in the extension dissemination program and adopting the inoculant technology, all else being equal, greater percentage of yield variability at the frontiers may be due to random noise rather than technical inefficiency. We observed similar distribution patterns in the net returns in Figures 4A.6 and 4A.7 in the appendix.



(a) Mediated-Adopters (b) No-Mediated-Non-Adopters

Figure 4. 5 Comparison of Yield (Kg/Ha) Distributions at the Inefficiency Frontier – Direct Effect



(a) Mediated- Non-Adopters (b) No-Mediated-Non-Adopters

Figure 4. 6 Comparison of Yield (Kg/Ha) Distributions at the Inefficiency Frontier – Indirect Effect

4.6.5 Robustness Check

By way of checking the robustness of our finding, we conduct further analysis and report the results in the appendix due to space constrains. First, we re-estimate a probit model for the binary adoption decision variable with our instrumental variable (IV) – community connection to national electricity grid (Z_1). This is to check the validity for the propensity of instrument compliers to adopt the inoculant away from the bivariate probit. Since it is possible that the statistical significance of (Z_1) in the bivariate probit model may have been driven by the presence of the mediator variable or its instrument. As shown in Table 4A.3, the IV (Z_1) is positive and statistically significant at 1% level with the magnitude of the coefficient slightly larger than the bivariate counterpart, suggesting that the significance of the instrument is not driven by any other factor. The significant and positive sign of the instrument propensity indicates that the instrument is valid and strong enough to be able to identify local average treatment effect.

In Table 4A.4, we also present a mixture of two normal distribution estimates for our continuous IV – distance to the nearest extension office (Z_2) used to identify the mediation effect on adoption. The intuition behind the identification property of the continuous IV to observe its mediation effect on adoption is that, along the IV's full distribution, it should be plausible to either observe an increasing or decreasing distribution as the probability to participate and adopt increases or otherwise (Frölich and Huber, 2017; Chen *et al.,* 2020). Figure 4A.1 in the appendix shows that the instrument met the pre-requisite condition, for identification of the mediation effect to be observed.

Table 4A.4 reports the estimates obtained from the estimation of the distributions at the instrument means. As shown in Table, both the first mean (μ_1) and the second mean (μ_2) of the mixture distribution are statistically significant (at 1% level) and have the expected signs. The first mean is negative, suggesting that as distance to nearest extension office decreases, the probability of a farmer participating in the extension program and adopting the inoculant increases, resulting in the impacts observed in this study. The mixing probability function ($f(p)$) of the distribution is also positive and statistically significant at 1% level, suggesting that the instrument is a monotonic increasing function in participation and adoption, which is also a necessary condition for local average treatment effect identification in the IV regression (Chen *et al*., 2020; Thomas *et al*., 2020). The significant and positive sign of the instrument propensity function indicates that the instrument is valid and strong enough to be able to identify local average treatment effect, and that our LATE estimates reported in this study are not driven by any incidental variable or matrix. The GMM model estimated is also just or exactly identified, assuming an identity weighting matrix as the initial weighting matrix.

Finally, we present the unconditional (i.e. conditional on observed and unobserved factors but not only on being a complier) mean estimates of the individual sub-population level distributions of the two outcomes in Figure 4A.8 panel (a) and (b) of the technical (in)efficiency gap profile of farmers in deciles. The results confirm the robustness in the mean distributions of the farm production structure reported in this study. In fact, the unconditional estimates in Figure 4A.8 show that, given observed and unobserved farmer-specific characteristics, some farmers within the 1 – 6 deciles perform efficiently above the best technical efficiency frontier in the population in the yield model in panel (a), and across all deciles in the net returns model in panel (b).

4.7 Policy Implications and Conclusions

Analyzing the welfare impacts of improved agricultural technologies and extension delivery programs can be challenging, because either of them can lead to welfare gains. The approach often employed in empirical analysis is to focus on one component and subsume the other in statistical distributional assumptions. In this study, we employ a new approach that evaluates simultaneously the two components and decomposes the welfare impacts attributable to each of the two components. We use recent farm level data of soybean farmers who participated in the extension dissemination program of legume inoculant technology in Ghana. We investigate, simultaneously, the impact of the inoculant technology adoption and the extension program participation on farmers' productivity, efficiency and welfare. We also decompose each of these impact measures into subcomponents whose impact paths can be traced to inoculant technology adoption, extension delivery that enhances farmers' technical knowledge, and the program participation decision.

Our findings revealed that investing in either development of improved agricultural technologies such as the inoculant or intensifying extension delivery programs lead to increased productivity, as well as efficiency and welfare gains. We also found that the contribution of adoption of improved agricultural technologies alone (i.e. inoculant adoption) can improve farm productivity by 72%, productivity gain due to improved farmer efficiency by 73%, and improvement in welfare by 77%. On the other hand, extension delivery program participation alone improved productivity by almost 28%, productivity gain due to improved farmer efficiency by 27%, and improvement in welfare by 23%. Although the results suggest that improved agricultural technologies impact is greater than extension delivery, we found that the synergic effect of the two is far greater than the individual effects.

Our findings show that investment in research development aimed at developing new agricultural technologies for farmers in developing countries such as Ghana can contribute to poverty alleviation. In the same vain, our results confirm the significance of improving farmers' access to extension services, given that extension agents provide farmers with detailed knowledge on new technologies. Our findings also reveal the significance of rural electrification in enhancing the diffusion of new agricultural technologies, suggesting that state sponsored rural electrification programs will go a long way to contribute to the adoption of new agricultural technologies, thereby increasing farm incomes and reducing rural poverty. This will also facilitate the deployment of new channels of extension delivery via information and communication technologies (ICT) channels which mostly use electricity for effective functioning. As argued in this study, investment in rural electrification will also drive the development and expansion in rural enterprises such as sales of agro-inputs and perishable agro-based products, which must be stored under specific storage conditions.

References

Abdulai, A. and W.E. Huffman (2000). Structural adjustment and efficiency of rice farmers in Northern Ghana. *Economic Development and Cultural Change, 48:503 – 521*.

Abdulai, A-N., and A, A. (2016). Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. *Environment and Development Economics, 22:177 – 201*.

Abdul-Rahaman, A., and Abdulai, A. (2018). Do Farmer Groups Impact on Farm Yield and Efficiency of Smallholder Farmers? Evidence from Rice Farmers in Northern Ghana. *Food Policy 81:95–105*.

Aigner, D., Lovell, C.A.K. and Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics, 6(1): 21- 37*.

Angrist, J. D., Imbens, G. W., and Rubin, D. B. (1996). Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association, 91(434): 444 – 455*.

Baron, R. M. and Kenny, D. A. (1986). The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology, 51(6):1173 – 1182*.

Battese, G. E. (1997). A Note on the Estimation of Cobb-Douglas Production Functions when some Explanatory Variables have Zero Values. *Journal of Agricultural Economics, 48(2): 250 – 252*.

Behr, A. (2010). Quantile regression for Robust Bank Efficiency Score Estimation. *European Journal of Operations Research, 200(2):568 – 581*.

Bernini, C., Freo, M., and Gardini, A. (2004). Quantile Estimation of Frontier Production Function. *Empirical Economics, 29:373 – 381*.

Bravo-Ureta, B. E. (2014). Stochastic Frontiers, Productivity Effects and Development projects. *Economics and Business Letters, 3(1):51 – 58*.

Bravo-Ureta, B. E., González-Flores, M., Greene, W., and Solís, D. (2020). Technology and Technical Efficiency Change: Evidence from a Difference in Differences Selectivity Corrected Stochastic Production Frontier Model. *American Journal of Agricultural Economics, 103(1): 362 – 385*.

Bravo-Ureta, Boris E, William Greene, and Daniel Solís. (2012). Technical Efficiency Analysis Correcting for Biases from Observed and Unobserved Variables: An Application to a Natural Resource Management Project. *Empirical Economics, 43: 55 – 72*.

Cabraal, R.A., Barnes, Doug F., Agarwal, S.G., (2005). Productive uses of energy for rural development. *Annual Review of Environment and Resources, 30:117 – 144*.

Chen, Y. T., Hsu, Y. C., and Wang, H. J. (2020). A Stochastic Frontier Model with Endogenous Treatment and Mediator. *Journal of Business and Economic Statistics, 38: 243 – 256* .

Chibeba, M.A., Kyei-Boahen, S., Guimarães, d-F.M., Nogueira, A.M. and Hungria, M. (2018). Feasibility of transference of inoculation-related technologies: A case study of evaluation of soybean rhizobial strains under the agro-climatic conditions of Brazil and Mozambique. *Agriculture, Ecosystems and Environment, 261: 230 – 240*.

Crowley, E., and Carter, S. (2000). Agrarian change and the Changing Relationships between Toil and Soil in Marigoli, Western Kenya 1900 - 1994. *Human Ecology, 28(3): 383 – 414*.

De los Santos-Montero, L., and Bravo-Ureta, B. E. (2017).Productivity Effects and Natural Resource Management: Econometric Evidence from POSAF-II in Nicaragua. *Natural Resources Forum, 41: 220–33*.

Dinar, A., Karagiannis, G., and Tzouvelekas, V. (2007). Evaluating the Impact of Agricultural Extension on Farms' Performance in Crete: A Nonneutral Stochastic Frontier Approach. *Agricultural Economics, 36:135 – 146*.

Dzanku, F. M., Osei, R. D., Nkegbe, P. K., and Isaac Osei-Akoto, I. (2020). Information Delivery Channels and Agricultural Technology Uptake: Experimental Evidence from Ghana. *European Review of Agricultural Economics, 00(00):1 – 39*.

Ferrara, G. (2020). *Stochastic frontier models using R*. Part III Chapter 9, pp. 299 - 326. In Financial, Macro and Micro Econometrics Using R, Handbook of Statistics Edited by Hrishikesh D. Vinod, C.R. Rao 42:s 1-333 Elsevier.

Ferrara, G., and Vidoli, F., (2017). Semiparametric stochastic frontier models: A generalized additive model approach. *European Journal of Operations Research, 258(2):761 – 777*.

Fortin, N., Lemieux, T. and Firpo, S. (2011). *Decomposition Methods in Economics*. In Handbook of Labor Economics, Chapter One, Elsevier.

Foyer, C. H., Siddique, K. H. M., Tai, A. P. K., Anders, S., Fodor, N., Wong, F-L., Ludidi, N., Chapman, M. A., Ferguson, B. J., Considine, M. J., Zabel, F., Prasad, V. P. V., Varshney, R. K., Nguyen, H. T., and Lam, H-M. (2018). Modelling Predicts that Soybean is Poised to Dominate Crop Production across Africa. *Plant Cell Environment, 42:373–385*.

Frölich, M., and Huber, M. (2017). Direct and Indirect Treatment Effects – Causal Chains and Mediation Analysis with Instrumental Variables. *Journal of the Royal Statistical Society B, 79(5):1645 – 1666*.

Gebre, G. G., Isoda, H., Rahut, D. B., Amekawa, Y., and Nomura, H. (2019). Gender differences in agricultural productivity: evidence from maize farm households in southern Ethiopia. *GeoJournal*, https://doi.org/10.1007/s10708-019-10098-y.

Giannakas, K., Tran, K., and Tzouvelekas, V. (2003). On the choice of functional form in stochastic frontier modeling. *Empirical Economics*, *28:75 – 100*.

Giller, K.E. (2001). Nitrogen Fixation in Tropical Cropping Systems. Second Edition. CAB International, Wallingford, UK.

Huang, C. J., and Liu, J. T. (1994). Estimation of a Non-Neutral Stochastic Frontier Production Function. *Journal of Productivity Analysis, (5): 171 – 180*.

Huang, C. J., Fu, T-T., Lai, H-P., and Yang, Y-L. (2017) Semiparametric Smooth Coefficient Quantile Estimation of the Production Profile. *Empirical Economics, 52:373 – 392*.

Huang, C. J., Huang, T. H., and Liu, H. H. (2014). A New Approach to Estimating the Metafrontier Production based on a Stochastic Frontier Framework. *Journal of Productivity Analysis, 42:241–254*.

Huth, P. K., and Allee, T. L. (2002). *The Democratic Peace and Territorial Conflict in the Twentieth Century*. New York: Cambridge University Press.

Imbens, G. W. and Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica*, *62(2):467- 475*.

Independent Evaluation Group -World Bank. (2008). The Welfare Impact of Rural Electrification: A Reassessment of the Costs and Benefits: an IEG Impact Evaluation. World Bank.

Kumbhakar, S. and Lovell, C.A.K. (2000). *Stochastic Frontier Analysis*. New York: Cambridge University Press.

Kumbhakar, S. C., and Tsionas, E. G. (2009). Joint Estimation of Technology Choice and Technical Efficiency: An Application to Organic and Conventional Dairy Farming. *Journal of Productivity Analysis, 31:151 – 161*.

Lai, H-P., Huang, C. J., and Fu., T-T. (2020). Estimation of the Production Profile and Metafrontier Technology Gap: A Quantile Approach. *Empirical Economics*, *58:2709 – 2731*.

Lupwayi, N.Z., Olsen, P.E., Sande, E.S., Keyser, H.H., Collins, M.M., Singleton, P.W., and Rice, W.A. (2000). Inoculant Quality and its Evaluation. *Field Crops Research 65:259-270*.

Martins, J. (2005). The impact use of energy sources on the quality of life of poor communities. *Social Indicator Research, 72(3):373 – 402*.

Meeusen, W., and van den Broeck, J., (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review, 18(2):435 – 444*.

Mutuma, S. P., Okello, J. J., Karanja, N. K., and Woomer, P. L. (2014). Smallholder farmers' use and Profitability of Legume Inoculants in Western Kenya. *African Crop Science Journal 22(3): 205–214*.

Pingali, P. L. (2012). Green Revolution: Impacts, Limits, and the Path Ahead. *PNAS, 109(31):12302 – 12308*.

Ronner, E., Franke, A. C., Vanlauwe, B., Dianda, M., Edeh, E., Ukem, B., Bala, A., van Heerwaarden, J. and Giller, K. E. (2016). Understanding variability in soybean yield and response to P-fertilizer and rhizobium inoculants on farmers' fields in northern Nigeria. *Field Crops Research, 186:133 – 145*.

Rurangwa, E., Vanlauwe, B. and Giller, K. E. (2018). Benefits of inoculation, P fertilizer and manure on yields of common bean and soybean also increase yield of subsequent maize. *Agriculture, Ecosystems and Environment 261:219 – 229*.

Takahashi, K., and Muraoka, R., and Otsuka, K. (2020). Technology Adoption, Impact, and Extension in Developing Countries: A Review of Recent Literature. *Agricultural Economics, 51:31 – 45*.

Thomas, D. R., Harish, S. P., Kennedy, R., Urpelainen, J. (2020). The effects of rural electrification in India: An instrumental variable approach at the household level. *Journal of Development Economics, 146:1 – 10*.

Triebs, T., and Kumbhakar, S. (2018). Management in Production: From Unobserved to Observed. *Journal of Productivity Analysis, 49:111 – 21*.

Ulzen, J., Abaidoo, R. C., Ewusi-Mensah, N. and Masso, C. (2018). On-farm evaluation and determination of sources of variability of soybean response to Bradyrhizobium inoculation and phosphorus fertilizer in northern Ghana. *Agriculture, Ecosystems and Environment, 267: 23–32*.

Ulzen, J., Abaidoo, R. C., Mensah, N. E., Masso, C. and AbdelGadir, A. H. (2016). Bradyrhizobium inoculants enhance grain yields of soybean and cowpea in Northern Ghana. *Frontiers in Plant Science, 7: 1770*.

van Heerwaarden, J., Baijukya, F., Kyei-Boahen, S., Adjei-Nsiah, S., Ebanyat, P., Kamai, N., Wolde-meskel, E., Kanampiu, F., Vanlauwe, B., and Giller, K. (2018). Soyabean Response to Rhizobium Inoculation across sub-Saharan Africa: Patterns of Variation and Role of Promiscuity. *Agriculture, Ecosystems and Environment, 261: 211 – 218.*

Vidoli, F., and Ferrara, G., (2015). Analyzing Italian Citrus Sector by Semi-nonparametric Frontier Efficiency Models. *Empirical Economics, 49(2):641 – 658*.

Villano, R., Bravo-Ureta, B. E., Solís, D., and Fleming, E. (2015). Modern Rice Technologies and Productivity in the Philippines: Disentangling Technology from Managerial Gaps. *Journal of Agricultural Economics 66: 129–54*.

Zhang, X., Davidson, E. A., Mauzerall, D. L., Searchinger, T. D., Dumas, P., and Shen, Y. (2015). Managing Nitrogen for Sustainable Development. *Nature Perspective, 528:51 – 59*.

Appendix

Tables

Table 4A. 1 Comparison of Adopters and Non-Adopters

Variables	Adopters Mean(S.E)	Non-Adopters Mean(S.E)	Mean Diff (S.E)
Yield	962.35(53.453)	691.53(47.57)	270.82***(71.75)
Farm Net Return	802.20(40.586)	879.87(47.37)	-77.67(62.21)
Age	43.133(0.727)	39.929(0.803)	3.205***(1.081)
Gender	0.696(0.026)	0.721(0.026)	-0.025(0.037)
Edu	2.853(0.271)	2.728(0.271)	0.125(0.383)
Land	4.88(0.235)	5.214(0.270)	-0.332(0.357)
Labor	7.649(1.980)	7.973(1.327)	-0.323(1.980)
Agrochem	3.726(0.343)	4.286(0.481)	-0.560(6.685)
Chemdumy	0.029(0.010)	0.020(0.008)	0.009(0.013)
Improvar	0.706(0.026)	0.694(0.027)	0.012(0.037)
Creditconst	0.797(0.023)	0.861(0.020)	-0.063**(0.031)
WCZ	0.565(0.028)	0.568(0.029)	-0.003(0.041)
Distmarket	2.372(0.261)	2.352(0.212)	0.020(0.338)
Soilqual	0.542(0.029)	0.473(0.029)	0.070*(0.041)
Rainfall	61.503(0.924)	61.769(0.953)	-0.265(1.327)
Comextoff	0.621(0.028)	0.629(0.028)	0.008(0.040)
Distextoff	15.78(1.155)	22.07(1.694)	-6.295***(2.037)
Electgrid	0.941(0.013)	0.949(0.013)	-0.008(0.019)
Testscore	61.692(1.647)	48.979(2.157)	12.713***(2.666)
Resemtech	38.824(2.017)	30.884(2.027)	7.939***(2.860)
Techdiff	0.307(0.015)	0.247(0.016)	0.060***(0.022)
Dislang	0.725(0.026)	0.663(0.028)	0.062*(0.038)
Comextoff	0.621(0.028)	0.629(0.028)	-0.008(0.040)
Observ. (N)	**306**	**294**	

Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors.

Table 4A. 2 Participation and Adoption Decisions (First-Stage Bivariate Probit Estimates)

Variables	AES-Participation (M)	Inoculant-Adoption (D)
	Coeffs.(S.E)	***Coeffs.(S.E)***
Const.	-3.061***(0.487)	-1.407**(0.611)
Age	0.022***(0.005)	0.007(0.007)
Gender	0.365***(0.152)	-0.397**(0.204)
Edu	0.014(0.048)	-0.017(0.058)
Edusq	-0.003(0.003)	0.0003(0.004)
lnland	-0.167(0.110)	0.003(0.135)
lnlaborsq	-0.015(0.019)	0.011(0.024)
Creditconst	-0.502***(0.179)	-0.009(0.231)
lnagrochem	0.013(0.032)	-0.028(0.040)
Chemdumy	0.059(0.454)	0.664(0.552)
Improvar	0.016(0.141)	-0.008(0.180)
WCZ	-0.209(0.137)	-0.127(0.179)
Distmarket	-0.008(0.015)	0.004(0.020)
Soilqual	0.619***(0.140)	0.229(0.172)
Rainfall	-0.006(0.004)	-0.003(0.005)
lntestsq	2.275***(0.200)	-0.038(0.202)
Tsresid	-2.861***(0.221)	0.023(0.209)
Adopt-inoculant *(D)*	1.657***(0.160)	-
Electgrid (Z_1)	-	3.200***(0.186)
Distextoff (Z_2)	-0.041***(0.013)	-
ρ_{md}	-0.715***(0.189)	
Wald test of ρ_{md}*=0*	18.27***	
LL	-359.078	
Wald Chi-sq	543.22***	
Observ.(N)		600

Note: ***, **, and * are 1%, 5%, and 10% level of significance; Values in brackets are standard errors.

Table 4A. 3 Estimates of Treatment Instrument Propensity (Z_1) – Electricity (Dummy)

Variables	Inoculant-Adoption ***Coeffs.(S.E)***
Age	0.007(0.007)
Gender	-0.406**(0.207)
Edu	-0.026(0.059)
Edusq	0.001(0.004)
lnland	0.015(0.136)
lnlaborsq	0.010(0.025)
lnagrochem	-0.044(0.041)
Chemdumy	0.759(0.572)
Improvar	0.030(0.182)
Creditconst	-0.044(0.231)
WCZ	-0.159(0.180)
Distmarket	0.003(0.021)
Soilqual	0.190(0.172)
Rainfall	-0.002(0.005)
lntestsq	-0.019(0.047)
Tsresid	-0.018(0.211)
Const	-1.390**(0.646)
Z1_inst	3.207***(0.189)
LL	-131.894
Wald Chi-sq	567.75***

Table 4A. 4 A Mixture-of-Normal Distribution for Mediation Instrument (Z_2)

Parameter	Distextoff(km)
	Coeffs.(S.E)
μ_1	-1.8030***(0.1865)
σ_1	1.0123***(0.0539)
μ_2	6.6236***(1.4828)
σ_2	1.7470***(0.1083)
$f(p)$	1.3012***(0.2895)

Figures

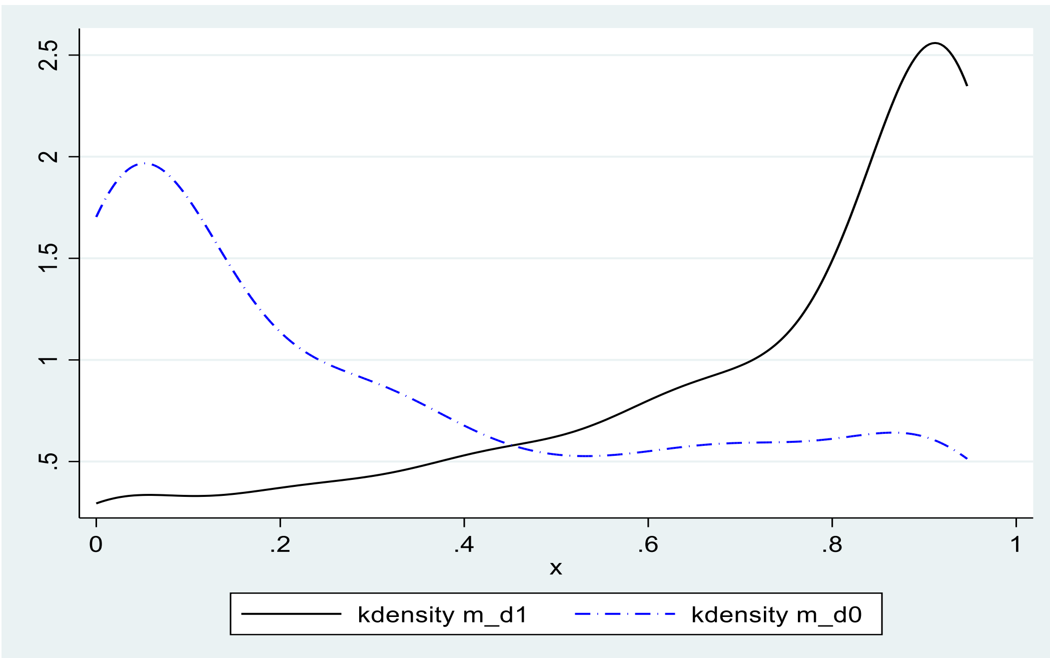


Figure 4A. 1 Probability Density Distribution for Identification of Treatment Sub-populations.

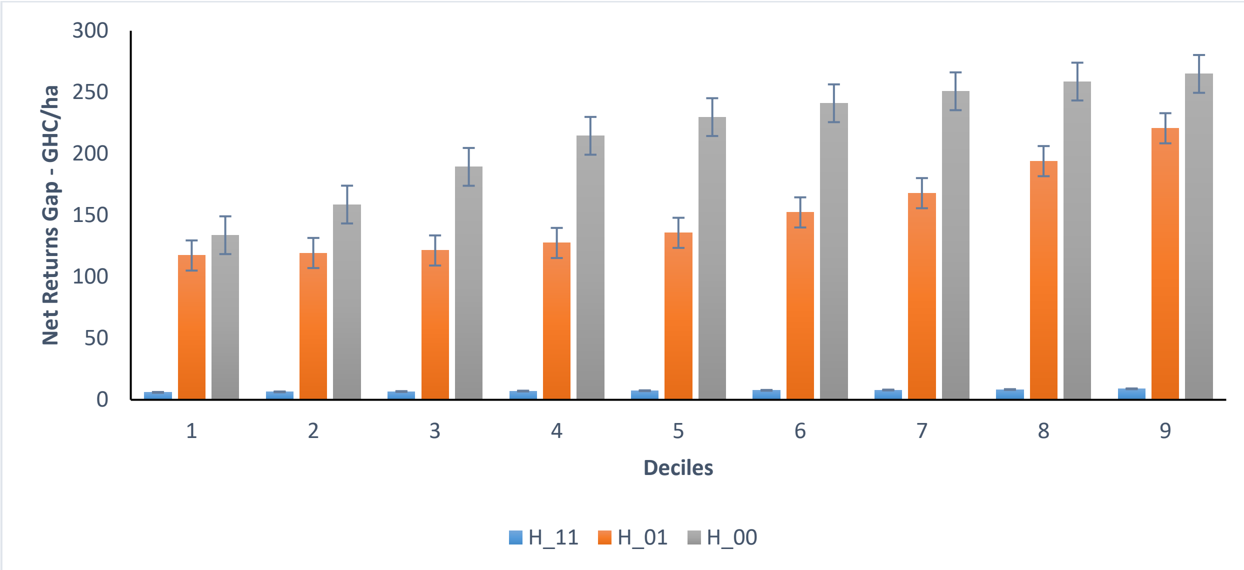


Figure 4A. 2 Net Returns Gap Profile at the Production Technology Frontier (GHC/Ha).

Where H-11, H-00 and H-01 indicate inoculant adoption with mediation, non-adoption non-mediation and non-adoption with mediation, respectively at the production Technology frontier function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different production technology frontiers, compared to farmers at the best production frontier operating at zero technological inefficiency.

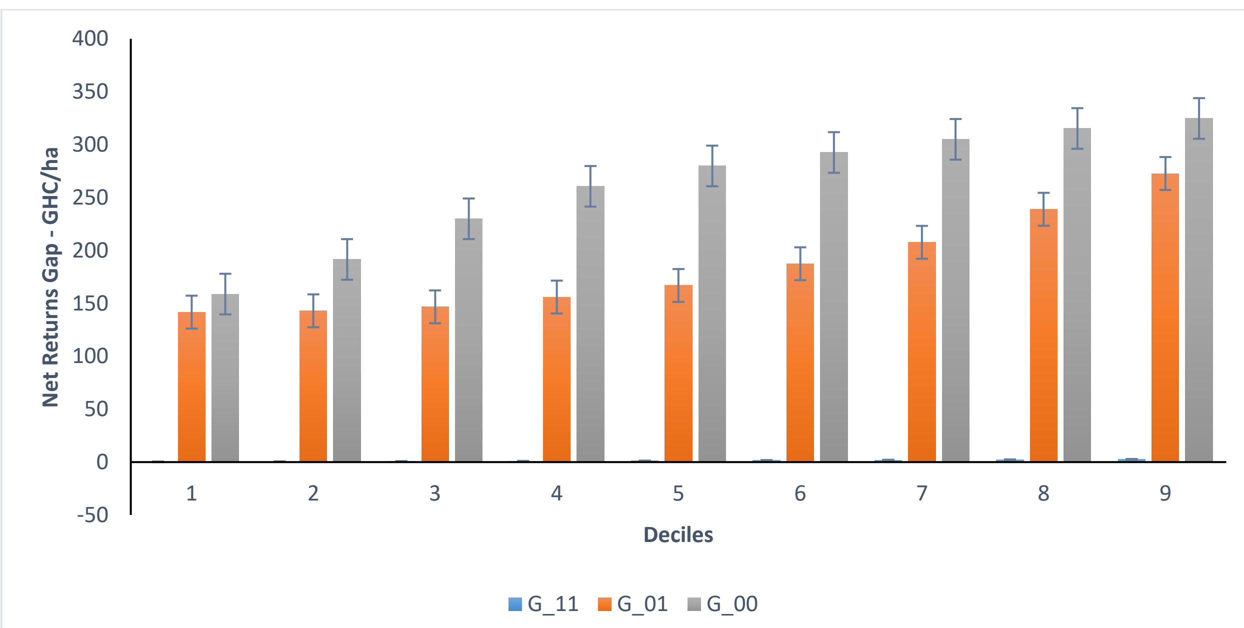
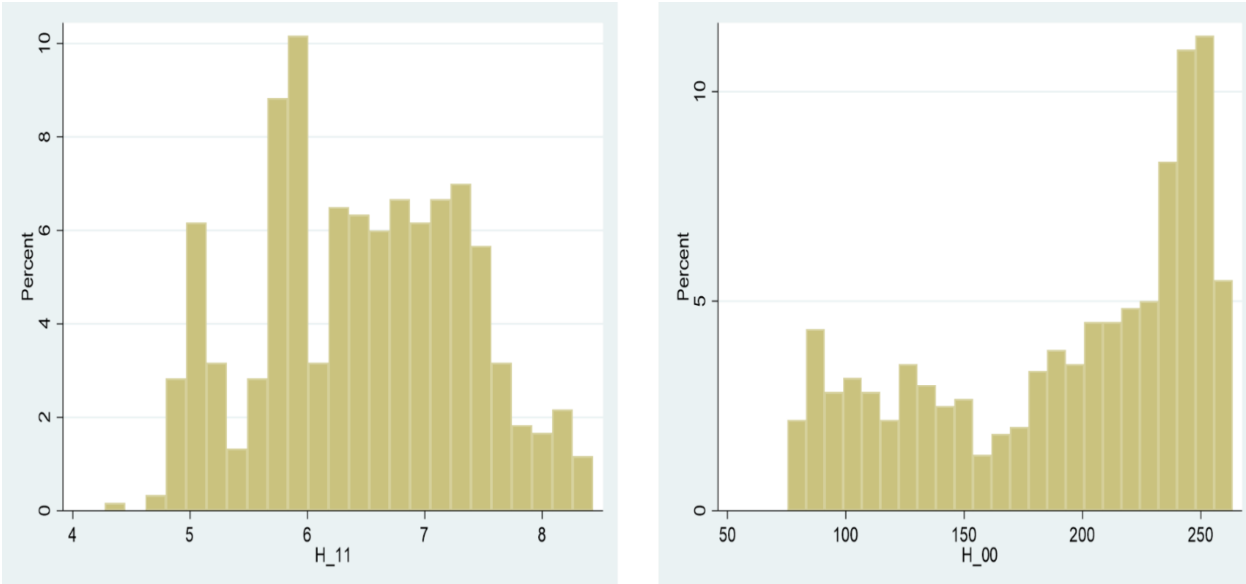
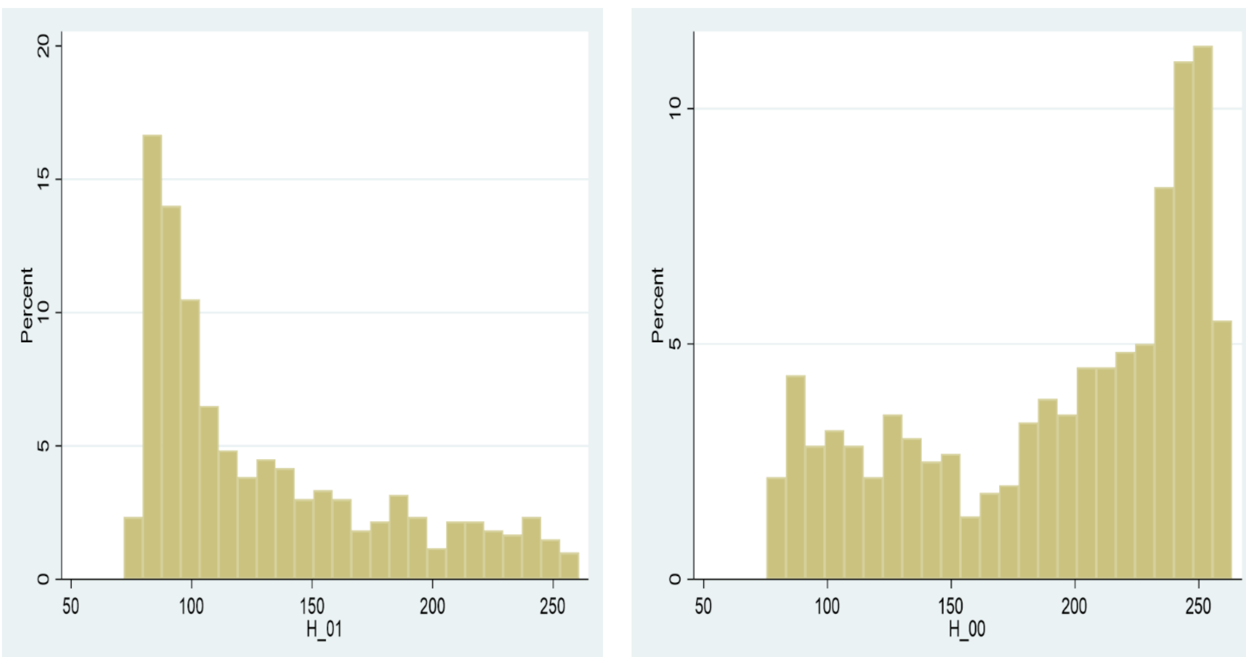


Figure 4A. 3 Net Returns Gap Profile at the Technical Inefficiency Frontier (GHC/Ha).
Where H-11, H-00 and H-01 indicate inoculant adoption with mediation, non-adoption non-mediation and non-adoption with mediation, respectively at the Technical inefficiency function of yield. The figure illustrates the yield gap profile in deciles of farmers operating at different levels of technical inefficiency, compared to farmers operating at zero technical inefficiency.



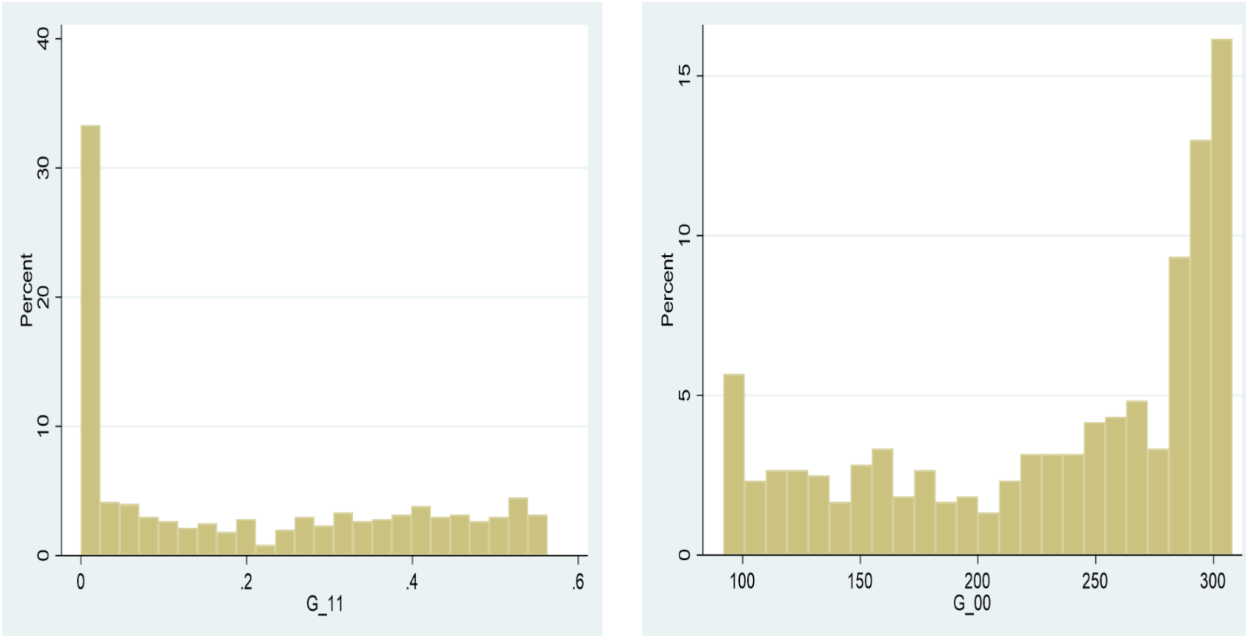
(a) Adoption with Mediation (b) No-Adoption No-Mediation

Figure 4A. 4 Comparison of Net Returns (GHC/Ha) Distributions at the Technology Frontier – Direct Effect



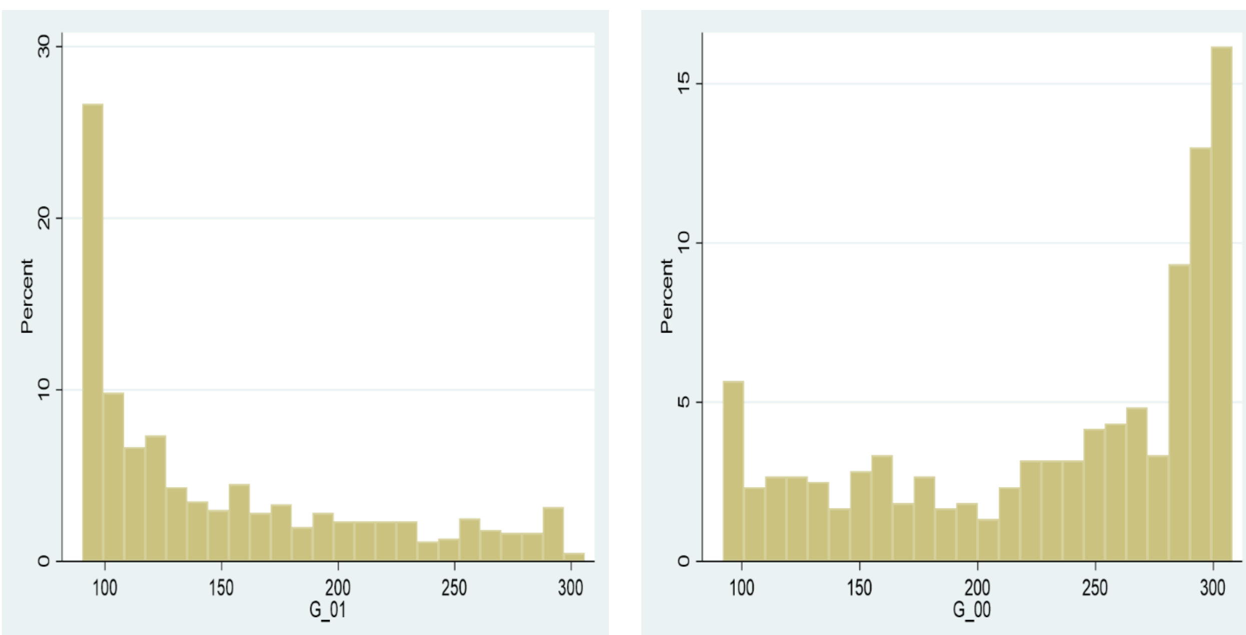
(a) No-Adoption with Mediation (b) No-Adoption No-Mediation

Figure 4A. 5 Comparison of Net Returns (GHC/Ha) Distributions at the Technology Frontier – Indirect Effect



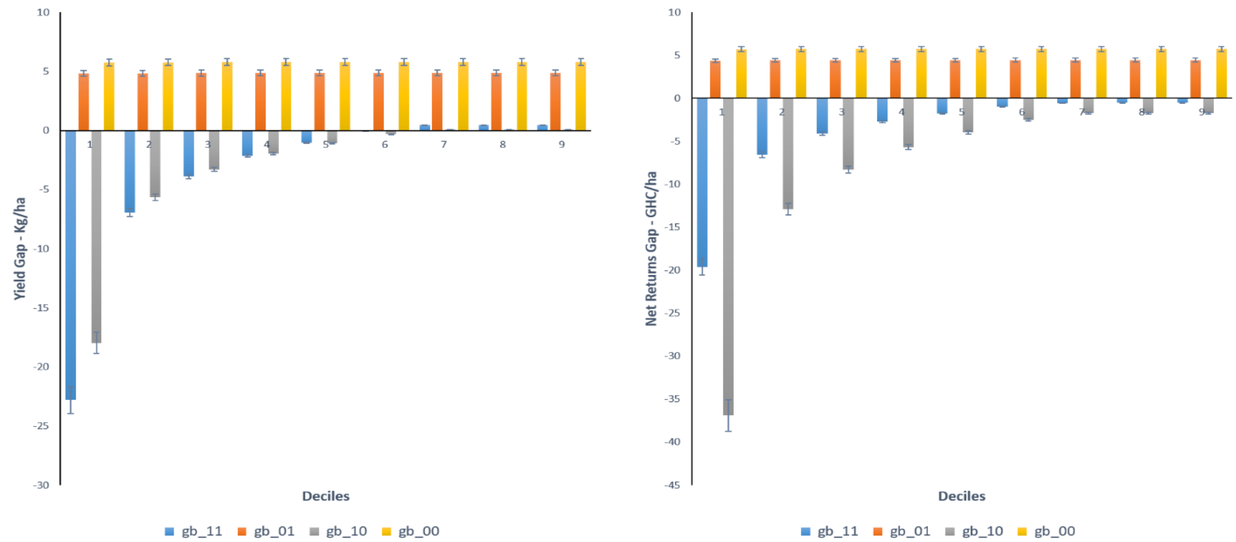
(a) Adoption with Mediation (b) No-Adoption No-Mediation

Figure 4A. 6 Comparison of Net Returns (GHC/Ha) Distributions at the Inefficiency Frontier – Direct Effect.



(a) No-Adoption with Mediation (b) No-Adoption No-Mediation

Figure 4A. 7 Comparison of Net Returns (GHC/Ha) Distributions at the Inefficiency Frontier – Indirect Effect.



(a) Yield (Kg/Ha) (b) Net Returns (GHC/Ha)

Figure 4A. 8 Unconditional Mean Gap Profiles at the Inefficiency Frontiers.

Chapter 5

Do *Egocentric* Information Networks Influence Technical Efficiency of Farmers? Empirical Evidence from Ghana

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Abstract

We investigate the impact of farmers' *egocentric* information network on technical efficiency and its distribution in the network, using observational data of 600 farmers from northern Ghana. We exploit community detection algorithms to endogenously identify homogeneous network communities with known structures to account for spatial heterogeneity, in a spatial stochastic frontier model that controls for social selection bias. The empirical results reveal that at the global network level, farmers' technical efficiency strongly correlate with that of farmers in their *egocentric* networks. Our findings also show that farmers who are technically less efficient tend to depend on the more efficient farmers in their networks to improve efficiency. We further find that failure to account for spatial heterogeneity can lead to underestimating technical efficiency of high (efficiency score >0.6) performing farmers, while overestimating that of medium (efficiency scores between 0.36 – 0.5) and low (efficiency scores between 0.1– 0.35) performing farmers. The findings suggest that identifying central farmers' in *egocentric* networks and improving their technical knowledge in a farmer-to-farmer extension organization, can contribute to improving the productivity of many farmers.

Keywords: Egocentric information network, Stochastic frontier analysis, Spatial heterogeneity, Technical efficiency, Technology adoption.

JEL: C45, D83, D85, O13 Q16

5.1 Introduction

Inadequate information on innovative agricultural technologies continue to be a major constrain and the jinx to low technology adoption among smallholder farmers in developing countries (Foster and Rosenzweig 2010; Suri 2011). The low technology adoption among farmers has been identified as one of the root causes of low productivity and high poverty incidence among smallholder farmers (Takahashi *et al.* 2020). Weak and ineffective extension services due to resource constraints to employ and equip extension agents to serve the needs of the widely dispersed smallholder farmers, who constitute majority of the farming population of the developing countries accounts for the inadequate information (Blum and Szonyi 2011).

The use of farmers' personal information networks is viewed as a potential information channel to leverage the limited number of extension agents to aid in the diffusion of information on improved technologies to farmers (Beaman and Dillon 2018; Valente 1996). The process of using personal information networks to diffuse information about new technologies or products in order to accelerate adoption or improve organizational performance is described in the literature as the network interventions approach (Valente 2012). One strategy of the network interventions approach that has become popular among development practitioners and organizational managers is the segmentation strategy. This strategy is cost effective and efficient, as it relies on passing the new information to an identified group of persons who act as change agents rather than trying to reach individual farmers (Fafchamps *et al*. 2021; Valente 2012). A major area of application of the segmentation strategy of the network intervention approach in agricultural development is the use of the lead farmer concept in peer-to-peer agricultural extension delivery.

The potential of farmers' networks to diffuse information about new technologies, due to social learning have been extensively explored in the literature within the last decade (Bandiera and Rasul, 2006; Conley and Udry, 2010; Banerjee *et al*., 2013; Beaman and Dillon, 2018; Di Falco *et* *al*., 2018). For instance, Kondylis *et al*. (2017) found that contact farmers' personal information networks played a significant role in the diffusion and adoption of sustainable land management practices among farmers in central Mozambique. In a similar study, Beaman and Dillon (2018) found that personal information networks played an important role in the diffusion, adoption as well as technical knowledge on new compost making technology among farmers in Mali. However, evidence suggest that there is strong correlation of knowledge gain on a given technology by farmers who learn from their personal information networks with those from whom they learn (Fafchamps *et al*., 2021). To the extent that farmers' knowledge correlate with their personal information networks, implies that the likelihood of farmers' technical (in)efficiency to correlate with that of the peers from whom they learn could be equally high. This may be due to factors such as informational inadequacies, willingness to share information, common shocks and differing absorptive capacity among individual farmers (Kondylis *et al*., 2017; Boschma, 2005).

Recent spate of studies have considered the potential correlation of technical efficiencies between contagious production units in the literature. For example, among neighboring electricity and chemical firms (e.g., Orea and Álvarez 2019; Kutlu *et al*. 2020), provincial and regional administrative units (e.g., Tsionas and Michaelides 2016; Gude *et al*. 2018; de Graaff 2020), airports and transportation terminals (e.g., Pavlyuk 2019), sport teams (e.g., Horrace and Jung 2018) and wine industries (e.g., Fusco and Vidoli 2013; Vidoli *et al*. 2016). In agricultural production, the influence of geographical and economic proximity on farmers' efficiency have also been considered. Examples include Druska and Torrace (2004) study on rice farmers in Indonesia, Schmidt *et al*. (2009) on regional farms in Brazil, Areal *et al*., (2012) on dairy farms in England and Wales, as well as Billé *et al*. (2018) study on olive farms in Italy. However, the form of contiguity considered by almost all these studies is based on geographical location, position, or distance (i.e. physical contiguity) between the production units or farms. The physical contiguity approach is based on the assumption that farmers embedded in social communities learn from their peers, given the similar environmental and social factors they face and the socio-economic relationships they share, thus creating a local *terroir effect* (Vidoli *et al*. 2016; Billé *et al*. 2018).

However, while the physical contiguity approach may account for environmental, climatic and edaphic factors in the production system, it is insufficient to address the issue of informational inadequacies among interacting farmers that lead to learning. Despite, the voluminous literature on the impact of the information networks on adoption of new technologies and yields, there is paucity of knowledge on how the network contributes to technical (in)efficiency in the production functions of the individual farmers who constitute the information network. This is important because the position of farmers in a network who are first to receive information about a new technology have distributional consequences among members in the network (e.g., Banerjee *et al*. 2013; Beaman and Dillon 2018).

The present study attempts to fill the knowledge gap on how information networks influence farmers' technical (in)efficiency. Specifically, we use a unique survey data of 600 soybean farmers to investigate the influence of farmers personal information networks (i.e., the *egocentric* networks) on their technical (in)efficiency and its distributive mechanisms in the network, while controlling for social selection bias. We estimate a spatial stochastic frontier analysis (SSFA) model that accounts for unobserved spatial heterogeneity, which presents a potential source of endogeneity in efficiency analysis and could bias the estimates (Kutlu *et al*. 2020; Qu and Lee 2015). The present study contributes to the literature by incorporating social network structure into efficiency analysis, using stochastic frontier analysis. To the best of our knowledge, this is the first attempt to consider the impact of social interactions in efficiency analysis.

The rest of the paper is organized as follows; sections 2 and 3 discuss the conceptual framework and the estimation strategy of the study, respectively. We then discuss the data and the empirical results in sections 4 and 5 respectively, while section 6 presents the conclusions of the study.

5.2 Conceptual Framework

5.2.1 Spatial Stochastic Frontier Analysis with Social Network Dependence

We assume that farmers are homogeneous in regards to their production technology. Let Y_i denote individual farmer's soybean output and X_i be a vector of production factors. The farmer's production function can be specified as follows;

$Y_i = ln(f(X_i; \beta_i)) + v_i - u_i,$ and $u_i \geq 0$, *[i =1,…,n]* (1)

where Y_i is a vector of log outputs (yield) of an individual farmer, X is a vector of production factors, β is a vector of parameters of interest, u represent the inefficiency term, and v the random error term, assumed to be *iid* with; $v \sim iid\ N(0, \sigma_v^2 \boldsymbol{I})$ and $u \sim iid\ N^+(0, \sigma_u^2 \boldsymbol{I})$, where $\boldsymbol{I}$ is an identity matrix.

The productivity performance of farmers producing under any given technology, without external influence on the farmers' technical abilities can be estimated from equation 1. However, when a farmer obtains technical knowledge of a given technology from other farmers through information exchange, the possibility of the farmer's technical ability to be influenced by informational inadequacies from the farmers they exchange information with becomes higher (Fafchamps *et al*. 2021; Kondylis *et al*. 2017). Hence, analysis of the farmer's productivity under any technology that ignores the influence of the informational inadequacies of other farmers in the farmer's production function, could suffer a potential bias, due to the unobserved informational inadequacies.

To account for the influence of other farmers' informational inadequacies in the production function of the farmer; let g_f represent village level farmer information network with $g_f(g_f = 1, \ldots, \mathrm{G}_{FN}) \in \mathrm{G_F}$, where $\mathrm{G_F}$ is a set of all farmer information networks across N villages.

Furthermore, let w_{ij} represent the link that exists between farmer i and j ($i \neq j$), defined as $w_{ij} = 1$, if farmer i shares agricultural information with farmer j, otherwise $w_{ij} = 0$, and $w_{ij} \in \boldsymbol{W_{ij}}$, where $\boldsymbol{W_{ij}}$ is the social contiguity matrix (or adjacency matrix). The social contiguity matrix is assumed to be undirected (i.e., $w_{ij} = w_{ji}$) and i cannot share information with i (i.e., $w_{ii} \neq 1$). In line with Fusco and Vidoli (2013) and Vidoli *et al*. (2016), we re-specify (suppressing the subscript) equation 1, as a spatial stochastic frontier model that accounts for the interdependency of the farmer's inefficiency on the information network as follows;

$$lnY = ln(f(X;\beta)) + v - (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\tilde{u} \qquad (2)$$

where $\boldsymbol{W}$ is the adjacency matrix of the network, ρ is the spatial lag parameter ($\rho \in [0,1]$), v and $\tilde{u}$ are the random error and latent unknown terms respectively, assumed to be distributed as $v{\sim}iid\, N(0, \sigma_v^2\boldsymbol{I})$ and $\tilde{u}{\sim}iid\, N(0, \sigma_{\tilde{\boldsymbol{u}}}^2\boldsymbol{I})$, respectively. The inefficiency term u in equation 1 is expressed as $u = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}$, and assumed to be distributed as $u{\sim}\, N^+(0, [(\boldsymbol{I} - \rho\boldsymbol{W})^{-1}(\boldsymbol{I} - \rho\boldsymbol{W}')^{-1}]\sigma_{\tilde{\boldsymbol{u}}}^2)$.

Similar specification has been employed in the stochastic frontier analysis literature (e.g., Areal *et al*. 2012), however, the specification employed here, is the one by Fusco and Vidoli (2013) and Vidoli *et al*. (2016). This specification is preferred, because, it adopts a one-stage estimation procedure which makes it more efficient and easy to compare with the standard stochastic frontier analysis with the spatial stochastic frontier analysis for consistency, since the spatial stochastic frontier model converges to the standard stochastic frontier model when $\rho = 0$. Furthermore, because the specification limits the analysis to only the inefficiency term in the stochastic frontier model, there is substantial reduction in the model's complexity (Vidoli *et al*. 2016).

5.2.2 Identification and Endogeneity Issues of Spatial Heterogeneity

One of the challenges in distinguishing spatial dependence from spatial heterogeneity is that, the latter arises due to structural changes, which is unobserved. That is, clusters (or spatial regimes) that are observed in reality varies in structure (i.e., they are non-homogeneous) over geographical or social space, resulting in the inverse problem (Anslin 2010). Spatial heterogeneity presents a potential source of endogeneity in efficiency analysis (Kutlu *et al*. 2020; Qu and Lee 2015). Accounting for this problem is always a challenge. In particular, when employing geographical based proximity measures as the weighting matrix (i.e., the contiguity matrix) because such measures do not easily change in reality. Another reason for the challenge is that, the identification problem is centered on the contiguity matrix. Recently, Billé *et al*. (2018) suggest employing a computer-based algorithm that can endogenously identify, in a data-driven approach, spatial homogeneous regimes or clusters from observed real-world spatial data, as a way to account for spatial heterogeneity. Following this approach, let $\widetilde{\boldsymbol{W}}$ represent the contiguity matrix of a homogeneous specific network community that can be identified from observed real-world information network data. By substitution, equation 2 can be re-specified, in terms of the specific network community adjusted contiguity matrix, as follows;

$$lnY = ln(f(X;\beta)) + v - (\boldsymbol{I} - \rho(\widetilde{\boldsymbol{W}}))^{-1}\tilde{u} \qquad (3)$$

where $\widetilde{\boldsymbol{W}}$ is a structurally adjusted weighting matrix for a homogeneous network community, and all other notations remain as defined earlier.

5.2.3 Impact of Spatial Effects on Productivity Performance

To assess the benefits farmers derive from the information network, we employ the structural imbalance distance measure expressed in Vidoli *et al*. (2016), as well as Fusco and Vidoli (2013) as follows;

$$d_{i_{\Delta \hat{E}}} = \frac{\hat{E}_{SFA_i} - \hat{E}_{SSFA_i}}{\hat{E}_{SFA_i}} * 100, \forall_i = 1, \dots, N \quad (4)$$

where $\hat{E}_{SFA_i}$ and $\hat{E}_{SSFA_i}$ are the predicted efficiencies at the standard stochastic frontier model and the spatial stochastic frontier model for individual farmer i and $d_{i_{\Delta \hat{E}}}$ is a distance measure of efficiency difference between the two models. A negative difference indicates improvement in efficiency (the reverse is true for efficiency loss) performance from the network, while the magnitude measures the extent of gains or otherwise from the network (Fusco and Vidoli 2013).

5.2.4 Distributive Mechanisms of Gains in Egocentric Networks

In this section, we estimate the determinants of efficiency gains and its distribution among farmers within an information network and across different networks. This is important for an informed policy on agriculture extension service delivery that employ network structures for technology information dissemination. In the spatial stochastic frontier analysis literature, contextual environmental factors are normally regressed on the efficiency distance measure (i.e., $d_{i_{\Delta \hat{E}}}$) and the coefficients interpreted as determinants. Given that the information network is composed of individual farmers sampled from a cross-section of smaller units of personal information networks and pooled together to form the village network (see Figure A1 in Appendix for a sample village network), makes it highly hierarchical. As such, we employ the spatial effect Cox proportional hazard model with individual level covariate adjustment, which is more appropriate (Bai *et al*. 2020; Banerjee and Dey 2005). In addition, the distribution of benefits within a social network is assumed to be nonlinear within the framework of social proximity and social embeddedness theory (Boschma 2005).

To this end, we follow the approach of Bai *et al*. (2020), which estimates a generalized additive spatial effect Cox model by employing a spatial smoothing function to adjust for individual farmer and network characteristics. Specifically, we estimate a spatial survival time-event Cox model, which is more appropriate for smaller number of units (Banerjee and Dey 2005). In addition, the interpretation of the sign of the distance measure of benefit $d_{i_{\Delta\hat{E}}}$, makes it amenable to survival analysis. We convert $d_{i_{\Delta\hat{E}}}$ to a binary event occurrence variable in which the negative sign indicating positive gains on efficiency performance is equal to 1 (implies the farmer benefits from efficiency gain due to the network) and 0, otherwise. Next, the individual farmer predicted mean efficiency score from the SSFA model (i.e., $\hat{E}_{SSFA_i}$) representing the efficiency level then becomes the survival time variable in the estimation. That is, the level of technical efficiency at which the individual farmer is said to have benefited, as a result of being member of the information network. In line with Bai *et al*. (2020), the generalized additive spatial effect Cox model for individual farmer i in information network g_f is specified as follows;

$$\lambda_i(g_f) = \lambda_0(g_f)\, exp\{\boldsymbol{X_i}\boldsymbol{\beta_i} + s_i\} \;\; = \eta_i = \boldsymbol{X_i}\boldsymbol{\beta_i} + s_i \qquad (5)$$

where $\lambda_i(.)$ is the benefit hazard function of farmer i in network g_f, X is a vector of observed factors that determine the farmer's spatial efficiency gains and its distribution across individual networks, s is a network-specific structural property. However, because the network-specific structural property has been accounted for in the adjusted weighting matrix (i.e., $\widetilde{\boldsymbol{W}}$), in order to ensure identification, we assume s_i in equation (5) to be equal to zero in the estimation.

5.3 Estimation Strategy

We estimate both equations 2 and 3 using maximum likelihood estimation procedure implemented in the R software (R Core Team 2017), by combining the packages offered by Fusco and Vidoli (2013) and Pavlyuk (2019). Equation 5 is estimated using partial likelihood estimation approach also in the R package offered by Bai *et al*. (2020). To ensure identification within the framework of the social network analysis, we account for social selection bias in all the models estimated by controlling for correlated peer effects and contextual effects (Manski 1993)[29]. A parsimonious empirical model we estimate can be specified as follows;

$$y_{i,g_f} = x_i\beta_i + \gamma_p + \theta_c + \tau_d + \varepsilon_i \qquad (6)$$

where y is the outcome variable (in this case, log yields and spatial efficiency performance gains) of farmer i in network g_f, x is a vector of observed farm characteristics, p, c and d denote farmer's peers, village and district level indicators, respectively, β is a parameter of interest, γ, θ, τ is a vector of peer, community, as well as district level fixed-effects, respectively that may correlate with the observed characteristics of the farmer and ε is a composite error term, defined as ($\varepsilon = v - (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\tilde{u}$). The efficiency calculation for each farmer follows the approach of Jondrow's *et al*. (1982) as expressed in Fusco and Vidoli (2013)[30].

5.4 Context and Data

5.4.1 Study Context

The study context is northern Ghana, where over the last decade scientific research organizations such as the International Institute of Tropical Agriculture (IITA) and the Council for Scientific and Industrial Research-Savannah Agricultural Research Institute (CSIR-SARI) and their partner

[29] The endogenous effect due to reflection problem of Manski (1993) does not apply in our context, since we are not estimating a spatially lagged output model.
[30] We refer readers interested in the likelihoods specifications to the relevant references cited in this work for details.

organizations employed Farmer Based Organizations (FBOs) concept to disseminate a new agricultural technology (known as the *Rhizobia* inoculant) to smallholder grain-legume farmers. The organizations used conventional extension approaches (e.g., field visits, on-farm and off-farm demonstrations, etc) as well as innovative communication channels such as Radio Listening Clubs (RLCs) and Video Documentaries (VDs) to disseminate and offer technical training to farmers through the FBOs in three regions (Northern, Upper East and Upper West) of northern Ghana. Members of the FBOs, then, become the initial farmers to disseminate or share their knowledge with other farmers in their communities to facilitate adoption of the new inoculant technology. Thus, the dissemination program sought to use the farmers' personal information (i.e., the *Egocentric*) networks to diffuse and promote adoption of the *Rhizobia* inoculant technology. This approach could generate unobserved spatial heterogeneity, in the performance of the technology across the population due to differences in individual disseminating farmers' cognitive proximity (Boschma 2005) and willingness to share knowledge on the new technology (Di Falco *et al*. 2018).

5.4.2 Survey of Farm Households

Our data is from a recent survey of farm households in the northern region of Ghana. The survey was conducted from June to August, 2018. The sample was drawn using a multistage sampling technique. Based on the proportion of beneficiary communities (78%) in the inoculant dissemination program and intensity of soybean production in Ghana, northern region was purposively selected. Cluster sampling technique was employed to zone the region into two clusters, consisting of eastern corridor zone (ECZ) and western corridor zone (WCZ). Based on participation status of districts in the dissemination program and intensity of soybean production at the districts level within the clusters, eight (8) districts, comprising of four (4) from each cluster were purposively sampled. From the ECZ, Yendi, Saboba, Chereponi and Karaga districts were selected, while in the WCZ, East Mamprusi, East Gonja, Savelugu and Kumbungu districts were selected. In consultation with the field officers and agriculture extension agents (AEAs) in the selected districts, 5 – 7 communities were proportionately sampled, based on dissemination program participation and the extension channel employed, as well as farmer population. One farmer-based organization (FBO) was randomly selected from a list of FBOs that participated in the dissemination program and another randomly selected from a list of FBOs that did not participate in the program, to compose the observed intervention network pool. We then employed a two-stage random sampling technique detailed in the next section below to sample 600 farm households, used for this analysis.

5.4.3 Data on Egocentric Networks

An *egocentric* network sampling technique is employed to sample members of *Ego-Alter* networks (*see* Krivitsky and Morris 2017; Schweinberger *et al*. 2020). Similar approaches have been employed in the literature (*e.g.* Badham *et al*. 2021; Yen *et al*. 2016; Cai et al. 2015) to sample real world networks in empirical studies. A two-stage random sampling technique is employed to sample members of the *egocentric* networks. In stage one, using a lottery approach, we randomly drew five farmers (as the *Egos* - seed or focal farmers) from each FBO in the observed intervention network pool. Following an initial interview with the *Egos*, using computer assisted personal interview (CAPI), a list of each farmer's information network members (INMs) was compiled as the *Alters*. In the second stage, the CAPI random number generator used farmers' unique identification numbers to randomly sample three *Alters* from each *Ego's Alter* list for interview. The total number of *Egos* and *Alters* for each village is 20, resulting in 20 x 20 undirected social contiguity matrix (i.e. $\boldsymbol{W_{ij}} = \boldsymbol{W_{ji}}$) for each sampled village or community. In order to avoid missing links due to missing information, a major problem confronting studies that employ sampled social networks, the data used for this analysis is restricted to five villages per district, totaling 30 villages across six districts (East Mamprusi, East Gonja, Savelugu, Kumbungu, Yendi and Karaga), where we have full data on both the *Egos* and the *Alters*. A total undirected social contiguity matrix size for this analysis is 600 x 600 block matrix, representing the aggregate village networks for the sampled farm households.

5.4.4 Network Community Detection

Based on network ecology theory and in line with Billé *et al*. (2018), we employ three computer software algorithms (i.e., Clauset *et al*., 2004; Newman and Girvan, 2004; Pons and Latapy, 2006) to identify three homogeneous virtual network communities with known structural properties, from observed real-world *egocentric* network data. The virtual network community approach is often employed as a pseudo experimental design in the network intervention literature to overcome data challenges that threatens identification and valid statistical inferences. Recent applications of this approach in the social network literature include; Simpson (2020), who use observed real-world *egocentric* network data of Cai *et al*. (2015;) in Stochastic Actor-Oriented Models (SAOM - a simulation based algorithm), to study the relationship between farm size and social ties formation among rice farmers in China. In technology adoption, Valente and Yon (2020) use similar approach as in the current paper, to study diffusion of health practices in social networks, while others employed purely simulation studies based on observed real-world network data to study network structure on adoption behavior, knowledge transfer and productivity (see e.g., Badham *et al*. 2021; Beaman *et al*. 2021). Though not in the context of social network but in productivity analysis, Billé *et al*. (2018), employed geographically weighting and adaptive weight smoothing algorithms (Cleveland and Delvin 1988; Polzehl and Spokoiny, 2000) to study spatial regimes in olive farm technologies in Italy. It is noteworthy to point out that, these applications are not in the context of technical efficiency analysis, as in the form employed in the current study.

In this study, we denote the three virtual network communities constructed as ***T0***, ***T1*** and ***T2***, each using a specific algorithm. The algorithms employed are based on modularity[31] maximization procedure, which optimizes a global criterion over all possible clustering in the network for community detection (Li *et al*. 2021; Geng *et al*. 2019). Clauset's *et al*. (2004) algorithm is employed to detect ***T1*** communities. The algorithm identifies virtual network communities around farmers (or edges) with high *eigenvector* centrality measure (i.e., a measure of social importance in the network community) from the observed real-world network data. Intuitively, the ***T1*** is assumed to correspond to choosing a lead farmer in a community based on the farmer's social importance. Newman and Girvan (2004) algorithm is employed to detect ***T2*** communities. This algorithm identifies virtual network communities around farmers with high *betweeness* centrality (i.e., a measure of power based on being a bridge for other farmers to pass through for information in the network) measure in the observed real-world network data. Intuitively, the ***T2*** is assumed to correspond to choosing a lead farmer in a community based on the farmer's power derived from being a bridge to access information. The *edge-eigenvector* and *edge-betweeness* community structures have received wide empirical application in the literature (e.g., Beaman and Dillon, 2018; Beaman *et al*. 2021; Fafchamps *et al*. 2021), due to their importance in information diffusion required for technology adoption. In order to identify the effects of network community structure on the economic outcomes of interest, we employed the algorithm of Pons and Latapy (2006) to construct a third network community ***T0***, which assumes a randomly distributed centrality measure in the network, as the virtual control community for comparison. This algorithm provides an *iid* situation for comparison, since it identifies virtual network communities based on the assumption that, the virtual communities observed in the network are randomly formed, and do not necessarily

[31] *Modularity*, is defined as a natural division of network nodes into densely connected subgroups (Newman and Girvan 2004).

form around any influential farmer (or node) within the network. Intuitively, the ***T0*** is assumed to correspond to randomly choosing any farmer in the community to be a lead farmer for the community. After identifying homogeneous network communities with known network structural properties around influential farmers in the network, we then construct a network-specific contiguity matrices ($\widetilde{\boldsymbol{W}}$) for each network community. The influence of three social ties or network properties namely; transitivity, degree-centrality and eccentricity, are analyzed for each detected network community. These social ties are chosen based on their importance and wider application in technology adoption studies using social networks in the literature (e.g., Beaman *et al*. 2021; Fafchamps *et al*., 2021; Simpson, 2020; Beaman and Dillon, 2018). Table 5.1 presents the layout of the adjusted matrices and the social ties.

Table 5. 1 Adjusted weighting matrices

	Network Community Structure		
Centrality Measure	**T*0*** *(Random)*	***T1*** *(Edge-eigenvector)*	***T2*** *(Edge-betweeness)*
Transitivity	$\widetilde{W}_1$	$\widetilde{W}_2$	$\widetilde{W}_3$
Degree-Centrality	$\widetilde{W}_4$	$\widetilde{W}_5$	$\widetilde{W}_6$
Eccentricity	$\widetilde{W}_7$	$\widetilde{W}_8$	$\widetilde{W}_9$

Note: $\widetilde{W}$ denotes the adjusted weighting matrix for the respective community.

By iterative substitution, each adjusted matrix ($\widetilde{\boldsymbol{W}}$) is then employed in the estimation of equation 3 of the empirical specifications to account for spatial heterogeneity effect, while the global contiguity matrix ($\boldsymbol{W}$) from the observed real-world network data is used to account for spatial dependence at the global network level, as expressed in equation 2.

5.4.5 Descriptive Statistics

Table 5.2 presents descriptive statistics of the data[32]. Average soybean yield of a farmer is 830kg/ha, cultivating on average 5ha of land to soybean and using an average labor of 8worker days/ha. About 51% of the farmers used inoculant, averaging 14g/ha, of which 70% of the farmers also used improved soybean seed variety. Average age of farmers in the sample is 42 years, who are predominantly male farmers (71%) with average years of schooling of 3years, living in an average of 6 member households.

Table 5.2 also presents the average network structural properties. Note that because the algorithms employed to construct the virtual network communities are based on the modularity maximization procedure, they are interpreted as modularity measures of the respective network communities. The three virtual communities are therefore described in terms of their modularity measures. The table shows that, average modularity of ***T1*** communities is 0.324, indicating that at least 32% of links in the information network is formed around an agriculturally important (i.e., successful farmer or past award winning farmer) farmer in the network. Average modularity of ***T2*** communities, is 0.332, indicating that at least 33% of links in the information networks is formed around powerful farmers (i.e., farmers serving as bridges for others to pass through for information). Average modularity of ***T0*** communities is 0.318, suggesting that about 32% of links in the network may be formed around any randomly chosen farmer within the networks. Table 5.2 further shows that, average transitivity (which measures the structural strength of ties or links in the network or cohesion) of the global network is 0.471, suggesting that at least 47% of farmers (or adjacent vertices) are connected together. Average eccentricity, which measures the shortest path distance (or *geodesic*) from the farthest node to any other node within a network is 2.7, meaning on average

[32] See Table A1 in the Appendix for the full descriptive statistics of the data.

a farmer in the network need to take 3 steps to reach the farthest farmer within the network, which is very short and easier for information flow within the network. Average degree-centrality of a network is 0.242, implying that at least a randomly chosen farmer in the network is connected to 24% of the farmers within the network.

Table 5. 2 Definition and Summary Statistics.

Variable	Definition	Mean	SD	Min	Max
Panel A: Farmer and Farm Level Factors					
Yield	Soybean yield per hectare (Kg/ha)	829.64	888.24	32.41	5703.87
Age	Age of farmer (years)	41.56	13.32	18	87
Gender	1 If farmer is male, 0 for female	0.71	0.46	0	1
Edu	Years of schooling	2.79	4.69	0	21
Hhsize	Number people in a household	5.79	3.05	1	27
Land	Total area of land planted with soybean (ha)	5.05	4.37	1	22
Labor	Total labor used in soy cultivation (Worker-days/ha)	7.81	24.23	0.20	274.73
Agrochem	Total amount of active ingredient in chemical used (kg/ha)	4.00	7.19	0	87.22
Chemdumy	1 If farmer uses agrochemical, Otherwise=0	0.03	0.16	0	1
Amtinouse	Total amount of inoculant used (kg/ha)	13.91	18.35	0	118.93
Inodumy	1 If farmer uses agrochemical, Otherwise=0	0.51	0.50	0	1
Improvar	1 If farmer uses improve seed variety, Otherwise=0	0.70	0.46	0	1
Creditconst	1 If farmer is not credit constrained, Otherwise=0	0.83	0.38	0	1
Extcont	Number of extension contacts	1.37	1.22	0	5
Distmkt	Distance to nearest market (km)	2.36	4.14	0.10	50.10
Soil	1 If soil quality is good, Poor soil quality=0	0.51	0.50	0	1
Rain	Amount of rainfall in (%)	61.63	16.24	20	100
Elgrid	1 If community is connected to the national grid for electricity supply, Otherwise = 0	0.51	0.50	0	1
Panel B: Network Structural Characteristics					
Random Structure (***T0***)	Average modularity of intervention communities	0.324	0.059	0.197	0.404
Edge-eigenvector Centrality (***T1***)	Average modularity of intervention communities	0.318	0.053	0.160	0.397
Edge-betweeness Centrality (***T2***)	Average modularity of intervention communities	0.332	0.067	0.151	0.424
Transitivity	Average transitivity of a network	0.471	0.034	0.391	0.530
Eccentricity	Average shortest path distance from the farthest nodes in the network	2.718	0.063	2.5	2.75
Degree-Centrality	Average centrality of the network based on degree connections	0.242	0.059	0.137	0.421

Note: *SD is standard deviation; Min and Max are minimum and maximum values respectively (See Appendix Table A5).*

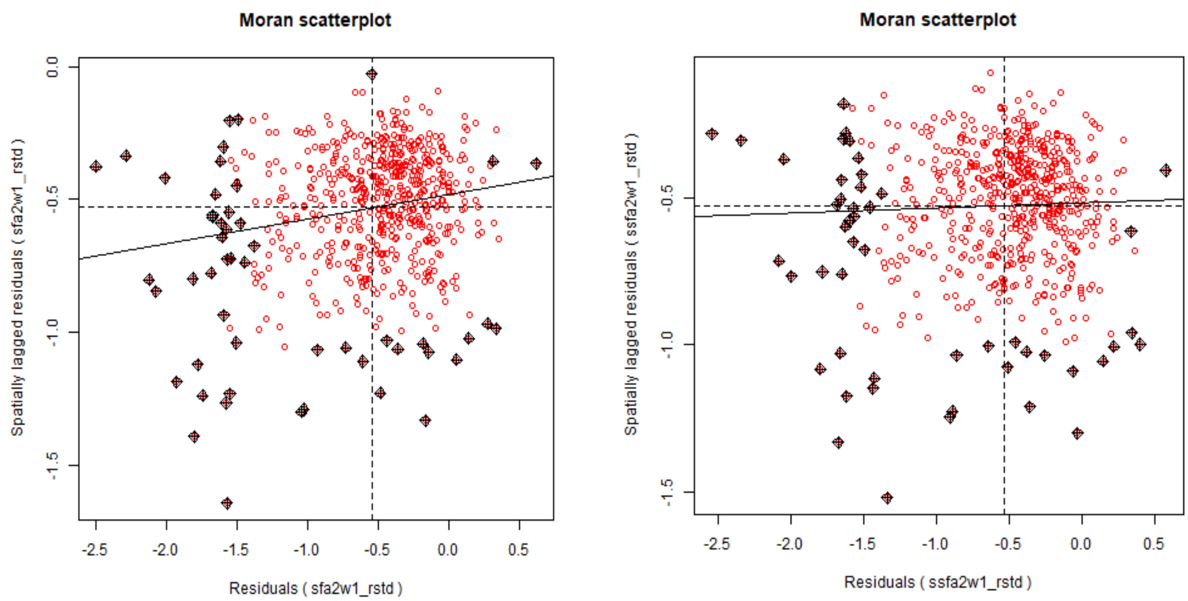
5.5 Empirical Results

This section presents estimates based on equations 2, 3, 4, and 5 in the empirical specifications, representing spatial dependence, spatial heterogeneity, efficiency gains from spatial heterogeneity, as well as determinants of efficiency gains and the distribution of the efficiency gains among farmers within the social space. For brevity, we focus the discussion on the parameter estimates that are germane to the objective set out in this study. However, the bulk of the estimates in respect of each equation is attached as appendix (see Appendix Table 5A.1) in order to save space but will be referred to, when the need arises.

5.5.1 Spatial Dependence of Efficiency

In Figure 5.1, Panels (**a**) and (**b**) present the global Moran's ***I*** plot of the residuals in the SFA and SSFA models, respectively. This is a correlation test for spatial dependence between the individual farmer's inefficiency and the inefficiency of the farmers in the information network, as expressed in equation 2 of the empirical specifications. This test is performed based on the residuals obtained from estimating equation 2 with the adjacency matrix ($\boldsymbol{W_{ij}}$) that defines the social contiguity or proximity of a farmer to other farmers in the observed real-world network. Panel (**a**) of Figure 5.1 shows a Moran's plot of the residuals from the SFA model, assuming no spatial dependence between the farmer's inefficiency and the inefficiency of farmers in their information network (i.e., $\rho = 0$). As reported below in Panel (**a**), the Moran's statistic (Moran's ***I*** = 0.092, *p-value* = 0.0001) is positive and statistically significant at the 1% level, indicating that the assumption of no spatial dependence as implied by the SFA model is rejected, in favor of SSFA. Figure 5.1 also shows a dense distribution of the residuals in the first quadrant of the Moran's plot in Panel (**a**), suggesting that highly inefficient farmers are more likely to be connected to highly inefficient farmers. The intuition is that inefficient farmers seek farming advice from peers who themselves are inefficient, thus, low quality advice leading to low performance. This finding is line with Fafchamps *et al.*

(2021), who found that knowledge of farmers tend to correlate with their peers from whom they seek farming advice.



(a) SFA Model (b) SSFA Model

(*Moran's I* = 0.092, *p-value* = 0.000, *LR* = 51.96, *p-value* = 0) (*Moran's* **I** = 0.018, *p-value* = 0.220, ρ = 0.188, *LR* = 57.74, *p-value* = 0)

Figure 5. 1 Comparing the effect of spatial dependence on correlations of residuals distribution.

Notes*: SFA and SSFA represent stochastic frontier analysis and spatial stochastic frontier analysis models, respectively; LR represents the statistic of the likelihood ratio test.*

The rejection of no spatial dependence means that we have to estimate a SSFA model to account for the dependence. Panel (**b**) of Figure 5.1 presents the Moran's plot for the SSFA model accounting for spatial dependence. As shown in Panel (**b**), the presence of spatial dependence (i.e., $\rho \neq 0$) could not be rejected (ρ = 0.188, *LR* = 57.74, *p-value* = 0.000). The *rho* is positive and statistically significant, suggesting that, at global level 19% of the farmer's inefficiency depends on the efficiency of the farmers from whom they seek farming advice. In terms of model fit, the *LR* (likelihood ratio) shows that the SSFA model outperformed the standard SFA, indicating that accounting for spatial dependence significantly improves the fit of the farmer's production function. The corresponding Moran's statistic (Moran's $\boldsymbol{I}$ = 0.018, *p-value* = 0.220) is not statistically significant at any conventional level, indicating that the SSFA model has sufficiently accounted for the spatial dependence. The distribution of the residuals in Panel (**b**) also shows that, the gap between the mean plot (i.e., the solid line) is now very close to the line of origin (i.e., the dash line), compared to Panel (**a**), suggesting that spatial dependence has been sufficiently addressed.

5.5.2 Spatial Heterogeneity in Efficiency

In Table 5.3, we present estimates based on equation 3 of the empirical specifications in three panels B, C, and D, representing transitivity, degree-centrality and eccentricity interventions, respectively, assigned to the three virtual network communities (i.e., $\boldsymbol{T0}$, $\boldsymbol{T1}$ and $\boldsymbol{T2}$). Each panel contains three models, with each model representing a specification with a different network-specific structure used to construct the adjusted weighting matrix (i.e., $\widetilde{\boldsymbol{W}}$) employed in the estimation of the model. The criteria for identification is that, after accounting for spatial heterogeneity, the spatial dependence structure as captured by ρ should vary according to the changing network structure (Anselin 2010). In addition, after accounting for spatial heterogeneity the local level spatial dependence as captured by the local[33] Moran's $\boldsymbol{I}$ statistic becomes statistically zero, such that the SSFA and the SFA models' parameters converges and the model is consistently estimated (Fusco and Vidoli 2013, Vidoli *et al*. 2016).

Panel A in Table 5.3 presents the global model for comparison. The global model only accounts for spatial dependence (as discussed in the previous section above) and not spatial heterogeneity. Hence, serves as a benchmark for detection of observed changes in the spatial dependence structure

[33] The local Moran's $\boldsymbol{I}$ statistic converges to the Local Indicators for Spatial Association (LISA) statistic after accounting for local or network level spatial dependence structure (Anselin 1995).

due to changes in the network-specific structure. We also present the local Moran's and kernel density plots of the model residuals, as well as the efficiency scores predicted at the production frontier in Figures 5.2 and 5.3, respectively. The local Moran's plot illustrates the effect of spatial heterogeneity on the distribution of the model residuals, while the kernel density plot illustrates the effect of accounting for spatial heterogeneity on the estimated farmers' technical efficiency. In the interest of brevity, we report only the model parameters that are common to this discussion, and place the full estimates of all the models in Table 5A.2 in the Appendix.

Table 5. 3 Summary estimates from the stochastic frontier models

Model	Matrix	SFA						SSFA							
	$\widetilde{W}$	$\sigma^2_{u_{sfa}}$	$\sigma^2_{v_{sfa}}$	λ_{sfa}	I_{sfa}	$\hat{E}_{sfa}$	LR_{sfa}	$\sigma^2_{u_{ssfa}}$	$\sigma^2_{\tilde{u}}$	$\sigma^2_{v_{ssfa}}$	λ_{ssfa}	I_{ssfa}	ρ	$\hat{E}_{ssfa}$	LR_{ssfa}
Panel A: Adjacency Matrix															
Global Model	W_0	0.470***	0.039***	3.488	0.092***	0.630	51.96***	0.463***	0.1%	0.039***	11.97	0.018	0.188	0.63	57.74***
Network-Specific Structure Models															
Panel B: Transitivity															
Model 1	$\widetilde{W}_1$	0.470***	0.039***	3.488	-0.002	0.630	51.96***	0.470***	0.3%	0.037***	12.54	-0.001	-0.000	0.63	53.94***
Model 2	$\widetilde{W}_2$	0.470***	0.039***	3.488	-0.004	0.630	51.96***	0.418***	0.1%	0.047***	8.88	-0.002	-0.000	0.64	65.08***
Model 3	$\widetilde{W}_3$	0.470***	0.039***	3.488	-0.004	0.630	51.96***	0.453***	0.1%	0.041***	11.00	-0.006	-0.000	0.63	56.56***
Panel C: Degree-Centrality															
Model 4	$\widetilde{W}_4$	0.470***	0.039***	3.488	-0.007	0.630	51.96***	0.376***	0.2%	0.058***	6.50	-0.002	-0.000	0.66	63.43***
Model 5	$\widetilde{W}_5$	0.470***	0.039***	3.488	0.002	0.630	51.96***	0.461***	0.1%	0.037***	12.41	0.001	-0.000	0.63	62.62***
Model 6	$\widetilde{W}_6$	0.470***	0.039***	3.488	-0.009	0.630	51.96***	0.419***	0.2%	0.046***	9.09	-0.002	-0.000	0.64	67.07***
Panel D: Eccentricity															
Model 7	$\widetilde{W}_7$	0.470***	0.039***	3.488	-0.014	0.630	51.96***	0.471***	0.1%	0.038***	12.41	-0.014	-0.000	0.63	52.71***
Model 8	$\widetilde{W}_8$	0.470***	0.039***	3.488	0.009	0.630	51.96***	0.473***	0.2%	0.036***	13.01	0.001	-0.000	0.63	57.17***
Model 9	$\widetilde{W}_9$	0.470***	0.039***	3.488	0.009	0.630	51.96***	0.399***	0.3%	0.054***	7.38	0.004	-0.000	0.65	52.10***

***Notes**: *, ** and *** are 10%, 5% and 1% level of significance. The Table presents estimates from equations 2 and 3 in Panel (A) and Panels (B, C and D), respectively. Panel **A**, presents estimates of the global model employed to account for spatial dependence, while the estimates in Panels **B, C** and **D**, present estimates on the network properties (transitivity, degree-centrality and eccentricity, respectively) that characterized the social ties among farmers within the egocentric information network community. Each of the three models represents a specific network community (**T0**, **T1** and **T2**, respectively) employed to account for spatial heterogeneity. SFA and SSFA are the stochastic frontier analysis and the spatial stochastic frontier analysis, respectively.*

Panel B of Table 5.3 contains three models 1, 2, and 3, each representing estimates obtained from equation 3, based on the adjusted matrices ($\widetilde{\boldsymbol{W}_1}$, $\widetilde{\boldsymbol{W}_2}$, and $\widetilde{\boldsymbol{W}_3}$, respectively) for virtual communities ***T0***, ***T1*** and ***T2***, respectively, characterized by high transitivity. The results in Panel B show that the coefficient of the spatial dependence parameter ρ, across all the three models are negative, compared to the positive coefficient in the global model. The negative coefficient suggests that the changes in the network-specific structure has lead to changes in the spatial dependence structure. In particular, the Moran's ***I*** statistic is also negative and not statistically significant, implying that all forms of observed and unobserved spatial heterogeneity have been addressed. The models (i.e., Models 1 – 3) that account for spatial heterogeneity in terms of the *LR* also perform better than the global model. The negative signs in all the models of both the SFA and SSFA indicate that the parameters are also consistently estimated. The implication of the negative spatial dependence structure suggests that less technically efficient (or highly inefficient) farmers are more likely to depend on more technically efficient (or less inefficient) farmers in their information network for farming advice. Intuitively, inefficient farmers tend to seek farming advice from highly efficient peers, since quality advice contributes to better performance. This finding is consistent with the lead farmer concept employed in farmer-to-farmer extension delivery systems (see Kondylis *et al*. 2017; Shikuku *et al*. 2019). We also observe that all the network communities have similar effects on the spatial dependence structure, meaning that no matter the nature of influence (i.e., social importance or power) of the most central farmer in the network community, the effect will be the same, as long as there is social cohesion (i.e., high transitivity) among farmers in the network community.

However, in terms of the proportion of the individual farmer's inefficiency variance (i.e., $\sigma_{\tilde{\boldsymbol{u}}}^2$) that is attributable to the inefficiency of the farmers in their information network, the randomly chose network communities (i.e., Model 1), accounts for higher variance (0.3%), compared to Models 2 and 3, respectively. The finding is an indication that randomly chosen lead farmers increases the level of inefficiency within the network, compared to those chosen based on social importance or power within the network community. This observation may be due to the fact that randomly chosen lead farmers, unlike others who have social importance or recognition to maintain, may require some material motivation in order to spend time to share quality information with peers, hence, the higher inefficiency observed among farmers in that network community. This observation is also in line with Shikuku's *et al*. (2019) finding that information sharing of randomly chosen lead farmers with their peers is weak, because of the absence of a private motivating factor, compared to lead farmers chosen based on the farmers' social importance in the village.

In terms of average efficiency score, Model 2 outperforms both Models 1 and 2, indicating that lead farmers chosen based on social importance of the farmer increases efficiency among farmers in the village. Intuitively, choosing best performing or award winning farmers within a community as lead farmers for extension delivery enhances learning and performance by other farmers, a finding that is in line with Shikuku *et al*. (2019) and Fafchamps *et al*. (2021).

Panel C in Table 5.3 also presents the results of Models 4, 5, and 6, each representing estimates based on the matrices ($\widetilde{\boldsymbol{W}}_{\boldsymbol{4}}$, $\widetilde{\boldsymbol{W}}_{\boldsymbol{5}}$, and $\widetilde{\boldsymbol{W}}_{\boldsymbol{6}}$, respectively) for virtual communities $\boldsymbol{T0}$, $\boldsymbol{T1}$, and $\boldsymbol{T2}$, respectively, characterized by farmer with high degree-centrality. The results show similar negative *rho* coefficients and statistically insignificant Moran's $\boldsymbol{I}$ statistic across all the three models, compared to the global model, indicating that changes in the network-specific structures lead to changes in the spatial dependence structure. The negative spatial dependence emphasize the earlier findings that less efficient farmers learn from more efficient farmers in order to improve their performance.

In terms of its impact on extension delivery organization, the choice of the lead farmer is important. For example, we observe that Model 4 which assumes choosing the lead farmer randomly, gives higher average efficiency (i.e., $\hat{E}_{ssfa}$) 66%, compared to any other model, suggesting that choosing a lead farmer randomly in a network community characterized by high proportion of popular farmers (i.e., *degree-centrality*) leads to higher performance. This observation highlights synergies in information sharing among farmers, needed for tacit social learning at the local level. The finding that the proportion of popular farmers within the network community structure has positive effect on efficiency is consistent with the social theory in diffusion studies, whereby the proportion of adopters of a new technology or behavior in a network influences the adoption decisions of other network members (see, Granovetter 1973).

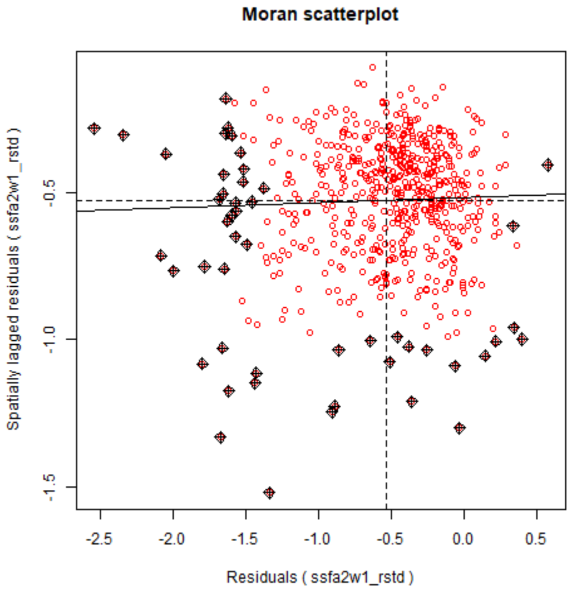
Also informative is the positive sign of the local Moran's $\boldsymbol{I}$ statistic in Model 5, which chooses a lead farmer based on social importance within the network community. The positive sign suggests that highly efficient farmers also share agricultural information or farming advice with peers who are equally technically efficient, to maintain their performance level (Kondylis *et al*., 2017). This observation is an indication of mutual relationship in information sharing among farmers in an information network.

Panel D of Table 5.3 presents the results of Models 7, 8, and 9, representing estimates based on the matrices ($\widetilde{\boldsymbol{W}_7}$, $\widetilde{\boldsymbol{W}_8}$, and $\widetilde{\boldsymbol{W}_9}$, respectively) for virtual communities ***T0***, ***T1***, and ***T2***, respectively, characterized by high eccentricity (i.e., shorter social distances or close proximity). The results in Panel D are consistent with that of panels B and C, in terms of the negative coefficients in the spatial dependence structure, compared to the global model. The results of Model 9 show that, average efficiency score of farmers in high *betweeness-centrality* communities is 67%, suggesting that in network communities characterized by powerful farmers, shorter social distances among all network members increases efficiency. This indicates that close social proximity in farmers' information networks may have high influence on members' efficiency, due to effective communication. However, in terms of inefficiency variance, it also accounts for higher (0.3%)

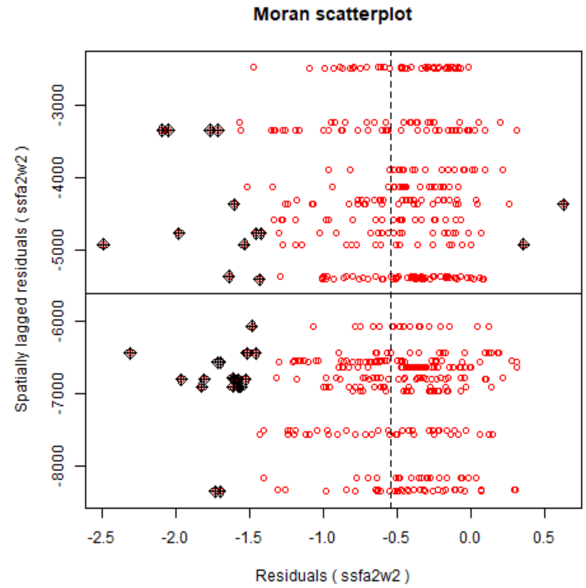
variation of the inefficiency among farmers in the network community, suggesting that increasing proximity could equally have greater consequences on inefficiency, in case the network is dominated by highly inefficient farmers.

We also observed a positive coefficient of the local Moran's ***I*** statistic in Models 8 and 9 respectively, suggesting that network communities formed around socially important and powerful farmers that maintain shorter social distance to all farmers within the network community, generate more mutual information sharing among farmers, compared to randomly structured network communities.

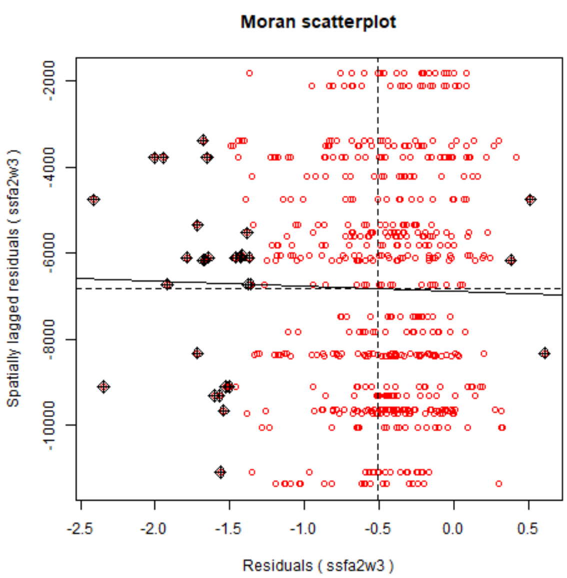
Furthermore, Figure 5.2 shows that the residual distributions in the SSFA models that account for spatial heterogeneity are now more even (i.e., Panels B, C and D), compared to the residual distribution in the global model (i.e., Panel A). We explore the effects of accounting for spatial heterogeneity on average efficiency score of the farmer. Figure 5.3 presents a kernel density plot of average efficiency scores predicted from all the nine models (i.e., Models 1 – 9), compared to the efficiency scores from the global model. The results in Figure 5.4 reveal that failure to account for spatial heterogeneity lead to underestimating the efficiency of high (i.e., efficiency score >0.6) performing farmers, while overestimating that of medium (i.e., efficiency scores ranging 0.36 – 0.5) and low (i.e., efficiency scores ranging 0.1 – 0.35) performing farmers.



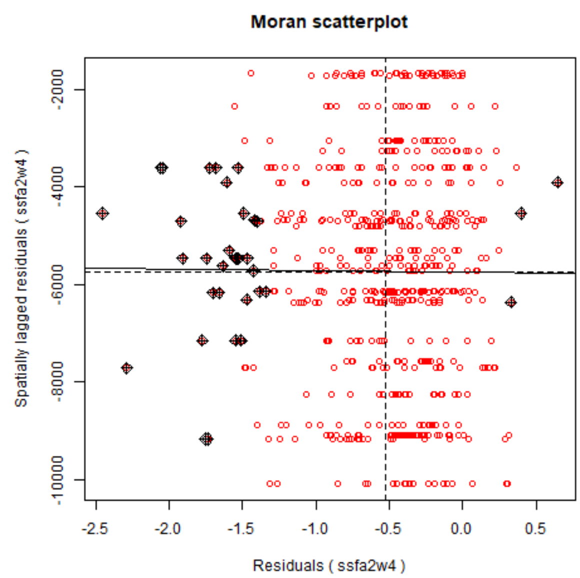
(a) Base Model (W)



(b) Model 1 ($\widetilde{W}_1$)



(c) Model 2 ($\widetilde{W}_2$)



(d) Model 3 ($\widetilde{W}_3$)

Figure 5. 2 Comparing the effect of spatial heterogeneity on the distribution of residuals.

Notes: *The Base Model accounts for spatial dependence, while Models 1-3 account for spatial heterogeneity using the adjusted social contiguity matrices* $\widetilde{W}_1, \widetilde{W}_2$ *and* $\widetilde{W}_3$, *representing matrices constructed using the pairing of the random walk modularity (i.e., Modwalk) and transitivity, the eigenvector modularity (i.e., Modledeigen) and transitivity, as well as the betweeness modularity (i.e., Modbetwn) and transitivity in the adjusted social contiguity matrix.*

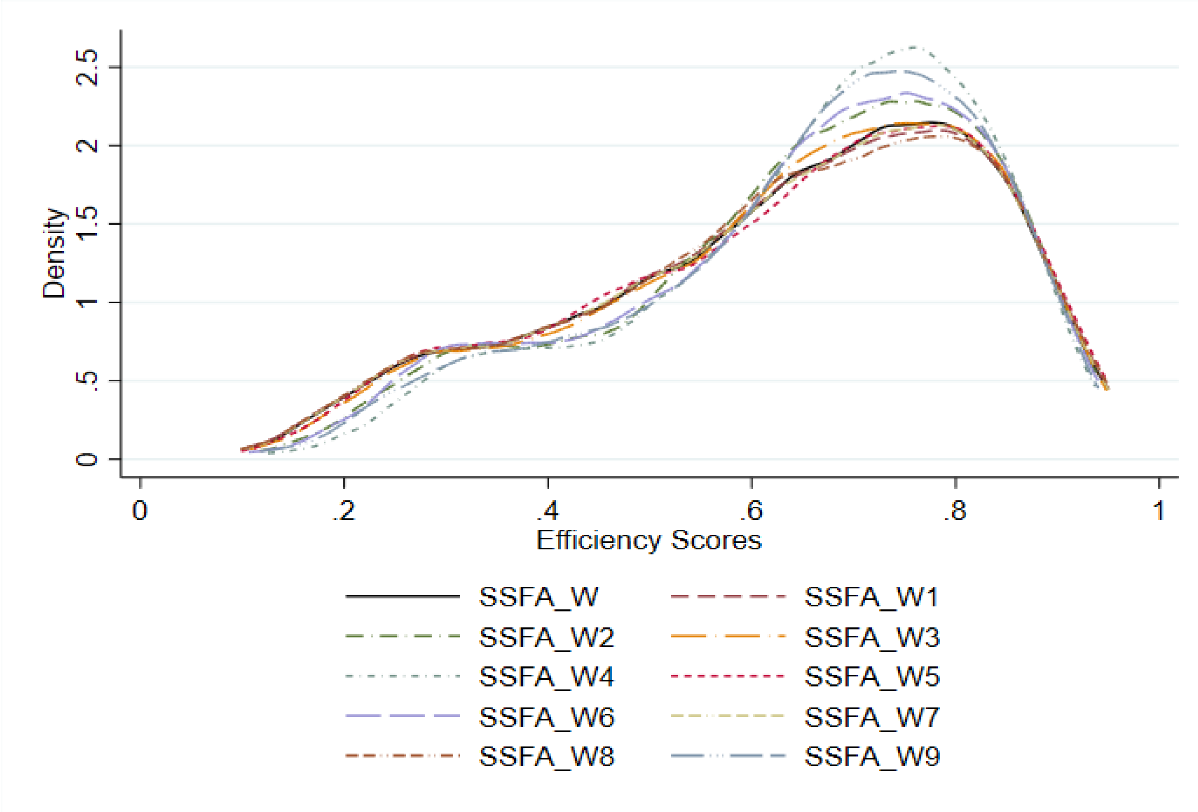


Figure 5. 3 Effect of spatial heterogeneity on farmers technical efficiency scores.

Notes: *SSFA represents spatial stochastic frontier analysis model, while the Ws represent the social contiguity matrices used in the estimation of the models to account for spatial effects. So, SSFA_W presents the base model estimated using W; SSFA_W1 represents model 1 estimated using the adjusted matrix $\widetilde{W}_1$, SSFA_W2 for model 2 using $\widetilde{W}_2$, SSFA_W3 for model 3 using $\widetilde{W}_3$, SSFA_W4 for model 4 using $\widetilde{W}_4$, SSFA_W5 for model 5 using $\widetilde{W}_5$, SSFA_W6 for model 6 using $\widetilde{W}_6$, SSFA_W7 for model 7 using $\widetilde{W}_7$, SSFA_W8 for model 8 using $\widetilde{W}_8$, SSFA_W9 for model 9 using $\widetilde{W}_9$.*

5.5.3 Impact on Efficiency Gains and Distributive Mechanisms

We now examine the impact of information networks on farmers' productivity, in terms of technical efficiency improvement (or otherwise), in the production process. Figure 5.4 presents the productivity gains in classes (both inter-class and intra-class) percentiles across all the models (i.e., *Models 1 – 9*), in comparison to the global model that accounts for spatial dependence and not spatial heterogeneity. Generally, Figure 5.4 reveals strong heterogeneity in both inter-class and intra-class distribution of productivity gains among farmers within and across each information network, suggesting that farmers' benefits differ according to individual influence in the network as well as the structural characteristics of the network community.

In particular, the figure shows that when the information network is characterized by high *transitivity* (i.e., social cohesion) productivity gains are higher (10^{th} to 60^{th} percentiles) in *eigenvector* centrality communities (i.e., *dW2*), compared to the *betweeness* centrality communities (10^{th} to 50^{th}) (i.e., *dW3*). However, the productivity gains are much lower (10^{th} to 30^{th}) in random communities (i.e., *dW1*), compared to the *edge-eigenvector* and *betweeness* centrality communities, respectively, suggesting that benefits differ according to the network structure (Beaman and Dillon 2018).

Also, the intra-class distribution of productivity gains follows similar pattern within the network community, suggesting that farmers' benefits differ according to individual influence or position within the network. This observation is also consistent with the literature on the distribution of economic benefits in embedded social relationships (Tan and Reddy 2021; Beaman and Dillon, 2018). The highest population of farmers are within the (10^{th} percentile) productivity class across all network communities, with the population of farmers decreasing as the productivity class size increases, suggesting that productivity gains may be higher among smaller groups (or cliques) of farmers, compared to larger groups. This finding is in line with Vidoli *et al*. (2016) as well as Di Falco *et al*. (2018), who found an inverse relationship between productivity gains and size of the farmer's network.

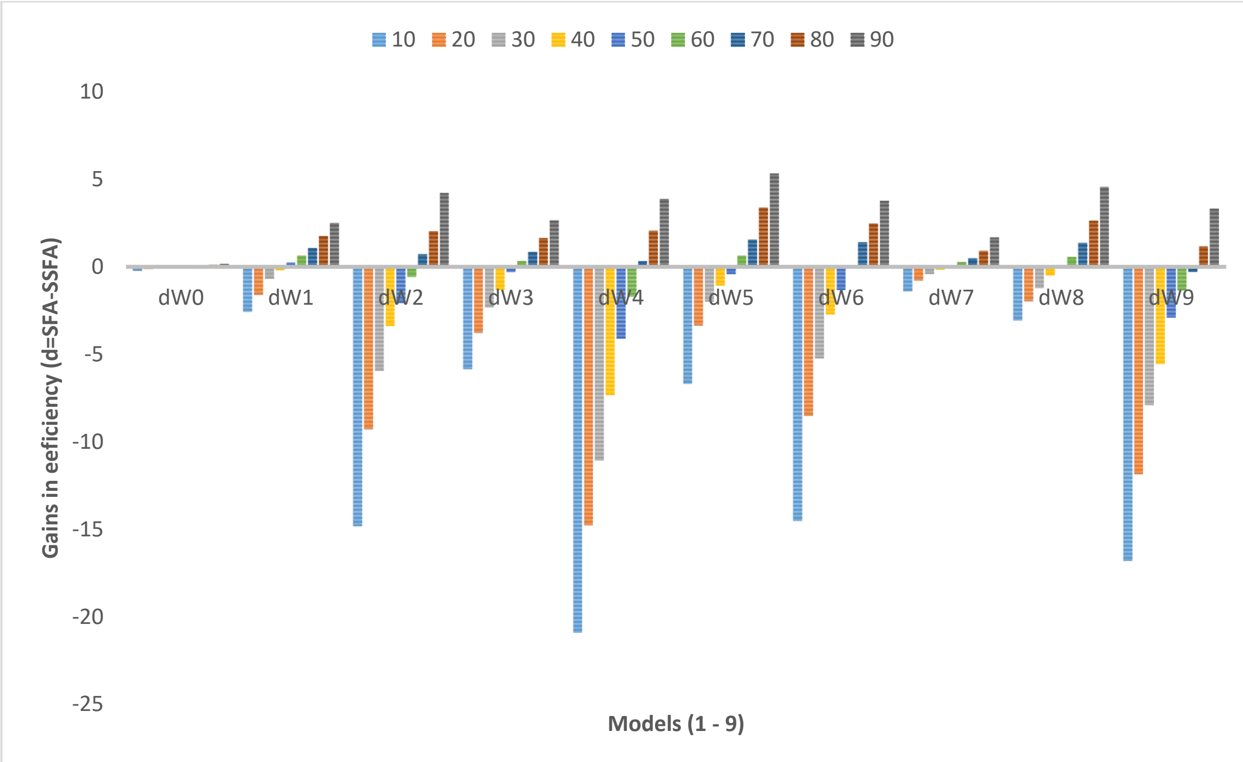


Figure 5. 4 Inter-class and Intra-class distributions of average efficiency gains in egocentric network communities.

Notes: *The estimates are based on equation 4. The dW0 denotes gains calculated based the global model, while dW1 – dW9 denote gains calculated based on Models 1 – 9, respectively. The bars at each model indicates percentiles, while comparison within a model is intra-class and between models is inter-class.*

On the other hand, in high *degree-centrality* (i.e., high popularity) networks, productivity gains are higher (10^{th} to 60^{th} percentile) in randomly communities (i.e., *dW4*), compared to *betweeness-centrality* (i.e., *dW6*) and eigenvector-centrality (i.e., *dW5*) communities, respectively. This finding suggests that in random communities the distribution of benefits may depend more on the individual farmer characteristics than the structure of the information network. By intuition, in communities with high number of influential farmers, productivity gains from the information network could be evenly distributed among farmers with at least a weakest link to the influential farmer, compared to other network communities. This finding is consistent with Beaman and Dillon (2018), who found high compositing knowledge in randomly structured network communities of male farmers with high centrality influence in the network, compared to other farmer network structures in Mali.

Furthermore, Figure 5.4 reveals that in high *eccentric*ity (i.e., shortest distance) networks, productivity gains are higher (10^{th} – 70^{th} percentiles) in *betweeness* centrality communities (i.e., *dW9*), compared to *eigenvector* centrality (i.e., *dW8*) and random (i.e., *dW7*) communities, respectively. This finding indicates that in high *eccentricity* network communities, an individual farmer's benefits from the network depends on their close proximity to farmers who serve as the information bridges to other farmers in the network community. This observation is intuitive as farmers with more knowledge on a technology are more likely to devote more attention to very close relations during information sharing, compared to any other farmers. Hence, effective communication occurs leading to high efficiency gains (Beaman and Dillon 2018; Akerlof 1997).

In addition, Figure 5.4 reveals that failure to account for spatial heterogeneity confounds farmers' productivity gains, as the global model (i.e., *dW0*) suggests equal productivity gains (10%) for all farmers in the information network, contrary to the heterogeneous classes of gains observed across all models. This finding supports recent literature (e.g., Shikuku *et al*. 2020; Shikuku *et al*. 2019; Kondylis *et al*. 2017) criticizing the lead farmer concept of extension delivery, where all farmers in the community are assumed to benefit equally from the lead farmer. Thus, implicitly overlooking the fact that benefits may differ according to the lead farmer's social influence in the community as well as the mode by which the lead farmer was chosen for the community[34].

[34] See Appendix 7 for more discussion on the distributive mechanisms.

5.5.4 Determinants of productivity gains in farmer information networks

In this section, we discuss the control variables from the Spatial Cox survival model in equation 5 of the empirical specifications, as factors influencing the likelihood of farmer's information network to contribute to productivity improvement of members of the network. Note that the coefficients discussed here are log hazard ratios from the spatial survival model. We interpret coefficients close to 1 as non-contribution to productivity gains, less than 1 as positive contribution to productivity gains and greater than 1, means negative contribution to productivity gains (i.e. productivity losses) (Sullivan, 2021). It is significant to note that the estimates discussed here are not determinants of (in)efficiency as in the spatial stochastic frontier analysis (SSFA) model. Due to space constraints, we attach the estimates of the SSFA models in the appendix (see Table 5A.2 in the Appendix), since their contribution to explaining the aggregate network behavior in this context is less important. The purpose of this discussion is to identify factors influencing productivity gains from farmers' *egocentric* networks, in order to inform extension delivery policies that leverage on such networks to reach farmers for technology adoption and productivity performance.

Table 5.4 reports estimates from the spatial Cox proportional hazard model. The table presents estimates from all the nine models (Models 1 – 9), compared to the global model. For brevity, we focus the discussion on the network level (i.e., the village level) factors that determine productivity gains from the network, since that is the target unit for policy action. We report the individual farmer level factors and district fixed effects in Table 5A.3 in the Appendix.

Panel B in Table 5.4 shows that the coefficient of average age (*Vage*) of farmers in the network is statistically significant and positive, suggesting that age density at the network does not contribute to explaining productivity gains from the network, though age may be important at the individual level.

Table 5. 4 Spatial Cox proportional hazard estimates

Variable	Global Model (W_0) Coeff. (S.E)	Model 1 ($\widetilde{W}_1$) Coeff. (S.E)	Model 2 ($\widetilde{W}_2$) Coeff. (S.E)	Model 3 ($\widetilde{W}_3$) Coeff. (S.E)	Model 4 ($\widetilde{W}_4$) Coeff. (S.E)	Model 5 ($\widetilde{W}_5$) Coeff. (S.E)	Model 6 ($\widetilde{W}_6$) Coeff. (S.E)	Model 7 ($\widetilde{W}_7$) Coeff. (S.E)	Model 8 ($\widetilde{W}_8$) Coeff. (S.E)	Model 9 ($\widetilde{W}_9$) Coeff. (S.E)
Vage	0.074*	0.108**	0.056*	0.074**	0.079***	0.133***	0.059	0.040	-0.033	-0.043
	(0.039)	(0.047)	(0.032)	(0.036)	(0.033)	(0.036)	(0.036)	(0.041)	(0.038)	(0.032)
Vgender	-0.036	1.762***	0.461	0.629	0.315	-1.265***	0.711*	-0.184	-1.093**	1.393***
	(0.502)	(0.580)	(0.406)	(0.439)	(0.393)	(0.484)	(0.416)	(0.507)	(0.520)	(0.420)
Vedu	-0.036	-0.471***	-0.190***	-0.229***	-0.137***	-0.105*	-0.165***	-0.024	-0.228***	-0.111**
	(0.064)	(0.086)	(0.059)	(0.066)	(0.056)	(0.062)	(0.059)	(0.058)	(0.067)	(0.050)
Vhhsize	0.556***	-0.385*	0.439***	0.665***	0.241*	-0.182	0.367***	-0.519***	0.540***	0.615***
	(0.178)	(0.222)	(0.144)	(0.171)	(0.134)	(0.152)	(0.154)	(0.172)	(0.174)	(0.153)
Vextcont	0.259	2.735***	0.080	1.497***	0.115	0.441	0.415	0.782*	0.380	0.475
	(0.435)	(0.700)	(0.364)	(0.371)	(0.330)	(0.336)	(0.328)	(0.474)	(0.422)	(0.326)
Vimpvar	-0.901*	-2.623***	-0.192	-0.445	-0.334	-0.967**	0.225	-1.880***	0.345	0.162
	(0.533)	(0.579)	(0.436)	(0.495)	(0.416)	(0.486)	(0.443)	(0.523)	(0.506)	(0.424)
Vinouse	-2.555**	2.061	-2.500***	-6.297***	-3.320***	-6.611***	-4.786***	-0.824	-2.500**	-1.985**
	(1.202)	(1.771)	(1.014)	(1.145)	(1.017)	(1.143)	(1.092)	(1.476)	(1.273)	(0.937)
Velgrid	0.921	-2.795	2.074	7.487***	3.343**	5.705***	5.147***	2.304	4.338**	1.514
	(1.843)	(2.565)	(1.539)	(1.784)	(1.599)	(1.895)	(1.728)	(2.335)	(1.879)	(1.406)
Vdistmkt	0.170***	0.207***	0.086	0.058	0.035	0.250***	0.098	0.071	0.166***	0.017
	(0.072)	(0.074)	(0.059)	(0.069)	(0.060)	(0.066)	(0.063)	(0.072)	(0.070)	(0.057)
Vfarmsize	-0.062	-0.004	-0.040	-0.057	-0.069*	-0.056	-0.096**	-0.102**	-0.146***	-0.041
	(0.053)	(0.047)	(0.039)	(0.046)	(0.040)	(0.053)	(0.048)	(0.051)	(0.056)	(0.041)
Vsoil	5.623***	11.290***	4.921***	7.142***	6.903***	4.121**	6.782***	6.704***	1.744	3.058**
	(1.928)	(2.234)	(1.697)	(2.006)	(1.785)	(1.770)	(1.893)	(1.904)	(1.899)	(1.550)
Vrain	-0.047*	0.019	-0.034	-0.013	-0.013	-0.005	-0.015	0.003	-0.001	0.014
	(0.027)	(0.029)	(0.022)	(0.023)	(0.022)	(0.026)	(0.024)	(0.028)	(0.027)	(0.021)
LRT (df=570)	*56.45***	*164.7***	*64.25***	*131.9***	*70.61***	*144.7***	*95.47***	*76.62***	*66.2***	*50.11***
Mean Beneficiaries	*45.50%*	*44.67%*	*64.83%*	*53.67%*	*68.33%*	*54.17%*	*59.83%*	*50.00%*	*49.50%*	*71.50%*
Observ.(N)	*600*	*600*	*600*	*600*	*600*	*600*	*600*	*600*	*600*	*600*

Notes*: *, ** and *** are 10%, 5% and 1% level of significance. The Table presents estimates from equation 5. Column 1, presents estimates of the global model employ to account for spatial dependence, while each of Columns* ***1 – 9*** *respectively, presents estimates on the network properties (transitivity, degree-centrality and eccentricity, respectively) that characterizes the social ties among farmers within the egocentric information network community. Each of the three models represents a specific network intervention community (****T0****,* ***T1*** *and* ***T2****, respectively) employed to account for spatial heterogeneity.*

This implies that benefits distribution in egocentric networks is mutual for all ages of farmers, who constitute the network. This observation is intuitive as people who share information benefits from each other's pool of diverse experiences.

The results in Panel B also show that the coefficient of average education (*Vedu*) of farmers in the network is negative and statistically significant (at 1% level), suggesting that density of educated persons in egocentric networks contributes positively to productivity gains of members of the network. The implication is that, the more educated persons in the farmer's *egocentric* network, the more productive the network becomes and vice versa. This is intuitive, as a network with high density of educated farmers means high cognitive proximity among members, a major requirement needed for accurate communication and effective information sharing in embedded social networks (Boschma 2005).

In Panel B of Table 5.4, gender (i.e., male = 1) distribution in the network shows a mixed effect. For instance, in network communities with high transitivity (i.e., Models 1 – 3), the density of male farmers in the egocentric networks does not contribute to explaining productivity gains of members in the network, compared to individual farmer level. Similar observation is made in high degree-centrality networks, particularly, in random and edge-betweeness network communities. However, in high eccentric network communities, the coefficient of gender is negative and statistically significant, suggesting that male farmers are more likely to obtain productivity improvement in the network, compared to female farmers in the network. This implies that the distribution of gender in information networks may have distributional inequalities, due to difference in social distances between male and female farmers, which is likely to affect the close proximity required for effective communication and information sharing.

Furthermore, Panel B of Table 5.4 shows that the density of average number of extension contacts (*Vextcont*) of farmers in the network do not contribute to explaining productivity gains, rather, it is the individual farmer's number of extension contacts that is important (in Panel A of Table 5.4). This is intuitive, as farmer's may not have to depend on the information network for farming advice, once all farmers have equal access to extension services, thus, underscoring the importance of egocentric networks in closing the information gap, stemming from inadequate extension staff to meet the needs of farmers.

In addition, the results in Panel B of Table 5.4 show that, the density of farmers using improved technologies such as improved crop variety (*Vimpvar*) and yield enhancement inputs (e.g., *rhizobia* inoculant – *Vinouse*) in the network have positive and statistically significant contribution to productivity gains for farmers in the network. This observation suggests that targeting egocentric networks in technology adoption programs will not only enhance diffusion of the technology but will also improve the performance of the technology, due to the potential of farmers to learn from the experiences of other farmers in their network communities.

In Panel B of Table 5.4, the coefficient of farm size is negative across all models, suggesting that either at individual or network level, farm size has positive and significant contribution to productivity gains, an observation that is consistent with applied economics literature. This observation is in line with Simpson (2020), who also observed positive relationship between farm size and agricultural landholding among rice farmers' *egocentric* networks in China.

On the other hand, the results in Panel B of Table 5.4 show that, poor soil conditions (i.e., *Vsoil*) and lack of amenities such as availability of electricity (i.e., *Velgrid*) at the village level, have negative and significant contribution to productivity gains (i.e., productivity losses) across the network communities.

Furthermore, the bottom row of Table 5.4 also reports the mean population of farmers that will be affected, in terms of productivity gains, due to extension policy based on each of the network community and the centrality measure, compared to the global model. The results in the table reveal that in network communities characterized by high *transitivity* (i.e., Models 1 – 3), *eigenvector centrality* communities have larger (65%) impacts, compared to *betweeness centrality* 54% and random (45%) communities, respectively. This finding suggests that in *egocentric* networks with high social cohesion among farmers, organizing extension delivery program around farmers with high *eigenvector centrality* (i.e., most successful farmers) in the community will be more beneficial to majority of farmers in the community, compared to high *betweeness centrality* farmers (i.e., powerful farmers). However, randomly chosen farmers in the community for extension delivery program will be less beneficial to majority of farmers in the community, compared to the two *centrality* measures.

In network communities with high *degree-centrality* (i.e., Models 4 – 6), the impact is larger in random communities (68%), compared to *betweeness-centrality* communities (60%) and *eigenvector-centrality* communities (54%), respectively. This finding suggests that in *egocentric* networks with highly popular farmers, organizing extension delivery program around randomly chosen farmers in the community will be more beneficial to majority of farmers in the community, compared to the two *centrality* measures. However, choosing either farmers with high *betweeness-centrality* or *eigenvector-centrality* will still benefit more than half of the population of farmers in the community.

However, the largest (72%) impact occurs in *betweeness-centrality* communities characterized by high *eccentricity*, compared to all network communities. This finding suggests that in *egocentric* networks of farmers with shorter social distances organizing extension delivery program around farmers with high *betweeness-centrality* may provide higher outreach to almost all farmers in the community, compared to both *eigenvector-centrality* and random farmers. However, choosing farmers either randomly or based on *eigenvector-centrality* will still benefit about half of the population of farmers in the community.

5.5.5 Robustness Checks

As robustness checks for the spatial heterogeneity observed in this study, we ignore the assumption that the information network is structured around either farmers with high *eigenvector-centrality* or *betweeness-centrality* in the community and assume a random community structure. Panels E and F of Table 5A.4 in the Appendix present the results of two models (i.e., Models 10 and 11) on the robustness checks. Panel E report estimates of Model 10, which accounts for spatial heterogeneity based on adjusted weighting matrix ($\widetilde{\boldsymbol{W}_{\mathbf{10}}}$) focusing on *transitivity* and *degree-centrality*, while Panel F reports that of Model 11 estimated based on ($\widetilde{\boldsymbol{W}_{\mathbf{11}}}$) focusing on *degree-centrality* and *eccentricity* of a random community structure. The results show that our findings are robust, as both the coefficient of the spatial dependence structure and the LISA statistic both have the negative signs, which is consistent with the random communities in Models 1, 4, and 7 of panels B, C and D, respectively. The *LR* statistics are also statistically significant at the 1% level, suggesting that the SSFA models accounting for spatial heterogeneity provide better fit of the farmers' production function.

In Figure 5A.2, we present kernel density plots of average efficiency scores predicted from models 10 and 11 (i.e., Models 10 – 11), compared to the efficiency scores from the global model, as robustness check of the effects of failure to account for spatial heterogeneity on farmers' efficiency scores as observed in this study. The results in Figure 5A.2 reveal the same patterns of underestimating high performing farmers, while overestimating that of low and medium performing farmers. Indicating that the findings as observed in this study is consistent and robust. All estimates on the robustness checks are reported the appendix, in order to save space.

5.6 Conclusions

In this study, we investigate the impact of farmers' *egocentric* information networks on technical efficiency in the production functions of farmers and its distributive mechanisms in the networks. Using community detection algorithms in a data-driven approach, based on observed real-world *egocentric* networks data of 600 soybean farmers from Ghana, we account for unobserved spatial heterogeneity on farmers' technical efficiency.

The empirical results generally reveal that farmers' technical (in)efficiency strongly correlate with that of farmers in their egocentric networks, suggesting that farmers who share farming information with inefficient farmers are more likely to be inefficient, compared to those who share information with highly efficient farmers. This also indicate farmers' readiness to learn from high performing peers in their egocentric networks in order to improve their own performance.

The results show that the *egocentric* network level of influence on technical (in)efficiency of farmers is network-specific and differ according to the nature of the social ties or influence between farmers in the network. The empirical results further reveal that network communities formed around farmers with social importance increases efficiency among farmers in the community through information sharing with highly efficient farmers in the network. Furthermore, the findings reveal that in networks of farmers with high *degree-centrality*, randomly structured relationship in the network, have greater impact on efficiency, compared to any other network community. These network communities generate synergies in information sharing among farmers, needed for tacit social learning at the local level. The findings also reveal mutual information sharing among highly efficient farmers in an information network, implying that technically efficient farmers also share agricultural information or farming advice with peers who are equally efficient so as to maintain their level of efficiency. We find that the density of educated persons in *egocentric* networks contributes positively to productivity gains of farmers in the network.

In terms of organizing extension delivery around farmers' *egocentric* networks, this study find that in highly social cohesion networks organizing extension delivery around farmers with high *eigenvector-centrality* in the community increases the efficiency of majority farmers, compared to farmers with high *betweeness-centrality*. Furthermore, we find that organizing extension delivery around randomly chosen farmers in highly cohesive networks decreases the number of farmers that will benefit from the network. In addition, the findings further reveal that in *egocentric* networks with highly popular farmers organizing extension delivery around randomly chosen farmers' increases efficiency of majority of the farmers in the community, though choosing either *betweeness-centrality* or *eigenvector-centrality* farmers still benefits more than half of the population of farmers in the community. Finally, we find that in *egocentric* networks of farmers with shorter social distances organizing extension delivery program around farmers with high *betweeness-centrality* increases the efficiency of almost the entire population of farmers in the community, though choosing farmers either randomly or based on *eigenvector-centrality* also benefits about half of the population of farmers in the community.

The study generally conclude that identifying central farmers' in egocentric networks and improving their technical knowledge in a farmer-to-farmer extension organization, can leverage the limited extension agents, to improve productivity of many farmers.

References

Akerlof, G. A. (1997). Social distance and social decisions. *Econometrica, 65(5):1005 – 1027*.

Anselin, L. (2010) Thirty years of spatial econometrics. *Papers in Regional Science, 89(1):3 – 25*.

Areal, F. J., Balcombe, K., and Tiffin, R. (2012). Integrating spatial dependence into stochastic frontier analysis. *Australian Journal of Agricultural and Resource Economics, 56(4):521 – 541*.

Badham, J., Kee, F., and Hunter, R.F. (2021). Network structure on simulated network interventions for behavior change. *Social Networks 64:55 – 62*.

Bai, L., Gillen, D. L., Bartell, S. M., and Viera, V. M. (2020). Mapping Smoothed Spatial Effect Estimates from Individual-Level Data: MapGAM. *The R Journal 12(1):32 – 48*.

Bandeira, O., and Rasul, L. (2006). Social networks and technology adoption in northern Mozambique. *Economic Journal, 116(514): 896-902.*

Banerjee, A., Chandrasekhar, A. G., Duflo, E., Jackson, M. O. (2013). The diffusion of microfinance. *Science, 341(6144), 1236498.*

Banerjee, S., and Dey, D. K. (2005). Semiparametric proportional odds models for spatially correlated survival data. *Life Time Data Analysis, 11:175 – 191*.

Beaman, L., and Dillon, D. (2018). Diffusion of agricultural information within social networks: evidence on gender inequalities from Mali. *Journal of Development Economics, 133:147-161.*

Beaman, L., Ben Yishay, A., Magruder, J., and Mobarak, A. M. (2021). Can Network Theory-Based Targeting Increase Technology Adoption?. *American Economic Review, 111(6):1918 – 1943*.

Billé, A.G., Salvioni, C., and Benedetti, R. (2018). Modelling spatial regimes in farms technologies. *Journal of Productivity Analysis 49:173 – 185*.

Blum, M. L., and Szonyi, J. (2011). *Investment requirements in extension to achieve zero hunger and adapt to climate change*. Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Bochma, R.A. (2005). Proximity and innovation: A critical assessment. *Regional Studies 39(1):61 – 74*.

Cai, J., De Janvry, A., and Sadoulet, E. (2015). Social networks and the decision to insure. *American Economic Journal: Applied Economics, 7(2):81 − 108*.

Clauset, A., Newman, M. E. J., and Moore, C. (2004). Finding community structure in very large networks. *Physical Review E, 066111 – 6*.

Cleveland, W. S., and Devlin, S. J. (1988). Locally weighted regression: an approach to regression analysis by local fitting. *Journal of American Statistical Association 83(403):596 – 610*.

Conley, T. G., and Udry, C. (2010). Learning about a new technology: pineapple in Ghana. *American Economic Review, 100(1): 35-69.*

de Graaff, T. (2020). On the estimation of spatial stochastic frontier models: an alternative skew-normal approach. *Annals of Regional Science, 64:267–285*.

De Janvry, A., Macours, K. and Sadoulet, E. (eds) (2017). *Learning for Adopting: Technology Adoption in Developing Country Agriculture*: FERDI, France: Clermont-Ferrand.

Di Falco S., Feri, F., Pin, P., and Vollenweider, X. (2018). Ties that bind: Network redistributive pressure and economic decisions in village economies. *Journal of Development Economics, 131:123 – 131*.

Druska, V., and Horrace, W. (2004). Generalized moments estimation for spatial panel data: Indonesian rice farming. *American Journal of Agricultural Economics, 86(1): 185 – 198*.

Fafchamps, M., Islam, A., Malek, A., and Pakrashi, D. (2021). Mobilizing P2P Diffusion for New Agricultural Practices: Experimental Evidence from Bangladesh. *The World Bank Economic Review, 00(0):1 – 26.*

Foster, A. D. and Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annual Review of Economics 2: 395 – 424*.

Fusco, E., and Vidoli, F. (2013). Spatial stochastic frontier models: controlling spatial global and local heterogeneity. *International Review of Applied Economics, 27(5):679 – 694*.

Geng, J., Bhattacharya, A. and Pati, D. (2019). Probabilistic Community Detection with Unknown Number of Communities. *Journal of the American Statistical Association, 114(526): 893 – 905*.

Granovetter, M.S. (1973). The strength of weak ties. *American Journal of Sociology*: *1360-1380*.

Gude, A., Álvarez, I., and Orea, L. (2018). Heterogeneous spillovers among Spanish provinces: a generalized spatial stochastic frontier model. *Journal of Productivity Analysis, 50:155 – 173*.

Horrace, W. C., and Jung, H. (2018). Stochastic frontier models with network selectivity. *Journal of Productivity Analysis 50:101– 116*.

Jondrow, C.A.J., Lovell, K., Materov, S. I., and Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics, 19(2 – 3): 233-238*.

Kondylis, F., Mueller, V., and Zhu, J. (2017). Seeing is believing? Evidence from an extension network experiment. *Journal of Development Economics, 125:1 – 20*.

Krivitsky, P. N., and Morris, M. (2017). Inference for social network models from egocentrically sampled data, with application to understanding persistent racial disparities in HIV prevalence in the US. *Annals of Applied Statistics, 11(1): 427 – 455*.

Kutlu, L., Tran, K.C., and Tsionas, M.G. (2020). A spatial stochastic frontier model with endogenous frontier and environ- mental variables. *European Journal of Operational Research, 286(1):389 – 399*.

Li, X., Chen, Y., and Xu, J. (2021). Convex relaxation methods for community detection. *Statistical Science, 36(1): 2–15*.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *Review of Economic Studies, 60(3): 531– 42*.

Newman, M. E. J and Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E, 69:026113 – 15*.

Orea, L., and Álvarez, I. (2019). A new stochastic frontier model with cross-sectional effects in both noise and inefficiency terms. *Journal of Econometrics, 213:556 – 577*.

Pavlyuk, D. (2019). Feature selection and extraction in spatiotemporal traffic forecasting: a systematic literature review. *European Transport Research Review, 11(6):1 – 19*.

Polzehl, J., and Spokoiny, V. (2000) Adaptive weights smoothing with applications to image segmentation. *Journal of Royal Statistical Society, 62:335 – 354*.

Pons, P., and Latapy, M. (2006). Computing communities in large networks. Using random walks. *Journal of Graph Algorithms and Applications, 10(2):191 – 218*.

Qu X., and Lee, L. (2015). Estimating a spatial autoregressive model with an endogenous spatial weight matrix. *Journal of Econometrics, 184:209 – 232*.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Schmidt, A. M., Moreira, A. R. B., Helfand, S. M., and Fonseca, T.C.O., (2009). Spatial stochastic frontier models: accounting for unobserved local determinants of inefficiency. *Journal Productivity Analysis, 31:101 – 112*.

Schweinberger, M., Krivitsky, P. N., Butts, C. T., and Stewart, J. R. (2020). Exponential-family models of random graphs: inference in finite, super and infinite population scenarios. *Statistical Science, 35(4): 627 – 662*.

Shikuku, K. M., and Melesse, M. B. (2020). Networks, incentives and technology adoption: evidence from a randomized experiment in Uganda. *European Review of Agricultural Economics, 47(5):1740 – 1775*.

Shikuku, K. M., Pieters, J., Bulte, E., and Läderach, P. (2019). Incentives and the diffusion of agricultural knowledge: Experimental evidence from Northern Uganda. *American Journal of Agriculture Economics, 101(4):1164 – 1180*.

Simpson, C. R. (2020). Farm size shapes friend choice amongst rice producers in China: Some evidence for the theory of network ecology. *Social Networks, 61:107 – 127*.

Sullivan, L. (2021). Survival analysis. SPH, Boston University, Access: https://sphweb.bumc.bu.edu.

Suri, 2011; Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica, 79(1):212 - 220.*

Takahashi, K., Muraoka, R., and Otsuka, K. (2020). Technology Adoption, Impact, and Extension in Developing Countries: A Review of Recent Literature. *Agricultural Economics, 51:31 – 45.*

Tan, Y. H., and Reddy, S. K. (2021). Crowdfunding digital platforms: Backer networks and their impact on project outcomes. *Social Networks, 64:158 – 172*.

Tsionas, E.G., and Michaelides, P.G. (2016). A spatial stochastic frontier model with spillovers: Evidence from Italian Regions. *Scottish Journal of Political Economy, 63(3):243 – 257*.

Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. *Social Networks, 18(1), 69-89*.

Valente, T. W. (2012). Network interventions. *Science 337*.

Valente, T. W., and Yon, G. G. V. (2020). Modeling Social Dynamics: Diffusion/Contagion Processes on Social Networks. *Special Issue, Health Education and Behavior, 1 – 4*.

Vidoli, F., Cardillo, C., Fusco, L., and Canello, J. (2016). Spatial non-stationarity in the stochastic frontier model: an application to the Italian wine industry, *Regional Science and Urban Economics.*

Yen, T-J., Fu, Y-C., Hwang, J-S. (2016). Alters as species: Predicting personal network size from contact diaries. *Social Networks 45:78 – 88*.

Appendix

Tables

Appendix 1: Peer, Village and District Level Data.

Table 5A. 1 Definition and Summary Statistics

Variable	Definition	Mean	SD	Min	Max
Panel C: Average Peer Level Factors					
Page	Peers average age in years	41.56	13.33	18	87
Pgender	Average proportion of male peers	0.71	0.45	0	1
Pedu	Peers average years of schooling	2.79	4.69	0	21
Phhsize	Peers average household size	5.79	3.05	1	27
Pland	Peers average area of land planted with soybean (ha)	5.05	4.37	1	22
Plabor	Peers average total labor used in soy cultivation (Worker-days/ha)	7.81	24.23	0.20	274.73
Pochem	Peer average total amount of active ingredient in chemical used (kg/ha)	4	7.19	0	87.22
Pamtino	Peers average total amount of inoculant used (g/ha)	13.91	18.35	0.0001	118.93
Pinousdumy	Average proportion of peers that used inoculant	0.51	0.50	0	1
Pvar	Average proportion of peers using improved variety	0.70	0.46	0	1
Pcredit	Average proportion of peers with not credit constraint	0.83	0.34	0	1
Psoil	Average proportion of peers with good quality soil	0.62	0.20	0.25	1
Prain	Average percentage of rainfall received by peers	61.63	16.24	20	100
Panel D: Average Village Level Factors					
Vage	Village average farmer age in years	41.56	4.15	32.25	52.85
Vgender	Village average proportion of male farmers	0.71	0.22	0.15	1
Vedu	Village average years of schooling	2.79	1.54	0.45	5.75
Vhhsize	Village average household size	5.79	1.18	4.25	9.45
Vland	Village average area of land planted with soybean (ha)	5.05	1.66	2.20	9.90
Vlabor	Village average total labor used in soy cultivation (Worker-days/ha)	7.81	9.70	1.001	54.59
Vchem	Village average total amount of active ingredient in chemical used (kg/ha)	4	2.12	1.10	11.69
Vamtino	Village average total amount of inoculant used (kg/ha)	13.91	3.97	4.96	19.82
Vinouse	Village proportion of farmers that use the inoculant	0.51	0.14	0.25	0.75
Vimpvar	Village proportion of farmers that use improve variety	0.70	0.19	0.30	1
Vcredit	Village proportion of farmers that are not credit constraint	0.83	0.14	0.40	1
Vextcont	Village average number of extension contacts	1.37	0.27	0.9	2
Vdismkt	Village average distance to nearest market (km)	2.36	1.36	0.45	5.82

Vsoil	Village average proportion farmers with good soil quality	0.62	0.08	0.48	0.80
Vrain	Village average rainfall in percent	61.63	6.90	49	74
Velgrid	Proportion of villages connected to the national grid for electricity	0.51	0.10	0.35	0.70
Panel E: Average District Level Factors					
Dage	District average farmer age in years	41.56	2.64	38.65	46.79
Dgender	District average proportion of male farmers	0.71	0.14	0.51	0.85
Dedu	District average years of schooling	2.79	0.90	1.44	4.04
Dhhsize	District average household size	5.79	1.04	4.94	8.01
Dland	District average area of land planted with soybean (ha)	5.05	0.59	4.39	6.01
Dlabor	District average total labor used in soy cultivation (Worker-days/ha)	7.81	3.62	3.18	15.03
Dchem	District average total amount of active ingredient in chemical used (kg/ha)	4	0.81	3.24	5.37
Damtino	District average total amount of inoculant used (kg/ha)	13.91	1.16	12.09	15.06
Dinous	District proportion of farmers that use inoculant	0.51	.05	0.44	0.6
Dvar	District proportion of farmers that use improve variety	0.70	0.07	0.62	0.82
Dcredit	District proportion of farmers that are not credit constraint	0.83	0.08	0.72	0.95
Dsoil	District average proportion farmers with good soil quality	0.62	0.06	0.52	0.72
Drain	District average rainfall in percent	61.63	6.13	52.6	69.2
Delecgrid	Proportion of farmers in districts connected to the national grid for electricity	0.51	0.05	0.47	0.60
Ddismkt		2.36	0.52	1.599	2.77

Note: SD is standard deviation; Min and Max are minimum and maximum values respectively.

Appendix 2: Full estimates from the spatial stochastic frontier (SSFA) models.

Table 5A. 2 Spatial Stochastic Frontier

	Global Model (W_0)	Model 1 ($\widetilde{W}_1$)	Model 2 ($\widetilde{W}_2$)	Model 3 ($\widetilde{W}_3$)	Model 4 ($\widetilde{W}_4$)	Model 5 ($\widetilde{W}_5$)	Model 6 ($\widetilde{W}_6$)	Model 7 ($\widetilde{W}_7$)	Model 8 ($\widetilde{W}_8$)	Model 9 ($\widetilde{W}_9$)
Variable	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**
Const.	1.575	0.540	-1.052	0.340	-2.283***	0.778	0.813	-1.099	0.573	-0.259
	(2.062)	(0.742)	(1.346)	(2.261)	(0.774)	(1.166)	(3.110)	(1.369)	(1.931)	(1.292)
lnagchem	-0.058	-0.063	-0.046	-0.068	-0.054	-0.076	-0.061	-0.057	-0.065	-0.013
	(0.097)	(0.096)	(0.098)	(0.097)	(0.100)	(0.095)	(0.096)	(0.097)	(0.095)	(0.098)
lnland	1.266***	1.292***	1.267***	1.292***	1.254***	1.289***	1.289***	1.302***	1.259***	1.256***
	(0.131)	(0.129)	(0.133)	(0.134)	(0.133)	(0.128)	(0.131)	(0.132)	(0.129)	(0.134)
lnlabor	0.164***	0.162***	0.138**	0.167***	0.140**	0.149**	0.158***	0.135**	0.149**	0.130**
	(0.066)	(0.066)	(0.067)	(0.067)	(0.069)	(0.066)	(0.067)	(0.067)	(0.066)	(0.068)
lnamtinouse	-18.443**	-18.79***	-18.35***	-18.84***	-18.94***	-17.67***	-18.57***	-18.70***	-19.15***	-20.20***
	(2.046)	(1.485)	(1.828)	(2.189)	(2.113)	(3.352)	(4.222)	(1.469)	(2.673)	(3.826)
lnagchemsq	0.067	0.072	0.065	0.075	0.068	0.084*	0.072	0.076	0.071	0.043
	(0.047)	(0.047)	(0.049)	(0.048)	(0.050)	(0.047)	(0.047)	(0.048)	(0.047)	(0.049)
lnlandsq	-0.284***	-0.311***	-0.280**	-0.309***	-0.305***	-0.314***	-0.311***	-0.322***	-0.280***	-0.268**
	(0.120)	(0.116)	(0.120)	(0.123)	(0.120)	(0.113)	(0.122)	(0.118)	(0.118)	(0.120)
lnlaborsq	-0.035	-0.035	-0.032	-0.036	-0.030	-0.035	-0.035	-0.030	-0.033	-0.025
	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)	(0.022)	(0.024)
lnamtinoussq	3.339***	3.39***	3.305***	3.396***	3.407***	3.172***	3.357***	3.363***	3.456***	3.645***
	(0.373)	(0.269)	(0.334)	(0.404)	(0.377)	(0.617)	(0.770)	(0.263)	(0.487)	(0.693)
Rain	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Impvar	0.014	0.018	0.025	0.018	0.021	0.028	0.017	0.014	0.018	0.018
	(0.038)	(0.038)	(0.039)	(0.039)	(0.040)	(0.038)	(0.038)	(0.039)	(0.038)	(0.040)
Soil	0.149*	0.120	0.123	0.120	0.132	0.139	0.120	0.113	0.122	0.121
	(0.090)	(0.091)	(0.091)	(0.091)	(0.093)	(0.088)	(0.095)	(0.091)	(0.091)	(0.092)
Chemdumy	0.094	0.092	0.074	0.087	0.106	0.090	0.100	0.098	0.106	0.116
	(0.125)	(0.125)	(0.126)	(0.125)	(0.126)	(0.123)	(0.127)	(0.125)	(0.127)	(0.130)
Extcont	-0.009	-0.009	-0.010	-0.010	-0.011	-0.008	-0.009	-0.007	-0.008	-0.010
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Creditcostr	0.007	0.007	0.025	0.004	0.002	0.024	0.012	0.017	0.011	0.002
	(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.045)	(0.045)	(0.046)	(0.045)	(0.046)
Dismkt	-0.003	-0.004	-0.004	-0.005	-0.005	-0.005	-0.004	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Inousedumy	28.39***	28.99***	28.40***	29.10***	29.33***	27.38***	28.62***	28.94***	29.54***	31.17***
	(3.107)	(2.244)	(2.785)	(3.314)	(3.223)	(5.043)	(6.426)	(2.220)	(4.055)	(5.803)

Plabor	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pochem	-0.015	-0.016*	-0.014	-0.016*	-0.014	-0.018**	-0.016*	-0.017*	-0.015	-0.009
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Pamtino	-0.138***	-0.140***	-0.134***	-0.139***	-0.138***	-0.128***	-0.138***	-0.136***	-0.142***	-0.149***
	(0.017)	(0.009)	(0.015)	(0.019)	(0.014)	(0.026)	(0.033)	(0.009)	(0.021)	(0.028)
Pland	0.093**	0.102***	0.091**	0.101**	0.106***	0.106***	0.102**	0.107***	0.092**	0.083**
	(0.044)	(0.042)	(0.044)	(0.045)	(0.044)	(0.041)	(0.045)	(0.043)	(0.043)	(0.044)
Vlabor	-0.003	-0.003	-0.002	-0.001	-0.001	-0.005*	-0.004	0.002	-0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Vland	0.038	0.039*	0.039	0.026	-0.016	0.029	0.037	-0.018	0.026	-0.038
	(0.026)	(0.022)	(0.029)	(0.024)	(0.028)	(0.025)	(0.024)	(0.024)	(0.023)	(0.028)
Vchem	0.013	0.011	0.001	0.013	0.045**	0.016	0.019	0.018	0.024	0.043***
	(0.019)	(0.016)	(0.017)	(0.016)	(0.020)	(0.017)	(0.016)	(0.019)	(0.016)	(0.017)
Vsoil	-1.030*	-1.002***	-1.392***	-0.893*	-1.154***	-0.386	-1.015	-0.912**	-1.104**	-1.068**
	(0.552)	(0.329)	(0.421)	(0.527)	(0.380)	(0.400)	(0.683)	(0.435)	(0.473)	(0.460)
Vrain	0.001	-0.001	0.000	-0.006	-0.005	0.006	0.001	-0.007	-0.002	-0.012*
	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Vamtino	0.000	-0.001	0.001	0.000	-0.008	0.002	-0.001	-0.012*	0.002	0.002
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
Vdismkt	0.025	0.026	0.006	0.014	-0.001	0.008	0.028	0.003	0.019	0.023
	(0.020)	(0.017)	(0.019)	(0.018)	(0.019)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)
Vvar	0.086	0.081	0.070	0.076	0.083	-0.030	0.062	0.244*	0.028	0.093
	(0.143)	(0.115)	(0.131)	(0.129)	(0.134)	(0.136)	(0.135)	(0.143)	(0.119)	(0.129)
Dland	0.213	0.278***	0.320***	0.233	0.372***	0.312***	0.287	0.185	0.276**	0.015
	(0.165)	(0.108)	(0.126)	(0.155)	(0.114)	(0.034)	(0.202)	(0.126)	(0.146)	(0.133)
Dlabor	-0.047*	-0.052***	-0.071***	-0.054*	-0.077***	-0.030***	-0.050	-0.071***	-0.057**	-0.085***
	(0.027)	(0.013)	(0.019)	(0.029)	(0.016)	(0.006)	(0.039)	(0.021)	(0.025)	(0.022)
Dchem	-0.403*	-0.461***	-0.521***	-0.442***	-0.580***	-0.417***	-0.486**	-0.407***	-0.494***	-0.465***
	(0.152)	(0.071)	(0.103)	(0.155)	(0.075)	(0.073)	(0.221)	(0.099)	(0.139)	(0.097)
Damtino	0.234**	0.260***	0.332***	0.277**	0.401***	0.174***	0.264	0.361***	0.286***	0.436***
	(0.119)	(0.053)	(0.085)	(0.128)	(0.076)	(0.028)	(0.169)	(0.095)	(0.108)	(0.092)
Drain	0.022	0.031***	0.043***	0.036*	0.052***	0.023***	0.025	0.046***	0.031*	0.043***
	(0.019)	(0.009)	(0.013)	(0.019)	(0.010)	(0.003)	(0.026)	(0.014)	(0.017)	(0.013)
sigmau2_dmu	0.463***	0.470***	0.418***	0.453***	0.376***	0.461***	0.471***	0.419***	0.473***	0.399***
	(0.061)	(0.056)	(0.052)	(0.062)	(0.049)	(0.048)	(0.073)	(0.048)	(0.064)	(0.054)
sigmav2	0.039***	0.037***	0.047***	0.041***	0.058***	0.037***	0.038***	0.046***	0.036***	0.054***
	(0.013)	(0.011)	(0.012)	(0.014)	(0.012)	(0.009)	(0.016)	(0.010)	(0.013)	(0.013)
LL	-347.84	-349.739	-344.172	-348.428	-344.996	-345.399	-350.355	-343.175	-348.124	-350.658

***Notes**: *, ** and *** are 10%, 5% and 1% level of significance. Column 1, presents estimates of the global model employ to account for spatial dependence, while each of Columns **1 – 9** respectively, presents estimates on the network properties (transitivity, degree-centrality and eccentricity, respectively) that characterizes the social ties among farmers within the egocentric information network community. Each of the three models represents a specific network intervention community (**T0**, **T1** and **T2**, respectively) employed to account for spatial heterogeneity. The Table presents the full SSFA estimates from equations 2 and 3, respectively.*

Appendix 3: Individual farmer controls and district fix effects.

Table 5A. 3 Spatial Cox proportional hazard estimates

	Global Model (W_0)	Model 1 ($\widetilde{W}_1$)	Model 2 ($\widetilde{W}_2$)	Model 3 ($\widetilde{W}_3$)	Model 4 ($\widetilde{W}_4$)	Model 5 ($\widetilde{W}_5$)	Model 6 ($\widetilde{W}_6$)	Model 7 ($\widetilde{W}_7$)	Model 8 ($\widetilde{W}_8$)	Model 9 ($\widetilde{W}_9$)
Variable	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**	**Coeff. (S.E)**
Panel A: Farmer's Own Characteristics										
Age	0.004	-0.002	0.002	-0.002	0.001	-0.003	-0.002	0.000	0.002	0.002
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Gender(Male=1)	-0.098	-0.185	-0.134	-0.130	-0.133	-0.135	-0.164	-0.067	-0.161	-0.184
	(0.165)	(0.174)	(0.138)	(0.150)	(0.132)	(0.147)	(0.143)	(0.160)	(0.153)	(0.128)
Edu	0.014	0.002	0.015	0.008	0.003	0.008	0.006	-0.008	0.004	0.008
	(0.015)	(0.017)	(0.013)	(0.015)	(0.013)	(0.015)	(0.014)	(0.015)	(0.016)	(0.012)
Hhsize	0.023	0.017	-0.004	-0.021	0.001	-0.010	0.002	0.023	-0.013	-0.001
	(0.022)	(0.025)	(0.019)	(0.022)	(0.018)	(0.022)	(0.020)	(0.022)	(0.023)	(0.018)
Creditr	0.195	0.286*	0.055	0.273	0.177	-0.247	0.170	-0.073	-0.130	0.074
	(0.177)	(0.168)	(0.143)	(0.167)	(0.144)	(0.157)	(0.154)	(0.161)	(0.166)	(0.138)
Elgrid	0.398	0.366	0.553**	0.541**	0.241	0.192	0.499**	-0.025	0.244	0.226
	(0.303)	(0.348)	(0.247)	(0.279)	(0.241)	(0.261)	(0.257)	(0.318)	(0.278)	(0.226)
Distmkt	-0.013	0.023	0.004	0.011	0.005	0.025**	0.000	-0.004	0.010	0.002
	(0.018)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.018)	(0.014)	(0.013)
Impvar	0.238	0.070	0.067	0.072	0.103	-0.102	0.157	0.251*	-0.023	0.018
	(0.150)	(0.152)	(0.122)	(0.138)	(0.120)	(0.137)	(0.132)	(0.144)	(0.143)	(0.113)
Farmsize	-0.050***	-0.013	-0.025*	-0.010	-0.009	-0.035**	-0.020	0.014	-0.010	-0.009
	(0.018)	(0.017)	(0.014)	(0.014)	(0.013)	(0.015)	(0.014)	(0.015)	(0.015)	(0.013)
Inouse	-0.293	-0.519	-0.874***	-0.982***	-0.650***	-0.324	-0.971***	-0.090	-0.065	-0.474**
	(0.310)	(0.348)	(0.254)	(0.286)	(0.247)	(0.269)	(0.265)	(0.322)	(0.284)	(0.231)
Rain	0.003	-0.013***	0.001	-0.003	-0.002	0.002	0.000	-0.001	-0.001	-0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Soil	-0.219	0.499	0.056	0.402	0.095	-0.021	0.131	0.164	0.181	0.190
	(0.349)	(0.349)	(0.286)	(0.323)	(0.280)	(0.333)	(0.305)	(0.332)	(0.347)	(0.276)
Extcont	-0.010	0.009	-0.013	-0.017	0.010	-0.048	-0.034	-0.001	-0.062	-0.008
	(0.053)	(0.051)	(0.044)	(0.048)	(0.043)	(0.049)	(0.046)	(0.051)	(0.051)	(0.042)
Panel C: District Fixed Effects										
Emamp(2)	0.646***	-0.217	0.907***	1.005***	0.963***	-0.300	1.024***	-0.468	0.367	0.461
	(0.399)	(0.404)	(0.316)	(0.351)	(0.314)	(0.462)	(0.353)	(0.369)	(0.376)	(0.293)
Karaga(3)	-1.655***	-0.045	-1.056***	-1.823***	-0.528	-0.150	-0.741*	0.740*	-1.684***	-1.164***
	(0.421)	(0.542)	(0.353)	(0.436)	(0.354)	(0.372)	(0.407)	(0.411)	(0.451)	(0.364)
Kumbungu(4)	-0.092	-2.503***	-0.216	-1.301***	-0.087	0.633	-0.189	-0.497	-0.434	-0.794*
	(0.563)	(0.660)	(0.463)	(0.525)	(0.452)	(0.542)	(0.507)	(0.528)	(0.533)	(0.426)
Savelugu(5)	0.596	-0.885**	0.661*	-0.100	0.256	-0.595	0.445	-0.753	-0.474	0.159
	(0.473)	(0.468)	(0.389)	(0.418)	(0.393)	(0.523)	(0.431)	(0.458)	(0.457)	(0.355)

Variable	Global Model (W_0) Coeff. (S.E)	Model 1 ($\widetilde{W}_1$) Coeff. (S.E)	Model 2 ($\widetilde{W}_2$) Coeff. (S.E)	Model 3 ($\widetilde{W}_3$) Coeff. (S.E)	Model 4 ($\widetilde{W}_4$) Coeff. (S.E)	Model 5 ($\widetilde{W}_5$) Coeff. (S.E)	Model 6 ($\widetilde{W}_6$) Coeff. (S.E)	Model 7 ($\widetilde{W}_7$) Coeff. (S.E)	Model 8 ($\widetilde{W}_8$) Coeff. (S.E)	Model 9 ($\widetilde{W}_9$) Coeff. (S.E)
Yendi(6)	-0.266	-1.821***	-0.250	-1.187***	-0.658***	0.208	-0.454	-1.246***	0.327	-0.278
	(0.337)	(0.425)	(0.283)	(0.325)	(0.281)	(0.346)	(0.310)	(0.305)	(0.341)	(0.257)
LRT (df=570)	*56.45***	*164.7***	*64.25***	*131.9***	*70.61***	*144.7***	*95.47***	*76.62***	*66.2***	*50.11***
Mean Beneficiaries	*273*	*268*	*389*	*322*	*410*	*325*	*359*	*300*	*297*	*429*
	(45.50%)	*(44.67%)*	*(64.83%)*	*(53.67%)*	*(68.33%)*	*(54.17%)*	*(59.83%)*	*(50.00%)*	*(49.50%)*	*(71.50%)*
Observ.(N)	***600***	***600***	***600***	***600***	***600***	***600***	***600***	***600***	***600***	***600***

Notes*: *, ** and *** are 10%, 5% and 1% level of significance. Column 1, presents estimates of the global model employ to account for spatial dependence, while each of Columns* ***1 – 9*** *respectively, presents estimates on the network properties (transitivity, degree-centrality and eccentricity, respectively) that characterizes the social ties among farmers within the egocentric information network community. Each of the three models represents a specific network intervention community (****T0****,* ***T1*** *and* ***T2****, respectively) employed to account for spatial heterogeneity. The Table presents estimates from equation 5.*

Appendix 4

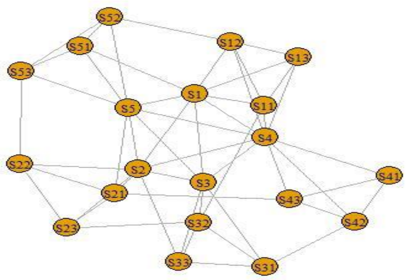
Table 5A. 4 Robustness Checks

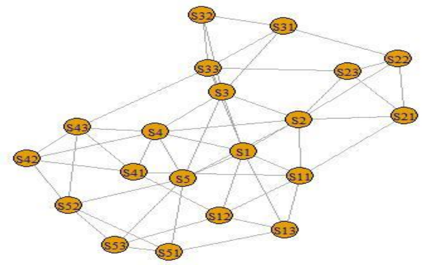
Model	Matrix	SFA						SSFA							
	$\widetilde{W}$	$\sigma^2_{u_{sfa}}$	$\sigma^2_{v_{sfa}}$	λ_{sfa}	I_{sfa}	$\hat{E}_{sfa}$	LR_{sfa}	$\sigma^2_{u_{ssfa}}$	$\sigma^2_{\tilde{u}}$	$\sigma^2_{v_{ssfa}}$	λ_{ssfa}	I_{ssfa}	ρ	$\hat{E}_{ssfa}$	LR_{ssfa}
Network-Specific Structure Models															
Panel E: Transitivity and Degree-Centrality															
Model 10	$\widetilde{W}_{10}$	0.470^{***}	0.039^{***}	3.488	-0.006	0.630	51.96^{***}	0.391^{***}	0.4%	0.053^{***}	7.38	-0.002	-0.000	0.65	68.23^{***}
Panel F: Degree-Centrality and Eccentricity															
Model 11	$\widetilde{W}_{11}$	0.470^{***}	0.039^{***}	3.488	-0.008	0.630	51.96^{***}	0.402^{***}	0.3%	0.051^{***}	7.93	-0.002	-0.000	0.65	62.91^{***}

***Notes**: *, ** and *** are 10%, 5% and 1% level of significance. Each of Panels **E and F** respectively, presents estimates on different combinations the network properties (transitivity, degree-centrality and eccentricity, respectively) that characterizes the social ties among farmers within the a randomly formed egocentric information network community. Each of the model (10 and 11) represents a specific random network intervention community, respectively, employed to account for spatial heterogeneity. The Table presents estimates from equation 3 in Panels E and F, respectively.*

List of Figures

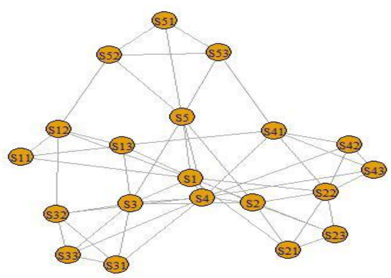
Appendix 5

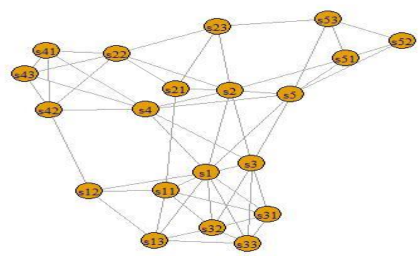




(a) Network in Village 1

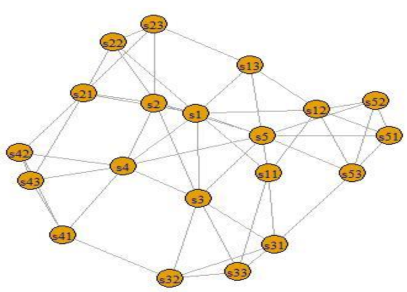
(b) Network in Village 2





(c) Network in Village 3

(d) Network in Village 4



(e) Network in Village 5

Figure 5A. 1 Sampled Information networks

Notes*: Each network represents Egos and their Alters sample in a single village. It can be observed that each of the networks shows a different structural relationship from the other.*

Appendix 6: Robustness Checks

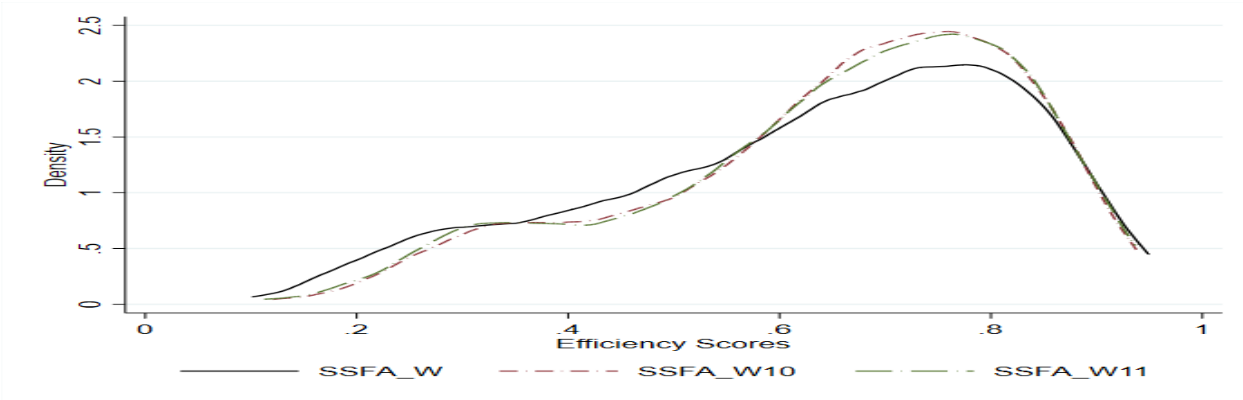


Figure 5A. 2 Effect of spatial heterogeneity on farmers technical efficiency scores.

***Notes**: SSFA represents spatial stochastic frontier analysis model, while the Ws represent the social contiguity matrices used in the estimation of the models to account for spatial effects. So, SSFA_W presents the base model estimated using W; SSFA_W10 represents model 10 estimated using the adjusted matrix $\widetilde{W}_{10}$, SSFA_W11 for model 11 using matrix $\widetilde{W}_{11}$.*

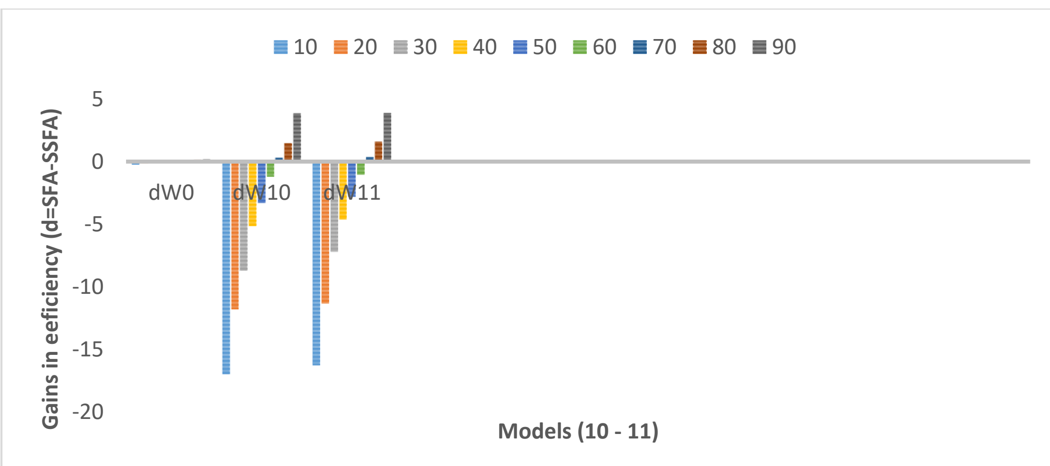


Figure 5A. 3 Inter-class and Intra-class distributions of average efficiency gains in egocentric network communities.

***Notes**: The estimates are based on equation 4. The dW0 denotes gains calculated based the global model, while dW10 and dW9 denote gains calculated based on Models 10 and 11, respectively. The bars at each model indicates percentiles, while comparison within a model is intra-class and between models is inter-class.*

Appendix 7: Threshold Distribution of Efficiency Gains in Egocentric Networks.

As noted in the literature (e.g., Di Falco *et al*. 2018; Boschma 2005), the benefits stream from economic relationships embedded in social relationships increases up to a threshold, after which adverse impacts arise, due to either lock-in effect or distributive pressure from an increased network size. On this basis, generalizing the behavior of the individual farmers' productivity gains distribution to be that of the entire network behavior will bias the findings.

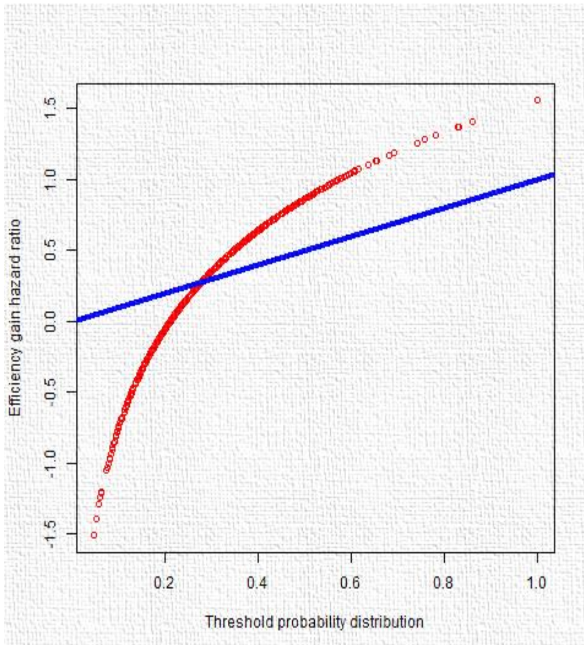
Figures A3, A4 and A5 present estimates explaining the general behavior of productivity gains' distribution mechanisms in the network communities. The results are derived from equation 5 in the empirical specifications. Each figure contains four panels (Panels (**a – d**)) and each panel represents a specific network community structure based on the model from which the estimates are obtained, with all models (Models 1 – 9) compared to the global model (Panel (**a**)). In general, all the figures reveal substantial heterogeneity in the threshold probability distribution of productivity gains across all the network communities.

Panel (**d**) in Figure A3 shows that, in high transitivity networks, the probability threshold for positive productivity gains is highest (0.4 or 40%) in network communities structured around powerful farmers, compared to the structure around important farmers (35%) and randomly chosen farmers (0.30) in Panels (**c** and **b**), respectively.

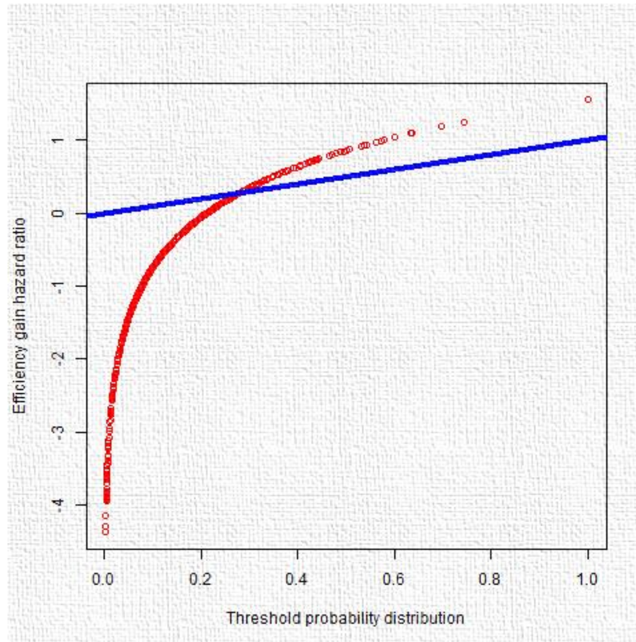
In networks characterized by farmers with high degree-centrality, Panel (**b**) in Figure A4 shows that, the probability distribution threshold is highest (0.8 or 80%) in network communities structured around randomly chosen farmers, compared to socially or agriculturally important farmers 64% and powerful farmers 25% in Panels (**c** and **d**), respectively.

For high eccentric network communities, Panels (**d** and **c**) in Figure A5 reveal that, the probability threshold increases up to (1.0 or 100%) in communities structured around powerful farmers and socially or agriculturally important farmers, respectively, and to some extent in networks structured around randomly chosen farmers 97% in Panel (**b**).

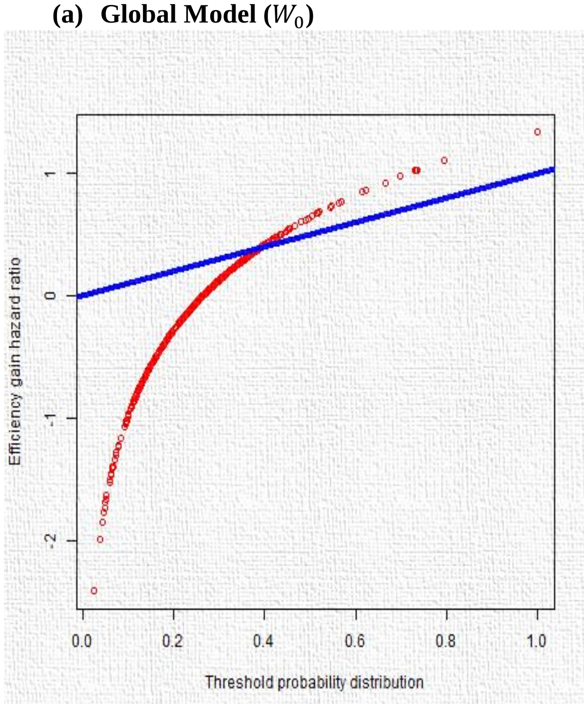
However, in comparison to the global Model in Panel (**a**), the results show that failure to account for spatial heterogeneity underestimates the threshold probability (0.24 or 24%) across all models.



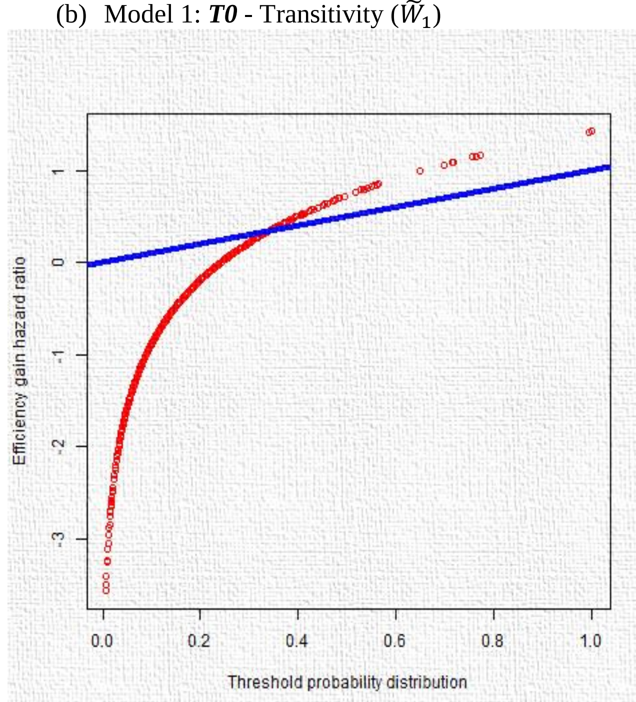
(a) Global Model (W_0)



(b) Model 1: ***T0*** - Transitivity ($\widetilde{W}_1$)



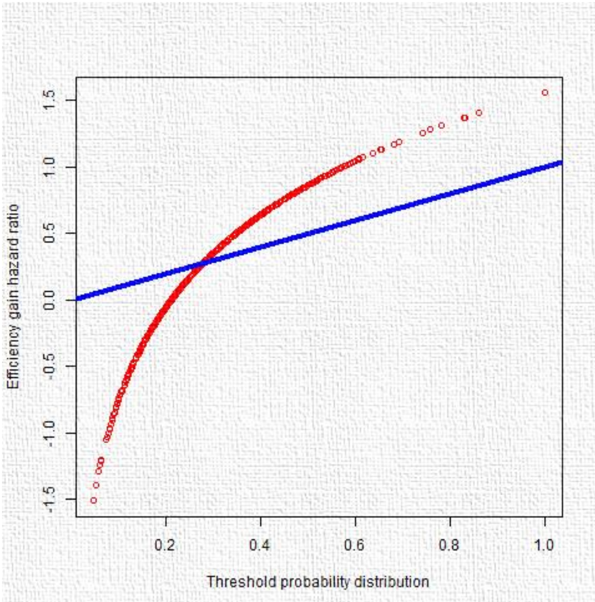
(c) Model 2: *T1* **- Transitivity ($\widetilde{W}_2$)**



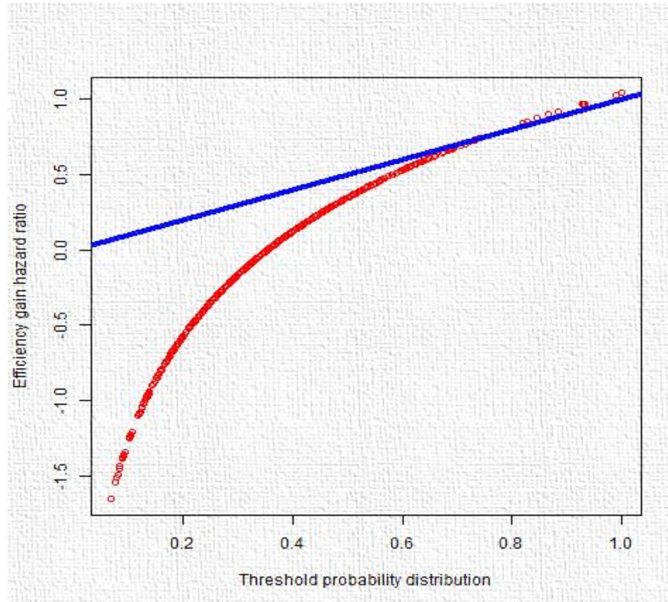
(d) Model 3: ***T2*** - Transitivity ($\widetilde{W}_3$)

Figure 5A. 4 Probability threshold distribution of efficiency gains of an egocentric information network.

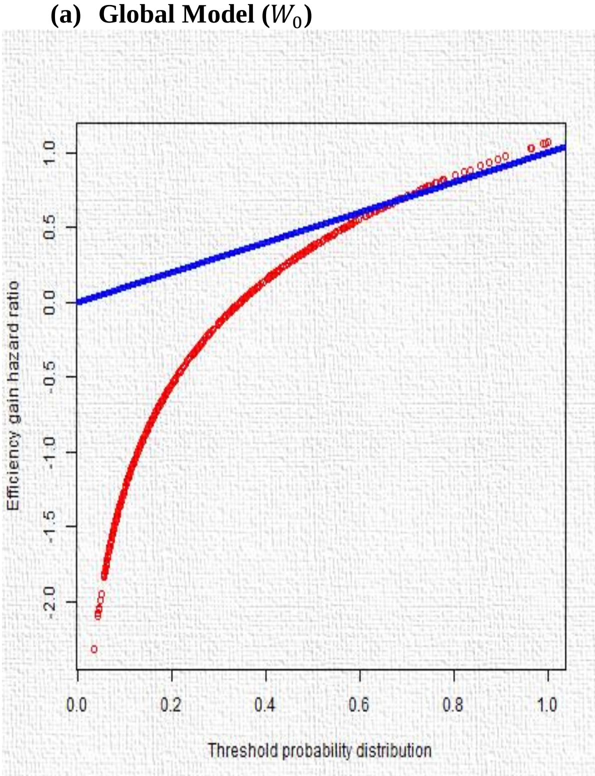
Notes: Each figure explains the efficiency gains distributive mechanism (or behavior) for given network community.



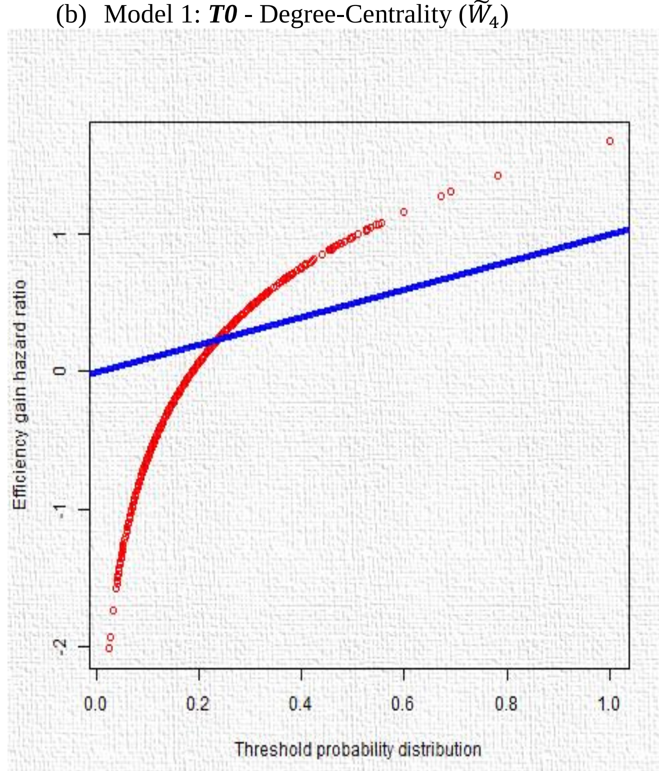
(a) Global Model (W_0)



(b) Model 1: ***T0*** - Degree-Centrality ($\widetilde{W}_4$)



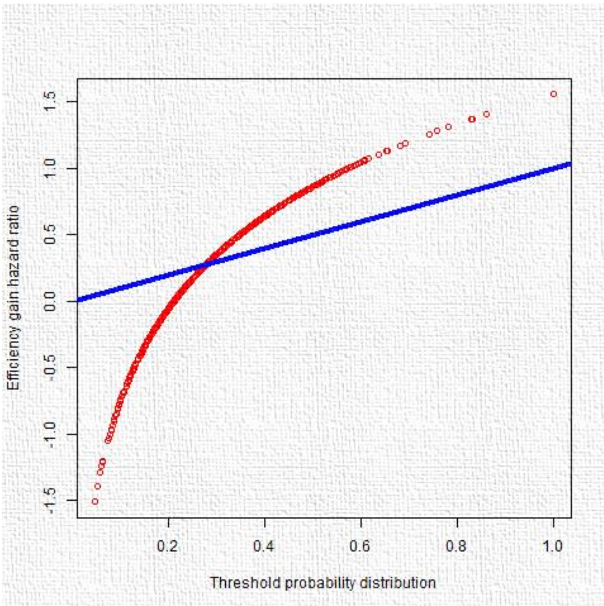
(c) Model 2: *T1* **- Degree-Centrality ($\widetilde{W}_5$)**



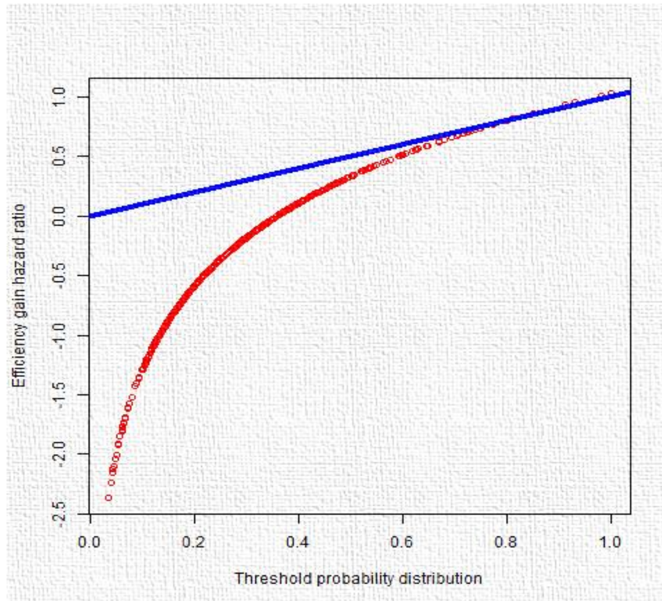
(d) Model 3: ***T2*** - Degree-Centrality ($\widetilde{W}_6$)

Figure 5A. 5 Probability threshold distribution of efficiency gains of an egocentric information network.

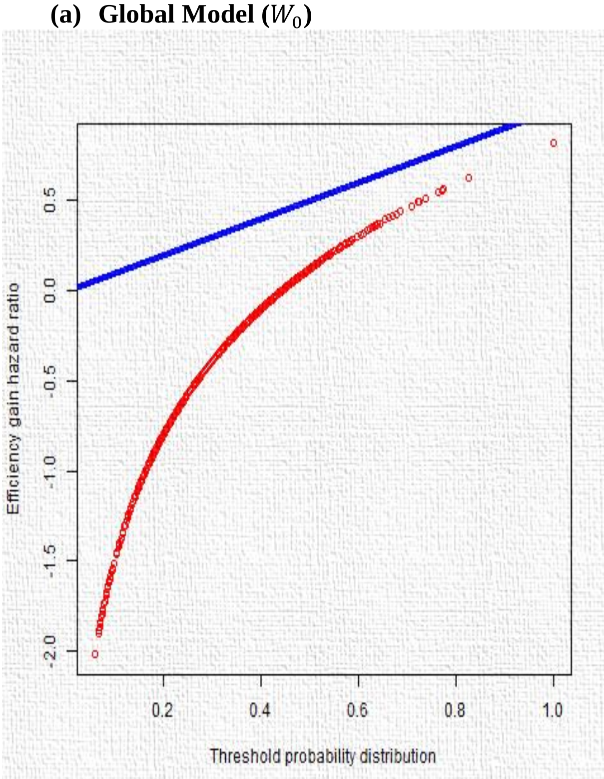
Notes: Each figure explains the efficiency gains distributive mechanism (or behavior) for given network community.



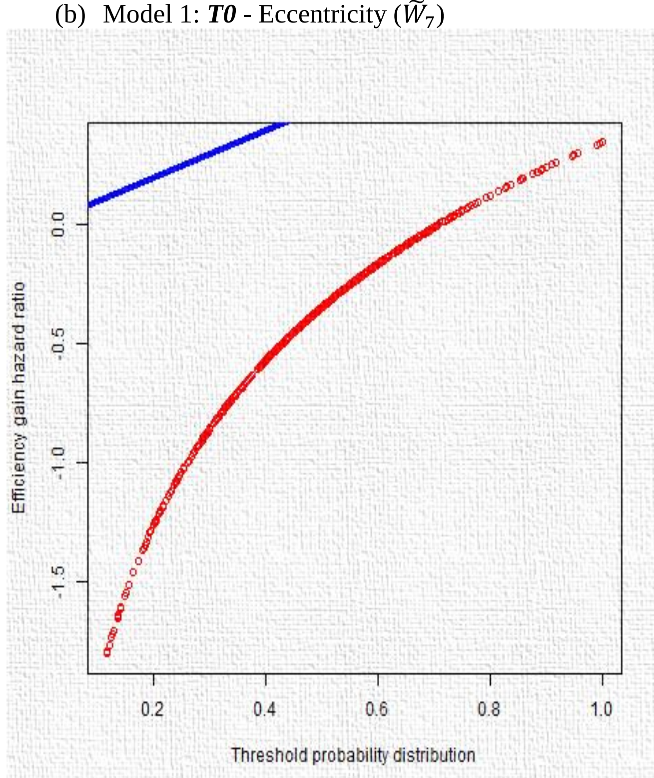
(a) Global Model (W_0)



(b) Model 1: ***T0*** - Eccentricity ($\widetilde{W}_7$)



(c) Model 2: *T1* **- Eccentricity ($\widetilde{W}_8$)**



(d) Model 3: ***T2*** - Eccentricity ($\widetilde{W}_9$)

Figure 5A. 6 Probability threshold distribution of efficiency gains of an egocentric information network.

Notes: Each figure explains the efficiency gains distributive mechanism (or behavior) for given network community.

Chapter 6

Summary, Conclusions and Policy Implications

Food availability all times and places is central to human development and a primary indicator of welfare. However, developing countries led by sub-Saharan Africa suffer perennial food insecurity due to low agricultural productivity. Central to boosting agricultural productivity is increasing crop yields and sustaining productivity gains, through the adoption of improved or new agricultural technologies, that mitigate the effects of climate change, enhances productive capacity of the soil and maximizes the genetic potential of crops and livestock by smallholder farmers. Spate of evidence show that, technology adoption is far below desired levels in the developing countries, partly, due to inadequate or lack of good and timely information as well as knowledge about existing new technologies that are necessary preconditions for technology adoption. The lack of information can be attributed to weak and ineffective extension services stemming from resource constraints to serve the needs of the widely dispersed smallholder farmers. This motivated the need to investigate the potential of other available communication channels (such video documentaries, radio listening clubs, etc) to leverage extension delivery to smallholder farmers, in order to increase technology adoption as well as bolster food production and welfare. The study, therefore, contributes to literature by assessing the impact of communication channels on food production and household welfare, using evidence from an ICT-led inoculant dissemination among smallholder soybean farmers in northern Ghana.

First, the study examined the impact of participation in information communication technology (ICT) based extension channels (henceforth, ICT-based) on farmers' technology adoption and welfare, compared to conventional extension channels. Next, the study analyzed the dynamics of technology adoption and its heterogeneous impact on different sub-population of farmers at multiple phases of technology adoption, who may be targeted by specific extension policies, in order to facilitate and sustain their adoption.

The study then simultaneously assessed the dual impact of extension participation and improved technology adoption on farm productivity, efficiency and welfare, decomposing each impact measure into subcomponents that can be attributed to both improved technology adoption and the extension participation. The study concluded by investigating the influence of farmers' egocentric information networks (i.e., personal social network contacts) on technical efficiency of farm productivity and its distribution mechanisms among members of the network.

6.1 Summary of empirical methods

The study employed novel impact assessment empirical methods that are robust to model miss-specification, identification, as well as simultaneity and endogeneity problems often encountered in impact assessment studies using observational data. Specifically, the study employed copula functions, dynamic treatment effect, and stochastic frontier treatment effect with endogenous mediator, as well as spatial stochastic frontier analysis.

Chapter two of the study employed copula recursive bivariate probit and mixed-copula endogenous switching regression analysis to examine the impact of participation in ICT-based extension channels on improved technology (i.e., the Rhizobia inoculant) adoption and its impact on farmers' technical knowledge, yields and farm net returns. The copula recursive bivariate probit was used for the binary outcome measure inoculant adoption, while mixed-copula endogenous switching regression analysis was used for the continuous outcome measures knowledge gains, yields and farm net returns. Both models employed two-stage estimation approach, where in the first-stage instrumental variables (IVs) were included to account for self-selection and omitted variable bias, while the second-stage estimated the potential outcomes. Standard selectivity correction models such as Heckman selection, endogenous switching regression, and double selection models, used in the literature to overcome selectivity bias relies on strong multivariate normality assumption for identification. However, the multivariate normality assumption is easily violated, when there is tail dependence in the distribution of at least one variable. The copula approach allows the modelling of selectivity based on multivariate non-normality assumption, but retaining the normality assumption as a special case. The copula approach induces a joint distribution by specifying the marginal distribution and the function that binds them together (i.e. the copula). Thus, parameterizing the dependence structure to encapsulate observable and unobservable factors, which then frees the location and the scale structures, enabling them to take different distributions. In particular, the copula recursive bivariate probit employed by the study is novel in the literature, in that, it employs additional instrumental variable different from the first-stage instrumental variables to identify binary outcomes in the second-stage, further improving the identification properties of the model. Thus, avoiding the identification problems that the classical recursive binary probit approach used in the literature suffers.

In chapter three, the study employed the dynamic treatment effect approach in a discrete setting to analyze heterogeneity in returns to farmers' technology adoption in a multi-stage decision framework. The dynamic treatment effect approach employed by the study was recently developed and relied on the synthetic cohort assumption to construct a dynamic setting from observational data, based on series of observed discrete decisions made by the farmer or the agent. Using state specific instrumental variables, the study estimated discrete factor structural choice model for each discrete adoption decision-making state, in a joint three-stage process. In the first-stage, a factor model was estimated to proxy unobserved wealth endowment heterogeneity that could potentially be endogenous to the adoption state transitional ability of farmers. In the second-stage, each discrete adoption state decision model was estimated with the inclusion of instrumental variables relevant to that state, in order to account for selection and omitted variable bias, as well as inclusion of the factor score predicted from the measurement model in the first-stage to account for unobserved ability or wealth endowment effect on the farmer's decision. The potential outcomes for both treatment effect of the treated (TT) and the untreated (TUT) were estimated in the third-stage conditional on the first and second stages. The DTE calculated both short-term and long-term impacts measures for average treatment effect (ATE), average treatment effect on the treated (ATT) and average treatment effect on the untreated (ATUT), as well as average marginal treatment effect (AMTE) for various sub-population of farmers. The study then estimated a generalized continuation ratio ordered probit model, as a measure of covariance between adoption state gains and the farmer's transition decision as well as factors influencing farmer's transition decision. Contrary to classical technology adoption studies that consider farmers' adoption decisions as static, ignoring the dynamic processes embedded in farmers' decision-making, the study recognized that farmers' technology adoption consist of multiple phases of decision-making that may span over several seasons or stages. As such, different population of farmers may be at different states in the adoption process, and therefore returns from technology adoption as well as policy strategies required to propel farmers at each state may be heterogeneous.

In chapter four, the study employed the stochastic frontier treatment effect with endogenous mediator model, which jointly estimated the impact of technology adoption and extension participation, and decomposed the impact into direct and indirect effects. Analyzing welfare impacts of improved technology adoption and extension participation can be challenging, because either of the two can lead to welfare gains. The approach employed by the study was recently developed and combined mediation analysis, treatment effect and stochastic frontier analysis within a single framework. In particular, the study addressed potential endogeneity from selection and omitted variable bias in both the adoption decision (i.e., the endogenous treatment) and the participation decision (i.e., the mediator) models, using binary recursive probit analysis in the first-stage. In the second-stage, a stochastic frontier regression that account for treatment heterogeneities among production units was then estimated via generalized method of moment (GMM) approach to obtain the potential outcomes. The impact was then calculated and decomposed into the direct effects on the technology frontier and the indirect effects on the technology frontier that go through the mediator, as well as the direct effects on technical efficiency and indirect effects on technical efficiency that go through the mediator. The impact measures computed were local average treatment effect (LATE) decomposed into direct local average treatment effect (DLATE) and indirect local average treatment effect (ILATE).

Chapter five, used spatial stochastic frontier analysis to investigate the impact of egocentric information networks on farmers' technical efficiency, productivity and its distributive mechanisms among farmers in the network. A major challenge in the literature is the difficulty in distinguishing the effect of spatial dependence, which results from the interdependence of the farmer's inefficiency on the egocentric information network, and spatial heterogeneity due to differences in network structures, which is unobserved and varied across networks (known as the inverse problem in the literature). The study employed a two-stage estimation process to address both spatial dependence and spatial heterogeneity, while accounting for social selection bias by controlling for both network contextual and location fixed-effects that may influence the probability of link formation as well as productivity. In the first-stage, the study employed spatial stochastic frontier model that specified the stochastic inefficiency term as a spatial error model (SEM), decomposing the inefficiency term into two parts, one that is directly due to the farmer's own inefficiency and the second part that is indirectly due to the farmer's egocentric information network (i.e., spatial dependence). In the second-stage, the study employed a data-driven approach, which used three different community detection algorithms to construct three artificial network communities with known structures and included in the stochastic frontier SEM model to account for spatial heterogeneity. Finally, due to the hierarchical nature of the egocentric networks, the study employed an additive spatial survival cox model to examine the distributive mechanisms of productivity benefits in egocentric information networks.

6.2 Summary of results

In chapter two, the empirical results show that ICT-based extension channels, perform better, in terms of inoculant knowledge gain 205%, yields 151% and farm net returns 88%, compared to conventional extension channels 42%, 148% and 86%, respectively. However, in terms of the likelihood of adoption, conventional extension channels had higher impacts on adoption, compared to ICT-based channels. The results suggest that both ICT-based and conventional extension channels are equally effective and can be used independently to disseminate information about new agricultural technologies to farmers. Furthermore, inter-channel comparison between ICT-based and conventional extension channels show that farmers who reside far away from extension agents tend to substitute ICT-based extension channels for conventional extension.

The study in chapter three, showed that high impact heterogeneity exists among farmers at different adoption states, the pursuit of which may be driving farmers adoption transition decisions. The study observed that farmers at advanced adoption states, on average, obtained yields and farm net returns that were more than twice that of the previous adoption states. Also, the study found that extension contact was central to the adoption process, through its influence on knowledge acquisition leading to adoption and continued adoption. The study found that free distribution of newly developed divisible agricultural technologies, such as the inoculant, to farmers during dissemination programs increased farmer awareness, knowledge acquisition, trial and take-up, but does not guarantee continued adoption. Rather, the existence of efficient input markets tend to drive the probability of continued adoption. Furthermore, the results revealed that the stronger the farmer’s anticipation of long-term benefits from adopting a particular technology, the higher the probability to continue their adoption of the technology, which is conditional on the markets being able to absorb the excess supply that may result from higher yields. Finally, the results revealed that there exist unrealized potential gains for farmers, who reach trial adoption states but could not continue to further adoption states, suggesting that different population of farmers may require different policy strategies to sustain their adoption.

In chapter four, the study revealed that both adoption of improved agricultural technologies and extension participation had varied influence on productivity, efficiency and welfare gains, however, the former's influence outweighed the latter. The adoption of improved technology alone raised farm productivity by 72%, farmer efficiency by 73%, and improvement in welfare by 77%. On the other hand, extension participation alone improved productivity by 28%, farmer efficiency by 27%, and improvement in welfare by 23%. Although the results suggest that the adoption of improved agricultural technology impact was greater than extension delivery, the study found that the synergic effect of the two was far greater than the individual effects. The study further revealed that rural electrification positively affects technology diffusion and adoption, through storage of agro-inputs and perishable agro-based products, which must be stored under specific storage conditions.

The study in chapter five showed that, farmers' technical efficiency strongly correlate with that of farmers in their egocentric information networks. Specifically, the study found that 19 percent of farmer's technical inefficiency emanates from their colleague farmers from whom they take farming advice, all things being equal. In addition, the study found that farmers who share farming information with technically efficient farmers, all things being equal, were more likely to be technically efficient. Though the study found mutual interdependency between technically efficient farmers, inefficient farmers were found to be more dependent on efficient farmers in their egocentric information networks, compared to efficient farmers. Thus, indicating that inefficient farmers were ready to learn from high performing peers in their egocentric information networks. The study revealed that to a large extent, the level of the egocentric information network influence on the technical efficiency of farmers was network-specific and varied according to the nature of social ties between farmers in the network community. For instance, network communities characterized by farmers with high eigenvector centrality and transitivity (i.e., social important farmers and social cohesion) experienced the highest increased efficiency, compared to other social ties. In terms of the number of farmers, study found that egocentric information networks characterized by high eccentricity and high betweeness centrality (i.e., shorter social distance and powerful information bridge farmers) have the potential to reach more farmers 72%, compared to all egocentric network communities. The study also found that the density of educated farmers in the egocentric information networks contributes positively to the networks impact on productivity gains of farmers in the network.

6.3 Policy implications

The fact that ICT-based extension channel comparatively outperformed conventional extension suggests that ICT-based extension services could be a viable alternative to conventional extension service provision. Hence, policy-makers should consider investing in expansion of ICT infrastructure such as installation of mobile communication masses across farming communities to improve the signal reception strength in these areas in order to scale-up the effectiveness of mobile phone, television and radio signals. This will enable state agencies and other stakeholders to minimize cost by employing limited but specialized staff to transmit agricultural extension information to farmers from centralized locations. Moreover, to the extent that ICT-based extension services remove direct person-to-person contact from extension service delivery, religious and cultural barriers could be overcomed, in order to promote equitable access to extension services by all farm households. In particular, female farm households living in conservative farming communities with strict socio-cultural and religious norms in the developing countries. Furthermore, the finding that access to electricity exerts a positive effects on farmers' likelihood of participation in ICT-based extension and inoculant adoption, suggests that policymakers investment in rural electrification could facilitate the extension delivery digitization to boost technology adoption, agricultural productivity, incomes, as well as food and nutrition security.

Finally, findings that there still exist untapped potential gains at some adoption states to be realized, implies that in technology diffusion and adoption policymakers should consider identifying and targeting different sub-population of farmers, who require special attention during extension program implementation, in order to maximize the program impact. The extension targeting policy will save resources and expand the outreach to benefit more farmers, thus increasing productivity at least cost.

Furthermore, findings that both extension participation and improved technology adoption show positive impact on productivity, efficiency and welfare, indicate that policymakers should invest in extension and research development aimed at developing new agricultural technologies in order to enhance food productivity and incomes of farm households. In addition, because the key IV (i.e., community connection to national electricity grid) used to identify the impacts show positive significant results, suggest that policymakers' investment on rural electrification in developing countries will go a long way to contribute to the adoption of new agricultural technologies, thereby increasing farm incomes and reducing rural poverty. The investment in rural electrification will also drive the development and expansion in rural enterprises such as sales of agro-inputs and perishable agro-based products, which must be stored under specific storage conditions. Finally, the investment in rural electrification will also facilitate the deployment of new channels of extension delivery via information and communication technologies (ICT) channels, as a long-term strategy to cut down public expenditure on extension delivery.

Finally, the findings that egocentric information networks play a critical role in influencing farmers' technical efficiency, implies that identifying central farmers' in egocentric networks and improving their technical knowledge in a farmer-to-farmer extension organization, can leverage the limited extension agents, to improve productivity of many farmers.

Appendices

Appendix 1: Household Survey Questionnaire

Part I: Survey Instrument (A)

Introduction:

This survey is part of a comprehensive study aim at *"Assessing the impact of ICT-Based Agricultural Extension Services on farmer knowledge, adoption, productivity, household welfare and farmers' willingness to pay for the service in Ghana."* The study is purely academic leading to an award of a PhD and does **NOT** intend to gather data on respondents for purposes of commerce, taxation, security or any other interest as to the detriment of the person, business, and human rights of respondents. I will therefore like to assure you of full anonymity and will not under any circumstance disclose any specific information attributed to you or your associates. Despite these assurances, you have the right to recuse yourself from taking part in the survey, if you think is necessary to do so. However, if you decide to go ahead and participate, it is my great pleasure to thank you for accepting to contribute to agricultural development policies of the country by offering yourself to be interviewed for purposes of generate data to this noble course. Once again, I thank you very much for participating.

SECTION A: TRACKING INFORMATION

A.1: Questionnaire Identification:

Questionnaire Number	*Start Time*	*End Time*	*Enumerator's Identity Code*	*Date*
Net Time				

A.2: Household Identification:

House Number	*Household Code*	*Respondent's Name*	*Contact Number*	GPS Coordinates		
				Longitude	*Latitude*	*Altitude*
Project Status		*Inoculant Usage Status*		*Respondent Type*		
Participant = [1] Non-Participant = [0]		User = [1] Non-User = [0]		Principal Respondent = [1] Principal Respondent's Spouse = [2] Principal Respondent's Network = [3]		

A.3: District Identification:

District Name	District Code	GPS Coordinates		
		Longitude	*Latitude*	*Altitude*

A.4: Regional Identification:

Region Name	Region Code	GPS Coordinates		
		Longitude	*Latitude*	*Altitude*

SECTION B: BACKGROUND OF RESPONDENT AND HOUSEHOLD INFORMATION

B: Background of respondent (A)

Status of Respondent in Household	Biographical Data	Socio-economic Data
Ba.1a. Head: Yes=[1]; No=[2] Ba.1b. If not head, relationship to household head: [ ] Ba.2a. Do you have any title in the community? [Yes=1]/[No=2] Ba.2b. If yes, specify……………………	Ba.3. Sex: Male=[1]; Female=[2] Ba.4. Age (yrs.): [ ] Ba.5a. Marital status: [ ] Ba.5b. If male and married, specify # of wives: [ ]	Ba.6. Religion: [ ] Ba.7. Years of schooling: [ ] Ba.8. Form of education: [ ] Ba.9. Ethnicity: [ ]

Relationship to HH: *1=Wife, 2=husband, 3=Sibling, 4=Relative, 5=Father-in-Law, 6=Mother-in-Law, 7= Other relations (specify)……………………*
Religion: *1=Islam, 2=Christianity, 3=ATR, 4=Others (specify)……………*
Marital Status: *1=Married, 2=Single, 3=Divorce, 4=Widow/Widower*
Form of Education: *1=Formal, 2=Non-formal education, 3= Islamic/Arabic 4=None, 5=Others (specify)………*
Ethnicity: *1=Dagomba, 2=Gonja, 3=Vagla, 4=Dagaati, 5=Wali, 6=Sissala, 7=Guru, 8=Kasen, 9=Bulu, 10=Kusasi, 11=Fulani, 12=Konkomba, 13=Binmoba, 14=Mamprusi, 15=Nanumba, 16=Bassari, 17=other (specify)…………*

B.10. Household Members Distribution (B)

HH Population Summary	Male Members	Ages (yrs)	Yrs of schooling	Female Members	Ages (yrs)	Yrs of Schooling
Total #of Males: [ ]	1st			1st		
Total #of Females:[ ]	2nd			2nd		
Total HH Size: [ ]	3rd			3rd		
	4th			4th		
	5th			5th		
	6th			6th		
	7th			7th		
	8th			8th		
	9th			9th		
	10th			10th		

B: Household Migration Information (C)

Bc.11. Within the last two years, has someone (including yourself) travel into the house from a different community or out of the house to a different community? Please provide your answers in the table below.

Travel Type	#of People: [ ]		Frequency of Travel (# of Times)	Destination of Travel	Have they returned? [Yes=1]/[No=2]
	#of Male	#of Female			
Move into the house from different community					
Move out of the house to different community					
Travel Destination Codes: *1=Community within the district, 2=Community in a different district within the same region, 3=Community in a different district in a different region*					

B: Household Occupation Information (D)

Bd.12a. Is farming your major occupation? [Yes=1]/[No=2]

Bd.12b. If farming is not your major occupation, please complete the table below.

Name of Major Occupation	Income/Month (GHC)

Bd.13. Aside your major occupation, which other minor occupation(s) do you engage in for a living? (Please give details of your other minor occupation(s) in the table below).

No.	Occupation	Yes=[1] No=[2]	Income per Week (GHC/wk)
1	Pito /Akpeteshi Brewing		
2	Palm Oil Processing		
3	Sheabutter/groundnut oil extraction		
4	Mining (quarrying, gold winning, etc)		
5	Corn Dough processor		
6	Charcoal/firewood selling		
7	Artisan (blacksmith, carpentry, tailoring, Mason, construction work, etc)		
8	Livestock/Fish farming		
9	Basket weaving/ Pottery		
10	General trade in agricultural produce		
11	Smock weaving		
12	General trade in non-agricultural produce		
13	Agro-inputs (Sell cutlasses, hoe, fertilizer, etc)		

14	Farm Hand		
15	Hire out equipment (tractor, bullock, donkey, etc)		
16	Butcher		
17	Gari Processing		
19	Petty trading/Retailing/Trader		
20	Teaching		
21	Crop farming		
22	Rural Telecommunication service (e.g mobile money, etc)		
23	Others (specify)……………………		

B: Households Resource Endowment (E)

Be.14. I will like to know which of the following productive assets do your household possess? (Please provide your answer in the table below)

Item	**Yes=1 No=2**	**How many (Number)**	**How much can you buy one of these items currently (GHC)**	**Who has more control over the assets in the household? Males=[1] Females=[0]**
Large livestock (oxen, cattle)				
Small livestock (goats, pigs, sheep)				
Poultry (Chickens, Ducks, Turkeys, Pigeons)				
Fish pond or fishing equipment				
Farm equipment (non-mechanized) e.g. Cutlass, hoe, bullock, etc				
Farm equipment (mechanized) e.g. tractor, plough, Sheller/Thresher, etc				
Nonfarm business equipment				
House (and other structures) that are rented out to tenants				
Large consumer durables (fridge, TV, sofa)				
Small consumer durables (radio, cookware)				
Cell phone				
Means of transportation (bicycle motorcycle, car)				

Be.15. Please I will like to know, whether in the past two years you have borrowed money from any source to assist your farming. Please provide details of your borrowing(s) in the table below.

Have you applied for credit in the last 2years? Yes=1 ; N=2	**If yes, what was the purpose for the credit?**	**From which lending source?**	**Outcome of credit application** *(Yes, I got all=1; Yes, I got but not all=2; No, I did not get=3)*	**How much did you apply for? (GHC)**	**How much did you get (GHC)**	**Did you apply for more? Yes=1; No=2**
Purpose of Credit Codes: 1=To farm, 2=To trade, 3=To buy a capital asset, 4=To buy food for the house, 5=To pay school fees, 6=To meet health needs, 7=Other (specify)………… **Lending Source Codes:** 1=Bank, 2=NGO, 3=MFI, 4=Money lender, 5=Friend/Relative, Other (specify)………						

Be.16. I like to know how you access land for your farming. Please provide your answer in the table below.

No.	**Farm Land**	**Land Size (acres)**	**Type of land ownership: (1) Owner cultivated (2) Rented (3) Cultivated on share crop agreement (4) Borrowed**
1	What is the total land size available to you for farming?		
2	What portion of the land is currently cultivated?		
3	What portion of the land is fallowing?		
4	What portion of your land is still virgin (uncultivated)		
	Other land not used for agricultural purposes (pieces, residential or commercial land)		
5	If land is owner cultivated, which of the following best describe your ownership?	(1) Family owned (2) Community owned (3) Personal ownership by purchase (4) Borrowed (5) Other (specify)…………………	
6	If land is borrowed or share cropped, what are the terms of agreement?	(1) Borrowed for a period for free (2) Share crop/income from sale 1:1 (3) Share crop/income from sale 2:1 (Land lord: tenant)	

		(4) Share crop/income from sale 1:2 (Land lord: tenant) (5) Other (specify) ....
	Costing of Land	
7	If land rented or purchased, how much do you pay for year?	GHC: [ ]
8	If leased, specific number of years and how much?	Duration (Yrs.): [ ] and Amount GHC: [ ]
9	If owner cultivated, how much could you have paid for it?	GHC: [ ] or Bags that could have been given to owner:[ ]
10	Will you consider making a permanent investment such planting trees on the land you currently cultivate?	Yes=[1]; No=[2]

B: Summary of Respondent Farming History (F)

Bf.17. For the past two seasons, what crop(s) did you cultivate? Please provide your answers in the table below.

No.	**Crop Type**	**Crop**	**Name of Variety**	**Plot Size/# of Acres**	**Cropping System** *[Mixed=1]/[Mono=2]*
Season (1): 2016					
Season (2): 2017					
Crop Type Codes: 1=legume grains, 2=cereal grains and 3=roots and tubers, 4=vegetable **Crop Codes:** 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)………. **Soyabean Varieties Code:** 1=Afayak, 2=Janguma, 3=Salintuaya, 4=Quarshie, 5=Others (specify)…………					

SECTION C: RESPONDENT FBO MEMBERSHIP INFORMATION

C.18. Please in the table below, I will like to know your involvement in group activities in the community.

Group Membership	**Is there any of these groups in this community or nearby community? (Yes=1; No=2)**	**Are you a member of the group? (Yes=1; No=2)**	**If a member, what is the total membership (# of People)** Total: [ ]		**How old is the group? (# of Years)**	**How long have you been in the group? (# of Years)**
			#of Male	**#of Female**		
Producer-Base FBOs, e.g. (Agricultural / livestock/ fisheries producer's group, etc.)						
Market and Value Addition-Based FBOs, e.g. (marketing groups, processing, etc)						
Water users' group						
Forest users' group						
Credit or microfinance group						
Mutual help or insurance group						
Civic groups (improving community) or charitable group (helping others)						
Local government						
Religious group						
Other (specify)						

C.19a. Sometime ago some groups from communities in this district were selected to benefit from an extension service support; please I will like to know whether your FBO/group was among those selected? Yes= [1];N =[2]

(Please if the answer to C.19a is no, go to question number C.25a).

C.19b.If yes to (19a) above, please complete the table below.

Which type of extension Service did your group receive?	**Number of Sessions Participated**	**Number of Sessions Not-Participated**	**Length of Time/Session**	**How was the venue of the sessions that you participated?** *(Enclose Venue=1; Open Venue=2)*
Extension Service Types: 1=Video Documentary, 2=Radio Listening, 3=Face-to-Face (Field days and Demonstrations) Contact, 4= Video Documentary, Radio Listening and Face-To-Face combined, 5=Video Documentary and Radio Listening combined, 6=Video Documentary and Face-To-Face combined, 7=Radio Listening and Face-To-Face combined, 8=Other (specify)……				

C.20. Please, how will you rate the **noise level** of the venue(s) in which the sessions you participated was held?

Very High=4	**High=3**	**Low=2**	**Very Quiet =1**
[ ]	[ ]	[ ]	[ ]

C.21. Please, how will you rate the **clarity level** of the video/radio content in the sessions that you participated?

Very High=4	**High=3**	**Low=2**	**Not Clear =1**
[ ]	[ ]	[ ]	[ ]

C.22. Which of these observations/opinions do you share concerning the sessions that you participated in?

No.	**observations/opinions**	**Level of Agreement: (1= strongly disagree , disagree=2, partly agree=3, agreed=4, strongly agree=5)**
Video Documentary		
	The people in the video did not appear to be in real farming situation.	
	I did not understand the language the people in the video were speaking.	
	There were breakages in the video	

	The pictures in the video were blurred	
	There were plenty people at the venue where I watch the video and so I could not see and hear very well	
	I was sick and so could not pay attention	
	I have hearing problem personally and so did not hear the people in the video very well	
Radio Listening Club		
	I did not understand the language the people in the radio were speaking.	
	There were breakages in the radio transmission	
	There were plenty people at the venue where I did the listening and so I could not hear very well.	
	I was sick and so could not pay attention	
	I have hearing problem personally and so did not hear the people in the radio very well	
Field Demonstrations/Field Days		
	I have hearing problem personally and so could not hear the very well	
	I was sick and so could not pay attention	
	I did not understand the language they were speaking.	
	There were plenty people so I could not hear and see very well.	

C.23. Since benefiting from the extension service, how many people have you shared the inoculant information with? [ ]

C.24. How many farmers have come to ask you about the inoculant? [ ]

C.25a. Has your group ever received support from any organization in the last two years? Yes=[1]; No=[2]

C.25b. If yes, which organization?..

C.26. What form of support did you receive? (Give details of the support received in the table below)

Form of Support	Yes=1; No=2	What was the purpose of the support?	How long did the support last? (Months)	How long did you participate? (Months)
Training				
Extension services				
Input credit				
Cash credit				
Watch videos				
Listened to radio				
Purpose Code: 1=New input use, 2=Processing, 3=Animal rearing, 4=Others (specify)………………				

SECTION D: INOCULANT INFORMATION

D: Farmer Awareness of Inoculant and Usage (A)

Da.27a. Have you heard of a new product called inoculant? Yes = [1] ; No = [2]

Da.27b. Which year did you first heard of it? [ ]

Da.27c. If yes to Da.27a above, give details about how you heard of the inoculant by completing this table below.

Source	**Yes=1 No=2**	**Location of Source** *(Within Community=1 Outside Community=2)*	**Distance to the source**	**Where did you first come to contact with the Source (s)?**	**How many minutes/days did you spend with the source in your first contact?**	**Since your first contact with the source (s), how many times did you contact the source (s) again?**	**How long did the subsequent contacts with source last?**
Input dealer							
Friend							
Family member							
Trader							
FBO							
Agric T.O							
SARI Extension Service							
Radio Set							
Radio from a mobile phone							
Radio from internet							
TV							

Video from a mobile PHONE							
Video from a mobile VAN							
Video set							
Video from internet							
Poster/Flier							
NGO							
Internet Website							
Tractor operator							
Others							

Da.28a. Have you used the inoculant? Yes = [1] ; No = [2]
Da.28b. If yes, when did you start using the inoculant? [ ]
Da.29. If you have not used the inoculant, do you have the intension to use it in future? Yes = [1] ; No = [2]

Da.30a. If no, why…………………………………………………………………………………

………………………………………………………………………………………………………

………………………………………………………………………………………………………

Da.30b. If yes, why do you intend to use it?..

……………………………………………………………………………………………………

……………………………………………………………………………………………………

(If no to question number Da.28a above attend to Da.29, Da.30a and Da.30b, and then skip to the next section).

Da.31. If yes to Da.28a, please provide your inoculant usage details in the table below.

Year	Crop	Crop Variety	Qty of Inoculant Purchased (# of packets) - A	Unit Cost (GHC) - B	Auxiliary Material Cost (GHC) - C	Qty of Inoculant Used (# of packets)	Qty of Inoculant Left (# of packets)
How long did you keep the inoculant before using it? (Days)……………………………							
Crop Codes: 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)………. **Soyabean Varieties Code:** 1=Afayak, 2=Janguma, 3=Salintuaya, 4=Quarshie, 5=Others (specify)…………							

Da.32a. Do you still use the inoculant? Yes = [1] ; No = [2]

Da.32b. If no, why have you stop using it?...

…………………………………………………………………………………………………

…………………………………………………………………………………………………

Da.33. If surplus inoculant was left as indicated in (column 8) of the table (Da.31) above, what did you do to the remaining inoculant (if any)?
a). Give out to somebody
b). Re-sold
c). Stored for future use
d). Nothing remained
e). Other (specify……………….)

Da.34a. How will you describe your crop yield in the year that you use the inoculant to your previous yield without the inoculant?
a). Very high, b). High, c). Normal, d). Low, e). Very low

Da.34b. Please provide details of your yield using the inoculant compare to previous yield without using inoculant in the table below

Year/Season	Crop	Crop Variety	**Plot Size (Acres)** *(Was it included in the # of plots given in the summary? [Yes=1;No=2])*	Total Yield (bags)	Qty Given Out (bags)	Qty Sold (bags)	Qty Consumed (bags)
With Inoculant							
Year 1							
Year 2							
Previous Yield Without Using Inoculant							
Year 1							
Year 2							
Crop Codes: 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)………. **Soyabean Varieties Code:** 1=Afayak, 2=Janguma, 3=Salintuaya, 4=Quarshie, 5=Others (specify)………….							

Da.34c. If you sold portion or the entire yield as in (column 7) in the table (Da.34b) above, please provide details of the sale(s) in the table below

Year/Season	**Crop**	**Period of Year Sold (Month)**	**Qty Sold (bags)**	**Unit Price (GHC)**	**Total Sales (GHC)**	**Point of Sale (Fill in code below)**	**Distance to Market (Miles)**	**Marketing Cost (GHC)**
Year 1								
Year 2								
Points of Sale: *Farmer's farm=1, Farmer's house=2, Own village market=3, Neighbouring community market=4, District capital market=5, Regional capital market=6, Distant market=7, FBO=8, NGO=9, Private company=10*								

Da.35. After using the inoculant, which other additional agro-input(s) did you use on that farm during that season? (Please provide details of other additional agro-inputs used on the farm in the table below)

Crop	**Agro-Input Name**	**Qty (# of bags or litres)**	**Unit Cost (GHC)/bag or litre**	**Auxiliary Cost (GHC)**	**Total Cost (GHC)**
Year 1					
Year 2					
Input Codes: 1=NPK, 2=SA, 3 Urea, 4=Weedicides, 5=Field pesticide, 6=Storage pesticides, 7=Organic (Animal manure, Biochar, Manure), 8=Inoculant, 9=Other (specify)………. **Crop Codes:** 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….					

Da.36. How will you compare the cost of using the inoculant in your farm production to that of fertilizer?
a). Very Cheap, b). Cheap, c). Costly, d). Very Costly, e). Don't Know

Da.37. How much cost in terms of labour did you spend on the following activities on the farm that you use the inoculant on? (Please provide details in the table below).

Farm Labour Use History

Crop	Activity	Family Labour				Hired/Communal Labour					
		Male		Female		Male			Female		
		# of Persons	# of days worked	# of Persons	# of days worked	# of Persons	# of days worked	Price/day	# of Persons	# of days worked	Price/day
Year 1											
Year 2											

Activity Codes: 1=Initial Land Preparation (clearing/ stumping), 2=Manual Ploughing/Ridging, 3=Planting/sowing, 4=1st Herbicide/weedicide application, 5=1st Manual Weeding, 6=1st Fertilizer application, 7=2nd Herbicide/weedicide application, 8=2nd Manual Weeding, 9=2nd Fertilizer application, 10=Pesticides/Fungicides application, 11=Harvesting, 12=Primary processing, 35=Bagging, 14=Transportation, 15=Feeding, 16=Other (specify)……….

Da.38. What mechanization services did you use on the farm that you used the inoculant? Please provide details of the services in the table below.

Tractor and Mechanization Services

Crop	**Activity**	**Mechanization Service Type**	**Unit Price (GHC)**	**Total Units**	**Equipment Ownership** *(Farmer's Own=1 Hired=2)*
Year 1					
Year 2					
Activity Codes: 1=Ploughing/Ripping, 2=Harrowing, 3=Harvesting, 4=Primary processing, 5=Transportation **Services Codes:** 1=Tractor, 2=Bullock/drawn animals, 3=Moto-King, Combine Harvester, 4=Sheller/Thrasher, 5=Other (specify)………					

D: Inoculant Knowledge Test (B)

(*This section is to be completed for Participant and inoculant User as well as dealers and researcher, trainers of inoculant***)**

Db.39. How many types of inoculants ***(according to the legume type)*** do you know of? [ ]

Db.40. Which of these crops seeds can the inoculant be applied directly on?

No.	**Crop**	**Correctly identified=1; Wrongly identified=0**
1	Cowpea	
2	Soya beans	
3	Groundnuts	
4	Maize	
5	Rice	
6	Yam	
7	Sorghum	
8	Millet	
9	Others (specify….)	

Db.41a. If you see an inoculant can you identify it? Yes=[1]; [No=[2]

Db.41b. If yes, which of these sachets contain an inoculant? (*Note inoculant types plus a placebo inoculant to be provided, as specimen, for physical identification test*).

No.	Specimen	Correctly identified=1; Wrongly identified=0
1	Specimen A	
2	Specimen B	
3	Specimen C	
4	Specimen D	
Total		

Db.42. What quantity of inoculant is recommended for an acre of land?
Number Packets: [   ] or in Kilograms: [   ]

Db.43. What is the recommended quantities of the items/materials use in the preparation and application of the inoculant? (Please provide your answers in the table below).

No.	Recommended Item/Material	Recommended Quantity Required
1	Water	
2	Sticker or Sugar	
3	Inoculant	
4	Seeds	
Total		

Db.44. Can you described how you used the inoculant in your farm? (*Please follow the steps as was described to you or by the person that taught you how to use the inoculant*)

I……………………………………………………………………………………………..

…………………………………………………………………………………………………

II………………………………………………………………………………………………

…………………………………………………………………………………………………

III………………………………………………………………………………………….

………………………………………………………………………………………………….

………………………………………………………………………………………………….

IV……………………………………………………………………………………………

…………………………………………………………………………………………………

V………………………………………………………………………………………………

…………………………………………………………………………………………………

VI……………………………………………………………………………………………

……………………………………………………………………………………………………

VII.……..………………………………………………………………………………………

……………………………………………………………………………………………………

……………………………………………………………………………………………………

Db.45. Which of the following statement(s) is or are true about inoculant preparations for application?

No.	Statement	True=1; False=0
1	Do not soak the seeds to wet before inoculation.	
2	Do not dry the inoculated seeds for less than 30mins to 1hr.	
3	Do not sun-dry the inoculated seeds.	
4	Moisten the seeds before inoculation.	
5	Avoid exposing the inoculant to heat	
6	Do not mix inoculated seeds with fertilizer or any chemical	
7	Do not plant inoculated seeds when the soil is dry and hot	
8	Preferably, plant inoculated seeds in the late afternoon or when the weather is cool	
9	Do not use expire inoculants to inoculate your seeds	
10	Check the label to ensure that you use the appropriate type of inoculant to inoculate your seeds	
11	Follow the right procedure to properly inoculate your seeds	
12	Use inoculant with improved seeds for better results	
Total		

Db.46. Why is it recommended to carry out the following activities in the preparation and application of the inoculant? Please provide your answers in the table below.

No.	Recommended Activity	Reason(s)
	Air-dry inoculated seeds under a shade or environment.	
	Using a sticker or (sugar solution) to moisten seeds before inoculation.	
	Adequately dry inoculated seeds before sowing.	

D: Perceptions and Usage Experiences (C)

Dc.47. What positive thing(s) have you observed on your farm or have you heard from those who have used the inoculant that have been attributed to the inoculant?

…………………………………………………………………………………………………

…………………………………………………………………………………………………….

…………………………………………………………………………………………………….

Dc.48. What negative thing(s) have you observed on your farm or have you heard from those who have used the inoculant that have been attributed to the inoculant?

…………………………………………………………………………………………………

…………………………………………………………………………………………………

…………………………………………………………………………………………………..

…………………………………………………………………………………………………..

Dc.49. In your observation or opinion, how can you compare fertility levels of fields/plots on which the inoculant has been used previously to fields/plots on which fertilizer has been used previously? Please provide your comparison in the table below.

Input Type	**Old Field/Plot Fertility Status**		
	Fertility levels deteriorates after sometime=1	*Fertility levels enhances after sometime=2*	*Don't Know=3*
Fertilizer			
Inoculant			

Dc.50. Does the inoculant application have any negative effect on any of the following?

No.	**Areas of Perceived effects**	**Yes=1; No=2**
1	Seed germination	
2	Soil fertility	
3	Plot weed level	
4	Pest and diseases in the plot	
5	Any other (specify)….	

Dc.51. What long-term effect(s) do you foresee the inoculant use to have on:

(i) Farm lands?…………………………………………………………………………
…………………………………………………………………………………………
…………………………………………………………………………………………

(ii) Humans/Animals?..
…………………………………………………………………………………………
…………………………………………………………………………………………

(iii) Any other (specify)………………………………………………………………
…………………………………………………………………………………………

Dc.52a. Which of the following constitute the recommended order for the application of the inoculant according to what you have heard from or being taught by the person(s)?

Recommended Procedure	**Step: [1, 2, 3, 4, 5, 6, 7]**
Measure 1 kg (or 1/2 Olonka) of the seeds to be inoculated in an appropriate basin/container	[ ]
Moisten the seeds with a sticker solution and stir uniformly	[ ]
Add about 5 g (or l leadcap of a mineral water bottle) of the inoculants to the moistened seed in the container	[ ]
Stir again gently and uniformly until the seeds are fairly evenly coated with the inoculants	[ ]
Spread the seeds on a sheet of canvas material and air-dry in a shade	[ ]
Allow inoculated seeds to dry for at least 30 minutes to 1 hour for inoculants to adequately stick onto the surface of the seeds	[ ]
Seeds can now be sown like the ordinary seeds	[ ]

Dc.52b. Which of the follow represents the recommended procedure for storing unused or left-over inoculant?

No	**Recommended Procedure for Storage**	**True=1; False=0**
1	If opened tier to close tightly/cealed before storage	
2	Store in a fridge	
3	Store in any cold place	
4	It is not good to store inoculant in a defreezer or freezing conditions	
5	Avoid storage that are expose to heat	
6	Do not make store inoculant tend to ice block	
7	Do not store inoculated seeds	
8	Store the inoculant under temperatures not above 40 degrees	
Total		

Dc.53. Which of the following opinion(s) do you share about the use of the inoculant?

No.	Opinions or Observations	(1= strongly disagree , disagree=2, partly agree=3, agreed=4, strongly agree=5)
1	The process of applying the inoculant is very difficult.	[ ]
2	The process of applying the inoculant is consistent with how traditionally people or our grandfathers use to add some blessings to their seeds before sowing them on the field.	[ ]
3	I have previously had extension contact on the use of the inoculant	[ ]
4	The questions on the knowledge test for the inoculant usage in this survey was very difficult for my understanding	[ ]

D: Cropping System Information (D)

Dd: Inter-Cropping (A)

Dda.54a. Did you inter-crop the field that you applied the inoculant on? Yes=[1]; No=[2]

(If no to question number Dda.54a, please skip and go to Ddb.55)

Dda.54b. If yes to Dda.54a, please provide details of the other crop(s) performance in the table below.

Year	Crop	Crop Variety	Farm Size (Acres)	Total Yield (bags)	Qty Given Out (bags)	Qty Sold (bags)	Qty Consumed (bags)
Crop Codes: 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….							

Dda.54c. Please, if you sold portion or the entire yield as in (column 7) in table (Dda.54b) above, provide details of the sale(s) in the table below.

Year	Crop	Period of Year Sold (Month)	Qty Sold (bags)	Unit Price (GHC)	Total Sales (GHC)	Point of Sale *(Fill in the code below)*	Distance to Market (km)	Marketing cost (GHC)
Points of Sale: *Farmer's farm=1, Farmer's house=2, Own village market=3, Neighbouring community market=4, District capital market=5, Regional capital market=6, Distant market=7, FBO=8, NGO=9, Private company=10*								

Dd: Crop Rotation (B)

Ddb.55a. Do you practice cropping rotation? Yes=[1]; [No=[2]

Ddb.55b. If yes to Ddb.55a, did you rotate in the field(s) that you applied the inoculant on the previous year with any crop? Yes=[1]; [No=[2]

(If no to question number Ddb.55b, please skip and go to E.59)

Ddb.55c.If yes to Ddb.55a, please provide yield details in the table below.

Year	Crop	Crop Variety	Farm Size (Acres)	Total Yield (bags)	Qty Given Out (bags)	Qty Sold (bags)	Qty Consumed (bags)
Crop Codes: 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….							

Ddb.55b. Please, if you sold portion or the entire yield as in (column 7) in table (Ddb.55a) above, provide details of the sale(s) in the table below.

Year	Crop	Period of Year sold (Month)	Total Qty Sold (bags)	Unit Price (GHC)	Point of Sale (Fill in code below)	Distance to Market (Km)	Marketing cost (GHC)
Points of Sale: *Farmer's farm=1, Farmer's house=2, Own village market=3, Neighbouring community market=4, District capital market=5, Regional capital market=6, Distant market=7, FBO=8, NGO=9, Private company=10*							

Ddb.56. What input types did you use on the rotated crops in that year? Please provide your answers in the table below.

Rotated Crop Inputs Use History

Crop	Agro-Input Name	Qty (# of bags or litres)	Unit Cost (GHC)/bag or litre	Auxiliary Cost (GHC)	Total Cost (GHC)
Input Codes: 1=NPK, 2=SA, 3 Urea, 4=Weedicides, 5=Field pesticide, 6=Storage pesticides, 7=Organic (Animal manure, Biochar, Manure), 8=Inoculant, 9=Other (specify)………. **Crop Codes:** 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….					

Ddb.57. How much cost in terms of labour did you spend on the following activities on the rotated crop field that year? (Please provide details in the table below).

Rotated Crop Labour Use History

Crop	Activity	Family Labour				Hired/Communal Labour					
		Male		Female		Male			Female		
		# of Persons	# of days worked	# of Persons	# of days worked	# of Persons	# of days worked	Price/day	# of Persons	# of days worked	Price/day

Activity Codes: 1=Initial Land Preparation (clearing/ stumping), 2=Manual Ploughing/Ridging, 3=Planting/sowing, 4=1st Herbicide/weedicide application, 5=1st Manual Weeding, 6=1st Fertilizer application, 7=2nd Herbicide/weedicide application, 8=2nd Manual Weeding, 9=2nd Fertilizer application, 10=Pesticides/Fungicides application, 11=Harvesting, 12=Primary processing, 35=Bagging, 14=Transportation, 15=Feeding, 16=Other (specify)……….
Crop Codes: 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….

Ddb.58. What mechanization services did you use on the rotated crop farm that year? Please provide details of the services in the table below.

Rotated Crop Tractor and Mechanization Services

Crop	Activity	Mechanization Service Type	Unit Price (GHC)	Total Units	Equipment Ownership *(Farmer's Own=1 Hired=2)*

Activity Codes: 1=Ploughing/Ripping, 2=Harrowing, 3=Harvesting, 4=Primary processing, 5=Transportation
Services Codes: 1=Tractor, 2=Bullock/drawn animals, 3=Moto-King, Combine Harvester, 4=Sheller/Thrasher, 5=Other (specify)……….

SECTION E: DIFUSION IN SOCIAL NETWORKS

E.59. Which of the following membership category best describe your living status in this community?

Category	Yes =1; No=2	If not born here, how long have you been living here?	If not born here, how many times do you visit your original place of abode within a year?	If not born here, how often do you call someone in your original place of abode to talk about farming? *(Always=4; Sometimes=3; Very Rare=2; Never=1)*
I was born in this community				
My family migrated to this community				
I am a visiting farmer/trader in this community				
I am from a different community but works in this community				
I am from a different community but married to a man in this community				
Others (specify)……				

E.60. Please I will like to know more about your friends and family in this community.

How many members of your family lives in this community?	How many of your friends live in this community?

E.61a. Do you know any farmer using the inoculant? Yes=[1]; No=[2]

E.61b. If yes to E.61a, please complete the table below.

# of farmers known using the inoculant?	Are they still using the inoculant? Yes=[1]; No=[2]; Don't Know=[3]	If no, why have they stop?

E.62. Please kindly provide me the name of persons you normally share farming ideas or discuss farming matters with in this community. *(Please provide list of persons in the table below)*

No.	**Name of Person**	**Location of Person (Village and House name)**	**What is your Relationship with the Person**
1			
2			
3			
4			
5			
6			
Relationship Codes: 1=Family member, 2=Friend, 3=Association member, 4=House neighbor, 5=Farm neighbor, 6=Schoolmate, 7= Colleague in the same house, 8=In-Law, 9=Others (specify)…..			

E.63. I will like to know more about your interactions with the persons in the table (E.62) above. *(Please provide details about your interactions in the table below).*

Name of Person	**Place of interaction**	**Frequency of interaction** *(Every day=6, Every week=5, Every Two Weeks=4, Every Month=3, Every Year=2, Once in While=1)*	**How often do you discuss farming issues with the person(s)?** *(Always=4; Sometimes=3; Very Rare=2; Never=1)*	**What score out of 5 will you give to things that the person ever told you about and it turns out to be true or correct.** *(Scale: 1 – 5; where 1 is least true and 5 is highly true)*	**How long have you known the person** *(no. of years)*
1st person					
2nd person					
3rd person					
4th person					
5th person					
Place of interaction Codes: 1=market, 2=mosque/church, 3=party office/shade, 4=outdoorings/weddings, 5=funerals, 6=journeying on a same vehicle, 7=football park/watching venue, 8=on the farm, 9=on the way to the farm, 10=Home visit, 11=Others(specify)………………					

E: Farmer Information Networks (A)

Ea.64a. Are you aware that in this community, some people had the opportunity to watch a video, (or attend field day or demonstration or listen to radio) about the inoculant? Yes=[1]; No=[2]

Ea.64b. If yes to E.64a, can you identify some of them by completing the table below?

No.	Name of Person	Location of Person (Village and House name)	What is your Relationship with the Person
1			
2			
3			
4			
5			
6			
7			
Relationship Codes: 1=Family member, 2=Friend, 3=Association member, 4=House neighbor, 5=Farm neighbor, 6=Schoolmate, 7= Colleague in the same house, 8=In-Law, 9=Others (specify)…..			

Ea.65. I will like to know more about your interactions with the persons you have identified in the table above. Please provide details about your interactions in the table below).

Name of Person	Place of interaction	Frequency of interaction *(Every day=6, Every week=5, Every Two Weeks=4, Every Month=3, Every Year=2, Once in While=1)*	How often do you discuss farming issues with the person(s)? *(Always=4; Sometimes=3; Very Rare=2; Never=1)*
1st person			
2nd person			
3rd person			
4th person			
5th person			
6th person			
7th person			
Place of interaction Codes: 1=market, 2=mosque/church, 3=party office/shade, 4=outdoorings/weddings, 5=funerals, 6=journeying on a same vehicle, 7=football park/watching venue, 8=on the farm, 9=on the way to the farm, 10=Home visit, 11=Others(specify)………………			

Ea.66. Has any of these persons shared the information that he/she heard or saw about the inoculant from the video or radio with you? Yes=[1]; No=[2]

Ea.67a. Have you asked any of these persons about the inoculant before? Yes=[1]; No=[2]

Ea.67b. If yes to Ea.67a, from which of these persons identified in the table above have you heard it from*? (Please provide details of what you heard from them in the table below).*

Name of Person	**Yes=1; No=2**	**How long have you known the person (no. of years)**	**What score out of 5 will you give to things that the person ever told you about and it turns out to be true or correct. (scale: 1 – 5; where 1 is least true and 5 is highly true)**
1st person			
2nd person			
3rd person			
4th person			
5th person			
6th person			
7th person			
8th person			
9th person			
10th person			

SECTION F: SOIL AND CLIMATE INFORMATION

F.68. How can you describe the general fertility of the land on which you have been cultivating for the past two seasons?

Very Fertile=1	Fertile=2	Somehow Fertile=3	Not Fertile=4
[ ]	[ ]	[ ]	[ ]

F.69. How will you describe striga (Bochaa) situation on your field of cultivation for the past two seasons?

Very severe=5	Severe=4	Somehow severe=3	Not severe=2	No Bochaa=1
[ ]	[ ]	[ ]	[ ]	[ ]

F.70. How will you rate the amount of rainfall in your farming area for the past two seasons? Please provide your rating ranging from a score of 1, very poor to a score of 5, very high in the table below.

Very poor=1	Poor=2	Somehow Good=3	Good=4	Very Good=1
[ ]	[ ]	[ ]	[ ]	[ ]

F.71. Does the community has the following amenities? Yes=[1]; No=[0]

Electricity	Phone Reception	Radio Reception	TV Reception	Market	Agric. T.O	Distance to district capital (Km)
[ ]	[ ]	[ ]	[ ]	[ ]		

SECTION G: FARM PRODUCTION INFORMATION FOR <u>ONLY</u> NON-PARTICIPANTS

(Please refer to question number (Bf.17) list of crops given by the respondent and complete the tables below for ***Non-Participant*** *and* ***Non-User farmers****)*

G.72.What number of bags did you obtain from your farm(s)? Please provide your answers in the table below.

Farm Output History

No	Crop	Crop Variety	Farm Size (# of Acres)	Total Yield (bags)	Qty Sold (bags)	Qty Consumed (bags)	Qty Given out (for labour & primary processing) (bags)
Year 1							
Year 2							
Crop Type Codes: 1=legume grains, 2=cereal grains and 3=roots and tubers, 4=vegetable **Crop Codes:** 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….							

G.73. Please, if you sold portion or the entire yield as in (column 6) in table (G.71) above, provide details of the sale(s) in the table below.

Year/Season	Crop	Period of Year sold (Month)	Total Qty Sold (bags)	Unit Price (GHC)	Point of Sale (Fill in code below)	Distance to Market (Km)	Marketing cost (GHC)
Points of Sale: *Farmer's farm=1, Farmer's house=2, Own village market=3, Neighbouring community market=4, District capital market=5, Regional capital market=6, Distant market=7, FBO=8, NGO=9, Private company=10*							

G.74. What input type(s) did you use on your crops? Please provide your answers in the table below.

Farm Input Use History

Input	1st Crop=[ ]		2nd Crop=[ ]		3rd Crop=[ ]		4th Crop=[ ]		5th Crop=[ ]	
	Qty/Acre	Unit Price (GHC)	Qty/Acre	Unit Price (GHC)	Qty/Acre	Unit Price (GHC)	Qty/Acre	Unit Price (GHC)	Qty/Acre	Unit Price (GHC)
Input Codes: 1=NPK, 2=SA, 3 Urea, 4=Weedicides, 5=Field pesticide, 6=Storage pesticides, 7=Organic (Animal manure, Biochar, Manure), 8=Inoculant, 9=Other (specify)……… **Crop Codes:** 1=soya bean, 2=groundnut, 3=cowpea, 4=maize, 5=sorghum, 6=millet, 7=rice, 8=yam, 9=cassava, 10=potato, 11=tomato, 12=onion, 13=sesame, 14=Other (specify)……….										

G.75. How much labour (including yourself) did you use on the farm(s)? Please provide your answers in the table below.

Farm Labour Use History

Crop	Activity	Family Labour				Hired/Communal Labour					
		Male		Female		Male			Female		
		# of Persons	*# of days worked*	*# of Persons*	*# of days worked*	*# of Persons*	*# of days worked*	*Price/day*	*# of Persons*	*# of days worked*	*Price/day*

Activity Codes: 1=Initial Land Preparation (clearing/ stumping), 2=Manual Ploughing/Ridging, 3=Planting/sowing, 4=1st Herbicide/weedicide application, 5=1st Manual Weeding, 6=1st Fertilizer application, 7=2nd Herbicide/weedicide application, 8=2nd Manual Weeding, 9=2nd Fertilizer application, 10=Pesticides/Fungicides application, 11=Harvesting, 12=Primary processing, 35=Bagging, 14=Transportation, 15=Feeding, 16=Other (specify)……….

G.76. What mechanization services did you use on the farm(s)? Please provide details of the services in the table below.

Tractor and Mechanization Services

Crop	Activity	Mechanization Service Type	Unit Price (GHC)	Total Units	Equipment Ownership *(Farmer's Own=1 Hired=2)*

Activity Codes: 1=Ploughing/Ripping, 2=Harrowing, 3=Harvesting, 4=Primary processing, 5=Transportation
Services Codes: 1=Tractor, 2=Bullock/drawn animals, 3=Moto-King, Combine Harvester, 4=Sheller/Thrasher, 5=Other (specify)……….

77a. Do you have any opinion or comment to add to this study? [Yes=1]/[No=2]

77b. If yes, state comment……………………………………………………………

END OF INTERVIEW
THANK YOU FOR TAKING PART IN THIS SURVEY

PART II: WTP FOR ICT-BASED AGRICULTURAL EXTENSION SERVICES

Survey Instrument (B) **Date:…………………………………**

Region:………… *District*…………….*Community*………………….. *House Number*………………………Tel:………………………

Gender: [M] / [F] *Category:* Participant [ ] Non-Participant [ ] *Questionnaire Number:* [ ] *Enumerator's Code:* [ ]

Introduction:

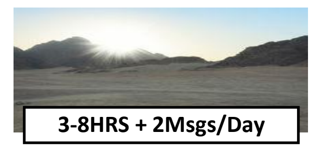
Imaging a situation where there exist very few or inadequate agricultural extension agents available to offer technical advices on good farming practices to farmers or deliver to farmers new techniques that can help increase their yield or farm output. Imagine that a certain organization wants to use modern technologies (e.g. mobile phones, videos, etc.) to offer technical advisory services and new techniques of farming to farmers at a cost. The system to offer this service to farmers is known as Agricultural Extension Services (AES). This is to bring agricultural extension services to farmers and facilitate farmers acquisition of new techniques of farming and good agronomic practices (GAPs) just like our mobile phones has shorten the distance between us and our friends and families across the world. There exist AES in other parts of the world and some parts of the country. This study is to help the organization know much about what farmers in this region will want the AES system to be and how much farmers in this region can afford to pay for such a service.

The CT-Script

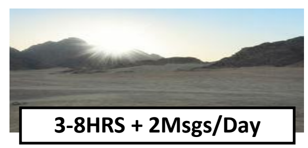
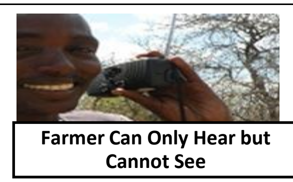
However, similar studies have been conducted among farmers elsewhere and in some parts of this region to find out how much they were willing to pay for the AES usage. Some of the farmers quoted prices as high as **GHC9 – GHC10/month**, some quoted **GHC7 – GHC8/month** and others quoted as low as **20pesewas – GHC1/month**. To some people, it seems that some of the prices that were quoted by the farmers in those parts of the region were not being very realistic. I want you to be very honest and realistic and look at the three (3) different types of the AES systems provided in the tables that follow from the next pages and decide which AES system you will be willing to pay for. I will like to draw your attention to the need for you to be very realistic in your choice and do not think that after all you will not be ask to remove money now. Who knows, in the near future you will be confronted with the reality of the service and you will have to pay. So please I entreat you to be very realistic in your choice of AES system type according to their cost of service provision and how much you will be willing to pay. Thank you in advance for taken your precious time to help contribute to the study that will help inform agricultural policies in the country.

I will like to assure you that the information you provide will be confidential and will not be attributed to you in anyway as may to harm you.

(C1/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] **CHOICE SET-1** **AES SERVICE ATTRIBUTES**	**AES-A**	**AES-B**	**AES-C**	**NONE**
Reliability and Responsiveness of the service				
Information Specificity and Usefulness of the service	 **100% Technical Knowledge and GAPs**	 **100% General Information**	 **50% Technical Knowledge + 50% General Information**	
Accessibility of the service				
Information accuracy and trust level of the service				
Cost of service delivery (GHS/Month)				
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

1. (C2/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] **CHOICE SET-2** **AES SERVICE ATTRIBUTES**	**AES-A**	**AES-B**	**AES-C**	**NONE**
Reliability and Responsiveness of the service	 Late or Delay Delivery	 On Time Delivery	 On Time Delivery	
Information Specificity and Usefulness of the service	 **50% Technical Knowledge + 50% General Information**	 **100% General Information**	 **100% Technical Knowledge and GAPs**	
Accessibility of the service				
Information accuracy and trust level of the service				
Cost of service delivery (GHS/Month)				
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

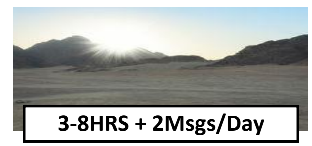
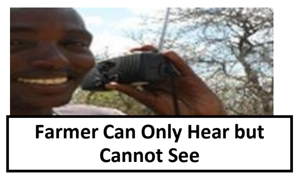
2. (C3/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] CHOICE SET-3 AES SERVICE ATTRIBUTES	AES-A	AES-B	AES-C	NONE
Reliability and Responsiveness of the service		 Late or Delay Delivery		
Information Specificity and Usefulness of the service	 **100% General Information**	 **100% Technical Knowledge and GAPs**	 **50% Technical Knowledge + 50% General Information**	
Accessibility of the service				
Information accuracy and trust level of the service		 Farmer Can Only Read Message	 Farmer Can Only Hear but Cannot See	
Cost of service delivery (GHS/Month)	 ¢3.2 – 4	 ¢4.2 – 5	 ¢0.2 – 1	
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

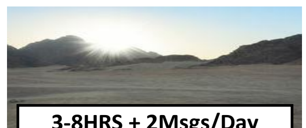
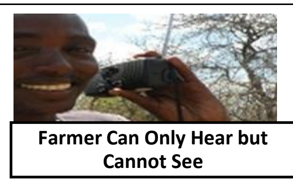
3. (C4/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C]				
CHOICE SET-4				
AES SERVICE ATTRIBUTES	**AES-A**	**AES-B**	**AES-C**	**NONE**
Reliability and Responsiveness of the service				
Information Specificity and Usefulness of the service	 **50% Technical Knowledge + 50% General Information**	 **100% Technical Knowledge and GAPs**	 **100% General Information**	
Accessibility of the service				
Information accuracy and trust level of the service				
Cost of service delivery (GHS/Month)				
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

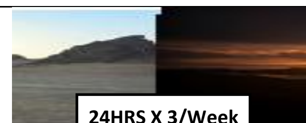
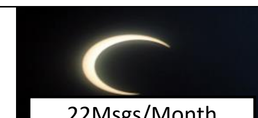
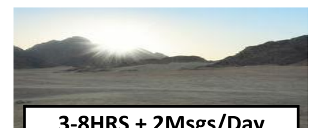
4. (C5/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] **CHOICE SET-5** **AES SERVICE ATTRIBUTES**	**AES-A**	**AES-B**	**AES-C**	**NONE**
Reliability and Responsiveness of the service				
Information Specificity and Usefulness of the service	 **100% Technical Knowledge and GAPs**	 **50% Technical Knowledge + 50% General Information**	 **100% General Information**	
Accessibility of the service				
Information accuracy and trust level of the service				
Cost of service delivery (GHS/Month)				
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

5. (C6/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] **CHOICE SET-6** **AES SERVICE ATTRIBUTES**	**AES-A**	**AES-B**	**AES-C**	**NONE**
Reliability and Responsiveness of the service	 Late or Delay Delivery	 On Time Delivery	 On Time Delivery	
Information Specificity and Usefulness of the service	 **100% Technical Knowledge and GAPs**	 **100% General Information**	 **50% Technical Knowledge + 50% General Information**	
Accessibility of the service	 3-8HRS + 2Msgs/Day	 24HRS X 3/Week	 22Msgs/Month	
Information accuracy and trust level of the service	 Farmer Can Only Hear but Cannot See	 Farmer Can Only Read Message	 Farmer Can See and Hear	
Cost of service delivery (GHS/Month)	 ¢2.2 – 3	 ¢3.2 – 4	 ¢4.2 – 5	
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

6. (C7/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] **CHOICE SET-7** **AES SERVICE ATTRIBUTES**	**AES-A**	**AES-B**	**AES-C**	**NONE**
Reliability and Responsiveness of the service	 Late or Delay Delivery	 On Time Delivery	 Late or Delay Delivery	
Information Specificity and Usefulness of the service	 **50% Technical Knowledge + 50% General Information**	 **100% General Information**	 **100% Technical Knowledge and GAPs**	
Accessibility of the service	 24HRS X 3/Week	 22Msgs/Month	 3-8HRS + 2Msgs/Day	
Information accuracy and trust level of the service	 Farmer Can See and Hear	 Farmer Can Only Hear but Cannot See	 Farmer Can Only Read Message	
Cost of service delivery (GHS/Month)	 ¢1.2 – 2	 ¢2.2 – 3	 ¢3.2 – 4	
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

7. (C8/C8). Please examine the three (3) different AES system types below, each with its own characteristics and cost of delivery.

BLOCK [A] [B] [C] CHOICE SET-8 AES SERVICE ATTRIBUTES	AES-A	AES-B	AES-C	NONE
Reliability and Responsiveness of the service				
Information Specificity and Usefulness of the service	 **100% Technical Knowledge and GAPs**	 **100% General Information**	 **50% Technical Knowledge + 50% General Information**	
Accessibility of the service				
Information accuracy and trust level of the service				
Cost of service delivery (GHS/Month)	 ¢0.2 – 1	 ¢1.2 – 2	 ¢3.2 – 4	
Which AES system will you be willing to pay for?	[ ]	[ ]	[ ]	[ ]

8. How often did you consider the following attributes of the AES system types before you finally make the choices that you made?

No.	Attributes	Never	Rarely	Sometimes	Always
1	*Reliability and Responsiveness of the service*	[ ]	[ ]	[ ]	[ ]
2	*Information Specificity and Usefulness of the service*	[ ]	[ ]	[ ]	[ ]
3	*Accessibility of the service*	[ ]	[ ]	[ ]	[ ]
4	*Information accuracy and trust level of the service*	[ ]	[ ]	[ ]	[ ]
5	*Cost of service delivery*	[ ]	[ ]	[ ]	[ ]

9. Please rate the AES attributes from '1' to '10', where '1' is the least important attribute of the AES system to you and '10' as the most important attribute of the AES system to you.

No.	Attributes	Rating Scores: (1, 2, 3, 4, 5, 6, 7, 8, 9, 10)
1	*Reliability and Responsiveness of the service*	[ ]
2	*Information Specificity and Usefulness of the service*	[ ]
3	*Accessibility of the service*	[ ]
4	*Information accuracy and trust level of the service*	[ ]
5	*Cost of service delivery*	[ ]

10. Please indicate to what extend do you agree or otherwise of the following statements?

No.	Attributes	Level of Agreement: (1= strongly disagree , disagree=2, partly agree=3, agreed=4, strongly agree=5)
1	*All the attributes of the AES system types were important in my choice decisions*	[ ]
2	*I understood fully the choice task I was faced with*	[ ]
3	*I understood more than half of the choice task I was faced with*	[ ]
4	*I understood less than half of the choice task I was faced with*	[ ]
5	*I was very realistic in making the choices as I will do in a real world situation*	[ ]

11. How do you perceived the current agricultural extension delivery in the country or region to be? Please indicate your perception by agreeing to or otherwise of the following statements

No.	Attributes	Level of Agreement: (1= strongly disagree , disagree=2, partly agree=3, agreed=4, strongly agree=5)
1	*I always get the extension agent anytime I want him/her*	[ ]
2	*The extension agent always bring me new ways of farming*	[ ]
3	*The extension agent always bring the same old ways of farming*	[ ]
4	*Most of the things the extension agent always tell me fail to happen*	[ ]
5	*The extension agent is very important and useful to me in my farming*	[ ]
6	*The extension agent has been very helpful to me in my farming*	[ ]
7	*Most of the information the extension agent tells me is always too late for me to use*	[ ]
8	*I don't always get the extension agent because I don't have anything to give him/her*	[ ]
9	*I don't always get the extension agent because I am too far away from where he/she is located*	[ ]
10	*I don't always get the extension agent because I think the extension agents are inadequate*	[ ]
11	*I don't always get the extension agent because I don't need his/her services in my farming*	[ ]
12	In the last 2 farming seasons, how many times have you had contact with the agricultural extension agent? **Season 1** [ ]; **Season 2** [ ]	
13	Do you have a mobile phone? Yes = [1] ; No = [2]	
14	Have you ever use a phone to call an extension officer? Yes = [1] ; No = [2] (if yes, go to the next question below)	
15	Within last two seasons, how many times have you called an extension officer with a phone? **Season 1** [ ]; **Season 2** [ ]	

12. How often do undertake the following activities?

No.	Activity	Never	Rarely	Sometimes	Always
1	Purchasing mobile phone credit	[ ]	[ ]	[ ]	[ ]
2	Mobile money transfer	[ ]	[ ]	[ ]	[ ]
3	Mobile money receipt	[ ]	[ ]	[ ]	[ ]
4	Purchasing of Video CD	[ ]	[ ]	[ ]	[ ]
5	Purchasing Music CD	[ ]	[ ]	[ ]	[ ]
6	Listening to radio	[ ]	[ ]	[ ]	[ ]
7	Watching video	[ ]	[ ]	[ ]	[ ]
8	Watching TV	[ ]	[ ]	[ ]	[ ]
9	Search internet for information	[ ]	[ ]	[ ]	[ ]
10	Have you ever bought anything online or using text message	[ ]	[ ]	[ ]	[ ]

13. How many times do you undertake the following activities in a week or month?

No.	Activity	Number of Times
1	Purchasing mobile phone credit	
2	Mobile money transfer	
3	Mobile money receipt	
4	Purchasing of Video CD	
5	Purchasing Music CD	
6	Listening to radio	
7	Watching video	
8	Watching TV	
9	Search internet for information	
10	Have you ever bought anything online or using text message	

14. Background data

Status of Respondent in Household	Biographical Data	Socio-economic Data
1. Head: Yes=[1]; No=[2] 2. If not head, relationship to household head: [ ] 3a. Do you have any title in the community? Yes=[1]; No=[2] 3b. If yes, specify……………………	4. Sex: Male=[1]; Female=[2] 5. Age (yrs.): [ ] 6a. Marital status: [ ] 6b. If male and married, specify # of wives: [ ]	7. Religion: [ ] 8. Years of schooling: [ ] 9. Form of education: [ ] 10. Ethnicity: [ ]
Relationship to HH: *1=Wife, 2=husband, 3=Sibling, 4=Relative, 5=Father-in-Law, 6=Mother-in-Law, 7= Other relations (specify)……………………* ***Religion:*** *1=Islam, 2=Christianity, 3=ATR, 4=Others (specify)…………* ***Marital Status:*** *1=Married, 2=Single, 3=Divorce, 4=Widow/Widower* ***Form of Education:*** *1=Formal, 2=Non-formal education, 3= Islamic/Arabic 4=None, 5=Others (specify)………* ***Ethnicity:*** *1=Dagomba, 2=Gonja, 3=Vagla, 4=Dagaati, 5=Wali, 6=Sissala, 7=Guru, 8=Kasen, 9=Bulu, 10=Kusasi, 11=Fulani, 12=Konkomba, 13=Binmoba, 14=Mamprusi, 15=Nanumba, 16=Bassari, 17=other (specify)…………*		

15. Please I may like to know your opinion or concern on this study that you may want to share with us

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THANK YOU FOR YOUR PARTICIPATION