

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

**The Contribution of Conservation Agriculture to Production Efficiency and Household
Welfare in Zambia**

Dissertation

Submitted for Doctoral Degree

awarded by the Faculty of Agricultural and Nutrition Sciences

of the

Christian-Albrechts-Universität zu Kiel

Submitted

M.Sc. Abdul Nafeo Abdulai

born in Ghana

Kiel, 2016

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werden.

Dedication

I dedicate this Thesis to my parents Alhaji Abdulai Issahaku Gbamebegu and Hajia Azaratu Abdulai and to my beloved wife Tanko Sahada for their support and prayer

Acknowledgement

All praises are due to Allah, the Most Gracious, the Most Merciful, the Architect of my life and this work. I am indebted to several individuals and institutions for their contributions to the realization of this milestone. I humbly acknowledge the immense support from my mentor Prof. Dr. Awudu Abdulai who supervised this work. His fatherly advice and encouragement is immeasurable in the journey to this mission. Thanks also to members of my doctoral exam committee; Prof. Dr. Martin Schellhorn, Prof. Dr. Heß, Prof. Dr. Diekötter and Prof. Dr. Christian H. Henning. A special acknowledgement is to the Deutscher Akademischer Austauschdienst (DAAD) for the opportunity and financial support extended to me and my family for the entire study period. I also wish to express my profound gratitude to Rob Moss, Hans Perk and the management of Solidaridad West Africa and Conservation Farming Unit of Zambia for their unflinching support in this noble course. I cannot forget my parent parents Alhaji Abdulai Isshakaku Gbambegu and Hajia Azaratu Abdulai, my wife Tanko Sahada and my kids Abdul Nafeo M.K. Suhiyini, Abdul Nafeo T. Jawad, Abdul Nafeo H. Maltiti and Abdul Nafeo N. Kasi for their unwavering and inestimable support towards the fulfilment of this goal. Same goes to the entire Gbambegu family. I also offer my hearty thanks to my colleagues at the University of Kiel; Dr. Linda Kleemann, Dr. Kai-Brit Bechtold, Dr. Rakhshanda Kousar, Dr. Silke Thiele, Dr. Rebecca Illichmann, Dr. Jan Dithmer, Dr. Christian Kulhgatz, Dr. Lukas Kornher, Dr. Taiwo Osun, Dr. Victor Owusu, Dr. Kolawole Ogundari, Dr. Steffi Dierks, Dr. Muhammad B. Bello, Dr. Sohail A. Makhdum, Wanglin Ma, Ding Zhao, Daniela Lueth, Anna Röhlig, Anna Heller, Abdul-Rahaman Awal, Issahaku Gazali, Shahzad M. Faisal, Jonas Peltner, Nelli Betke, Lawrence O. Oparinde, Marie Kamrad, Christian Levke, Anna Tigges, Christoph Richartz, Corinna Schoppe and Nicola Benecke. I share the joy and success of this noble work with you all.

Kiel, July 2016

Abdul Nafeo Abdulai

Abstract

Sustainable agriculture is deemed to have environmental, social and economic opportunities for growers, laborers, consumers and policymakers in the entire food system. It is been documented that, the common conventional farming practices in developing countries, which involve frequent ploughing of farm lands, slash- and-burn and monoculture operations gradually degrade the physical and chemical qualities of tropical soils, including those in sub-Saharan Africa. To restore soil health, mitigate the detrimental impacts of climate change and facilitate the attainment of food and nutrition security, especially in SSA, it is imperative to either harness existing knowledge or adopt new technologies. Several pieces of evidence indicate that agricultural production systems like conservation agriculture technology have the potential to rehabilitate degraded soils and improve productivity in a sustainable manner. To motivate the adoption and diffusion of conservation agriculture technology and to sustain the use of the technology in SSA calls for a comprehensive study to understand the prospects of conservation agriculture in relation to economic, environmental and social attributes of sustainable agriculture. Notably, the history of conservation agriculture technology in SSA is linked to maize-based production systems mainly focusing on economic and environmental indices of sustainability. In contrast, this study contributes to the literature by being the first of its kind to holistically examine conservation agriculture of maize farmers with reference to economic, social and environmental indices of sustainability. The study first examines allocative and scale efficiency and the determinants of inefficiency among maize farmers in Zambia, using a zero-inefficiency stochastic frontier model to account for both inefficiency and full efficiency to ensure unbiased efficiency estimates. Second, this study employs a discrete time duration model to explore the role of peer effects through farmers' social and institutional networks as well as farmers' risk attitude in the adoption and diffusion of conservation agriculture technology. In particular, a principal components analysis is employed to compute latent

variables that are important in analyzing the impact of information transmission from stock of adopters that the farmer associates with, access to extension services and access to farmers' associations. To the extent that farmers consider the impact of risk in the technology diffusion process, profit moments including, mean, variance, skewness and kurtosis are used to determine upward and downward risks. Also, a selectivity-corrected meta-frontier approach that accounts for potential selection bias and technology heterogeneity is employed to explore the impact of conservation agriculture on environmental efficiency of maize farmers, with respect to nitrogen fertilizers recovery. Finally, the determinants of adoption and impact of conservation agriculture technology adoption on farm output, throughput accounting ratio and poverty situation of households in Zambia are estimated. The empirical results show that, unlike the stochastic frontier model, the zero-inefficiency stochastic frontier model successfully allows for both fully efficient and inefficient firms to be accounted for in the estimation procedure. The estimates also reveal the presence of scale economies, with the zero-inefficiency stochastic frontier model better predicting scale efficiency compared to the stochastic frontier model. Furthermore, farmers practicing conservation agriculture are environmentally more efficient than conventional farmers. Also the adoption of conservation agriculture technology increases maize output and farm throughput accounting ratio but reduces household poverty. The results also reveal that farmers' years of schooling, risk preferences, social networks, access to credit, extension services and machinery as well as soil quality positively influence adoption and diffusion of conservation agriculture technology. The findings also show that inefficiency is explained by the level of education, access to extension services, distance to markets, access to credit, gender and land ownership.

Zusammenfassung

Nachhaltiger Landwirtschaft werden ökologische, soziale und ökonomische Chancen für Landwirte, Arbeiter, Konsumenten als auch politische Entscheidungsträger im gesamten Nahrungsmittelsektor zugesprochen. Es ist jedoch belegt, dass übliche, konventionelle landwirtschaftliche Praktiken in Entwicklungsländern, welche mit einem regelmäßigen Pflügen des Ackerlandes, Brandrodungen als auch Monokulturen im Zusammenhang stehen, die physikalische und chemische Qualität tropischer Böden, einschließlich derer in Ländern südlich der Sahara (SSA), sukzessive degradieren. Um die Bodengesundheit wiederherzustellen, die negative Einflüsse des Klimawandels zu lindern und die Errungenschaften von Nahrungsmittel- und Ernährungssicherheit, gerade in SSA, zu fördern ist es absolut notwendig sich existierendes Wissen zu Nutzen zu machen oder neue Technologien zu einführen. Verschiedene Belege deuten darauf hin, dass landwirtschaftliche Produktionssysteme, wie ressourcenschonende landwirtschaftliche Systeme, das Potenzial dazu haben, geschädigte Böden wieder herzustellen und die Produktivität auf eine nachhaltige Art und Weise zu verbessern. Um die Annahme und Verbreitung ressourcenschonender landwirtschaftlicher Systeme voranzutreiben und die Nutzung von Technologien in SSA zu unterstützen ist eine umfassende Studie über die Aussichten von ressourcenschonender Landwirtschaft erforderlich, um Erkenntnisse über nützliche ökonomische, ökologische und soziale Eigenschaften nachhaltiger Landwirtschaft zu erlangen. In der Vergangenheit wurde ressourcenschonende Landwirtschaft in SSA, mit dem Hauptschwerpunkt auf Wohlfahrtseffekte der Nachhaltigkeit, im direkten Zusammenhang mit Mais-basierten Systemen betrachtet. Im Gegensatz dazu, ist die vorliegende Studie die erste ihrer Art, die ressourcenschonende landwirtschaftliche Tätigkeit von Maisbauern in Sambia ganzheitlich betrachtet und dabei sowohl Wohlfahrtseffekte, als auch die Auswirkungen auf Lebensumstände und den gesamten Planeten berücksichtigt. Zunächst untersucht die Studie durch die Nutzung eines Zero-Inefficiency-Stochastic-Frontier-Modell, Allokations- und Größeneffizienz, sowie die Einflussfaktoren von Ineffizienzen bei Maisbauern in Sambia. Dadurch können sowohl Ineffizienzen, als auch vollkommene Effizienz berücksichtigt werden, was eine unverzerrte Schätzung garantiert. Zweitens nutzt die Studie ein diskretes Durationsmodell, um die Rolle von Gruppeneffekten durch soziale und institutionelle Netzwerke der Landwirte, als auch deren Risikobereitschaft bezüglich der Annahme und Verbreitung von ressourcenschonenden Landwirtschaftstechnologien zu untersuchen. Genauer wird eine Hauptkomponentenanalyse (Hauptkomponentenanalyse) genutzt um latente Variablen zu erzeugen, welche für die Analyse des

Einfluss von Informationsübertragungen von Nutzern ressourcenschonender Landwirtschaft, mit denen die Landwirte in Verbindung stehen, auf den Zugang zu Beratungsdiensten und landwirtschaftlichen Organisationen, notwendig sind. Sofern Landwirte den Einfluss des Risikos im Verbreitungsprozess von Technologien berücksichtigen, werden die Momente der landwirtschaftlichen Gewinne, wie Mittelwert, Varianz, Schiefe und Kurtosis genutzt, um Chancen und Risiken zu bestimmen. Des Weiteren wird ein selektivitätskorrigierter, stochastischer meta-frontier-Ansatz, welcher Selektionsverzerrung und technologische Heterogenität berücksichtigt, genutzt, um den Einfluss von ressourcenschonender Landwirtschaft auf die ökologische Effizienz von Maisbauern, in Bezug auf Stickstoffdüngemittel Rückgewinnung, zu untersuchen. Abschließend werden die Einflussfaktoren der Annahme, sowie der Einfluss der Annahme ressourcenschonender Technologien auf den Output der bäuerlichen Betriebe, die Durchsatzrate und die Armutssituation sambischer Haushalte geschätzt. Die empirischen Ergebnisse machen deutlich, dass das Zero-Inefficiency-Stochastic-Frontier-Modell, im Gegensatz zum Stochastic-Frontier-Modell, erlaubt vollständige effiziente, als auch ineffiziente Firmen in das Schätzverfahren aufzunehmen. Ebenso wird das Vorhandensein von Skaleneffekten mit dem Zero-Inefficiency-Stochastic-Frontier-Modell besser gezeigt, als durch das einfache Stochastic-Frontier-Modell. Des Weiteren weisen Landwirte mit ressourcenschonender Landwirtschaft eine höhere ökologische Effizienz als konventionelle Landwirte auf. Darüber hinaus erhöht die Annahme ressourcenschonender landwirtschaftlicher Technologien den Mais-Output und die Durchsatzrate des landwirtschaftlichen Betriebs während sie die Armut der Haushalte verringert. Die Ergebnisse ergeben weiter, dass die Jahre der schulischen Ausbildung der Landwirte, ihre Risikopräferenzen, soziale Netzwerke, Zugang zu Krediten, Beratungsdienste und maschinelle Anlagen, ebenso wie die Bodenqualität, die Annahme und Verbreitung von ressourcenschonenden landwirtschaftlichen Technologien positiv beeinflussen. Die Resultate zeigen zudem, dass Ineffizienz durch den Bildungsgrad, den Zugang zu Beratungsdiensten, die Entfernung der Betriebe zu Märkten, den Zugang zu Krediten, dem Geschlecht und Grundbesitz, erklärt werden kann.

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Chapter 1

General Introduction

1.1 Background

Over the last half-century, the Green Revolution has transformed agricultural practices and contributed to substantial increases in global food production. This focused on the cropping of higher-yielding varieties, and intensification in the use of high levels of complementary inputs, such that fertilizers replaced soil quality management, while the use of herbicides for weed control became a substitute for crop rotation (Swaminathan, 2013). This phenomenon has correspondingly contributed to the depletion of natural resources of many agro-ecosystems. Thus, endangering future productivity, and burdening the environment with greenhouse gas emissions, and other negative externalities such as nitrate run-off from excessive fertilizer application, as well as soil degradation (Godfray et al., 2011). In the light of imminent climate change-related risks, it is further worrying to note that agricultural practices (including deforestation) account for about one third of greenhouse gas emissions (Rosenzweig and Tubiello, 2007).

In spite of these challenges, it is projected that the world population will soar from 7 billion to 9 billion between now and 2050 (Alexandratos and Bruinsma, 2012). Moreover, in the short to medium terms, agriculture through food production systems will be pivotal to the attainment of the 2030 agenda for sustainable development. In particular, agriculture will be a major driver for the attainment of sustainable development goal (SDG) II, targeted at ending hunger, achieving food and nutrition security and promoting sustainable agriculture by 2030 (UN, 2015; FAO, 2016). As noted by Bruinsma (2009), within the context of current trends, it is estimated that agricultural production must increase by 70 percent globally, and by almost 100 percent in developing countries in order to meet food demand alone by 2050.

The outmost challenge therefore rests on how to surmount the constraints of conventional production systems and shore up production to match-up with current and burgeoning future

demands for food, feed and fibre in a sustainable manner¹. In effect, nothing short of a new agricultural production paradigm is needed to attain sustainable production (McIntyre et al., 2009; Godfray et al., 2011; Jat et al., 2014; Manda et al., 2015). In particular, Godfray et al. (2011) indicate that concentrating on sustainable production systems has the potential to simultaneously increase yields, improve input use efficiency and reduce the negative environmental effects of food production.

Among others, soil health is a prerequisite to sustainable crop production, especially given that about 99% of world food comes from the soil (Jat et al., 2014). It is common knowledge that, even with the best planting materials and complementary inputs, the agronomic potential of crops cannot be achieved on a degraded soils with multi-physical, chemical and biological constraints. It is worth noting that, although not all agricultural practices necessarily lead to the degradation of soil quality, it is obvious that poor tillage practices will have a heavy toll on soil quality, which will in turn impacts negatively on the sustainability of the production systems. Verhulst et al., (2010) indicated that, the rampant degradation and severe decline of soil quality from agricultural activities raise questions on how sustainable current agricultural production practices are.

It is proven that conventional farming practices, including frequent ploughing of land gradually degrade the soil physical structure, cause soil compaction, accelerate soil erosion and decrease the chemical biological quality of soils. (e. g. Eswaran et al., 2001; Brady and Weil, 2007; Lumpkin and Sayre, 2009). These have led to progressive organic matter depletion, contamination of water bodies by sediments, decline of family farms, increasing costs of production, continues neglect of the living and working conditions for farm laborers, as well as disintegration of economic and social conditions in rural communities. Jat et al. (2014) further indicate that due

¹ Conventional production includes practices such as crop residue burning or deep soil inversion to control weeds and prepare the seedbed (FAO, 2001).

to ploughing, soil particles become finer, allowing less moisture to enter the soil system and less to be retained for uptake by crop roots. Also, higher temperatures lead to faster organic matter depletion and soil fertility decline is much faster in the tropical than temperate areas. This development is more disturbing for sub-Saharan Africa (SSA), where average productivity is relatively low.

To restore soil health, mitigate the detrimental impacts of climate change and facilitate the attainment of the SDG II, especially in SSA, it is imperative to either harness existing knowledge or adopt new technologies. Specifically, it is argued that existing scientific knowledge and technologies have the potential to decreasing the yield gaps within and between countries and increase average yields by two to three fold in many parts of Africa (Godfray et al., 2011). Several pieces of evidences from developing countries show that farm practices that conserve resources improve on the supply of environmental services and increase productivity (Swaminathan, 2013). For instance, a review by Pretty et al., (2006) of 286 agricultural development projects in 57 low-income countries, covering 37 million hectares, demonstrate that average crop yields increase by 79%, through more efficient use of water, reduced use of pesticides, carbon sequestration and soil quality improvement.

Moreover, it is widely documented that agricultural production systems like conservation agriculture technology have the potential to rehabilitate degraded soils and improve productivity in a sustainable manner (e.g. Verhulst et al., 2010; Godfray et al., 2011; Swaminathan, 2013; Jat et al., 2014; Manda et al., 2015). In conservation agriculture technology, less than 15 % of the soil surface is tilled, about 30% of soil surface is covered with organic residue, and there is judicious selection of crop species including legumes for rotation, either in sequence or association. This phenomenon is meant to simultaneously enhance the soil structure, rooting environment, nutrients and moisture retention, and to avoid the build-up of pests and diseases. Hence, even with seasonal cropping on a particular piece of land, there will be no detrimental effect on yields (Vaneph and

Benites, 2001).

The Nebraska (2013) and Lusaka (2014) declarations on conservation agriculture (CA) and Climate Smart Agriculture pillars of the FAO (2013), further suggest that a carefully implemented conservation agriculture (CA) technology can serve as a vehicle to sustainable agriculture. In the light of these, CA is being promoted as a sustainable agricultural system in SSA. In particular, Mazvimavi et al. (2012) show that in Zimbabwe, CA has a significant contribution to total maize production averaging 50% of output share. Also, CA adoption is being considered as a significant measure for the amelioration of the effects of greenhouse gas emissions on global climate change. Furthermore, with the emergence of carbon credit payments to farmers, including those in SSA, further financial benefit could accrue to CA adopters (COMOCO, 2014; FAO, 2015).

It is estimated that, from 1999 to 2003, CA adoption grew from 45 million ha to 72 million ha and further grew to 111 million ha by 2009 worldwide (Derpsch et al., 2009). According to Kassam et al. (2014), CA is currently being practiced on nearly 155 million ha globally. Brazil is touted as the most famous CA success story and the main tropical country that has developed CA into commercial farming. The dissemination of CA in Brazil is credited to a combined effort of initiatives from farmers and farmers' associations, research, policy, NGOs, public as well as private sector networks (Lahmar, 2008).

In general, CA has five main objectives including; (i) simultaneous achievement of increased agricultural productivity and enhanced ecosystem services; (ii) enhanced input-use efficiency, including water, nutrients, pesticides, energy, land and labour; (iii) judicious use of external inputs derived from fossil fuels (such as mineral fertilizers and pesticides) and preference for alternatives (such as recycled organic matter, biological nitrogen fixation and integrated pest management); (iv) protection of soil, water and biodiversity through the use of 'minimum soil surface disturbance' and maintaining organic matter cover on the soil surface to protect the soil and enhance soil organic matter and soil biodiversity; and (v) use of managed and natural biodiversity of species to build

systems' resilience to abiotic, biotic and economic stresses, with an underlying emphasis on improving soils organic matter content as a substrate essential for the activity of the soil biota (Kassam and Friedrich, 2011).

Historically, CA adoption in SSA often relies on donor projects or a combination of “push” and “pull” factors aimed at changing the status quo (Baudron et al., 2009)². For instance, CA adoption in Ghana used to be significant, but stagnated after donor funding and promotion ended (Milder et al., 2011). Mazvimavi and Twomlow (2009) argue that there is evidence that farmers who have lower risks have adopted CA without external incentives, especially by learning from neighbors. However, in most cases, vulnerable smallholders in SSA are unlikely to adopt CA spontaneously. The FAO (2010) labels Zambia and eleven other countries as CA focal countries in Africa, with Zambia as the most successful story in the region³. In spite of the potential benefits from CA, like many other technologies in SSA, of the 155 million ha of global CA adoption, only 1.2 million ha is in Africa, and practiced on about 200, 000 ha in Zambia (Kassam et al., 2014).

To motivate the adoption and diffusion of CA and to sustain the use of the technology in SSA requires a comprehensive study on the prospects of conservation agriculture to the realization of economic, environmental and social attributes of sustainable agriculture (Wall et al., 2013). To the extent that much of the history of CA in SSA is linked to maize-based systems, this study contributes to the literature as the first of its kind to examine conservation agriculture from economic, environmental and social lenses of sustainable agricultural, with particular reference to maize farmers in Zambia.

² Pull factors arise when knowledge and resources to do so are adequate and appealing. Push factors may manifest when a crisis or set of substantially new conditions require a response.

³ Angola, Botswana, Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, Swaziland, Tanzania, Zambia, and Zimbabwe

1.2 Conservation Agriculture defined

Conservation agriculture (CA) emerged as a response to land degradation and severe droughts in most important agricultural regions. These include the 1930s dustbowls in the USA, the water erosion in the tropical and subtropical regions of Brazil in the early 1970s, the devastating wind erosion in Canada in the mid-1970s, the droughts in Australia in 1970s and severity of soil erosion and land degradation in many other important agricultural regions (Ribeiro et al., 2007; Jat et al., 2013). Depending on the degree of inclusiveness, practitioners, researchers, and promoters of conservation agriculture use several synonyms including, zero tillage, reduced or minimum tillage, conservation farming, direct drilling, precision farming, as well as resource efficient agriculture to refer to the same concept. The term conservation agriculture (CA) and its principles were adopted in the First World Congress on Conservation Agriculture in 2001, jointly organized by the FAO and the European Conservation Agriculture Federation in Madrid (Vanepf and Benites, 2001). The overarching goal of CA is to make better use of agricultural resources through an integrated soil, water and biological resource management systems, such that, the use of external inputs can be minimized without jeopardizing potential returns (FAO, 2001; Knowler and Bradshaw, 2007).

The FAO (2015) defines Conservation Agriculture (CA) as an approach to managing agro-ecosystems for improved and sustained productivity, increased profits and food security, while preserving and enhancing natural resource base and the environment. It entails the observation of three main principles; 1) continuous minimum mechanical soil disturbance; 2) permanent organic soil cover and 3) diversification of crop species grown in sequence and/or association. In line with farm practices, Phillips and Young (1973) define minimum or no- tillage as a system of planting crops into untilled soils by opening a narrow slot, trench or band only of sufficient width and depth to obtain proper seed coverage. Organic soil cover is a cropping system that maintains a ground cover of 30% from cover crops and crop residues retained including crop residue left after harvest (Anonymous, 1986). Diversification of crop species involves growing crops, mainly annuals in

sequence through rotation or association, and for perennials, including a balanced mix of legume and non-legume crops (Friedrich et al., 2016).

Milder et al. (2011) indicate that these principles are indications that conservation agriculture would nourish and enhance the natural biological processes that support soil fertility, nutrient cycling, and hydrological cycling by contributing to boost crop yield, reduce the need for external inputs, increase farm profitability, and reverse land degradation. Paudel et al. (2011) indicate that precision farming technology of CA is generally touted to have both increased profit and environmental quality. Golden Valley Agricultural Research Trust GART (2004) of Zambia, indicates that, cover crops are able to sequester CO₂ considering their large photosynthesis activities through the capture, conversion and store CO₂ in the soil. CA practices that sequester soil organic matter contribute to environmental quality and the development of sustainable agricultural systems. Feder and Umali (1993) also argue that CA is sustainability focused as it seeks to provide income, utility and innovation benefits.

1.3 Conservation Agriculture in Zambia

In Zambia, the conservation agriculture (CA) technology is being implemented by the Zambian National Farmers Union (ZNFU), led by the Conservation Farming Unit (CFU) and the Golden Valley Agricultural Research Trust (GART) since 1996, the government and non-governmental organizations. The adoption and promotion of CA technology in Zambia is aimed at optimizing the use of purchased inputs, increasing crop production and productivity, improving household incomes, mitigating adverse climate change impacts, reducing incidence of labor constraints, diversifying crop production and improving soil fertility as well as food and nutrition security (Haggblade and Tembo, 2003; Kassam et al., 2009; NAIP, 2013). On the assumption that it is unrealistic for farmers to adopt sustainable practices like CA without policy and institutional support, couple of CA technology policy pronouncements and programs have been pursued by the

Zambian Ministry of Agriculture and Livestock (e.g. FNDP, 2006; SNDP, 2010; NAIP 2014-2018)⁴.

Although, Zambia is considered as a success story for the adoption of CA in SSA (FAO, 2009), from policy perspective, and like many technologies introduced in SSA, the adoption of CA technology in Zambia can still be considered to be slower than expected⁵. For instance, whilst it was envisaged that by the year 2015, about 600,000 Zambian smallholder farmers (about 50% of national total) should have adopted CA principles on their farms, only 75,000 Zambian smallholder farmers practiced conservation agriculture in 2003 and 200,000 by 2013 (Hagglade and Tembo, 2003; Kassam et al., 2014). That notwithstanding, the relative slower adoption rate is not a justification that actual welfare impacts do not accrue to adopters of improved technologies (Bellon et al., 2006; Becerril and Abdulai, 2010).

The ZNFU considers CA as an integrated technology including concentrating tillage and fertilizer (synthetic and or organic) in permanent rip lines or planting stations, retaining crop residues after harvest and inter-cropping or rotating crops with nitrogen fixing legumes on up to 30% of the cultivated area. Completing land preparation before the onset of planting-rains to take advantage of nitrogen flush is important in CA technology in Zambia. The early land preparation and planting is very critical to crop yield as maize yields fall by 1–2% for every day planting is delayed after the first possible planting date, while cotton losses are estimated at 250–350 kg/ha per week delayed (Hagglade and Tembo 2003). CA does not exclude the use of external inputs, hence adequate weed control with herbicides, liming and chemical fertilizer application form part of the CA practices in Zambia. The ZNFU also promotes the cropping of complementary perennials such

⁴ Fifth National Development Plans (FNDP); Sixth National Development Plans (SNDP); National Agriculture Investment Programme (NAIP).

⁵ It is estimated that only about 200,000 farmers had adopted CA in Zambia by the year 2013 compared to the expected 600,000 by 2015.

as *Faidherbia albida* (a leguminous tree), and live fences. In effect, the ZNFU therefore advocates that CA must involve maintaining an environment in the crop root-zone that optimizes soil biota, such that plant roots are able to access the requisite nutrients and water, making minimum tillage the most important CA operation across Zambia (Kassam et al., 2009).

Often not all these principles have been applied as farm household are constrained with numerous challenges (Giller et al., 2009; Wall et al., 2013). A recent survey by Chapoto et al. (2016) suggests that in 2013/ 2014 production season, 58% of maize producing households in Zambia practiced the rotation of cereals with legumes, while 46% were leaving crop residues on the field and incorporating it into the soil. Minimum tillage is implemented either manually by digging of planting station (basin technology) or ripping. The basins are permanent planting stations measuring 30 cm long, 15 cm wide and 15–30 cm deep per planting season. Depending on the interrow spacing and the level of precision, between 15,700 and 19,000 basins are prepared per hectare. Seeds and other inputs like lime, fertilizer, manure or compost are precisely placed in the basins. This practice only disturbs the soil where the crop will be established, leaving the surrounding soil untouched. Good basins should improve water harvesting and infiltration.

Ripping is a form of reduced tillage like permanent basins where grooves are created in the soil for seeds to be planted and nutrients applied. It could be oxen-based, where a Magoye ripper⁶ is mounted normally on trained bullocks for making of ripe line or mechanized, where a mechanized ripper is mounted on a tractor for ripping. Good ripped lines like basins should improve water harvesting and infiltration. It is recommended by the ZNFU that the ripe lines should be permanent (as in basins) and spaced 75–90 cm apart every year even if crops are rotated. The principle is that, only the crops in the ripped lines will benefit from the nutrients, moisture and other soil substrates.

⁶ The Magoye ripper is a Zambian innovation which was developed at Zambian Ministry of Agriculture and Cooperatives research station of Magoye. About 4000 to 6000 CA farmers in Zambia used the Magoya ripper during 2002/03 season (Haggblade and Tembo, 2003)

Ripping (especially mechanized) is deemed to be an ideal way to break the hardpan underneath of degraded and continuously ploughed land.

It is recommended that, to break the hardpan and take advantage of nitrogen flush as well as increase water infiltration and moisture retention, ripping should be done during the dry season just before the onset on the planting rains (Jonsson and Oscarsson 2002; Nolin and von Essen 2005). The basin technology is the most accurate in depth and width for planting stations as well as fertilizer application rate compared to the ripping technologies. However, the basin system is labor intensive and mainly limited to small scale operations compared to the mechanized and oxen ripping technologies. In hard and rocky soils, the basin and oxen technologies are difficult to implement. Despite the advantages of mechanized ripping, including commercialization, only 1% of maize producing households in Zambia use it compared to 10.7% for oxen ripping and 11.4% for basins (Chapoto, 2016).

1.4 Geographical and agro-ecological structure of Zambia

The Republic of Zambia is a resource-endowed country with massive mineral deposit (especially copper). It is based in southern Africa, and located between latitudes 8° and 18° south and longitudes 22° and 34° east. The country is bordered by the Democratic Republic of Congo to the north, Tanzania to the north-east, Malawi to the east, Mozambique, Zimbabwe, Botswana and Namibia to the South, and Angola to the west. Zambia covers a total land mass of 752,612 square kilometers, with an estimated population of about 15,474,000 people in 2015. It has ten administrative provinces and 107 districts, with Lusaka as the Capital town (CSO, 2013). See the map of Zambia in figure 1 below.

The country has three main topographical features namely, mountains with an altitude of at least 1,500 meters above sea level, plateau area with an altitude ranging from 900 to 1,500 meters and lowlands with an altitude between 400 and 900 meters. The climate in Zambia is best described

as tropical wet-dry climate controlled by moist, warm equatorial and maritime tropical air masses characterized by three distinct seasons; a cool and dry season from May to August, a hot and dry season from September to November and a warm and wet season from December to April.

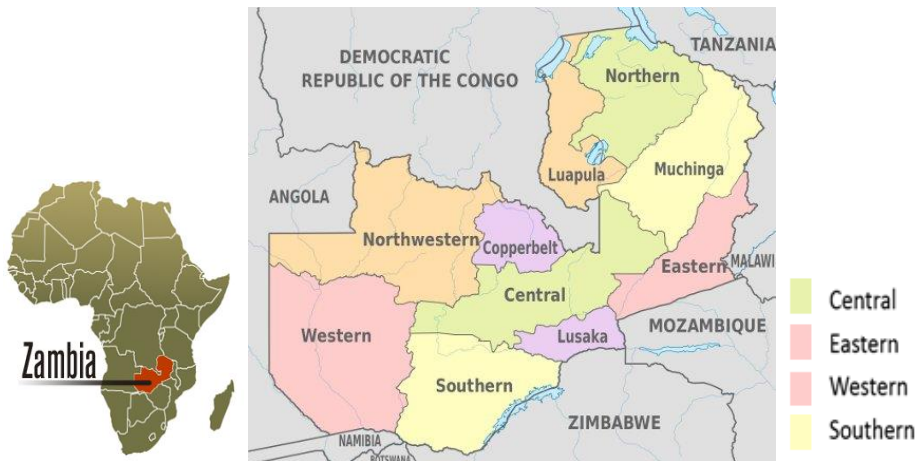


Figure 1: Map of Zambia.

Source: Bingham et al. (2016).

http://www.zambiaflora.com/images/zambia_administrative_divisions.png

Like many SSA countries, Zambia experiences a unimodal rainfall pattern with average rainfall ranging from 650 to 1500mm per annum. Depending on annual rainfall, Zambia is classified into three major ecological zones presented in figure 2. Region I constitutes about 12% of the land area of Zambia and covers parts of Southern, Eastern and Western provinces. It is characterized by loamy to clayey soils in the valley floor and course to fine loamy shallow soils in the escarpment. It experiences less than 800 mm of rainfall annually. The region has potential for production of irrigated crops, like winter maize and most suitable for cotton, sesame, sorghum and millet production. Except for the valley part which is consequently hot and humid, the region is suitable for extensive cattle production.

Region II is sub divided into Region IIa and IIb and in total constitutes 42 % of the country, covering the Central, Lusaka, Southern and Eastern provinces. Soils in the area are inherently

fertile. Annual rainfall in the region averages between 800 to 1,000 mm. In Region IIa a variety of crops including, maize, cotton, tobacco, sunflower, soy beans, irrigated wheat and groundnuts are grown. This region is also suitable for flowers, paprika and vegetable production. Region IIb covers Western province and dominated by sandy soils. It is suitable for production of cashew nut, rice, cassava and millet, including vegetable and timber production. The region is also highly suitable for cattle and poultry production. Region III is associated with high annual rainfall, mostly high than 1,000 mm up to 1,500 mm. It constitutes 46 % of the country's total land area, comprising Copperbelt, Luapula, Muchinga, Northern and Northwestern provinces. With the exception of the Copperbelt, soils in the region are highly leached and acidic. The area has a potential for the production of millet, cassava, sorghum, cowpeas, groundnuts, coffee, sugarcane, rice and pineapples. Irrigation and fish farming are also part of the agricultural potential of the Region.

1.5 Poverty profile of Zambia

As in many sovereign states, the Government of the Republic of Zambia (GRZ) considers poverty as an important indicator of household welfare and national development. The Central Statistics Office (CSO) of Zambia is often commissioned by government to conduct household surveys and report among others, on the poverty statistics of Zambia since the 1960s.

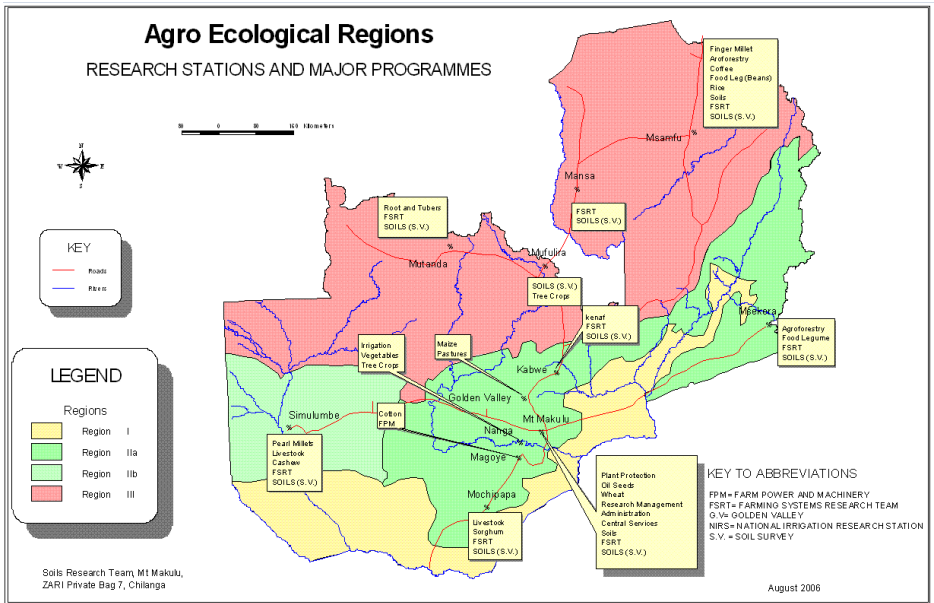


Figure 2: Agro-ecological Regional Map of Zambia (2006)

These surveys assess the living conditions of Zambians, measure progress and results of development, and provide information on indicators contained in the National Development Plan. The Living Conditions Monitoring Surveys (LCMSs), which evolved from the Priority Surveys of 1991 and 1993 has become the primary source for estimations of poverty within the country (Chibuye, 2011; de la Fuente et al., 2015).

Over the past decade, Zambia has achieved high and sustained growth, as well as macroeconomic stability and now considered a lower middle-income country. Much of this economic growth was observed during the implementation of the Fifth National Development Plan (2006) implemented from 2006 to 2010, where the economy grew at an average of 6% compared to -2% in 1995. However poverty level remains high (CSO, 2012; IMF, 2012; de la Fuente et al., 2015). Recent studies by de la Fuente (2015) and Chapoto et al. (2016) indicate that average Zambian poverty headcount in 2015 was between 60 – 76%, while 61 - 69.5 %, 68 - 75.8%, 79 - 84.3 % and 80-83% are poverty levels for the Central, Southern, Eastern and Western provinces,

respectively. The national average does not seem to be different from the 74% percent of 1993. These studies also indicate average rural poverty of 73.3% in 2015, compared to 84% in 1993 (Chibuye, 2011).

The government is committed to reducing poverty as well as food and nutrition insecurity through the implementation of sustained economic growth and poverty reduction in a Sixth National Development Plan (SNDP) [2011], focusing on broad-based pro-poor growth, employment creation and human development. Among others, the Constituency Development Fund and the targeted Social Cash Transfer Scheme are being scaled up to supplement household incomes and to reduce extreme poverty and its inter-generational transfer. Also the Food Security Pack program, which provides small packages of seed and fertilizer to targeted agricultural households is a flagship national social transfer program aimed to address poverty and food and nutrition insecurity.

1.6 Agricultural Sector of Zambia

The Zambian economy is primarily driven by mining, agriculture, construction, transport and communication sectors. Although the fiscal budget of the government of Zambia is historically financed by revenue from mineral exports (especially copper), the agricultural sector remains the most important source of livelihood and source of employment in Zambia. The agricultural sector is key to the development of the Zambian economy and will be the engine of growth for the next decade and beyond. It contributes about 20% to the country's real GDP as well as 39% of earnings from non-traditional exports and 10% of total export earnings. It also employs over 70% of the country's population, with 78% women and 69% of men engaged in agriculture. Increase in rural incomes from agriculture will therefore result in overall poverty reduction and increased food and nutrition security (Sitko et al., 2011).

In spite of the significant contribution of agriculture to the Zambian economy, government budgetary allocation to the sector has been hovering around 6%, which is below the 10% Maputo

Declaration (2003) target under the Comprehensive Africa Agriculture Development Programme (CAADP). It is however argued that, taking into account the supplementary budget for the procurement of surplus maize under the Food Reserve Agency, actual government spending on agriculture and rural development has been exceeding 10% of its total budget since 2007 (NAIP, 2014). The crop and livestock sub-sectors dominate the agricultural landscape and consume about 88% of the agricultural budget of Zambia (SNDP, 2011). The production season normally starts in November and ends in May with higher precipitation between January to March. With its high dependence on unpredictable and unevenly distributed rains, the agricultural sector is often prone to droughts.

It is estimated that about 58% of Zambia's total land area (about 39 million ha) is classified as having medium to high potential for agricultural production, but only 15 percent of the potential arable land is cultivated (ZDA, 2013). This suggests that there is a great potential for expanding and improving production and productivity, using the countries' fertile land resource base, favorable climatic conditions and abundant water resources for irrigation (Sitko et al, 2010). Moreover, the FAO indicates that Zambia has about 500,000 ha potential irrigable land for farming, yet until 2008 less than 30% of the potential irrigable area was utilized. Since then 200,000 ha have been equipped for irrigation of wheat, sugar cane, vegetables and fruit production (Mendes et al., 2014).

Based on the scale of production unit, Zambian farmers are categorized into small-scale farmers (< 5 ha), medium-scale or emergent (5-20 ha) and large-scale (> 20 ha). The small-scale farmers are mainly subsistent farmers who use few external inputs and predominantly use hand hoes for cultivation. About 72% of all small-scale farm households cultivate less than 2 hectares of land annually and are incapable to produce enough surplus for sale in order to benefit from government spending on agriculture. The medium-scale farmers use improved seeds and fertilizers and sell most of their production. These farmers commonly use a combination of manual, animal

draft power and tractors. Large-scale commercial farmers apply high levels of purchased inputs and use oxen or machinery for farm operations. They produce almost exclusively for direct market sale or feed their grain to livestock kept on the farm. Large-scale farmers make up only 4% of farm households, but cultivate 22% of all cropped land (Sitko et al., 2011).

1.7 Maize Production in the study area

Maize is a major food staple in Zambia, with an annual per capita consumption of about 133 kilograms. It supplies over half of Zambian household calories requirements and its availability is the main indicator to judge the country's food and nutrition security status (CSO, 2012, World Bank, 2013). The most developed crop market in Zambia is the maize market, under the Food Reserve Agency regulated by the *Zambian Food Reserve Act, 2005*. Like most Sub-Saharan Africa (SSA) countries, in normal years Zambia nears self-sufficiency in maize, imports in bad years, and exports in good years. The agricultural crop sector of Zambia is biased towards maize with about 89% of households in Zambia growing maize, compared to 51% and 34% for groundnuts and cassava (second and third), respectively. In terms of total land area allocated to crops, this corresponds to about 54%, 8% and 11% for maize, groundnut and cassava, respectively. In the same vein, the proportion of household involved in the production of maize in the Central, Eastern, Southern and Western provinces of Zambia are 95.0%, 99.5%, 94.7% and 86.0%, respectively, with 90.4 % men and 86.3% women participants (Chapoto et al, 2016).

On average, farmers in Zambia produce about 2.6 metric tonnes per hectare (tons/ha) of maize with fertilizer and 1.4 tons/ha without fertilizer, which is far below the 5 tons /ha under Comprehensive Africa Agriculture Development Programme (CAADP). Maize yields with fertilizer in the Central, Eastern, Southern and Western provinces are about 2.5, 2.6, 1.9, and 2.0 tons/ha, respectively. For maize production without fertilizer, about 1.7 ton/ha is recorded for Central province, 1.6 tons/ha for the Eastern province, 1.2 tons/ha for the Southern province and

0.9 tons/ha for the western province.

1.8 Structure of the Thesis

This study is a collection of journal articles and structured as follows. In chapter 2, the study examines allocative and scale efficiency of maize farmers in Zambia. To the extent that efficiency varies widely across farms in under-developed economies including Zambia, it is important that in measuring farm efficiency, we employ techniques that account for both inefficiency and full efficiency to ensure unbiased efficiency estimates. Over three decades now, the commonly used stochastic frontier model assumes that all firms are inefficient. In this specification, inefficiency is non-negative, and the probability of inefficiency being exactly zero is also zero. In this study, we employ a zero-inefficiency stochastic frontier model to examine farm household efficiency, focusing on allocative efficiency and the key determinants of efficiency among Zambian maize farmers.

Given that allocatively efficient households are not necessarily scale efficient, this study also explores scale economies among these farm households using zero-inefficiency stochastic frontier model. The results show that, unlike the stochastic frontier model, the zero-inefficiency stochastic frontier model successfully allows for both fully efficient and inefficient firms to be accounted for in the estimation procedure. The estimates also reveal the presence of scale economies, with the zero-inefficiency stochastic frontier model better predicting scale efficiency compared to the stochastic frontier model. The findings also show that inefficiency is explained by the level of education, access to extension services, distance to markets and access to credit.

Chapter 3 examines the role of peer effects through farmers' social networks, as well as institutional networks such as extension services in the adoption and diffusion of conservation agriculture technology. In particular, a principal components analysis is employed to compute latent variables that are important in analyzing the impact of information transmission from stock of

adopters that the farmer associates with, access to extension services and access to farmers associations. Observed variables used for the computation of the latent variable for stock of previous adopters who are farmer's close associates are the stock of previous adopters in the sample, stock of village adopters as well as farmer's close associates within some age and level of education brackets. The latent variable for education is determined using variables like whether farmer has access to extension services, distance to extension outlets and number of extension visits. To compute the access to farmers' association latent variable, membership of farmer associations and frequency of association's meeting attendance variables are used.

To the extent that farmers consider the impact of risk in the technology diffusion process, profit moments including, mean, variance, skewness and kurtosis are used to determine upward and downward risks. Given the discrete nature of measuring the time to technology diffusion process, a dynamic discrete-time hazard model is employed in the estimation of the time path to adoption (Wooldridge, 2010). The empirical results show that conditional on several potentially confounding factors, technology adoption and diffusion is positively and significantly influenced by farmers' access to information from social networks and institutional networks like extension services. Adoption decisions are also found to be significantly influenced by farmers' schooling, access to credit, participation in non-farm work, farm size and farmers' risk preferences.

In chapter 4, the study explores the impact of conservation agriculture on environmental efficiency of maize farmers in Zambia, by comparing nitrogen fertilizers recovery between farms who practice conservation agriculture and those using conventional farming technologies. Compared to the plethora of studies that analyze technical and allocative efficiency of farm households in SSA, a recent meta-analysis by Ogundari (2014) reveals that no study has examined environmental efficiency of farms in the region and in particular on technology heterogeneity. This study therefore contributes to the literature by examining the impact of conservation agriculture on environmental efficiency of maize farmers in Zambia, by exploring the utilization of nitrogen

fertilizers amongst farms practicing conservation agriculture and conventional farming technologies.

This chapter analyzes technical and environmental efficiency of conservation agriculture technology among farmers in Zambia, with particular reference to the use of nitrogen fertilizers. This is within the context that, with the ever growing human population and improving world's food supply, demand for nitrogen fertilizers, from the Haber–Bosch process, which has sustained about half of the human population will continue to increase. On the contrary, some unintended negative externalities in the form of reactive nitrogen arise from the use of nitrogen fertilizers in agriculture (Erismann et al., 2008). In economies like Zambia where farm level measurement of nitrogen efficiency is either expensive or there are non-existing reputable laboratories, a Nitrogen Index tier zero tool (NITZ) developed by the United States Department of Agriculture is employed in generating a nitrogen balance sheet at the farm level. Saynes et al. (2014) were the first to use it in their study of N_2O emissions from nitrogen fertilizer in Mexico. The NITZ is a simple user-friendly tool that conducts a quick assessment of the effects of nitrogen fertilizer or manure management practices without any laboratory measurements.

As conservation agriculture technology may improve farmers' access to better technology, a selectivity-corrected meta-frontier approach is used to account for potential selection bias and technology heterogeneity. The empirical results suggest that farmers practicing conservation agriculture are environmentally more efficient than conventional farmers. The findings also show that, environmental efficiency is significantly influenced by gender, access to credit, farming experience, years of schooling, land ownership and distance to markets. Moreover, farmers practicing conservation agriculture are found to be technically more efficient than those using the conventional technology.

Given that household economic welfare is critical to attaining sustainable agriculture, chapter 5 examines the determinants of adoption and impact of conservation agriculture technology

adoption on farm output, returns on investment and poverty situation of households in Zambia. Following the theory of constraints and estimate the returns on investment along the throughput accounting ratio framework, as there are some sunk costs associated with some of the factors of production like land and family labor. To account for potential selectivity bias from observable and unobservable factors in the estimation strategy, an endogenous switching regression model is employed to estimate the impact of the technology of continuous outcomes like farm output, throughput accounting ratio, poverty gap and severity of poverty, while a recursive bivariate probit model is used in the estimation of a binary outcome like poverty headcount. The empirical findings demonstrate that the adoption of conservation agriculture technology increases maize output and farm throughput accounting ratio and reduces household poverty. Moreover, the results reveal that farmers' years of schooling, social networks, access to credit, extension services and machinery as well as soil quality positively influence adoption of conservation agriculture technology.

The rest of dissertation is organized as follows. Chapter 2 examines allocative and scale efficiency among maize farmers in Zambia using a zero inefficiency stochastic frontier approach. The role of social and institutional networks in promoting the diffusion of conservation agriculture in Zambia is presented in Chapter 3, while chapter 4 estimates the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. In chapter 5, the focus is on Impact of Technology on Household Welfare, including output, throughput accounting ratio and poverty. Chapter 6 presents conclusions and policy recommendations of the study.

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Chapter 2

Allocative and Scale Efficiency among Maize Farmers in Zambia: A Zero Inefficiency Stochastic Frontier Approach

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Abstract

The commonly used stochastic frontier model assumes that all firms are inefficient. In this specification, inefficiency is non-negative, and the probability of inefficiency being exactly zero is also zero. To the extent that efficiency varies widely across farms in under-developed economies, it is important to employ techniques that account for both inefficiency and full efficiency to ensure unbiased efficiency estimates. In this study, we employ a zero-inefficiency stochastic frontier model to examine allocative efficiency and scale economies, as well as key determinants of efficiency among Zambian maize farmers. The results show that, unlike the stochastic frontier model, the zero-inefficiency stochastic frontier model successfully allows for both fully efficient and inefficient firms to be accounted for in the estimation procedure. The estimates also reveal the presence of scale economies, with the zero-inefficiency stochastic frontier model better predicting scale efficiency compared to the stochastic frontier model. The findings also show that inefficiency is explained by the level of education, access to extension services, distance to markets and access to credit.

Key words: Zambia, efficiency measurement, zero-inefficiency

2.1 Introduction

In many developing economies, particularly in sub-Saharan Africa (SSA), improving agricultural productivity remains a necessary condition for economic growth, poverty reduction and improving food and nutrition security (Schaffnit-Chatterjee, 2014). In particular, productivity increases will facilitate the release and reallocation of essential production factors like land, labor, and capital from agriculture to the non-agricultural sectors. As pointed out by Collier and Dercon (2009), the recent experiences of fast growing Asian economies suggests that, increases in agricultural productivity supported by increases in labor productivity is fundamental to the success of developing economies. Evidence from China shows that a large part of the productivity increase in agriculture between 1965 and 1985 is attributable to efficiency improvements, resulting from institutional changes (Fan, 1991).

Efficiency facilitates economic planning of an industry by giving an indication of how much output can be increased without absorbing additional resources (Farrell, 1957). Some of the countries in SSA have recorded modest productivity gains in agriculture after the introduction of economic reforms during the mid-1980s (World Bank, 2013). Wouterse (2010) however argues that, higher yields do not necessarily translate to higher efficiency, as higher yields may simply be due to higher input usage. As noted by Ali and Byerlee (1991), if farmers are reasonably efficient, then increases in productivity require new inputs and technology to shift the production function upward.

In view of the relevance of efficiency to development policy, several studies on farm efficiency have been conducted in developed and under-developed economies using parametric and non-parametric methods (see for example, Abdulai and Huffman, 2000; Murova and Chidmi, 2013; Hart et al., 2015; Andriamasy et al. 2015). These techniques specify inefficiency of decision making units (DMU) to be inherently unobservable and non-negative, premising that the production behavior of a DMU is bounded between full efficiency and inefficiency.

Over the past three decades, the stochastic frontier (SF) model, which is the common parametric efficiency estimation technique, has been widely used to examine efficiency and the determinants of inefficiency among firms. The model specifies the unobserved error of the production, cost, revenue, profit or distance functions to accommodate for both random shock and inefficiency. Given the behavioral assumption of the inefficiency distribution, firms that are fully efficient in the sample of interest cannot be directly observed, hence the probability of having full efficiency is zero. In this regard, the traditional SF model specifications assume inefficiency distribution of all firms without due recognition for probability of full efficiency. Thus, in a given sample even fully efficient firms are assumed to be inefficient. On the contrary, the neoclassical production theory assumes that all firms are fully efficient. These opposing assumptions postulate that, in a given population of similar firms, there is a probability of a firm being fully efficient or inefficient. Failure to account for the presence of subsets of both fully efficient and inefficient firms in an empirical model is therefore likely to bias firm efficiency estimates, either towards inefficiency (as in the SF case) or full efficiency (as in the neoclassical case), and hence sub-optimal firm policies and decisions.

Available empirical evidence also suggest the presence of fully efficient firms in a given sample (e.g. Bos et al., 2010). Recent literature also suggests that some maize farmers in Africa, including Zambia are allocatively and technically fully efficient (e.g. Zalkuwi et al., 2010; Chiona, 2012). However, the efficiency specifications used in these studies are not clear on the specific approach used in identifying these sub-groups in the sample. To overcome this problem, Kumbhakar et al. (2013) proposed a zero inefficiency stochastic frontier (ZISF) model, which accounts for both regimes of fully efficient and inefficient firms. The ZISF⁷ model is similar to the latent class model, where members within a given population are segregated into sub-groups with

⁷ This terminology is used by Kumbhakar et al. (2013).

regards to their peculiar attributes. But whilst the latent class specification of the SF accounts for technology heterogeneity and inefficiency in light of regime membership, the logic of the ZISF model within the latent class framework accounts for full efficiency and inefficiency among firms.

In this study, we employ the ZISF model to examine the cost efficiency of Zambian maize farmers, using farm-level data collected in 2013. Maize is a major food staple in Zambia, with an annual per capita consumption of about 133 kilograms, and supplying over half of the calories requirements (World Bank, 2013). Like most Sub-Saharan Africa (SSA) countries, in normal years Zambia nears self-sufficiency in maize, imports in bad years, and exports in good years. A recent World Bank (2009) study of commercial agriculture in Africa showed that production costs of maize in Zambia and Mozambique were double those in Thailand, a competitive maize producer, a finding that indicates inefficiencies in resource use in the African countries. Notably, high costs for inputs, larger labor inputs, and high transport costs tend to impact on the competitiveness of the maize sector in Zambia.

The crop forecast of Zambia shows that increase in maize production in recent years has been attained through the expansion of land under maize cultivation rather than through productivity improvements.⁸ However, declining land availability may limit the possibility of output increases through land expansion, calling for sustained productivity increases and efficient allocation of resources. Significant increases in productivity through better use of inputs will therefore be essential for the continuous growth in maize output. This requires a better understanding of the relationship between market indicators, household characteristics, and allocative efficiency. A better understanding of this relationship will be quite helpful to policy makers in creating efficiency-enhancing policies. Given that technical and allocative efficiency do not necessarily guarantee

⁸ For example, although maize production in Zambia between the 2000/2001 and 2010/2011 increased from 957,437 to 2,786,896 MT, the corresponding farm land also increased from 748,314 ha to 1,311,295 ha within the same period (Mason et al., 2011).

optimal scale of operation, the study also examines the scale efficiency of farms in the sample.

This article contributes to the literature by operationalizing the ZISF on cross-sectional farm household data of typical SSA farm businesses to examine farm level allocative and scale efficiencies and the determinants of inefficiency. The ZISF results reveal that there are both fully efficient and inefficient firms among Zambian farmers. In particular, the SF approach tends to underestimate the variance of inefficiency relative to the ZISF approach, suggesting that failure to account for full efficiency in the SF is likely to bias farm inefficiency and policy. To the best of our knowledge, only previous studies like Kumbhakar et al. (2013) and Rho and Schmidt, (2013) have employed the ZISF modelling approach to examine inefficiency. Whilst Kumbhakar et al. (2013) focused on cost efficiency of banks in the USA, Rho and Schmidt (2013) investigated the technical efficiency of rice farmers in the Philippines.

The remainder of the study is organized as follows. The next section describes the conceptual framework of the study, while section three presents the data and variables employed in the empirical analysis. The empirical specification and results are discussed in sections four and five, respectively. The final section highlights on some conclusions and policy implications.

2.2 Conceptual framework

The conceptual model of the ZISF is set up in an integrated framework of the SF model that simultaneously accounts for both fully efficient and inefficient firms in a probabilistic framework. Consider maize farming in Zambia to be a production industry where farmers combine various factors of production like land, labor, capital and other inputs to produce given levels of output. In line with microeconomic theory, with a given technology and inputs, most maize farm enterprises will aim to maximize their output at minimum cost. Given input and output prices and their respective quantities, the appropriate standard against which to measure the performance of farmer *i* shifts from the production frontier to either cost, revenue, or profit frontiers. The behavioral

assumption that then confronts farmer i falls into the paradigm of cost minimization, or revenue and profit maximizations.

To the extent that maize farmers produce homogenous output (except for varietal differences), they only differ in their cost of production and levels of output. Given the relatively higher associated transaction costs in pursuit of revenue and profit maximization among Zambian farmers, the appropriate behavioral assumption of a typical Zambian maize farmer to a large extent will depend on cost minimization⁹. We therefore assume that a typical maize farmer i in Zambia, faces strictly positive vector of factor prices, $\mathbf{w} = (w_1, \dots, w_N) \in R_{++}^N$, and input quantities, $\mathbf{x} = (x_1, \dots, x_N) \in R_{++}^N$, and attempts to minimize the cost $(\mathbf{w}'\mathbf{x})$, subject to the given output level, \mathbf{q} , and factor prices that influence cost. Given that Zambian maize farmers are price takers in the input market and there is higher demand for their maize output, the farm's total cost frontier can be used to describe the cost minimizing behavior of a typical maize farmer. For a differentiable cost frontier, Kumbhakar and Lovell (2000) indicate that the input gradient $(\nabla_{\mathbf{w}})$ of the cost frontier gives the vector of cost-minimizing input demand equations $x(q, \mathbf{w}) = \nabla_{\mathbf{w}} c(q, \mathbf{w})$. In this case, farmer i is efficient, if he¹⁰ is operating on the cost frontier, that is if $w_A'x = c(q, \mathbf{w})$ and $x = x(q, \mathbf{w})$; and inefficient if he is operating above the cost frontier, $w_A'x > c(q, \mathbf{w})$ and $x \neq x(q, \mathbf{w})$, where w_A denotes actual factor prices. The stochastic cost frontier model outlined below has been widely used in estimating allocative efficiency of farmers in several studies (e.g. Parikh et al., 1995).

Stochastic cost frontier model

The traditional stochastic cost frontier model for farmer i is specified as:

$$C_i = x_i' \beta + (v_i + u_i) \quad \text{for } i = 1, \dots, n \quad (1)$$

⁹ For example, transport costs alone in the production of maize in Zambia are more than double those of Thailand (World Bank, 2009).

¹⁰ We use the male form because majority of the farmers are males.

where C_i denotes a scalar of total cost of production, x_i is a $k \times 1$ vector of covariates of factor prices and level of output, β is $k \times 1$ vector of parameters to be estimated, v_i is the random term (white noise) assumed as $v_i \sim i.i.d. N(0, \sigma_v^2)$, and u_i is systematic error term accounting for inefficiency and assumed as $u_i \sim i.i.d. N^+(0, \sigma_u^2)$; nonnegative half-normal (Aigner et al., 1977).

The non-negativity assumption of inefficiency ($u_i \geq 0$) suggests that, we can have both inefficient farms ($u_i > 0$), and fully efficient farms ($u_i = 0$). This phenomenon characterizes the farmers into regimes of fully efficient and inefficient farms, respectively. However, the formulation of the traditional SF model fails to explicitly allow for simultaneous estimation of both regimes. Following Kumbhakar et al. (2013), we formulate a Zero Inefficiency Stochastic Frontier (ZISF) model within the regime membership framework to account for both inefficient and fully efficient farms.

Zero Inefficient Stochastic Frontier Model

$$\begin{aligned} \text{ZISF} &\rightarrow C_i = x'_i \beta + v_i \quad \text{with probability } p \\ C_i &= x'_i \beta + (v_i + u_i) \quad \text{with probability } (1 - p) \end{aligned} \tag{2}$$

where p denotes the probability of a farm being fully efficient or $u_i = 0$, and $(1 - p)$ denotes the probability of a farm being inefficient or $u_i > 0$. Introducing the regime membership analogy as in latent class models transforms the composed error term of the SF (ε_{si}) = $v_i + u_i$ to that of the ZISF (ε_{zi}) such that, $\varepsilon_{zi} = v_i + u_i[1 - 1(u_i = 0)]$, where $p = E(1(u_i = 0))$.

This setup is a generalization of both the standard SF model (none of the firms is fully efficient) and the neoclassical production theory (all firms are fully efficient). If all firms were fully efficient, the ZISF and SF models would be identical to the neoclassical production theory. On the other hand, if none of the firms is fully efficient, the ZISF model reduces to a SF model. Accounting for full efficiency in the ZISF model allows for consistent efficiency estimates of both truly inefficient and fully efficient firms (Kumbhakar et al., 2013).

The estimation of firm specific inefficiency under the SF and ZISF models follow the logic of Jondrow et al. (1982) (hereafter JLMS), where estimators of inefficiency here are the conditional means of the inefficiency term. Whilst the SF inefficiency estimates the traditional JLMS, the ZISF is a transformed JLMS, with p accounting for full efficiency. Following Kumbhakar et al. (2013), we specify the ZISF normal, posterior and censored JLMS models, respectively. Table 2.1 presents the JLMS specifications of the SF and ZISF models.

Table 2.1: Definition of SF and ZISF Specifications

Description	Specification
1. Jondrow et al. (1982) (JLMS); $u \sim N^+(0, \sigma_u^2)$ conditional distribution of u given ε	$f(u \varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \left[\frac{\phi((u-\mu_*)/\sigma_*)}{\Phi\sigma_*(-\varepsilon/\sigma_0)} \right] \quad (4)$
2. Conditional inefficiency estimator of the stochastic frontier model SF-JLMS for $N^+(\mu_*, \sigma_*^2)$	$Es(u \varepsilon_{si}) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \sigma_* \left[\frac{\phi(\varepsilon_i \lambda / \sigma)}{1 - \Phi(\varepsilon_i \lambda / \sigma)} - \left(\varepsilon_i \lambda / \sigma \right) \right] \quad (5)$
3. Conditional inefficiency estimator of the zero-inefficiency stochastic frontier model ZI-JLMS for $N^+(\mu_*, \sigma_*^2)$	$Ez(u \varepsilon_{zi}) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = (1-p) \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \left[\sigma_* \frac{\phi\left(\frac{\varepsilon}{\sigma_*}\right)}{\Phi\left(\frac{\varepsilon}{\sigma_*}\right)} - \varepsilon_i \right] \quad (6)$
4. Posterior JLMS of the ZISF model	$\check{u}_i = (1 - \check{p}_i) \hat{u}_i \quad (7)$
5. Censored JLMS	The pre-determined bench mark (eg. 95%) of \check{P}_i

Note: Composed error tem of the SF model (ε_{si}) = $v_i + u_i$; $v_i \sim i. i. d. N(0, \sigma_v^2)$; $u_i \sim i. i. d. N^+(0, \sigma_u^2)$; Composed error term of ZISF model $\varepsilon_{zi} = v_i + u_i[1 - 1(u_i = 0)]$; $\mu_* = -\varepsilon\sigma_u^2/\sigma_0^2$; $\lambda = \frac{\sigma_u}{\sigma_v}$; $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$; $\sigma_0 = \lambda/\sigma$; $\sigma_* = \sqrt{(\sigma_u \sigma_v / \sigma)}$; posterior estimate of probability of full efficiency probability (\check{p}_i) = $\frac{\check{p}f(v)}{\check{p}f(v) + (1-\check{p})f(\varepsilon)}$, \check{u}_i ; the ZI-JLMS efficiency estimator; Es ; SF-JLMS; Ez ; ZISF-JLMS; zero inefficiency probability estimator \check{p} .

In the normal ZISF case, since full efficiency is associated with p and inefficiency with $(1 - p)$, the marginal density of the convoluted error term of the ZISF model ($f(\varepsilon_{zi})$), with respect to the error components of the SF model (ε_s) is expressed as:

$$f(\varepsilon_z) = pf(v) + (1 - p)f(\varepsilon_s) \quad (3)$$

where the density function of the random term (v) is $f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \exp\left(-\frac{v^2}{2\sigma_v^2}\right) = \frac{1}{\sigma_v} \phi\left(\frac{v}{\sigma_v}\right)$, and the density function of ε_s , $f(\varepsilon_s) = \frac{2}{\sigma} \phi\left(\frac{\varepsilon}{\sigma}\right) [1 - \Phi\left(\frac{u}{\sigma_u}\right)]$, $u \geq 0$, $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density and cumulative distribution functions, respectively, and $\sigma = \sqrt{(\sigma_u^2 + \sigma_v^2)}$.

The density function of the ZISF model is a mixture of normally distributed random variables and convoluted density of the normal/half-normal SF model. Hence, the likelihood function of the ZISF model can be driven from any array of the standard densities of the SF model. The identification of the variance of the inefficiency distribution (σ_u^2) in the SF model is through moment restrictions on the composed density of the inefficiency and random components (skewness of the composed error distribution). In the ZISF, the model identification breaks down when $\lambda \rightarrow 0^{11}$, as the inefficient and the fully efficient membership become indistinguishable. This intuitively implies that as $\lambda \rightarrow 0$ the firms get closer to full efficiency and does not pose a problem. Measuring inefficiency in the ZISF framework with the view that truly inefficient firms are less efficient than in the traditional SF entails either constructing posterior JLMS or censored JLMS of the ZISF (refer to Table 2.1).

As indicated by Rho and Schmidt (2013), this ‘posterior’ probability is not a true posterior probability as in Bayesian sense and does not require a prior distribution of the parameters. For the censored JLMS, a pre-determined bench mark (e.g. 95%) of the ‘posterior’ probability estimate is specified such that firms whose efficiency scores are beyond the pre-determined bench mark are deemed fully efficient and assigned scores of $p = 0$.

Various factors including farmer and farm household characteristics could be responsible for the observed inefficiency in the sample. As in many developing agricultural economies with the prevalence of subsistence farming, the scarce farm business inputs may be allocated to various uses

¹¹ λ is defined in Table 2.1.

on the basis of their marginal shadow values. Marginal shadow values and marginal value productivities can differ for each of the inputs such that inefficiency may result. In the SF model, inefficiency across farms is modelled as a linear function of the inefficiency term u_i and of a set of covariates as:

$$u_i = z_i' \gamma + \omega_i \tag{8}$$

where z_i is an $m \times 1$ vector of exogenous variables that influence inefficiency, γ is an $m \times 1$ vector of parameters and ω_i is a random variable truncating the normal distribution with mean zero and variance σ_{ui}^2 at $-z_i' \gamma$ (Battese and Coelli, 1995).

In the ZISF case, a natural extension of the SF is therefore to parameterize the probability of full efficiency. Since the regime membership is binary, the probability of full efficiency or inefficiency in relation to other covariates can be expressed as a logit or probit model. Reifschneider and Stevenson (1991) and Kumbhakar et al. (1991) propose simultaneous estimation of the deterministic term and the inefficiency structure using maximum likelihood methods. The parameters of the cost and inefficiency models are estimated by maximizing the log-likelihood function (Kumbhakar and Lovell, 2000) as:

$$L_i(\beta, \sigma_u, \sigma_v) = -\frac{1}{2} \ln \sigma_i^2 + \ln \left[\phi \left(\frac{\sum_i^n \ln f(C_i - X_i' \beta - \mu_i)}{\sigma_i} \right) \right] - \ln \left[\Phi \left(\frac{\mu_i}{\sigma_{ui}} \right) \right] + \ln \left[\Phi \left(\frac{\mu_i \sigma_{ui}^2 - \varepsilon_i \sigma_i^2}{\sigma_i^2 (\sigma_{ui})} \right) \right] \tag{9}$$

Scale efficiency

Besides using the translog cost function to estimate inefficiency, it can also be employed to estimate scale efficiency (e.g. Qushim et al., 2015). Within a given production technology, it is possible that a decision making unit (DMU) is both technically and allocatively efficient but not scale efficient. Scale efficiency is evaluated against the principle of economies of scale. Economies of scale from

the cost function is described as the elasticity of cost with respect to output¹². Returns to scale (RTS) of the cost function (RTS_c) is expressed as the reciprocal of the sum of elasticities of cost with respect to the output elasticity ($RTS_c = (\sum_m \partial \ln C / \partial q_m)^{-1}$). It measures the proportional increase in cost given an increase in output.

A DMU is considered to be too small in its scale of operations, when it operates on the increasing returns to scale part of the variable return to scale (VRS) cost function ($RTS_c > 1$), implying that a proportional increase in output will result in a less than proportionate increase in cost. Thus, the scale of operation is said to be below optimum and as such the firm will benefit from expansion. On the other hand, a DMU is regarded as too large, if it operates on the decreasing returns to scale part of the VRS cost function ($RTS_c < 1$), implying that a proportional increase in output will result in a more than proportionate increase in cost. Thus, the scale of operation is said to be below optimum and as such the firm will benefit from scale reduction.

Testing for Zero inefficiency

In standard testing problems, all parameters are identified under the null and alternative hypotheses, where parameter values in the null hypothesis are interior points of the maintained hypothesis. In testing for zero inefficiency, the hypothesis of zero-inefficiency $H_0 : p = 1$ (or inefficiency, $H_0 : p = 0$) lies on the boundary of the parameter space of the maintained hypothesis. A set of high level conditions under which the asymptotic null distributions of the pseudo likelihood ratio (PLR) and score tests can be determined. In the random coefficient regression, the asymptotic null distribution of the test statistics can be considered a nuisance parameter value, but given consistent estimates of any unknown nuisance parameters, p -values can be obtained by simulation (Andrews, 2001).

Chen and Liang (2010) demonstrate that, when a nuisance parameter like p lies on a boundary,

¹² Returns to scale and economies of scale are equivalent measures, if and only if the product is homothetic (Chambers, 1983).

hypothesis testing regarding this parameter gives asymptotic mixture distributions. Here, we abstract from a simple t -test approach of using the standard errors of ML estimates and rather use the pseudo-likelihood ratio (PLR) test logic proposed by Chen and Liang (2010), which is defined as $PLR = -2(L_N - L_{ZI})$, where L_N is the log likelihood of the normal linear model (evaluated using the standard OLS estimates) and L_{ZI} is the log likelihood of the ZISF model. As in Chen and Liang (2010), it can be shown that:

$$\frac{\partial \ln f(\varepsilon)_i}{\partial p} = \frac{1}{f(\varepsilon)_i} \left[\sigma_v^{-1} \phi(\varepsilon/\sigma_v) - \frac{2}{\sigma} \phi\left(\frac{\varepsilon}{\sigma_v}\right) \Phi(-\varepsilon/\sigma_0) \right] \quad (10)$$

with zero expectation under $p = 1$ and $f(\varepsilon)_i$ denotes pdf of firm i . Coelli (1995) indicate that, testing for fully efficient behavior in the SF model gives the log-likelihood ratio statistic that is distributed as a mixture of χ^2 distributions.

The PLR test has an asymptotic distribution that constitutes a 50:50 mixture of inefficient χ_0^2 distribution and fully efficient χ_1^2 distribution, similar to Coelli (1995). Since the test is on the probability of being fully efficient (but not the variance of the inefficiency distribution), the test for full efficiency here is that, rejection of the null implies the presence of efficiency in the ZISF model and inefficiency in the SF model.

2.3 Data and definition of variables

Data used in this study are from a farm household recall survey of maize farmers of the Zambian National Farmers union (ZNFU), conducted from August to November, 2013. A multistage stratified random sampling technique was employed to select 406 maize farmers from 12 districts across 4 provinces in Zambia.

Table 2.2: Summary Statistics and definition of variables

Variable		Mean	SD	Min.	Max.
Household and farm characteristics					
Farm Size	Cultivated farm size in hectares	3.31	3.92	0.50	30.00
Output	Total maize output in metric tonnes	6.29	6.39	0.40	50.00
Cost	Total cost of production (ZMW)	4748.00	5659.22	345.00	51350.00
Land price	Annual land rent (ZMW)	559.10	652.84	75.00	5250.00
Labor price	Annual wage rate (ZMW)	516.50	629.12	60.00	5100.00
Capital price	Tractor, oxen and manual cost of land preparation (ZMW)	573.60	629.09	50.000	5750.00
Other direct expenses	Sum of the total cost of fertilizer, herbicide, lime and pesticide (ZMW)	746.773	3362.45	1.00	34100.00
Seed price	Cost of seed (ZMW per hectare)	793.70	866.34	80.000	7200.00
Education	Farmer's level of Education in years	4.66	2.92	0.000	14.000
HHS	Farmer's Household size, number of people	5.67	2.15	2.000	12.000
Extension	Access to extension services (1=yes, 0=no)	0.59	0.49	0.000	1.000
Credit	Access to credit dummy (1=yes, 0=no)	0.59	0.49	0.000	1.000
Sandy soil	Soil type (1=sand, 0=clay or loam soil)	0.22	0.42	0.000	1.000
Clay soil	Soil type (1=clay, 0=sand or loam soil)	0.28	0.45	0.000	1.000
Distance to market	Distance to permanent market (km)	4.42	2.48	0.000	12.000
Central	1 if farm is located in Central province, 0 otherwise	0.225	0.419	0	1
Eastern	1 if farm is located in Eastern province, 0 otherwise	0.250	0.434	0	1
Southern	1 if farm is located in province, 0 otherwise	0.233	0.421	0	1
Western	1 if farm is located in Eastern province, 0 otherwise	0.294	0.456	0	1

Note: At the time of the survey, 1 U.S. dollar = 5.37 ZMW.

To arrive at this, first, 12 districts were randomly selected from Zambia, each been a stratum. In each district, three to four agricultural camps¹³ were then randomly selected, within which three farmer groups were randomly selected from each zone. About three to four farmers were randomly selected from these groups in proportion to the size of the group for the interview. Face-to-face interviews were conducted by enumerators who spoke both English and the local language and supervised by one of the authors, using a detailed structured questionnaire. The survey gathered information on farm household characteristics, farm production pattern, input use and prices, yields and output prices.

The variables used in the analysis are presented in Table 2.2. The table reports the means and standard deviations, as well as the minimum and maximum values of these variables. The reported data relate to the 2012 production season. The average farm size is 3.3 hectares, varying between 0.5 and 30 hectares. Farm output ranges from 0.4 to 50 metric tonnes, with average output being 6.3 metric tonnes. The variable denoting cost is the imputed total cost of farm inputs for the production season including land, labor, capital and other inputs (like seed, fertilizer, herbicides and pesticides) used in maize production. The land price variable is the annual land rent (lease or opportunity cost of own land)¹⁴. As in Abdulai and Huffman (2000), the capital price is computed as the sum of the cost of hiring animal and mechanical power by farmer i in producing maize. Seed price is the cash expenditure on maize seeds by farmer i . Labor cost is total labor cost by farmer i , including hired and family labor valued at opportunity cost¹⁵. Price of other inputs include the sum of actual expenditure (including cost of transportation and application) on herbicides, fertilizer, pesticides and

¹³ Agricultural camp in Zambia is a management unit of agricultural camp officer, comprising a catchment area of up to eight different zones of different villages.

¹⁴ The opportunity cost is the monetary value of owner-operated land that the household would have received or paid for renting the land.

¹⁵ The opportunity cost of family labor is the monetary value of wages that the household would have received or paid for hiring equivalent unit of family labor.

lime by farmer i on maize.

We also include farm and household demographic variables like education, household size, access to extension, access to credit, soil type and distance to market in the analysis of the determinants of cost efficiency. The variable education measures household head's level of education in years. We consider the variable education to be an important determinant of efficiency bearing in mind the human capital theory that, improving the allocative skills of a farmer is related to his level of education (Huffman, 1977). Additional years of schooling is expected to influence farmer's ability to gather and analyze relevant data for informed farm decisions. Household size is an indicator of potential family labor that could support the farm business. On the other hand, it also indicates the level of burden on the limited household resources, especially with respect to feeding, clothing and shelter, which can influence household's allocative efficiency. The household size variable is the number of people residing within the farm household with common income and financial obligations.

As in Krishnan and Patnam (2014), access to information from institutional sources was accounted for using visits by extension agents. Access to extension is expected to improve farmers' level of exposure to information on farm practices and farm inputs. Access to extension is measured as whether farmer had contact with an extension agent on the production methods within the past three production seasons. Access to the right information at the right time will better inform a DMU on when and how best to act, which will contribute to improving allocative efficiency. In the rural farm setting, extension agents serve as intermediaries between agricultural agencies (government, development partners and input dealers) and farmers. They are community farm business heads who receive information and relay it to farmers. Access to extension services is expected to improve farmers' awareness of relevant farm practices and sources of farm inputs, which is likely to improve farmers' allocative efficiency.

The credit variable is an indicator of farmers' access to credit ranging from formal sources

(like banks and micro-credit agencies) to informal ones (like money lenders, friends and family relations), and is used to capture the extent to which farmers are liquidity constrained. The variable is measured as whether the farmers obtained credit in the production season, and whether they tried to access more credit than they obtained. We consider farmers as liquidity-constrained if either they sought for, but were unable to obtain credit, or obtained less than their requirement. Farmers' access to credit is hypothesized to shift the farmers' liquidity constraint outward by facilitating farmers' timely procurement of inputs, and hence improving farm efficiency.

Heterogeneous environmental production conditions such as soil conditions may influence the production process and cost of production. When such differences are observed and captured by proxies, they can be incorporated into the model so that measured efficiency is conditional upon these factors. However, the omission of such heterogeneity may overstatement cost inefficiency and lead to biased estimates of the parameters (Sherlund et al., 2002). We include soil type as a variable to account for environmental heterogeneity. We also include provincial dummies to account for location fixed effects.

Transaction and transportation costs differences among farm households is likely to influence the cost of production and cost efficiency. As indicated by the World Bank (2009), high transport costs tend to affect the competitiveness of maize production in Zambia. We include a variable on distance to the nearest market measured as the distance to the next bigger village or town, with market for farm inputs and outputs. The distance for farmers residing in villages or towns with such markets is zero. This variable captures the relative transportation and market information transaction cost associated with a particular farm household. The farther the distance to the market, the more time and related cost required to source input and output market information, as well as higher transportation costs in moving farm inputs from the market centers to the farm and farm produce to the market.

2.4 Empirical specification

To estimate the SF and ZISF cost models, we employ a translog functional form. Kumbhakar and Lovell (2000) indicate that the translog cost frontier is a flexible functional form and provides second-order approximation to well-behaved cost frontier at the mean of the data. It places no a priori restrictions on the substitution of inputs and allows the economies of scale to vary with the output level. The translog approximation for farmer i of factor prices m relative to n factor prices can be written as:

$$\begin{aligned} \ln C_i = & \beta_0 + \beta_q \ln q_i + \sum_{m=1}^4 \beta_m \ln w_{mi} + 0.5 \beta_q (\ln q_i)^2 + 0.5 \sum_{m=1}^4 \sum_{n=1}^4 \beta_{mn} \ln w_{mi} \ln w_{ni} + \\ & + \sum_q \sum_{m=1}^4 \beta_{qm} \ln q_i \ln w_{mi} + v_i + u_i \end{aligned} \quad (11)$$

where C_i , q_i , and w_{mi} denote total cost, output level and factor prices, respectively, v_i is the random term (white noise) with $v_i \sim i.i.d. N(0, \sigma_v^2)$, and u_i is the nonnegative systematic error term accounting for inefficiency and $u_i \sim i.i.d. N^+(0, \sigma_u^2)$. We also assume that the Young's symmetry restrictions, $(\beta_{mn} = \beta_{nm})$ and $(\beta_{qm} = \beta_{mq})$ hold.

The dependent variable C_i , is total cost of production. The independent variables of the cost frontier model comprise output quantity and factor prices. Given that the cost function is homogenous of degree one in all factor prices (Zardkoohi, 1986), we follow previous studies and impose linear homogeneity restriction by normalizing the logarithm of cost and factor prices with respect to the logarithm of the seed price (Farsi et al, 2005; Kumbhakar et al., 2013). Thus, total cost of production (C_i) and factor prices (w_i) are normalized by price of maize seed. Output (q_i), is measured as total maize yield in tons. Five factor prices were identified and used for the empirical analysis. These include; w_1 ; annual rent per hectare input normalized by price of maize seed, w_2 ; money wage of farmer i normalized by price of maize seed, w_3 ; price of capital input computed as the sum of the cost associated with hiring animal and mechanical power normalized by price of maize seed, w_4 ; other direct expenses computed as sum of money price of fertilizer, herbicide, lime

and pesticide, normalized by price of maize seed and w_5 is the money price per hectare of maize seed.

The inefficiency specification in the SF is $u_i \sim N^+(0, \sigma_i^2)$, such that:

$$u_i = \gamma_0 + Edu\gamma_1 + HHS\gamma_2 + Ext\gamma_3 + Cre\gamma_4 + San\gamma_5 + Clay\gamma_6 + Mkt\gamma_7 + \omega_i \quad (11a)$$

In the ZISF case, we assume that the probability of potential determinants of inefficiency affecting full efficiency is related to the logit specification expressed as:

$$p_i = \frac{\exp(\gamma_0 + Edu\gamma_1 + HHS\gamma_2 + Ext\gamma_3 + Cre\gamma_4 + San\gamma_5 + Clay\gamma_6 + Mkt\gamma_7)}{1 + \exp(\gamma_0 + Edu\gamma_1 + HHS\gamma_2 + Ext\gamma_3 + Cre\gamma_4 + San\gamma_5 + Clay\gamma_6 + Mkt\gamma_7)} \quad (11b)$$

The variables Edu, HHS, Ext, Cre, San, Cla, Mkt as described in section 3 denote education, household size, access to extension, access to credit, sandy soil, clay soil and distance to permanent market, respectively.

2.5 Empirical Results

As indicated earlier in the theoretical and empirical models, we employ a translog cost functional form to estimate the cost frontier and inefficiency models simultaneously¹⁶. The analysis, calculations and graphics are done within the R-studio environment¹⁷. Table 2.3 reports the estimates of the composed error terms of the SF and ZISF models, respectively, as well as zero-inefficiency probability in equation (2). The estimate of the probability of being zero inefficient is 52 %, which is statistically significant at the 1% level. The p -value of this estimate is obtained using the PLR test discussed in Section 2 under hypothesis testing. While the estimates of the noise variance of the ZISF and SF models are 0.145 and 0.152, respectively, the estimates for the variance of inefficiencies of the ZISF (0.256) is about 45% bigger than that of the SF (0.177).

¹⁶ We tested this against the Cobb-Douglas specification and Cobb-Douglas specification rejected at the 1 % level of significance in both the SF and ZISF specifications.

¹⁷ R packages including, ‘frontier’ (Coelli and Henningsen, 2013), ‘minqa’ (Bates et al., 2014), and ‘numDeriv’ (Gilbert and Varadhan, 2012) were used.

Table 2.3: Parameter estimates for the noise components of the SF and ZISF models

	Standard SF		ZISF	
	coefficient	p-value	coefficient	p-value
σ_v	0.145	0.000	0.154	0.000
σ_u	0.177	0.000	0.256	0.000
p			0.521	0.000

Note: The asymptotic p-value for the estimate of p is based on the pseudo-likelihood ratio statistic.

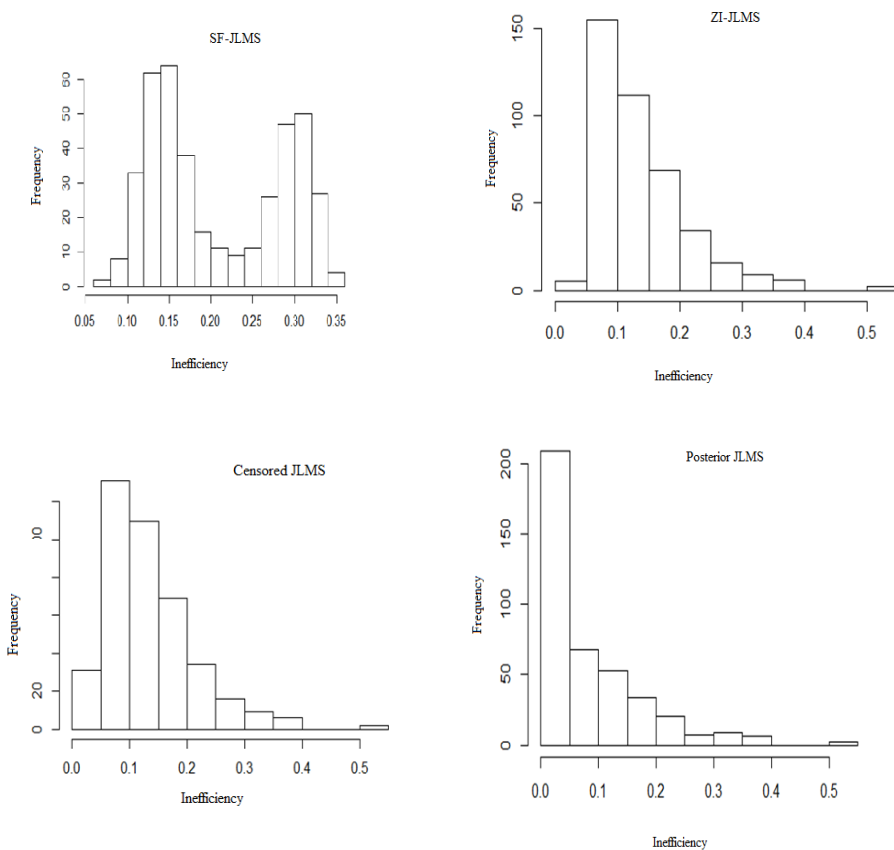


Figure 2.1: Histograms for inefficiency and posterior probabilities for the SF and ZISF maximum likelihood estimators. variance of the inefficiency component for the inefficient farms is much higher.

This result is intuitive and supports the fact that the specification relating to the noise component of the composed error terms of both the SF and ZISF are similar, but tend to differ in that of the inefficiency component. As indicated by Kumbhakar et al. (2013), the lower estimates of the inefficiency variance of the standard SF model is attributed to the presence of fully efficient farms¹⁸, which tend to pull down the variance. The summary statistics and pattern of the four measures of inefficiency are reported in Table 2.4 and figure 2.1, respectively. Whilst Table 2.4 reports the first quartile, median, mean, third quartile and standard deviation of the various measures of inefficiency, figure 2.1 (histograms) shows the pattern of these inefficiencies. The SF (SF-JLMS), ZISF normal (ZI-JLMS), posterior (posterior JLMS) and Censored (censored JLMS) inefficiency scores are reported in rows 1, 2, 3 and 4, respectively in Table 2.4 and the same nomenclature is adopted in figure 2.1.

The SF-JLMS estimates are from the standard SF model (5), while the ZI-JLMS estimates are obtained from the ZISF model (6) (refer to Table 2.1). The posterior JLMS estimates are from specification (7), and the censored JLMS are obtained by censoring the posterior JLMS at 95 %. As reported in Table 2.4 and consistent with Kumbhakar et al. (2013), in all cases, the SF-JLMS show higher levels of inefficiency, followed by the ZI-JLMS, the censored JLMS, and then the posterior JLMS. This pattern is clearer in figure 2.1.

From figure 2.1, the lowest inefficiency score reported in the SF-JLMS is 0.06, indicating that all farms are inefficient, a finding that is consistent with the traditional SF specification. This concurs with the study by Zalkuwi et al. (2010), who reported about 97% cost efficiency for maize producers in Nigeria, compared to the full efficiency scores (100%) reported in the ZISF approaches, resulting in higher inefficiency estimates of the SF-JLMS. Moreover, most of the inefficiency estimates of the SF-JLMS are in the range of 15% and 30 % in the histogram, compared to around 10% to 15 %

¹⁸ For which the variance is zero.

in both the ZI-JLMS and censored JLMS, and about 10 % in the posterior JLMS histogram, respectively. As the censored JLMS attain full efficiency at 95%, as expected, the censored JLMS histogram reports more fully efficient farms compared to the ZI-JLMS. The posterior JLMS efficiency estimates in the histogram perfectly mimics the probability of full efficiency reported in Table 2.3.

Table 2.4: Summary statistics for various measures of inefficiency of ZISF

Inefficiency measure	1 st Quart	Median	Mean	3 rd Quart	SD
SF-JLMS	0.138	0.179	0.208	0.293	0.079
ZISF-JLMS	0.083	0.118	0.138	0.169	0.078
Posterior JLMS	0.005	0.035	0.083	0.138	0.101
Censored JLMS	0.065	0.116	0.120	0.169	0.096

Notes: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1%, respectively.

The estimates therefore indicate that the SF measure of inefficiency overestimates the level of inefficiency, compared to when we really account for the existence of both inefficiency and full efficiency in the ZISF case. Table 2.5 reports coefficients and standard errors of the cost frontier and inefficiency models of the SF and ZISF models. These estimates are similar to most stochastic cost frontier studies (e.g. Parikh et al., 1995; Farsi et al., 2005). The estimates of the regression results to a large extent show some similarity in the deterministic component (particularly with signs and level of significance) of the SF and ZISF models. However, there are remarkable differences in the signs of the estimates of the determinants of inefficiency of the SF and ZISF components. As expected, the estimates of the first-order terms of output and factor prices of the cost frontier for both the SF and the ZISF models have the expected positive signs, indicating a linear relationship between the total cost of production with respect to output and factor prices¹⁹.

¹⁹ This supports the axiom that the cost function monotonically increases with output and factor prices.

Table 2.5: Maximum Likelihood Estimates of Translog Cost frontier of SF and ZISF

Variable	SF		ZISF	
	Coefficient	SE	Coefficient	SE
<i>Cost frontier model</i>				
Constant	1.577***	0.009	1.558***	0.008
ln q (output)	0.003	0.008	0.007	0.006
ln w1(land)	0.179***	0.030	0.176***	0.031
ln w2(labor)	0.163***	0.030	0.163***	0.031
lnw3(capital)	0.160***	0.010	0.160***	0.009
lnw4 (other direct expenses)	0.303***	0.005	0.304***	0.005
0.5(ln w) ²	0.086	0.091	0.080	0.082
ln w1 x ln w2	-0.034	0.079	-0.027	0.071
ln w1 x ln w2	0.023	0.026	0.015	0.024
ln w3 x ln w4	-0.042***	0.016	-0.014	0.017
0.5(lnw2) ²	0.129	0.080	0.124*	0.073
ln w2 x ln w3	-0.049**	0.024	-0.040**	0.022
ln w2 x ln w4	0.009	0.015	0.040***	0.015
0.5(ln w3) ²	0.075***	0.011	0.072***	0.010
lnw3 x ln w4	-0.039***	0.005	-0.036***	0.005
0.5(ln w4) ²	0.011***	0.001	0.109***	0.001
0.5(ln q) ²	-0.0001	0.005	-0.003	0.004
ln q x ln w1	0.013	0.005	0.010	0.013
ln q x ln w2	-0.011	0.014	-0.011	0.013
ln q x ln w3	0.009*	0.005	0.007*	0.004
ln q x ln w4	0.003	0.007	0.004	0.003
<i>Inefficiency model</i>				
Constant	0.025***	0.144	-1.122***	0.103
Education	-0.006***	0.043	2.141***	1.121
Household size	-0.004	0.022	0.025	0.160
Extension	-0.017***	0.138	2.032***	1.160
Credit	-0.018***	0.002	1.332**	0.597
Sandy soil	-0.040	0.097	-1.048	0.776
clay soil	0.0006	0.091	0.271	0.173
Provincial dummy variables	Yes	Yes	Yes	Yes
Distance to market	0.001***	0.0002	-0.827***	0.094
Log likelihood		-77.351		-87.658

Notes: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% ,respectively

Since the total cost and their regressors are in logarithms and normalized by one factor price, the coefficients of the first order terms of the cost frontier model are interpretable as cost elasticities evaluated at the sample mean (Farsi et al., 2005). For instance, the coefficient for land price indicates that increasing the annual rent of land by a kwacha (ZMW) will result in an increase in total cost of maize production by about ZMW 0.179 and ZMW 0.176 in the SF and ZISF cases, respectively. The factor price elasticity estimates of the SF and ZISF also support the assumption that the cost function is homogenous of degree one and that the cost minimizing factor prices is non-decreasing in w .

As indicated earlier, the translog function simultaneously estimates both cost and inefficiency models. The parameter estimates and standard errors of the major determinants of inefficiency in relation to the cost efficiency of the sample are reported in line with the inefficiency model of the SF (equation 11a) and full efficiency model of the ZISF (equation 11b). The reported estimates of the determinants of inefficiency of the SF and ZISF are similar in the level of significance. The results concur with heteroscedasticity model (SF) and the logit + heteroscedasticity model (ZISF) of Rho and Schmidt (2013). The differences in the reported signs of these inefficiency determinants is intuitive in the sense that, as the estimates of the inefficiency model of the SF relate to the inefficiency term, u_i (equation 11a), that of the ZISF relate to the probability of zero-inefficiency p_i (equation 11b). A positive SF coefficient indicates a positive impact on inefficiency and vice versa. On the other hand, positive ZISF coefficient indicates a positive impact on full efficiency and vice versa.

For brevity, we discuss only variables that are statistically significant at conventional levels. The coefficient of the variable representing education in the SF model is negative and positive in the ZISF model, indicating that higher levels of education reduce inefficiency, or increase full efficiency, a finding that is consistent with the results of Ng'ombe and Kalinda (2015) for Zambia.

As expected, the estimate of the extension variable is negative in the SF (positive in the ZISF) and significantly different from zero at the 1% level, suggesting that extension has a negative impact on inefficiency (positive impact on full efficiency).

Access to extension services improve farmers' access to relevant information on better farming practices and in some cases inform farmers on sources of desired farm inputs for specific tasks. The positive (negative) and statistically significant relationship between access to credit and efficiency in the ZISF (SF) model, suggests that farmers who are liquidity constrained tend to experience higher cost inefficiency. This result is in line with the findings by Parikh et al. (1995), who showed that access to credit reduces farmers' cash constraints for farm input in Pakistan and increase efficiency. The result is also consistent with the recent study by Ng'ombe and Kalinda (2015), who found that access to credit improves farm efficiency in Zambia. A negative and statistically significant relationship is found between the distance to market and cost inefficiency of the ZISF (positive relationship in the case of SF), suggesting that longer distances to market tend to increase cost inefficiency, or reduces cost efficiency. As argued by Coelli et al. (2002) in their study on Bangladesh, longer distances to markets tend to increase transportation and transaction costs, thereby increasing cost inefficiency.

As indicated in section 2.3, we used the translog cost frontier estimates of the SF and ZISF to estimate returns to scale (RTS) in both cases. The density plots of both RTS cases as presented in figure 2.2 indicate nearly identical estimates (about 1.1). The notable differences in the peakedness and tailedness of the SF and ZISF plots suggest a relatively higher kurtosis of the ZISF compared to that of the SF. As noted by Balanda and MacGillivray (1988), increasing kurtosis is associated with movement of probability mass from the shoulders of the distribution into the center and tails.

RTS for ZISF and SF

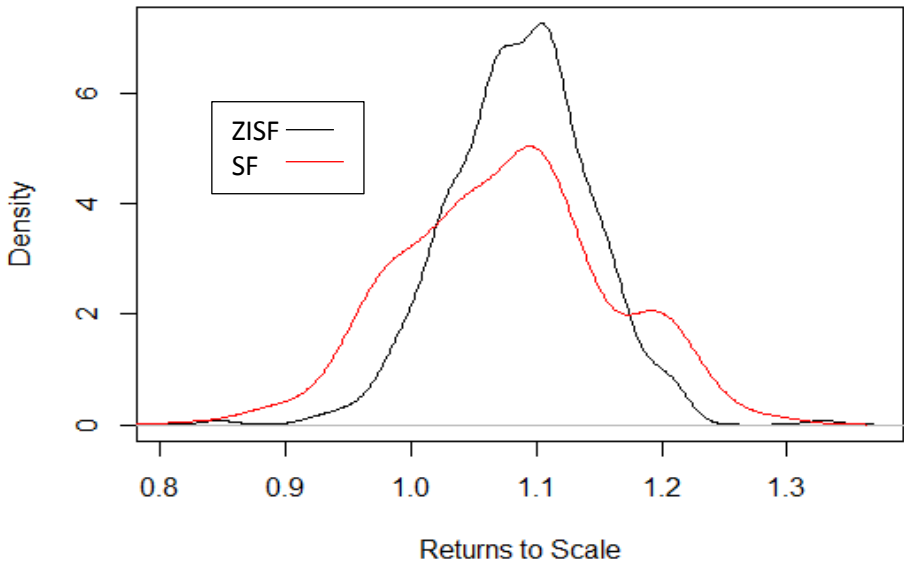


Figure 2.2: Returns to Scale of ZISF and SF cost function

This suggests that the ZISF predicts the scale efficiency more precisely compared to that of the SF. The RTS plots in both the SF and the ZISF are more than unity, indicating that the farmers are not optimal in their scale of operations and that, a proportional increase in outputs will lead to a less than proportional increase in cost. In such a case, scale economies are said to exist, in the sense that the scale of operations is below optimum, and it will be beneficial for the farmers to expand. Kimhi (2003) also reports the existence of scale economies for maize production in Zambia. The results contradict Schultz's (1964) poor-but-efficient hypothesis for peasant farmers in traditional agricultural setting, but probably support the argument by Collier and Dercon (2009) that, the agenda for African agriculture growth should be to introduce commercial agriculture on a competitive basis. Also, Paul et al. (2004) in examining the potential of smaller farms to compete with larger entities in the US indicate that, the primary factor inhibiting the competitiveness of smaller farmers is in

their inability to improve cost efficiency by expanding their scale of operations and diversity. The findings further confirm the notion that, most farms in developing countries, particularly SSA operate at sub-optimal levels (e.g. Ogundari et al., 2006).

2.6 Conclusion and Policy Implications

In this study, we examined the efficiency of maize production in Zambia, using a translog cost frontier approach for the traditional stochastic frontier (SF) model and the zero-inefficiency stochastic frontier (ZISF) model. Whilst the ZISF approach accounts for the presence of a subset of fully efficient farms in the sample (ZI-JLMS, posterior JLMS, or censored JLMS), the SF approach fails to do so. The ZISF model serves as a realistic and useful generalization of the traditional SF techniques, by characterizing the inefficiency landscape to simultaneously account for the presence of both fully efficient and inefficient farm sub-samples within a given sample. The ZISF also provides different options to defining the benchmark farms in a statistically meaningful manner as opposed to the current practice of using the farm with the lowest level of inefficiency in the sample or some given percentage of farms.

The empirical results showed that the SF approach tend to overstate inefficiency. Average inefficiency scores were found to be 20.8 % for the SF and 13.8 %, 8.3 % and 12 % for the ZI-JLMS, posterior JLMS and censored JLMS, respectively. The probability of having fully efficient farmers in the sample was about 52 % and significantly different from zero at the 1% level of significance. The results also revealed that cost inefficiency could be reduced by improving farmers' access to credit and extension services, providing rural education and by improving roads and transport services. Furthermore, estimates showed that scale economies existed, as the scale of operations were below optimum, suggesting that increasing farm size and allowing relatively scarce resources (e.g., farm land) to be transferred among farm households could help enhance allocative efficiency.

The findings from the study have some policy implications on cost efficiency among Zambian maize farmers. In particular, the negative relationship between education and inefficiency suggests that investing in rural education through the provision of literacy centers across Zambia will improve farmers' access to education services to enhance the allocative ability of farmers and as such help in reducing cost inefficiency. This is attainable through the enforcement of the youth and adult literacy policy in the Ministry of Finance (2014). The reported positive influence of extension services on efficiency supports the widely held view that, agricultural extension services play a major role in enhancing farm business efficiency in SSA. Improving farmers' access to timely credit packages including cash and input credit would contribute to decreasing farm level cost inefficiency.

The negative and statistically significant relationship between distance to market and inefficiency suggests that longer distances to market tend to increase transport costs, and as such cost inefficiency. Policy initiatives through improving roads and transport infrastructure will motivate private sector participation and ensure functioning input and output markets, hence improving cost efficiency. In this light, pursuing a comprehensive urban and feeder roads infrastructural policy within the Link Zambia 8,000 project in line with the National Agricultural Investment Plan (2014) and Zambia Development Agency Sector Profile (2014) of Zambia will contribute to improve farmers' access to markets. Furthermore, maize farmers in Zambia stand the chance of benefitting from economies of scale if they expand their scale of operations. The finding of scale economies indicates that development of a land market will be useful in improving efficiency of resource use, as farmers can effectively engage in land transfers to enhance farm efficiency. Generally, the findings show that market prices for output and inputs are important in the farmers' resource allocation decisions, and tend to support economic reforms that are aimed at making farmers more market oriented, with less government interventions.

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Chapter 3

The role of social and institutional networks in promoting the diffusion of Conservation Agriculture in Zambia

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Abstract

In this study, we use recall data from farmers in Zambia to examine the role of peer effects through farmers' social networks, as well as institutional networks such as extension service in the adoption and diffusion of conservation agriculture technology. We employ a dynamic discrete-time hazard model to capture the time path to adoption. The empirical results show that conditional on several potentially confounding factors, technology adoption and diffusion is positively and significantly influenced by farmers' access to information from social networks like peers and institutional networks like extension services. Adoption decisions are also found to be significantly influenced by farmers' schooling, access to credit, participation in non-farm work, farm size and farmers' risk preferences

Keywords: Technology diffusion, conservation agriculture, social network, peer influence, extension services.

3.0 Introduction

Understanding the patterns and drivers of adoption and diffusion of agricultural technologies is fundamental to formulating better policies and programs for increasing productivity and ensuring food and nutrition security. In view of increasing resource scarcity, adverse climate change impacts and ever growing population, several authors have argued that policy should intensify efforts to promote production systems that support productivity and health of agro ecosystems (e.g. Lobell et al, 2008; Jat et al., 2014). Lobell et al. (2008) postulate that, climate change alone could significantly reduce crop yields and increase yield variability in many regions of the world, including 20-35% decrease in maize yields in Southern Africa by 2030. Policies and programs on current agricultural systems should therefore be more proactive, by either promoting the adoption and diffusion of new technologies, or continuously improving on existing systems.

Conway (1997) noted that in spite of the significant contribution of the Green Revolution to substantial increases in crop productivity through external input packages in the last quarter of the 20th century, subsequent agricultural systems need to be ‘double green’ by contemporaneously boosting productivity as well as protecting the environment. Over the last few decades, there have been growing concerns in many parts of the world, including sub-Saharan Africa (SSA) on soil productivity and environmental implications of the common conventional farming (CF) systems²⁰. These systems continually destroy the natural soil structure, soil organic matter and soil ecosystem (Montgomery, 2007). Pampel and van Es (1977) indicate that conservation agriculture (CA) is a better ‘environmentally profitable’ alternative to CF, since it is good for the environment and at the same time economically viable.

²⁰ Conventional farming refers to the seasonal perpetual and intensive tilling of farm land (by hoe, disc or plough), mono cropping and slash-and-burn of crop residue.

The FAO (2010) identified Zambia and eleven other countries²¹ as CA technology focal countries in Africa, with Zambia considered as the success story for CA uptake in SSA. Given that the policy environment tends to influence the adoption and diffusion of new agricultural technologies, there was a policy pronouncement in Zambia in 1999 that, CA had become part of the Zambian National Agricultural Policy, with an aim of increasing the number of smallholder farmers practicing CA to 600,000 by the year 2015. However, like many other technologies introduced in SSA, the adoption of CA technology has been much slower than expected. Therefore, empirical analysis on the adoption and diffusion of CA technology, and in particular, on how farmers' social and institutional networks play out in these processes will shed some light on the factors driving the uptake of the technology.

Many technology adoption studies normally employ static limited dependent variable models to compare the characteristics of adopters and non-adopters and determine which variables statistically correlate with adoption (e.g. Fuglie, 1999). These approaches are restrictive in cases where the effect of regressors on the time-path to adoption and the effect of time-varying covariates on adoption are relevant (Burton et al., 2003; Dadi et al, 2004; Abdulai and Huffman, 2005). Specifically, the adoption process of CA may be gradual, as farmers learn by doing, or learn from others. Dadi et al. (2004) and Abdulai and Huffman, (2005) therefore employed continuous duration models in their studies to assess the diffusion of agricultural technology.

This study contributes to the literature on conservation agriculture and technology diffusion by using a discrete time hazard model to analyze the pattern of adoption and diffusion, as well as the factors that drive the diffusion of CA in Zambia. Using a discrete time hazard model ensures that the discrete nature of measuring the adoption period is considered in the empirical process (Wooldridge, 2010). Specifically, we utilize recall data from a recent survey of 408 maize farmers

²¹ Angola, Botswana, Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, Swaziland, Tanzania, Zambia, and Zimbabwe.

in Zambia to examine the role of social and institutional networks in the adoption and diffusion of conservation agriculture technology. By accounting for the role of these factors in the diffusion process, our study relates to the recent literature on the impact of social learning and institutional networks on technology adoption (Conley and Udry, 2010; Krishnan and Patnam, 2014; Genius et al., 2014).

As noted by Conley and Udry (2010), capturing the degree of information transmission through social interaction and extension services and their roles in the diffusion of a new technology is an arduous task. Manski (1993) also pointed out that an individual exerts influence on the group just as the group influences the individual. Moreover, the fact that a farmer is more likely to adopt a new technology soon after his neighbors have done so might be due to some unobserved variable that is spatially and serially correlated, rather than learning. Hence, a correlation between group adoption and individual adoption may have little to do with social learning.

In his study on adoption of coffee pruning technology in Peru, Weber (2012) uses a natural experiment to overcome these problems in order to identify the social learning. Krishnan and Patnam (2014) employ instrumental variables approach to address the potential endogeneity problem. In this study, we use the approach suggested by Genius et al. (2014) to analyze the impacts of social networks and extension agents on technology diffusion. We employ information on the socioeconomic characteristics of farmers' peers and farmers' access to information on the technology from extension services and farmers' associations. We specifically use this information in a principal components analysis to compute factors that capture the unobserved variables that are important in analyzing the impact of information transmission through social networks and extension agents on technology adoption.

The rest of the paper is structured as follows. In the next section, we describe conservation agriculture in Zambia and in section 3, we outline the conceptual framework used in this study. Sections 4 and 5 present the empirical strategy and data for the study, respectively. Empirical results

are presented in section 6, while the final section highlights the main conclusions and policy implications of the study.

3.2 Conservation Agriculture in Zambia

The introduction of conservation agriculture (CA) in Zambia coincided with the bankruptcy of Zambia's key agricultural parastatals in the 1990's and the collapse of world copper prices, which for decades had largely financed the Zambian government fiscal expenditures, including the agriculture sector. The change of government in 1991 also influenced the abrupt end to subsidy on maize prices and farm inputs in Zambia (Haggblade and Tembo, 2003). Moreover, the dry spells in the past, especially, that of the 1992 cropping season, motivated a paradigm shift for farmers to adopt pragmatic input use measures and timely planting approaches, resulting in the current CA technology in Zambia. On the basis that CA can optimize the use of purchased inputs and reduce costs, CA came top as one simple technology that could be promoted in Zambia (Kassam et al., 2009). The Zambia Ministry of Agriculture and Livestock (MAL) in collaboration with other relevant stakeholders, envisaged that, with the policy pronouncement on CA for Zambia in 1999, about 600,000 Zambian smallholder farmers (about 50% in the country) should have adopted CA principles by the year 2015. However, it is estimated that only about 200,000 farmers were practicing CA by 2013.

There are three main CA technology implementing stakeholders in Zambia namely, the government through MAL and FAO, the Zambian National Farmers Union (ZNFU) through the Conservation Farming Unit (CFU) and Golden Valley Agricultural Research Trust (GART) and non-governmental organizations (NGOs), respectively. The ZNFU is the pioneer of CA in Zambia and had been implementing CA since 1996 in the Central, Eastern, Southern and Western Provinces. Following the 1999 policy pronouncement, MAL teamed up with the ZNFU to develop standard training materials and to intensify the training of farmers on CA technology across Zambia, starting

with 12 districts in the ZNFU CA operating provinces.

In line with the universally accepted CA principles of the FAO, the ZNFU implements CA by localizing tillage and fertilizer application in permanent rip lines or planting stations, ensuring adequate weed control, retaining crop residues after harvest, planting cover crops and rotating crops with nitrogen fixing legumes. The ZNFU also promotes the cropping of complementary perennial vegetation such as *Faidherbia albida* (a leguminous tree), and live fences (Aagaard, 2009). Completing land preparation before the onset of planting-rains to take advantage of nitrogen flush and reduce the average waiting time to planting is also considered a critical CA requirement in Zambia. For example, Haggblade and Tembo (2003) indicate that maize yields decline by 1–2% for each day of delay in planting after the first possible planting date, while cotton losses are estimated at 250–350 kg/ha per week of delayed planting. The CA technology therefore ensures that these losses are reduced to a minimum and contribute to reducing food and nutrition insecurity in Zambia (Amelia, 2014).

3.3 Conceptual framework

The conceptual framework used in this study follows the literature on technology diffusion. Four types of effects have been documented to explain the diffusion of new technologies over time. These include stock, rank, order, and epidemic effects. The rank effects is based on the assumption that potential adopters of a technology differ in their inherent investment and returns characteristics, resulting in different preferred adoption dates, such that firms achieving high returns adopt earlier compared to their low returns earning counterparts (David, 1969). On the other hand, the stock effects model follows that, the expected benefits from adoption decline with increasing number of adopters, until a point where the number of cumulative adopters have a large enough impact on the market, such that adoption is no longer profitable.

With the order effects, a firm's position in the adoption order determines its net returns from

adopting the technology, in the sense that firms higher in the adoption order tend to obtain higher returns. Hence, if a firm expects the future number of adopters to be high, it will decide to adopt earlier. The order effects can be linked to differences in access to information, market, strategic behavior and managerial skills. The epidemic model proposed by Mansfield (1961) postulates that the decision to adopt by a potential adopter at any given date and the probability of diffusion of the technology in a given population is a function of awareness and receipt of sufficient information about what the technology is and how to use it. In this case, as the number of adopters increase, awareness about the technology is enhanced, and the diffusion process increases, for at least in the early periods.

Karshenas and Stoneman (1993) developed a framework that captures the various effects used to explain technology diffusion. In this framework, the optimal time of adoption and diffusion of a technology is assumed to be a function of related benefits from adoption. A farmer chooses to adopt the technology at the time when the expected benefits from adoption is optimal, compared to the benefits from postponing adoption. In line with Karshenas and Stoneman (1993), we specify the gross benefits derived by farmer i from adopting the CA technology as

$$g_{it} = f(R_{it}, S_{it}, O_{it}, E_{it}) \quad (1)$$

where t is the adoption date, g_{it} denotes the gross benefit to farmer i in period t , (R_{it}) is rank effects of farmer i at period t , S_{it} is the stock effects or the number of farmers already using the CA technology in period t in relation to farmer i and O_{it} denotes the expected change in number of adopters in the period after t , representing the order effects of farmer i where as E_{it} is the epidemic and other effects of farmer i in period t . In the present study, the epidemic effects relate to learning from social and institutional networks such as neighbors who have adopted the technology, farmers' association and extension services. Inherent characteristics like firm size, age, education, household size and gender are considered as rank effects (Karshenas and Stoneman, 1993).

We assume that a farmer i has a range of adoption dates, he chooses to adopt CA at the time when the expected benefit from adoption is optimal, compared to the benefits from delaying adoption. We also assume that on adopting the CA technology, the farmer continues to use the technology in subsequent production seasons²². The choice of optimal time (t^*) to adopt is determined by meeting two principal conditions; the necessary or profitability condition and the sufficient or arbitrage condition. The profitability condition can be pursued within the net present value (NPV) framework. Taking into consideration the NPV and time-value of adopting an irreversible CA technology after period $t - 1$, we adopt a dynamic programming formulation to model the adoption decision, such that the choice to adopt depends on the NPV from adoption [$g_{(it)A}$] and the NPV from non-adoption [$(t - 1)g_{(it)C}$] (Kimhi and Bollman, 1999). We hypothesize that the likelihood of farmer i adopting the technology at time t increases as the NPV from adopting turns positive, relative to practicing conventional farming. This is expressed as

$$N_{it} = [g_{(it)A} - (t - 1)g_{(it)C}] \geq 0 \quad (2)$$

where N is the latent index of unobserved net benefits from adopting the technology, conditional on a set of covariates. Taking into consideration the possibility of adopting in each future time period, the arbitrage condition is such that, over a range of time periods of positive NPV, the optimal time to adopt the CA technology is the one when profit is optimum and this is expressed as

$$y_{it} = \frac{d[N_{it}\exp(-rt)]}{dt} \leq 0 \quad (3)$$

where r is the discount rate. This implies that the net real benefit from adoption must not be increasing over time. The CA adoption decision for farmer i is therefore optimal at the time when it is perceived that, the CA technology is more profitable than the CF technology and that the adoption induced gains exceed the value of waiting for more information, or improvements in the CA technology. Given that over time, the distribution of the disturbance term is invariant across

²² There was no disadoption among the farmers in our sample.

farmers and depends on y , we specify the arbitrage condition as

$$y_i(t) + \varepsilon \leq 0 \quad (4)$$

where ε is the stochastic error term.

The probability that adoption will occur in time period t given that adoption has not taken place up to the beginning of time t relates to the hazard and survival functions. Following Karshenas and Stoneman (1993) and Mansfield (1961), we specify a function of the hazard rate or failure function as

$$\lambda_i(t) = \Pr[y_i(t) + \varepsilon \leq 0] = V[-y_i(t)] \quad (5)$$

where $V[-y_i(t)]$ denotes the distribution function of the stochastic error term.

Discrete- Time Hazard function

The hazard function allows for the approximation of the probability of adopting the CA technology. Time to adoption can be viewed as continuous time event, especially if it is possible to order the time to adoption of the individuals under observation. Wooldridge (2010) however noted that, in spite of the fact that time to adoption may be assumed to be continuous, measurements of periods of adoption are necessarily discrete. With reference to the adoption of CA in Zambia, farmers are observed to adopt the technology on annual basis. This phenomenon does not strictly take into account the actual date and time of individual adoption, but rather the interval (yearly) of adoption which falls under the grouped or banded duration data framework.

Grouped duration data arises when each duration is only known to fall into a certain time interval, such as weekly, monthly, or even annually. Suppose T , the discrete random variable for the time at which the spell occurs is taking on set of values $\{1, 2, \dots\}$, with probability mass function for adoption time $f(t) = \Pr(T = t)$; ($t = 1, 2, \dots$) and cumulative distribution function for adoption $F(t) = \Pr(T \leq t) = f(1), f(2), \dots, f(t)$, the discrete time hazard rate (λ_{it}) can be defined as

$$\lambda_{it} = \Pr(T = t | T \geq t) = \frac{\Pr(T = t)}{\Pr(T > t)} = \frac{\Pr(T = t)}{1 - \Pr(T \leq t - 1)} = \frac{F(t) - F(t - 1)}{1 - F(t - 1)} \quad (6)$$

As in Singer and Willet (1993) and Jenkins (1995), the probability that adoption occurs at time t is a product of the conditional probabilities that adoption did not occur in period 1 through to t , but only occurs in period t . Following Jenkins (1995) the hazard probability at t is expressed as

$$\Pr(T_i = t) = \lambda_{it} \cdot \prod_{j=1}^{t-1} (1 - \lambda_{ij}) = \left[\lambda_{it} / (1 - \lambda_{it}) \right] \cdot \prod_{j=1}^t (1 - \lambda_{ij}) \quad (7)$$

whilst the survivor probability at t is expressed as

$$\Pr(T_i > t) = \lambda_{it} \cdot \prod_{j=1}^t (1 - \lambda_{ij}) \quad (8)$$

The likelihood function with respect to the hazard probability for the whole sample is

$$L = \prod_{i=1}^n [\Pr(T_i > t)]^{c_i} [\Pr(T_i = t)]^{(1-c_i)} \quad (9)$$

where $c_i=1$ for censored observations and 0, otherwise.

The conditional probability of adoption given other covariates can then be modelled in discrete-time duration, using likelihood density functional forms as if the spells occurred continuously²³. The discrete time hazard function of adoption with respect to given covariates can then be expressed as

$$\lambda_{it}(t; X_i) = \Pr(T_i = t | T \geq t, X_{it}) \quad (t = 1, 2, \dots) \quad (9)$$

with X denoting a vector of covariates including rank, stock, order and epidemic effects which may vary with time. These covariates may be time-invariant or time varying. On selecting an appropriate parametrization strategy, estimation can then follow maximum-likelihood framework.

²³ The discrete-time model can be viewed as an approximation of a given continuous-time model (Jenkins, 1995).

3.4 Empirical estimation strategy

Like many empirical specifications, the hazard model can be estimated non-parametrically, semi-parametrically (eg. Cox, 1972; Meyer, 1990), or parametrically (e.g. Genius et al. 2014). Without covariates, or when the covariates are qualitative (e.g. gender), non-parametric methods like the Kaplan-Meier (1958), Nelson (1972) and Aalen (1978) can be used to estimate the hazard function, or compare the survival function for the qualitative variable (Cleves et al. 2004). To the extent that both parametric and semi-parametric approaches give consistent estimates, the parametric approach is more efficient, if the distributional assumption is correct (Meyer, 1990). We therefore employ a parametric approach in this study.

Generally, the hazard rate either monotonically increases, decreases or is constant with time. Hence, a variety of functional forms have been proposed for duration models, including the logistic, log-logistic, Weibull, exponential, lognormal, Gompertz and gamma distributions (Jenkins, 1995). The most commonly used are the Weibull, exponential or Gompertz distributions. To ascertain the appropriate distribution for our estimation, we estimate a non-parametric smoothed hazard model (Figure 3.1) which empirically describes the rate of CA adoption among farmers over the period. Figure 3.1 shows a sigmoid shaped baseline hazard characterizing the rate of diffusion, initially slow and later sharply increasing with time.

This pattern allows for the specification of the baseline hazard in line with the Weibull distribution. Particularly with agricultural technology, whereby farmers learn and acquire information at different rates with respect to their human capital endowments and strategic behavior, the Weibull distribution is considered reasonable in this study. The discrete time hazard rate or the probability of adopting CA at time t by farmer i given that he has not yet adopted the technology can be expressed in relation to household and farm characteristics as (Jenkins, 1995)

$$\lambda_i(t; \beta) = 1 - \exp(-\exp[b(j) + \beta' X_i]) \quad (10)$$

where j is the duration spell which characterizes the baseline hazard common to all households and

X denotes a vector of covariates including the rank, stock, order and epidemic effects, b and β are vector of parameters to be estimated.

We account for unobserved household heterogeneity (frailty), by transforming equation (9) as (Jenkins, 2005)

$$\lambda_i(t; \beta|v) = 1 - \exp(-\exp[b(j) + \beta' X_i] + u) \quad (9)$$

such that v is an unobservable individual farm household effect that scales the no-frailty component and $u \equiv \log(v)$. As Jenkins (2005) indicates, on the assumption that u is normally distributed with mean zero, the likelihood distribution can be estimated in line with the discrete proportional hazard rate.

3.5 Data and definition of variables

The data used in this study are from a farm household survey conducted from August to November, 2013 in the Central, Eastern, Western and Southern provinces of Zambia, where conservation agriculture is known to be quite prominent. A multistage sampling technique was employed to draw 408 farmers, covering 12 districts in Zambia. To start with, all the four provinces were purposively selected, such that all Zambian National Farmers Union (ZNFU) members in these CA prominent regions had the chance to be included in our sample. In consultation with ZNFU members, each province became a stratum. Since there were no much differences in the estimated number of CA adopters in these provinces, 3 districts were randomly selected per province. In each district, 5 agricultural camps²⁴ were then randomly selected, and within which 3 farmer groups were randomly selected from each zone. Individual CA farmers and their non-CA counterparts were then randomly selected from the groups. Enumerators who spoke both the local language and English were hired to interview the selected farmers, using a questionnaire. The survey gathered information on

²⁴ Agricultural camp in Zambia is a management unit of agricultural camp officer comprising a catchment area of up to eight different zones of different villages.

household characteristics, farm production pattern, input use and prices, average yields and output prices, social and institutional network variables, and other structural characteristics. Additional information was acquired from the ZNFU, MAL and FAO offices in Lusaka.

As indicated previously, CA entails accomplishing an integrated technology of three main linked principles, which include minimum tillage, maintenance of permanent or semi-permanent organic soil cover and crop rotation, either in sequence or association to enhance synergies. In line with Burton et al. (2003), we define adopters as farmers who practiced one or more of the CA principles outlined above, while those who did not practice any of the principles are considered as non-adopters in this study. Following this definition, we identified 183 non-adopters and 225 adopters, comprising of 92, 101, 95 and 120 farmers from the Central, Eastern, Southern and Western provinces, respectively. Given that CA was formally introduced by the ZNFU in 1995/96 farming season, the year 1996 is regarded as the first year for adoption. Adoption spell for individual farmers ended at their adoption date. The farmers who had not adopted until 2013 were censored, indicating that the adoption process was still in progress and these farmers could adopt at a later date²⁵. Those who started farming after 1996 are considered to be left-truncated and the duration spell for such farmers should be adjusted to start from the year they started farming²⁶. For our sample, all the farmers were already farming before 1996, as such no left truncation problems are encountered.

The approach for analyzing grouped or interval duration data summarizes the information on staying in the initial state, or exiting in each time interval in a sequence of binary outcomes (Sueyoshi, 1995). In effect, the data set is treated as an unbalanced panel data where each cross-

²⁵ Adopters and nonadopters are considered as uncensored and censored observations, respectively.

²⁶ Left truncation occurs when a subject enters (comes at risk) late. Spell duration for such a subject is adjusted to start from the date of observation (Cleves et al., 2004).

sectional observation is a vector of binary responses over the duration spell, along with covariates. As outlined in Jenkins (1995), if farmer i is censored, the binary dependent variable is equal to 0 for all of i 's duration spell, but for adopters, the binary dependent variable is equal to 0 for all of i 's duration spell before adoption and 1 for the year of adoption. In relation to the sample size and taking into consideration individual sample duration spells, 5861 observations are used in the empirical analysis, comprising of 2567 adopters and 3294 nonadopters.

Table 3.1 presents means and standard deviations of the variables used in the analysis. In particular, it indicates that the sample is male dominated (about 75%), with average age of 38 years and 6 years of schooling per household head. The average farm size is about 3 ha, majority (87%) are land owner-operators, with about 7 people residing in the farm household. About half (48%) of the farmers had access to credit. Table 3.2 reports the mean differences in the variables for adopters and nonadopters, with their corresponding t -values. The t -values suggest that there are some significant differences between adopters and nonadopters of the CA technology, with respect to farm-level and household characteristics.

The variables reported in Tables 3.1 and 3.2 include both time-variant and time-invariant covariates. Time varying covariates are variables that vary with time, whilst time in-variant covariates remain the same over time. Covariates considered as time varying in this study include, profit accruing to a farmer, duration spell to adoption and age of the farmer²⁷. All other covariates are assumed to be time-invariant. Farm size is an indicator of the level of resource endowment, with larger farm size indicating more household resource endowment. The farm size variable is measured as the area of cultivated farm land by farm household. Karshenas and Stoneman (1993) consider size to have positive scale effects on adoption of new technology and net negative effect on survival. However, Zilberman (1984) argues that because of less financial pressure on large

²⁷ To account for the time varying nature of profit, the consumer price index is used as a discount factor.

farms to search for new ways of improving productivity and incomes, size may have a negative effect on adoption of CA technology. Age of household head is used as a proxy for farm household farming experience, especially in the study area where agriculture is the main occupation of most farm households. The episode splitting method is employed to generate person-period observations and control for the time varying nature of age of farm household head and taking into account the duration spell up to adoption date (Jenkins, 2005). The education variable in this study is measured as the number of years of schooling by the household head. Additional years of schooling is expected to influence farmer's ability to gather and analyze relevant data for informed farm decisions (Huffman, 2001).

A variable on the distance to permanent market of the farmer is included to capture the impact of input and output markets on adoption. It is expected that the farther the distance to markets, the higher the cost involved in sourcing inputs and marketing farm products, and as such the lower the incentive to adopt. We also include a variable for land tenancy arrangement to capture the impact of tenure security on the diffusion of CA technology. As suggested by Abdulai et al. (2011), tenure security tends to enhance the use of soil-improving technologies. Access to credit here is used to capture the extent to which farmers are liquidity constrained. The variable is measured as whether the farmer obtained credit within the last three production seasons, and whether he tried to access more credit than was available to him. Farmers who required credit and could not access it and those who received credit, but were denied additional credit are deemed to be liquidity constrained. The variable machinery indicates whether a farmer owns a tractor and or magoya ripper²⁸. Owning farm implements enhances farmers' access to CA machinery and is therefore expected to speed-up farmers' adoption of CA.

²⁸ The Magoye ripper is a Zambian innovation which was developed in 1996 at Zambian Ministry of Agriculture and Cooperatives research station of Magoye (Dutch funding).

Table 3.1. Variable names, definition and descriptive statistics of sample

Variable	Variable description	Sample mean	Standard deviation
Age	Age of household head in years	37.616	12.684
Gender	1 if farmer is male, 0 otherwise	0.751	0.562
Education	Number of year of schooling by household head	5.735	2.609
Household size	Number of people residing in household	6.996	2.015
Credit	1 if farmer has access to credit, 0 otherwise	0.477	0.499
Farm size	Cultivated farm size in hectares	3.306	3.896
Profit	Farmers' profit in Zambian kwacha	3170.678	5344.512
Owner	1 if farmer is land owner-operated, 0 otherwise	0.865	0.342
Extension contact	1 if farmer had at least a contact with extension agent, 0 otherwise	0.490	0.500
Extension visits	Number of contacts visits to the farm	2.327	2.942
Extension outlet	Distance to nearest extension outlet (km)	5.521	2.521
Association membership	1 if the farmer belongs to a farmer association, 0 otherwise	0.295	0.456
Association meetings	Average association meetings attended in a year	0.497	0.745
Stock of adopters	Stock of previous adopters in the sample at adoption	62.210	9.707
Neighbor	Number of adopters in the village prior adoption	3.337	4.712
Homophilic adopters	Stock of homophilic adopters by age and education	12.806	9.707
Market	Distance to permanent market (km)	4.314	3.675
Machinery	1 if the farmer owns a tractor or Magoya ripper, 0 otherwise	0.808	0.394
Non-farm	1 if the farmer participated in non-farm employment, 0 otherwise	0.584	0.493
Eastern	1 if farm is located in Eastern province, 0 otherwise	0.275	0.446
Western	1 if farm is located in Western province, 0 otherwise	0.282	0.450
Southern	1 if farm is located in Southern province, 0 otherwise	0.222	0.416
Central	1 if farm is located in Central province, 0 otherwise	0.223	0.416
Sample size		408	
Number of observations		5861	

Table 3.2: Mean differences between censored and uncensored groups

Variable	Uncensored	Censored	Difference
	group	group	
	Estimates	Estimates	
Age	36.293	38.647	-2.354***
Gender	0.692	0.798	-0.106***
Education	6.614	5.049	1.565***
Household size	6.831	7.126	0.295***
Credit	0.948	0.109	0.477***
Farm size	3.238	3.358	-0.120
Profit	5393.452	1438.479	3170.678***
Owner	0.881	0.852	0.028***
Association membership	0.660	0.011	0.649***
Association meetings	1.099	0.027	1.072***
Neighbors	3.979	2.836	1.143***
Homophilic adopters	14.297	11.645	2.652***
Extension contact	0.993	0.098	0.895***
Extension visits	4.719	0.464	4.719***
Extension outlet	6.614	5.049	1.565***
Market	4.704	4.011	-0.693***
Machinery	0.562	0.814	0.014*
Non-farm	0.636	0.601	-0.039***
Eastern	0.305	0.251	0.053***
Western	0.259	0.301	-0.041***
Southern	0.192	0.246	-0.053***
Central	0.243	0.208	0.036***
Sample size	223	185	
Number of observations	2567		3294

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

As in Abdulai and Huffman (2005), we consider age to influence adoption and diffusion of technology. Following Karshenas and Stoneman (1993), variables with expectations are derived under the assumption of perfect foresight. Thus, the expected change in the cumulative number of adopters is measured as $S_{t+1} - S_t$, with S_t representing the stock of previous adopters at the adoption date. To minimize potential endogeneity in predicting the expected cumulative previous adopters, the two-stage estimation procedure suggested by Murphy and Topel (1985) is adopted. In the first stage, a time autoregressive model is used to predict S_{t+1} . The predicted S_{t+1} values are then used as the total expected change in adopters.

Information transmission measurement

As indicated earlier, the role of information transmitted through social networks and extension agents on adoption and diffusion is quite important (e.g. Bandiera and Rasul, 2006; Genius et al. 2014; Krishnan and Patnam, 2014)²⁹. Specifically, Bandiera and Rasul (2006) indicate that farmers' social networks tend to influence their decision to adopt new technologies. Genius et al. (2014) and Krishnan and Patnam (2014) demonstrate that both social networks and extension services are important determinants of technology adoption and diffusion. In line with Genius et al. (2014), we argue that farmers receive information directly and indirectly from their social and institutional networks which influence technology diffusion. Manski (1993) identified three types of effects in measuring the impact of social network, namely; (i) endogenous effects; the propensity of an individual to behave in a particular way is influenced by peer outcomes (ii) exogenous (contextual) effects; an individual behaves as his peers because they share similar environmental and observable characteristics, and (iii) correlated effects; peers behave alike because they have similar

²⁹ Social network refers to members of a social structure and the links among them through which information as well as good and services flow.

(unobserved) characteristics. Based on these effects, the challenge in the estimation of social network effects on diffusion is the reflection problem, which relates to identifying and disentangling appropriate reference peer effects. In a linear-in-means model, peer effects depend on the functional relationships between these effects, which may introduce perfect collinearity between the expected mean outcomes.

To control for the reflection problem regarding the sourcing of information within social and institutional networks, we employ three latent variables that are potentially relevant for measuring the effect of access to information on the diffusion of CA technologies. In particular, we follow Genius et al. (2014) and use observable indicators in a factor analytic model to proxy the impact of these three latent variables. These variables include the stock of homophilic adopters in farmer's reference group, exposure to extension services and level of involvement in farmers' associations³⁰. The stock of homophilic adopters and involvement in farmers' association variables are used to capture the effect of social network. The exposure to extension services variable is an indicator of farmers' level of access to institutional structures and information on farm practices and inputs from extension services.

The following three observable indicators are used to describe the number of adopters in the respondents' reference group. The first is the stock of previous adopters in the sample in the year the farmer adopted the technology, while the second indicator referred to as neighbors are the stock of previous adopters in farmer's village or town prior to adoption. The third indicator relates to the homophilic adopters, defined as stock of adopters belonging to the same age group and having similar education levels (Rogers, 2003). As in Genius et al (2014), we identify farmers with 6-year age range to belong to the same age group, and 2-year range of education to have similar education.

The latent variable for farmers' association involvement is determined by whether a farmer

³⁰ Homophily is the degree to which individuals who interact are similar in certain attributes, such as beliefs, education, social status, and the like (Rogers, 2003).

belongs to a farmers' association or not, and for farmers who are members of an association, the average number of association meetings that they attend in a year. We determine the latent variable for exposure to extension services using three observed extension variables. These include access to extension services, measured as whether the farmer had contact with extension agents over the last three production seasons prior to adoption and distance to the nearest extension outlet. The third observed extension variable is contacts with extension agents, defined as the number of contacts a farmer had with extension agents within the three year period to adoption.

We estimate the latent variables from a factor analytic model using the eight observable variables in a principal components framework, with varimax rotation to generate orthogonal component estimates.

Table 3.3: Estimation Results of Factor Analytic Model

	Stock of homophilic adopters	Extension exposure	Association involvement
Stock of adopters	-0.084	0.412	0.446
Neighbors	0.366	0.050	-0.015
Homophilic adopters	0.842	0.051	0.046
Extension access	0.359	-0.129	-0.101
Extension outlet	0.100	0.185	0.439
Extension visits	0.010	0.870	-0.406
Association membership	-0.071	0.132	0.648
Association meetings	0.074	0.024	0.640

For convenience, we drop subscripts and express the relationship between the observed and latent variables as

$$\mathbf{p} = \boldsymbol{\mu} + \boldsymbol{\eta}\mathbf{C} + \mathbf{v} \tag{10}$$

where \mathbf{p} denotes the eight observed variables; $\boldsymbol{\mu}$ is a vector of constants corresponding to the mean of \mathbf{p} ; \mathbf{C} represents the (3 x 1) latent components; $\boldsymbol{\eta}$ is a (8 x 3) matrix of constants, \mathbf{v} is an (8 x 1) random vector with zero mean and variance-covariance matrix $\boldsymbol{\Psi} = \text{diag}(\psi_1^2 \dots \psi_8^2)$; \mathbf{p} and \mathbf{C} are

assumed to be multivariate normal, with \mathbf{C} and \mathbf{v} uncorrelated .

The estimates from the factor analytic model specified in equation (10) are presented in table 3.3. The estimated factor loadings indicate that the heaviest loadings for factor 1 come from the variables related to homophilic adopters and neighbors, hence factor 1 is labeled as homophilic adopters. For factor 2, the main contributing variables are the ones related to access to extension services and labeled as extension exposure. Variables related to association membership are the main contributors to factor 3, hence the corresponding factor is labeled as association involvement. It is significant to mention that all pair-wise correlations between the eight observed indicators are significant at the 0.001 level, and that all the indicators are used to predict the three latent variables. These results are not presented in the interest of brevity. The estimated latent variable scores are included in the duration model of equation (12).

Risk measurement

Like any new technology with its inherent uncertainties, CA technology may equally be perceived as a risky venture, as farmers will have to learn new practices and vary their operations to adhere to the relevant principles. For instance, implementing the minimum tillage principle entails investing in new implements, while maintaining crop cover presents significant opportunity costs, as there will be stiff competition for crop residue for other purposes such as livestock feed and fuel (Giller et al., 2009).

To the extent that farmer i is forward looking and can form expectations about all conjectures of future profits, and given that most farming systems in Zambia are uncertain due to over dependence on natural climatic conditions like rainfall, we assume that within the production process, farmers face production risk in relation to a given technology. Following Koundouri et al. (2006) and Di Falco and Chavas (2009), we estimate the production risk in line with the four

moments of profit within an OLS estimation procedure.³¹ Estimating the moments of profit empirically follows a sequential estimation procedure by first regressing profit on farm inputs and other farm level socioeconomic covariates as

$$\pi_i = \vartheta(x_i, Z_i, \beta) + \mu_i \quad (11)$$

with π_i denoting profit per hectare, x_i vector of variable inputs per hectare, Z_i is a vector of other farm-level and household characteristics, β the parameters to be estimated and μ_i the residual. The estimates of the profit function are presented in Table 3.A1 in the appendix. The residual of the profit function is the estimate of the first moment of the profit function. The variance, skewness and kurtosis are estimated raising the first moment of profit to the corresponding power and regressing on the same set of explanatory variables to obtain the respective residuals. These are then included as variables M_k in equation (12).

The duration model is then specified as³²

$$\begin{aligned} \lambda_i(t; \beta|v) = 1 - \exp \left(-\exp \left[b(J_{it}) + \beta_1 Age_{it} + \beta_2 Age_{it}^2 + \beta_3 Gend_{it} + \beta_4 HHS_{it} + \beta_5 Educ_{it} \right. \right. \\ \left. \left. + \beta_7 Cred_{it} + \beta_8 Mdist_{it} + \beta_9 NFarm_{it} + \beta_{10} Fsize_{it} + \beta_{11} Own_{it} \right. \right. \\ \left. \left. + \beta_{12} Machi_{it} + \delta ChangAdopt_{it} \right. \right. \\ \left. \left. + \sum_{m=1}^3 c_m C_{mit} + \sum_{k=1}^4 \alpha_k M_{kit} + \sum_{r=1}^4 \phi_r R_{rit} \right] \right) \quad (12) \end{aligned}$$

where j is the duration spell characterizing the baseline hazard common to all households, R_r denotes regional fixed effects and M_k the moments of profit described in the risk section below.

Potential endogeneity problems may arise in the estimation of the hazard function. In particular, farmers' may self-select themselves to participate in non-farm employment, while access

³¹ First, second, third and fourth moments are the mean, variance, skewness and kurtosis, respectively.

³² The indicators are used to predict the three latent variables as all the pair-wise correlations between the eight observed indicators are significant at 0.001 level.

to credit and adoption decision may be jointly determined. We employ a two-stage procedure proposed by Rivers and Vuong (1988) to account for this potential endogeneity. In the first-stage, we specify the potentially endogenous variables as functions of all other exogenous variables including a set of instruments that are assumed to be correlated with the given endogenous variable, but uncorrelated with the error term in the hazard function. For identification, a suitable strategy is employed such that we include a variable that strongly influences the potential endogenous variable but does not influence the diffusion process. For the access to credit equation, we use distance to source of capital which influences access to credit but not the diffusion process as instrument. Due to limited non-farm jobs in the rural areas, farmers located very far away from provincial capital are normally resource constrained, and find it difficult to seek non-farm jobs in the cities.

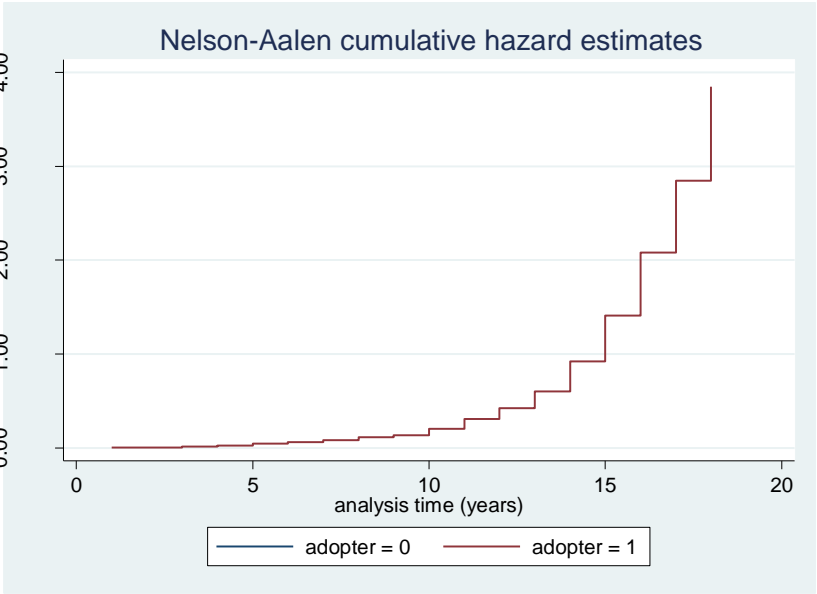


Figure 3.1a: Nelson-Aalen smoothed hazard estimate

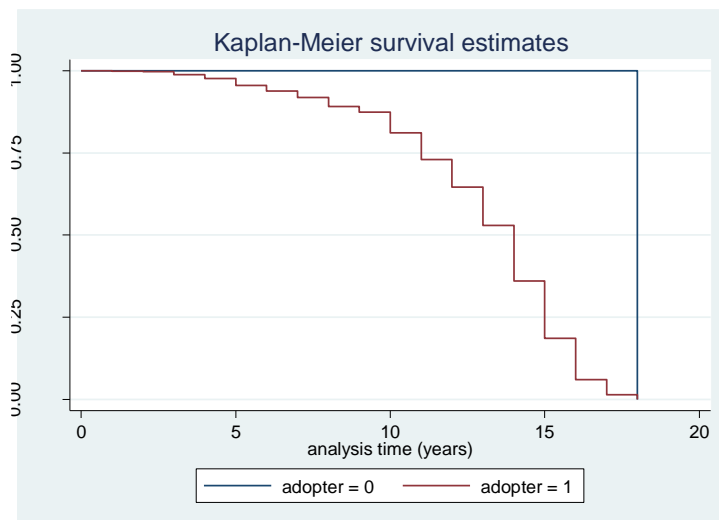


Figure 3.1b: Kaplan-Meier survival function for sample

Distance to the provincial capital is employed as instrument in the nonfarm work specification. In the second stage, the observed values of these variables and their corresponding residuals are incorporated into the hazard model.

3.6 Empirical results

The empirical strategy employed here includes both non-parametric and parametric approaches. Both approaches take into consideration the censoring nature of the data. Figure 3.1b presents the non-parametric Kaplan-Meier estimators of the survival function for adopters where horizontal axis depicts the duration spells (in years), whilst the vertical axis indicates the probability of survival. Figure 3.1b describes the relationship between the proportion of adoption and adoption spell. The estimates from the hazard curve in figure 3.1a indicates that the number of adopters increase overtime, while the Kaplan-Meier survival function in figure 3.1b reveals that number of non-adopters decline over time, both suggesting that there is positive duration dependence in the survival process, such that the number of adopters increased over time. A Weibull distribution was assumed

in the parametric estimation of the complementary log-logistic (proportional hazard)³³ function employed in the estimation.

Table 3.4 reports the maximum likelihood estimates of the hazard function for adoption of CA technology. Also reported in the table are test statistics for the specification. The estimated p -value of the likelihood ratio test statistic for unobserved heterogeneity is 0.363, suggesting the absence of any unobserved heterogeneity in the duration spell. The likelihood ratio test for the location dummy is significant, suggesting potential differences in provincial adoption rates, with slower rate of adoption in the Eastern provinces, the farthest province from Lusaka. The residuals of the potential endogenous variables are also presented in the table. Specifically, the residuals for non-farm work and access to credit are not statistically significant at conventional levels, suggesting the absence of simultaneity bias and that the coefficients are consistently estimated (Wooldridge, 2010). The χ^2 -statistic for the validity test of the over-identifying restrictions also fail to reject the exclusion restriction that the instruments employed affect adoption only through non-farm work and credit variables.

In the interest of brevity, we only interpret variables that are significantly different from zero in the hazard function estimates presented in Table 3.4. The estimates are interpreted by their signs, with a positive coefficient suggesting that the variable speeds up adoption and vice versa. The coefficient of the baseline hazard is positive and significant, indicating that adoption increases over time. This finding is consistent with the smoothed hazard and Kaplan-Meier estimates in Figure 3.1a and 3.1b, respectively, showing positive duration dependence in the adoption process. The positive and significant estimate of age suggests that older farmers, who are more experienced in farming are able to make informed decisions of an innovation and seek to be among the innovators

³³ We tested this against the logistic specification using Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) to ascertain the appropriate model and the complementary log-logistic model was confirmed to be appropriate.

and early adopters of a beneficial technology, rather than belonging to the late adopters or laggards. The positive effect of age on adoption and diffusion is consistent with the results by Genius et al. (2014). The estimates for both age and age-squared variables are significant, but positive for age and negative for age-squared, confirming the presence of life cycle effects. The estimates show that increasing age increases the probability of adoption up to 49 years beyond which adoption rate declines, indicating that both farming experience and planning horizon affect the adoption of CA technology.

The positive and significant coefficient of the education variable indicates that more educated farm household heads are likely to adopt the technology faster, a finding that is in line with the view that education is important in helping farmers in their decisions to adopting new innovations and technologies (Huffman 2001). The coefficient of the owner variable is positive and significant at conventional level, suggesting that owner-operated landholding households are more likely to adopt CA faster than the non-owner operated counterparts. The coefficient for the farm size variable is positive and significant, suggesting scale effects on adoption, with a higher probability of large scale farmers adopting the CA technology earlier. The positive and significant estimate of access to credit indicates that farmers who are liquidity constrained are more likely to adopt the technology slowly compared to their counterparts who are not liquidity constrained, and can afford to pay for complementary inputs of the technology. This finding is consistent with the results reported by Abdulai and Huffman (2005) for Tanzania. The positive and significant coefficient for non-farm work suggests that farmers participating in non-farm work are likely to adopt the technology faster. In spite of the fact that participating in nonfarm work is likely to reduce the time investment required to implement the new technology, it is an avenue to generate additional income that could be invested in procuring the needed implements and other complementary inputs for the technology.

We jointly test for heterogeneity among farmers in their farm and household characteristics,

representing the rank effects outlined previously, using age, gender, education, household size, credit, farm size and non-farm variables. The test statistic reported in Table 3.4 is found to be significant at the 1% level, which implies that different inherent characteristics among potential adopters of the technology will result in different returns from its use, a finding that is consistent with the rank effects. The coefficients for the latent variables representing extension exposure, stock of homophilic adopters and association involvement are all positive and significantly different from zero, indicating that increasing contacts with extension agents, active participation in farmers' association and increasing number of peers practicing the technology tend to have a positive influence on the diffusion of the technology.

The positive relationship between diffusion and stock of homophilic adopters variable as well as exposure to extension services variable are consistent with the findings by Genius et al. (2014) and Krishnan and Patnam (2014) for Ethiopia and Greek Island of Crete, respectively. The findings from these social and institutional network variables, which conform to the epidemic effects described previously, confirm that there are epidemic effects in CA adoption process. In particular, the estimates for stock of homophilic adopters and farmer's association indicate an influence of peer effects on the adoption and diffusion of CA, where farmers learn from members within their social network. The homophilic adopters variable, which also captures the stock of farmers that already practiced the technology, also suggests the presence of stock effects in the diffusion process. The coefficient of the order effect variable, represented by expected change in the cumulative number of adopters is positive and significantly different from zero, indicating a progressive effect on the rate of adoption, and categorizing the farmers into the various classes of adopters³⁴.

The estimates of the coefficients of the four moments of profit variables (i.e., expected profit, profit variance, profit skewness and profit kurtosis) are also reported in the table 3.4. As indicated

³⁴ Rodgers (2003) categories adopters into innovators, early adopters, early majority, late majority, and laggards

earlier, the first and second moments relate to risk aversion, whilst the third and fourth moments indicate loss aversion. The coefficients of the risk aversion moments are positive and statistically significant, indicating that higher marginal benefits will hasten adoption. On the other hand, the coefficients of loss aversion variables are negative with kurtosis, the fourth profit moment, significantly different from zero, suggesting that higher potential losses will slow the adoption rate. These findings indicate that farmers in Zambia exhibit both risk and loss aversion attitude in adopting new technologies. The findings concur with the results reported by Garrido and Zilberman (2008) for Spanish farmers.

The reported hazard ratio for a covariate like extension exposure (1.36) therefore indicates that, farmers with additional access to extension visit have a conditional probability of adoption of about 1.4 times compared to their non-member counterparts. The percentage change estimates indicate percentage increase or decrease of the covariate on the hazard rate. For example increasing access to credit by 1% will result in 480% increase in the hazard rate. Table 3.5 presents the marginal effect estimates of the hazard rate of CA adoption, comprising the hazard ratios and the respective percentage changes.

The hazard ratios are obtained by exponentiation of the coefficients in Table 3.4 and are interpreted as marginal effects of the discrete time proportional hazard model as in Abdulai and Huffman (2005). A hazard ratio less than one suggests that an increase in the regressor will lead to a decrease in the hazard rate, while hazard ratios greater than one will result in an increase in the hazard rate.

Table 3.4. Maximum likelihood estimates of parameters for hazard function for adoption of CA among ZNFU farmers

Variable	Coefficient	Std. Err.
Constant	-11.461***	1.151
Baseline hazard	0.596**	0.283
Age	0.195***	0.053
Age squared	-0.002***	0.001
Gender	-0.067	0.195
Household size	0.009	0.044
Education	0.078**	0.036
Credit	1.758***	0.646
Market distance	-0.425***	0.147
Non-farm work	0.267**	0.135
Association involvement	1.415***	0.421
Homophilic adopters	0.267***	0.092
Extension exposure	0.307***	0.109
Expected change in number of adopters	0.084**	0.038
Farm size	0.115***	0.029
Owner	0.439*	0.238
1st profit moment	1.269***	0.240
2nd profit moment	0.513**	0.209
3rd profit moment	-0.045	0.050
4 th profit moment	-0.046*	0.025
Machinery	0.322	0.225
Eastern	-0.656**	0.271
Western	0.274	0.257
Southern	0.098	0.262
Credit residual	0.011	0.022
Non-farm residual	0.010	0.046
Log likelihood for the model	$(\chi^2(25))$	-563.809
	<i>p</i> – value	0.000
Likelihood ratio test for unobserved heterogeneity		0.363
Likelihood ratio test for over identification	$(\chi^2(2))$	2.81
	<i>p</i> – value	0.245
Likelihood ratio test for rank effects	$(\chi^2(7))$	33.82
	<i>p</i> – value	0.000
Likelihood test of location dummy	$\chi^2(3)$	12.33
	<i>p</i> – value	0.0063
Sample size		408
Number of observations		5861

Notes: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively

In particular, the estimates for stock of homophilic adopters and farmer's association indicate an influence of peer effects on the adoption and diffusion of CA, where farmers learn from members within their social network.

Table 3.5: Maximum Likelihood Estimates of Hazard Ratio

Variable	Hazard ratio	Percentage change
Age	1.216***	21.60
Gender	0.935	-6.50
Household size	1.009	9.00
Education	1.082**	8.20
Credit	5.803	480.30
Market distance	0.654***	-34.60
Non-farm work	1.306***	30.60
Association involvement	4.117***	311.70
Homophilic adopters	1.306***	30.60
Extension exposure	1.360***	36.00
Expected change in number of adopters	1.088**	8.80
Farm size	1.121***	12.10
Owner	1.551*	55.10
1st profit moment	3.557***	25.57
2nd profit moment	1.671**	67.10
3rd profit moment	0.956	-4.40
4th profit moment	0.955**	-4.50
Machinery	1.380	38.00

Notes: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The homophilic adopters variable, which also captures the stock of farmers that already practiced the technology, also suggests the presence of stock effects in the diffusion process. The coefficient of the order effect variable, represented by expected change in the cumulative number of adopters is positive and significantly different from zero, indicating a progressive effect on the rate of adoption, and categorizing the farmers into the various classes of adopters³⁵.

The estimates of the coefficients of the four moments of profit variables (i.e., expected profit,

³⁵ Rodgers (2003) categories adopters into innovators, early adopters, early majority, late majority, and laggards

profit variance, profit skewness and profit kurtosis) are also reported in the table 3.4. As indicated earlier, the first and second moments relate to risk aversion, whilst the third and fourth moments indicate loss aversion. The coefficients of the risk aversion moments are positive and statistically significant, indicating that higher marginal benefits will hasten adoption. On the other hand, the coefficients of loss aversion variables are negative with kurtosis, the fourth profit moment, significantly different from zero, suggesting that higher potential losses will slow the adoption rate. These findings indicate that farmers in Zambia exhibit both risk and loss aversion attitude in adopting new technologies. The findings concur with the results reported by Garrido and Zilberman (2008) for Spanish farmers.

Table 3.5 presents the marginal effects estimates of the hazard rate of CA adoption, comprising the hazard ratios and the respective percentage changes. The hazard ratios are obtained by exponentiation of the coefficients in Table 3.4 and are interpreted as marginal effects of the discrete time proportional hazard model. A hazard ratio less than one suggests that an increase in the regressor will lead to a decrease in the hazard rate, while hazard ratios greater than one will result in an increase in the hazard rate. The reported hazard ratio for a covariate like extension exposure (1.36) therefore indicates that, farmers with additional access to extension visit have a conditional probability of adoption of about 1.4 times compared to their non-member counterparts. The percentage change estimates indicate percentage increase or decrease of the covariate on the hazard rate. For example increasing access to credit by 1% will result in 480% increase in the hazard rate.

3.7 Conclusions

In the spirit of sustainable agriculture, the promotion of conservation agriculture (CA) as an improved technology has received considerable attention in recent times. In Eastern and Southern Africa, CA technology is gaining significance, with numerous activities and promotion programs

from both government agencies and civil society organizations. This study has examined the role of social networks and extension services, as well as other farm characteristics in the diffusion of CA technology among farmers in Zambia. A discrete-time duration model was used to examine the time path to CA technology adoption taking into consideration the heterogeneity among farmers in their farm and household characteristics, as well as risk preferences. We used a factor analytic model to generate scores for the social and institutional network variables, which are then included in the duration model to account for potential endogeneity of sources of information.

The empirical results suggest that CA technology diffusion is duration dependent with progressive rate of adoption. We also found that CA technology diffusion positively and significantly influenced by access to information from institutional networks, like exposure to extension services and social networks such as association involvement, as well as contacts with peers who had adopted the technology. Farmers' association and peers provide a convenient platform for farmers to share ideas and learn from each other and hence impact positively on the diffusion of conservation agriculture technology. Access to extension services improves access to institutional and policy information, which enhances the diffusion of the technology.

Another interesting finding is the observation that farmers are risk averse and tend to consider both absolute and down side risks in the adoption process, a finding that suggests that policy makers need to take into consideration farmers' risk preferences when introducing new technologies to enable them accurately predict the adoption patterns. We also established that heterogeneity in farm and household characteristics like age, gender, education, access to credit and farm size significantly influenced the diffusion process. In particular, more educated household heads, land owner-cultivators, households with large farm holdings, and those that had access to credit adopted the technology faster, suggesting the significance of both human and physical resource endowments in technology adoption and diffusion.

The findings of this study suggest that, extension agents who provide information about the

new technology to farmers are quite important in promoting the adoption of these technologies, and should therefore be encouraged and supported by policy makers and program implementers with the requisite logistics and expertise. Given that there are no natural barriers to information flow amongst farmers and considering the socially interlinked extended family system in Zambia, enhancing social networks through the formation of farmers' associations and the promotion of the community lead - farmer extension systems stand a better chance to enhance adoption of the technology. As widely documented in the literature, improving farmers' access to credit is a way of helping them to overcome imperfect financial markets, making it easier for them to adopt new technologies. Hence, policy design should include measures that contribute to enhancing access of farmers' to adequate and timely financial resources.

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Appendix

3. A: Profit function

Profit	Coefficient	Std. Err.
Output	0.089***	0.002
land price	-0.013	0.824
labour price	0.029***	0.008
Capital price	-0.011***	0.003
Other cost prices	-0.001***	0.000
Other cost prices squared	3.149	35.241
Land x labour	0.001**	0.000
Land x capital	0.001***	0.000
land x others	-6.378	70.482
Land price squared	0.000	0.001
Capital price squared	-0.015	0.034
labour price squared	0.001***	0.000
Education x extension	-0.010***	0.002
Extension x age	0.000	0.000
HHS	-0.049***	0.007
Education x extension	0.042***	0.010
Age	0.064***	0.002
Extension office	0.161***	0.014
Extension contact	0.725***	0.042
Credit	0.688***	0.064
Credit x extension	0.003	0.011
Constant	30.997	256.644
R-squared		0.598
Adjusted R-squared		0.596

Notes: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Chapter 4

Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia

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Abstract

This paper explores the impact of conservation agriculture on environmental efficiency of maize farmers in Zambia, by comparing nitrogen fertiliser recovery between farms that practice conservation agriculture and those using conventional farming technologies. The nitrogen index tier zero tool is employed in generating a nitrogen balance sheet at the farm level. As conservation agriculture technology may improve farmers' access to better technology, we employ a selectivity-corrected meta-frontier approach to account for potential selection bias and technology heterogeneity. The empirical results suggest that farmers practicing conservation agriculture are environmentally more efficient than conventional farmers. The findings also show that, environmental efficiency is significantly influenced by access to credit, farming experience and years of schooling of household head, land ownership and distance to markets. Moreover, farmers practicing conservation agriculture are found to be technically more efficient than those using the conventional technology.

Keywords: Meta-frontier model, Technical efficiency, Environmental efficiency, conservation agriculture.

4.1 Introduction

Attaining sustainable agriculture entails the pursuance of resilient agricultural practices that support comprehensive synergies in increasing agricultural productivity and maintaining the ecosystem. This requires judicious use of farm inputs including fertilisers. With the ever growing human population, the demand for fertilisers, especially nitrogen (N) fertilisers to support food production will continue to increase. Erisman et al. (2008) note that, while over 78% of the atmosphere is composed of nitrogen, the supply of nitrogen fertilisers in commercial quantities is mainly facilitated through the Haber–Bosch nitrogen process of industrial ammonia synthesis. Galloway et al. (2008) indicate that, about 80% of nitrogen from the Haber–Bosch process is used in the production of mineral fertilisers.

In spite of the tremendous benefits from the Haber-Bosch process, it is estimated that only half of fertilisers applied to crops are utilised, with the rest lost to the atmosphere, soil and aquatic ecosystems (Galloway et al., 2008). The unintended consequence from the Haber–Bosch process has been linked to some negative environmental externalities, including increases in air and water pollution. Notwithstanding the potential adverse impacts of fertilisers, estimates show that total fertiliser consumption is expected to increase from about 183 to 201 million metric tonnes between 2013 and 2018, with about 60% share from nitrogen fertilisers. Although fertiliser application rates are currently low in sub-Saharan Africa (SSA), the use of nitrogen fertilisers is projected to double within this same period (FAO, 2015).

Given that maize is a staple crop in many countries in SSA including Zambia, significant amounts of fertilisers are normally applied to increase maize output in order to meet demand in the region. While output growth is required to meet the increasing demand for food in SSA, continuous increases in fertiliser use without considering options to mitigate losses from runoff, leaching and volatilisation of nitrogen fertilisers could have negative environmental consequences.

Dobermann and Cassman (2002) point out that, with good management practices, nitrogen

recovery from maize could be improved from 37% to 80%, suggesting the relevance of enhanced agricultural technologies in mitigating the emission of GHG in the coming years. In line with the Nebraska declaration on conservation agriculture and other conventions, conservation agriculture (CA)³⁶ is regarded as one technology that could enhance food productivity and environmental efficiency relative to conventional farming (Stevenson et al., 2014). The FAO (2010) describes conservation agriculture as a concept for resource-saving agricultural crop production that strives to achieve acceptable profits through higher and sustained production levels, and concurrently conserving the natural environment. Valuing social cost with regards to carbon dioxide emission into the atmosphere suggests that, CA technology is a potential candidate to harness the desired economic, environmental and social synergies of sustainable agriculture (Wei, et al., 2010).

Assessing the environmental impact of CA with particular reference to the utilisation of nitrogen fertilisers largely depends on the ability to generate a nitrogen balance sheet of quantity of nitrogen (N) consumed in producing the output and quantity of nitrogen that is unutilised (surplus). This may require vigorous laboratory analysis, with complex computer models and technical expertise in modelling soil biogeochemistry and nitrogen dynamics. Hence, some studies account for nitrogen surplus using weights like the International Panel on Climate Change (IPCC) default value of 1% of N applied or N released through mineralisation of organic matter in mineral soils (e.g. the eutrophication power of 1 adopted by Coelli, et al., 2007)³⁷. However, in their recent study on Mexico, Saynes et al. (2014) demonstrate that this approach underestimates nitrogen emission by more than two fold. Some other related literature employ National Farm Accountancy Data (e.g.

³⁶ Conservation agriculture relies on the key principles of minimum soil disturbances, retaining permanent crop residue and crop rotation with incorporation of fertilisers into the soil. Conventional farming is referred to as the seasonal perpetual and intensive tilling of farm land (by hoe, disc or plough), mono cropping and slash-and-burn of crop residue.

³⁷ Recent data suggest that this emission factor could be disaggregated into environmental factors and management related factors. Countries that are able to disaggregate their activity data from all or some of these factors may choose to use disaggregated emission factors (IPCC, 2006).

Reinhard et al., 1999; 2002), while others have used national nutrient management tools (e.g. Ramilan et al., 2009). In economies like Zambia there are no standard national nutrient management tools, soil nutrients test is beyond the reach of many subsistence farmers, and soil testing laboratories are either of lower standards or non-existent. The current study differs from other studies in the generation of farm level nitrogen balance sheet by using the Nitrogen Index Tier Zero tool (described in the conceptual framework and data sections, respectively) developed and validated by Saynes et al. (2014).

Over the last two decades, numerous studies have analysed technical and allocative efficiency of farmers in SSA (e.g. Abdulai and Huffman, 2000). A meta-analysis by Ogundari (2014) summarises the findings of these studies. What is clearly missing is an examination of the environmental externalities of agricultural production in this region. This study therefore contributes to the literature by examining the impact of CA technology on environmental efficiency of maize farmers in Zambia. In particular, it explores crop utilisation of nitrogen fertilisers amongst farms practicing CA and conventional farming technologies. We also consider potential technology heterogeneity among these farms and employ a multi-stage approach to examine environmental efficiency in a meta-frontier framework, while correcting for selection bias that may arise from both observable and unobservable factors.

Although the study follows technical and environmental efficiency estimation strategies, it is unique in several ways (e.g. Reinhard et al, 2002; Rao et al., 2012; Nguyen, 2012). First, it differs from other productivity and efficiency studies on conservation agriculture that assume a common technology for all production units (e.g. Ng'ombe and Kalinda, 2015). We employ a meta-frontier model that accounts for technology heterogeneity among farm households. In spite of recent applications of a selectivity-corrected stochastic frontier model in efficiency measurement (e.g. Bravo-Ureta et al., 2012; González-Flores et al., 2014; Villano et al., 2015), this study is the first to employ the framework in the estimation of environmental efficiency. As in González-Flores et al.

(2014) and Villano et al. (2015), we use both propensity score matching (PSM) method and Greene's (2010) sample selection approach to address these issues in a meta-frontier framework. To the best of our knowledge, this is also the first study to employ the Nitrogen Index Tier Zero tool dataset within a frontier framework.

The rest of the paper is organised as follows. In the next section, conservation agriculture from the perspective of Zambia is described. Sections 3 and 4 discuss the conceptual framework and the analytical strategy employed, respectively. The data and empirical specification are presented in section 5, while section 6 discusses the empirical results. The final section presents conclusions and policy recommendations.

4.2 Conservation Agriculture in Zambia

According to the FAO (2010), Zambia and eleven other African countries³⁸ are CA focal countries in Africa, with Zambia considered as the success story of CA uptake in the region. To the extent that policy influences the adoption of agricultural technologies, there was a policy pronouncement in Zambia in 1999, suggesting that CA technology becomes part of the Zambian National Agricultural Policy. This was aimed at increasing crop production and productivity, mitigating adverse climate change impacts, reducing the incidence of labour constraints, diversifying crop production and improving soil fertility, as well as increasing farm income and household food and nutrition security.

There are three main CA implementing agencies in Zambia, namely, the government through the FAO and the Ministry of Agriculture and Livestock (MAL), the Zambian National Farmers Union (ZNFU), through a collaboration between Conservation Farming Unit (CFU) and Golden Valley Agricultural Research Trust (GART) and other agencies broadly regarded as Non-

³⁸ Angola, Botswana, Lesotho, Madagascar, Malawi, Mozambique, Namibia, South Africa, Swaziland, Tanzania, Zambia, and Zimbabwe.

Governmental Organisations, respectively. The ZNFU considers CA as an integrated technology with three main linked principles, namely, minimum soil disturbance, maintenance of permanent or semi-permanent organic soil cover and diversification of crop species. The CA technology entails localising tillage and incorporating fertilisers in permanent rip lines or planting stations, ensuring adequate weed control, retaining crop residues after harvest and inter-cropping, or rotating crops with nitrogen fixing legumes.

The ZNFU also promotes the cropping of complementary perennial vegetation such as *Faidherbia albida* (a leguminous tree), and live fences. Completing land preparation before the onset of planting-rains to take advantage of nitrogen flush and to reduce the waiting time to planting is equally considered a critical CA technology requirement in Zambia. In particular, Haggblade and Tembo (2003) indicate that, on the on-set of the first possible planting rains, maize yields decline by 1–2% for each day of delayed planting. Conservation agriculture technology therefore ensures that these losses are reduced to a minimum, thus contributing to higher output and reducing food and nutrition insecurity in Zambia as well as reducing environmental degradation (Neubert, 2011).

4.3 Conceptual framework

The conceptual framework used in this study follows the Law of Conservation of Mass, which states that matter can be changed from one form to another, mixtures can be made or separated, and pure substances can be decomposed, but the total amount of mass remains constant. In effect, the total quantity of nitrogen fertilisers applied in a system is fixed, only part of it may contribute to the generation of the desired output and the surplus may be environmentally detrimental. More importantly, as much as nitrogen is a macro-nutrient for the growth and development of plants, reactive nitrogen cascade from leaching, runoff and volatilisation of synthetic nitrogen tend to modify the balance of greenhouse gases. It also decreases stratospheric ozone, increases soil acidification, enhances tropospheric ozone, and catalyses the formation of secondary particulates

in the atmosphere (Erismann et al., 2008). More so, nitrous oxide (N_2O) is considered one of the major non- CO_2 greenhouse gas (GHG) emitters, with agriculture regarded as the biggest anthropogenic source (Reay et al., 2012). For instance, in 2005, emissions from agricultural activities, largely from soil tillage and application of nitrogen fertilisers, accounted for approximately 60% of total global anthropogenic emissions of N_2O (Smith et al., 2007).

In essence, it might be problematic to quantifying the exact economic and environmental consequences of inputs like nitrogen fertilisers. But the ability to reasonably establish a nitrogen balance sheet at the farm level with respect to nitrogen recovered and nitrogen surplus is an indication of the potential economic benefits and environmental burden that may arise from the application of nitrogen fertilisers. Here, the Nitrogen Index Tier Zero tool (NITZ) is used in generating the nitrogen balance. Saynes et al. (2014) are the first to use it in their study of N_2O emissions from nitrogen fertiliser in Mexico based on only nutrient management practices. In this study, we argue that, beyond nutrient management practices, other farm and household confounding factors may influence household nitrogen use efficiency. We therefore examine household environmental efficiency with respect to nitrogen efficiency using nitrogen balance scores from the NITZ tool in a stochastic production frontier (SPF) framework.

In empirical analysis of environmental efficiency, the potential environmentally detrimental element is either considered an input, with input-orientation strategies (e.g. Reinhard et al., 1999; 2002) or an output, and efficiency estimates follow an output-orientation (e.g. Färe et al., 1989; Cuesta, et al., 2009). On assuming weak disposability in the output orientation, an extra pollution variable is incorporated into the production model and estimated by distance and directional functions. For instance, Färe et al. (1989) and Cuesta et al., (2009) employed deterministic and stochastic hyperbolic and enhanced hyperbolic distance approaches, respectively. Coelli et al. (2007) indicate that, although previous applications did not consider material balance in their empirical study, specifications in the study by Färe et al., (1989) and their likes violate the material

balance condition. Materials balance is fundamentally an adding up condition, which essentially indicates that ‘‘what goes in must come out’’.

To the extent that nitrogen is applied as an input and only the unexpected surplus may be environmentally detrimental, the material balance of a product like nitrogen is calculated as the amount of nitrogen that enters the farm in inputs minus the amount that leaves the farm bound up in useful output. We follow the input oriented estimation strategy by Reinhard et al. (2002) which draws from the material balance framework adopted by Coelli et al. (2007) for phosphorous. This approach avoids the introduction of extra pollution variable into the model, be it input or weak disposable bad output. This also complies with the underlying adding up condition in material balance and demonstrates that environmental pollution can be reduced under efficient use of inputs. This approach is pragmatic, particularly when the potential environmental burden is directly linked to the application of inputs like nitrogen fertilisers.

4.4 Analytical strategy

This study employs the stochastic production frontier (SPF) model to estimate technical and environmental efficiency of maize producing households in Zambia, with the assumption that farmers in our sample exclusively practice either CA technology, or otherwise. The SPF model is specified as:

$$Y_{ij} = f(\mathbf{X}, \mathbf{D}_C) + \varepsilon_{ij}, \quad \varepsilon_{ij} = (v_{ij} - u_{ij}) \quad (1)$$

where Y_{ij} denotes a scalar of outputs of farmer i using technology j , \mathbf{X} is a vector of inputs and other explanatory variables, \mathbf{D}_C is a dummy variable capturing the effect of CA technology and ε_{ij} is the error term, which is composed of v_{ij} , the random term (white noise) and u_{ij} , the systematic error term capturing inefficiency (Aigner et al., 1977). Given that farmers self-select themselves into adoption and non-adoption, selectivity bias may arise from both observable and unobservable

factors.

4.1 Sample selection in stochastic production frontier

The propensity score matching (PSM) is one common technique used to address selectivity bias (Khandker et al., 2010). The PSM is used to construct statistically comparable counterfactual group of adopters and non-adopters to correct for observable biases from the sample. This entails using a binary choice model (a probit model in this case) to generate predicted probability of adoption (propensity score), conditional on pre-treatment observed covariates of adopters and non-adopters, and expressed as

$$d_i = 1[\beta'z_i + \omega_i > 0], \omega_i \sim N(0,1) \quad (2)$$

where d_i is a binary variable, equal to one for adopters, and zero for non-adopters, z is a vector of explanatory variables in the sample selection model, β is a vector of parameters to be estimated and ω_i is the error term in the selection equation (Greene, 2010).

In the literature it is assumed that unobserved factors in the PSM model may be correlated with the error term in the SPF model, resulting in selection bias. Sample selection correction models are then employed to correct for sample selection due to unobservable factors (e.g. Kumbhakar et al., 2009; Lai et al., 2009; Greene, 2010). The specifications in these applications are very similar, but differ in their assumptions about how the selection mechanism relates to the error terms. Specifically, Greene (2010) assumes that selection bias is attributable to v_i , while Kumbhakar et al. (2009) and Lai et al. (2009) assume selectivity is related to u_i and ε_i , respectively. The models by Kumbhakar et al. (2009) and Lai et al. (2009) require computationally demanding log likelihood functions (Greene, 2010; Villano et al., 2015).

We follow the framework presented by Bravo-Ureta et al. (2012) and Villano et al. (2015), using PSM to correct for biases stemming from observable factors and Greene (2010) SPF sample selection correction model to account for selection bias from unobservable factors as in Heckman's selection correction model. Murphy and Topel (2002) correction is employed to adjust the standard

errors. Greene (2010) indicates that (Y_i, X_i) in equation (1) is observed only when $d_i = 1$ in equation (2). The error structure is such that

$$\begin{aligned} v_i &= \sigma_v V_i \text{ with } V_i \sim N(0,1) \\ u_i &= |\sigma_u U_i| = \sigma_u |U_i| \text{ with } U_i \sim N(0,1) \\ (\omega_i, v_i) &\sim_i N_2[(0,1), (1, \rho\sigma_v, \sigma_v^2)] \end{aligned} \tag{3}$$

where ρ is the sample selection correction variable for non-linear models. The model parameters are estimated using the BFGS approach and asymptotic standard errors are obtained using the BHHH estimator.³⁹ Selectivity bias due to unobservable factors is considered to exist, if ρ is statistically significant (Greene, 2010), which motivates the estimation of technology heterogeneity in a selectivity corrected meta-frontier framework.

4.2 Meta-frontier approach

A single production frontier is normally employed to estimate technical and environmental efficiency when firms use the same technology. Given that adopting CA technology may improve farmers' access to better technology, a meta-production frontier, which describes an envelope of the neoclassical production frontier with reference to group heterogeneity is a more suitable approach (Hayami and Ruttan, 1985). A meaningful efficiency comparison between CA technology adopters and non-adopters fits well in a special case where frontiers for both groups are such that adopters and non-adopters have a common reference efficiency scores. In effect, point estimates should have both group specific frontiers and a meta-frontier.

Battese et al. (2004) developed a meta-frontier model for the estimation of technology gaps among producers under different technologies relative to the potential technology available to the whole industry. The meta-frontier model facilitates reliable decomposition of efficiency into group specific efficiencies and meta-technology ratio, which enables the interpretation of group efficiency

³⁹ See Greene (2010) for details on the model and its estimation as well a review of alternative models.

as well as technology gap scores. Following the environmental efficiency framework of Reinhard et al. (1999, 2002) and Battese et al. (2004) meta-frontier logic, we estimate both technical and environmental efficiency for nitrogen fertiliser application in the meta-frontier (MF) framework. In this framework, environmental efficiency is measured as the ratio of minimum feasible nitrogen surplus to observed quantities of nitrogen surplus, at given conventional input and output levels (Reinhard et al., 2002).

In this context, we assume that farmers in our sample differ in their technology levels, and practice either CA technology, or otherwise. The stochastic production frontier is defined as

$$Y_{ij} = f(X_{ij}, E_{ij}, \alpha_j) e^{v_{ij} - u_{ij}}; \quad i = 1, 2, \dots, N, \quad j = 1, 2, \dots, M \quad (4)$$

where Y_{ij} denotes the output for the i^{th} farm, of the j^{th} group; X_{ij} is a vector of inputs used by the i^{th} farm, under the j^{th} technology; E_{ij} is the quantity of nitrogen surplus of farm i under group j , α_j denotes the parameters of the j^{th} technology to be estimated, v_{ij} and u_{ij} are the random (white noise) and systematic inefficiency error terms, respectively, of i under technology j , independent of u_{ij} , a nonnegative term related to technical and environmental efficiency. We assume heteroscedasticity of the one-sided error term (v_{ij}) to reflect factors under the farmer's control (Caudill and Ford, 1993).

Battese et al. (2004) define the meta-frontier (MF) as a deterministic parametric function of a specified functional form, whose values are at least not smaller than the deterministic production frontiers of all the different groups involved. Hence, the deterministic meta-frontier model for both CA adopters and non-adopters can be expressed as

$$Y_i^* \equiv f(X_i \alpha^*) = e^{X_i \alpha^*}; \quad i^* = 1, 2, \dots, N^* \quad (5)$$

where Y_i^* denotes the output for the MF function, X_i is a vector of inputs including nitrogen

fertilisers and α^* denotes the vector of parameters to be estimated⁴⁰. The observed output for the i^{th} firm defined by the SPF for the j^{th} group in (4) and (5) is alternatively expressed in terms of the MF function as

$$Y_i = e^{-u_{ij}} \times \frac{e^{X_i \alpha_j}}{e^{X_i \alpha^*}} \times e^{X_i \alpha^* + v_{ij}} \quad (6)$$

where the first term on the right hand side in the above equation is technical efficiency (TE) of farmer i relative to the stochastic frontier of group j .

As in Reinhard et al. (2002) and Kouser and Qaim (2015), we argue that the logarithm of the output of an environmentally efficient producer can be obtained by replacing the observed quantity of nitrogen surplus (E_i) in equation (4) with the minimum feasible nitrogen surplus and setting $u_i = 0$. Setting equation (4) and the output of the environmentally efficient producer equal, and solving for $\ln EE_i = \ln E_i^* - \ln E_i$ yields the environmental efficiency estimator

$$\ln EE_i = \left[-(\alpha_e + \sum_j \alpha_{je} \ln X_{ij} \ln E_i) \pm \left\{ (\alpha_e + \sum_j \alpha_{je} \ln X_{ij} \ln E_i) - 2\alpha_{ee} u_i \right\}^{0.5} \right] / \alpha_{ee} \quad (7)$$

In this case, we calculate environmental efficiency by assuming a positive squared-root term in equation (8)⁴¹. The environmental efficiency estimation is simply a mathematical derivation of equation (4) at full efficiency. In relation to the meta-frontier, the environmental efficiency (EE) of farmer i relative to the stochastic frontier of j^{th} can be expressed as

$$EE_i = \frac{E_i^*}{E_{ij}} \quad (8)$$

where E^* is the minimum feasible nitrogen surplus and E is the observed quantity of nitrogen surplus as in equation (7).

The second term on the right-hand side of equation (6) is the meta-frontier technology ratio

⁴⁰ For parsimony we indicate that the environmentally detrimental input (E_i) is part of X_i in equations (5), (6), (7) and (10)

⁴¹ For further details on positive squared-root refer to Reinhard et al. (1999).

(MTR) for farmer i in group j , and can be expressed as

$$MTR_i = \frac{e^{X_{ij}\alpha_j}}{e^{X_i\alpha^*}} \quad (9)$$

The technical and environmental efficiencies relative to the meta-frontier functions are therefore the products of group specific technical and environmental efficiencies and MTR. Technical and environmental efficiencies of the meta-frontier are then expressed as

$$TE_{ij}^* = TE_{ij} \times MTR \quad (10)$$

$$EE_{ij}^* = EE_{ij} \times MTR \quad (11)$$

The MTR captures productivity and environmental efficiency differences between CA and non-CA adopters and lies between zero and one.

We obtain the MF parameters by either minimising the sum of the squared or sum of absolute deviation of the distance between the MF and the group frontiers at the observed vector of inputs for farms in the groups (Battese et al., 2004)⁴². This involves solving the optimisation problem below

$$\begin{aligned} \min L &\equiv \sum \sum_{i=1}^N (\ln f(X_i, E_i, \alpha^*) - \ln f(X_i, E_i, \hat{\alpha}_j))^2 \\ \text{s. t. } &\ln f(X_i, E_i, \alpha^*) \geq \ln f(X_i, E_i, \hat{\alpha}_j) \text{ for all } i \end{aligned} \quad (12)$$

By minimising the objective function ($L^* \equiv \bar{X}\alpha^*$), equations (12) can be solved subject to the linear restrictions, where \bar{X} is the mean of \mathbf{x} -vector elements for all observations⁴³. Here, $\hat{\alpha}_j$ is treated as fixed, so that the second term in the summation is constant with respect to the minimisation. By simulation, the standard errors for the MF parameters can be estimated (Battese et al., 2004).

⁴² For brevity, we present only the minimisation for the sum of the squared deviation.

⁴³ The double summation signs in equations (10) indicates summation over all indices, including the farms (denoted by j) within the different groups.

4.5 Data and specification

The data used in this study are drawn from a recent farm household survey conducted between August and November, 2013 in the Central, Eastern, Western and Southern provinces of Zambia. These provinces contribute more than 60% to maize production in Zambia and considered the prominent CA technology provinces⁴⁴. A multistage sampling technique was employed to select 408 farm households across 12 districts in these provinces. In the first stage, all four provinces were purposively selected, such that there would be equal opportunity for all CA technology farmers in these provinces to be included in the sample. Each province became a stratum, and in consultation with farmers and extension agents, and also given that there were no differences in the estimated number of adopters in all provinces, 3 districts each were randomly selected per province. In each district, 5 agricultural camps⁴⁵ were then randomly drawn, within which 3 farmer groups were randomly selected. Individual CA farmers and their non-CA counterparts were then randomly selected from the groups.

Face-to-face interviews were conducted on the selected farmers by enumerators who spoke both English and the local language, and supervised by one of the authors, using a detailed structured questionnaire. The survey gathered information on household characteristics, output, input use and other related characteristics. The dataset relates to the 2012 production season. As argued by Feder and Umali (1993), components of agricultural package may complement each other, although some of them may be adopted independently. From the logic of Feder and Umali (1993), farmers who practiced one or more of the main CA principles (minimum tillage, crop rotation and permanent crop cover) are termed adopters.

Because this study is focused on environmental efficiency with respect to the use of nitrogen

⁴⁴ Ministry of Agriculture & Cooperatives and The Central Statistical Office, Zambia 2010 and 2011 Crop Forecast Surveys.

⁴⁵ Agricultural camp in Zambia is a management unit of agricultural camp officer comprising a catchment area of up to eight different zones of different villages.

(N) fertilisers, we employ the nitrogen index tier zero tool (NITZ) to examine the difference between total N in the system and total above ground uptake as nitrogen surplus. The NITZ is a simple user-friendly tool that conducts a quick assessment of the effects of nitrogen fertiliser or manure management practices without using any laboratory data inputs. Depending on project needs and level of complexity, a tier classification system has been developed within the NITZ (Delgado et al., 2008; Delgado et al., 2011; Saynes et al., 2014)⁴⁶. Figure 4.1 displays quantitative and qualitative results of the NITZ (see Saynes et al., 2014 for details on the implementation of the NITZ)⁴⁷. Total nitrogen in the system is calculated as sum of both inorganic and organic nitrogen from all sources in the system. These include initial soil nitrogen, atmospheric added nitrogen and liquid nitrogen added through irrigation and dry matter nitrogen from organic and inorganic sources⁴⁸.

Above ground uptake indicated in figure 4.1 is estimated from the NITZ as the product of crop yield and the quantity of nitrogen used per unit of output. Farm level quantities of nitrogen fertilisers were readily available to implement the nitrogen tier index zero tool (NITZ). The NITZ explicitly splits the quantity of nitrogen applied into nitrogen in the output and nitrogen surplus, hence complying with the material balance principle. Generally, Zambian maize farmers, and the farmers in the sample in particular apply D-Compound (10-20-10) as basal and urea as top dress (IFDC, 2013). The D-compound and urea fertilisers contain 10 % and 46 % nitrogen, respectively. Given that there are no differences in atmospheric and other nitrogen deposition sources between adopters and non-adopters, we limit the nitrogen quantities to only quantities applied in the 2012 production season. We use rainfall data from the Climate Change Knowledge Portal of the World Bank Group in the NITZ. We also adopt soil type bulk density in the estimation process (e.g. 1.4 for loam soils).

⁴⁶ Complex models are tier three tools, while simpler models are tier two and one tools (Shaffer and Delgado, 2002, Delgado et al., 2008).

⁴⁷ In consultation with the developers of the Nitrogen Index Tier Zero Tool, we use the regional N-Index Malawi

⁴⁸ For the purpose of this study, we consider only nitrogen fertiliser applications in 2012.

In line with the farming practices in Zambia, while non-CA farmers adopt surface placement, CA farmers incorporate fertilisers in the soil.

We account for heterogeneity in farm and household characteristics by including variables like gender, education and age of household head, access to extension and credit, soil quality and distance to market in the analysis of the determinants of technical and environmental efficiency. We account for access to information from institutional sources using visits by extension agents (Krishnan and Patnam, 2014). The access to credit ranges from formal sources (like banks and micro-credit agencies) to informal ones (like money lenders, friends and family relations), and captures the extent to which farmers are liquidity constrained. The variable is measured as whether farmers obtained credit in the production season, and whether they tried to access more credit than they obtained. We consider farmers as liquidity-constrained, if either they sought for, and were unable to obtain credit, or obtained less than their requirement. Access to credit is expected to shift farmers' liquidity constraint outward and facilitate their timely procurement of inputs, thereby improving farm efficiency.

Heterogeneous environmental production conditions such as soil condition may influence the production process. Following Sherlund et al. (2002) we include soil quality and regional fixed effect dummies as proxies for environmental conditions. Available evidence suggest that the subjective reporting of soil condition by African farmers are quite accurate (e.g. Suri, 2011). Since dry season land preparation is considered a unique CA technology principle, and considered to influence input use and output. With regards to early planting date and nitrogen flush, we include seasonal dummies for land preparation in the model (Haggblade and Tembo, 2003). We also include a variable on distance to the nearest market, measured as the distance to the nearest bigger village or town, with market for farm inputs and output. The definitions of the variables employed in the econometric estimation are presented in Table 4.1.

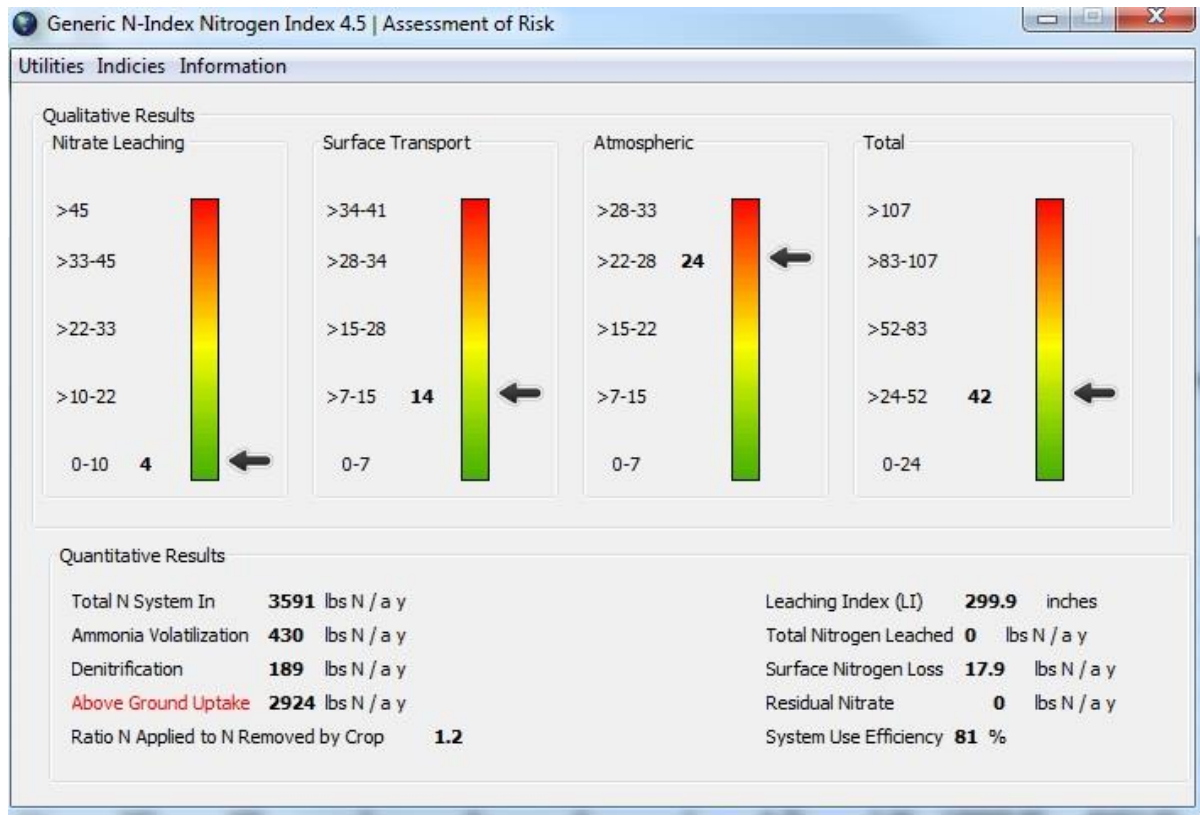


Figure 4. 1: Assessment screen of the Nitrogen Index tier zero tool with both qualitative and quantitative results.
Source: Authors' estimates

Empirical strategy

A translog functional form is employed to estimate technical and environmental efficiency, respectively⁴⁹. To be able to directly interpret the coefficients of the first-order terms as elasticities at the sample mean, we start by employing the log input mean correction strategy ($\log X_i - \log \bar{X}$), with \bar{X} denoting mean of X (Coelli et al., 2003). A multi-stage empirical estimation strategy is employed to account for sample selection and technology heterogeneity.

We start by estimating a probit model using observable farm and household characteristics to generate adoption propensity scores. This facilitates matching of CA technology adopters and non-adopters to correct for observable selectivity bias. We employ the nearest-neighbour and kernel matching algorithms⁵⁰. In the nearest neighbour case, a maximum of five matches per adopter with maximum tolerance (caliper) of 0.01 is used. We also employed an Epanechnikov kernel matching with bandwidth of 0.05. By comparing the means, the nearest neighbour produced better-matched samples, thus, the analysis is based on the samples obtained from the nearest neighbour matching method. Out of the 407, the procedure yielded a total of 372 matched observations, comprising 202 adopters and 170 non-adopters.

Table 4.1 reports the means of the variables for unmatched and matched samples of CA technology adopters and non-adopters. In contrast to the significant differences in most of the variables in the unmatched samples, the estimates indicate that there are no significant differences between the means of observable characteristics of adopters and non-adopters after matching. Thus, the balancing condition of the covariates is fulfilled (Leuven and Sianesi, 2003). The region of common support (see figure 4.2) indicating the area with positive density within $d = 1$ and $d = 0$

⁴⁹ We tested the translog against the Cobb-Douglas specification and the Cobb-Douglas specification was rejected at the 1 % level of significance.

⁵⁰ Other matching algorithms include caliper and radius matching as well as stratification and interval matching (Khandker et al., 2010).

distributions is between 0.017 and 0.99. Based on the propensity scores, the Greene (2010) selectivity correction variable is then estimated and included in the stochastic frontier model.

The empirical specification of the translog function for the stochastic frontier technical efficiency for a particular technology is expressed as

$$\ln Y_i = \alpha_0 + \sum_j \alpha_j \ln X_j + \alpha_e \ln E_i + 0.5 \sum_j \sum_m \alpha_{jm} \ln X_{ij} \ln X_{im} + \sum_j \alpha_{je} \ln X_{ij} \ln E_i + 0.5 \alpha_{ee} (\ln E_i)^2 + v_i - u_i \quad (14)$$

where \ln denotes natural logarithm, Y_i is total output, and the independent variables X_i denote vector of input quantities (including land, seed and nitrogen fertilisers) and E_i is the quantity of environmentally detrimental input (nitrogen surplus), v_i is the random term (white noise), and u_i is the nonnegative systematic error term accounting for inefficiency. It is also assumed that $\alpha_{jm} = \alpha_{mj}$. To avoid potential multicollinearity in the model, and given that labour and capital inputs have zero nitrogen content to support the environmental efficiency estimation, we follow previous studies on environmental efficiency (e.g. Coelli et al., 2007; Nguyen et al., 2012), and limit the input variables to land, seeds, nitrogen fertilisers and nitrogen surplus. Specifically, Coelli et al. (2007) demonstrate that the material balance analogy, which is focus of our study, allows for the possibility for some inputs (or outputs) to have zero amounts of the material of interest.

Various factors including farm household characteristics could be responsible for technical and environmental inefficiency. Wang and Schmidt (2002) demonstrate that in the stochastic frontier framework, a single-stage procedure is the appropriate approach to jointly estimate inefficiency and the determinants of inefficiency. The technical inefficiency and environmental efficiency across farms is modelled as a linear function of the inefficiency term u_i and of a set of covariates as

$$u_i = z_i' \gamma + \omega_i \quad (15)$$

where z_i is an $m \times 1$ vector of exogenous variables that influence inefficiency, γ is an $m \times 1$

vector of parameters and ω_i is a random variable truncating the normal distribution with mean zero and variance, σ^2 at point of truncation $z_i'\gamma$ (Battese and Coelli, 1995).

Unlike jointly estimating the determinants of technical efficiency with the deterministic component of the production frontier, Reinhard et al. (2002) indicate that the determinants of environmental efficiency are not required to be jointly estimated with the production frontier. We therefore estimate the determinants of environmental efficiency in a two stage approach. In the first-stage, environmental efficiency is calculated from parameter estimates describing the structure of production technology at full efficiency. Since environmental efficiency is calculated (as in equation 8) without a predetermined distributional assumption as in technical efficiency, this phenomenon does not violate the independently identically distributed assumption raised by Battese and Coelli (1995). Hence, environmental efficiency can be estimated by expressing the logarithm of the minimum feasible nitrogen surplus as a function of other covariates of equation (15) in the second stage.

The choice of an appropriate model for the second stage regression to avoid misleading results is not trivial in empirical analysis (e.g. Simar and Wilson; 2007; Ramalho et al., 2010)⁵¹. Because of the bounded nature of efficiency scores]0, 1], linear specifications or, tobit models are used to relate inefficiency scores to exogenous factors in Reinhard et al. (2002) environmental efficiency framework (e.g. Reinhard et al., 2002; Kouser and Qaim, 2015). As in linear probit models, Ramalho et al. (2010) argue that, linear specification of the second stage regression may not be appropriate since it violates the conceptual requirement that the predicted values of efficiency scores lie within a range of 0 to 1. Moreover, the marginal effect in the second stage regression of constant change in covariate over the entire range of efficiency scores, is not compatible with the bounded nature of efficiency scores.

⁵¹ Simar and Wilson (2007) provides an extensive list of references to second stage efficiency estimation.

Simar and Wilson (2007) and McDonald (2009) indicate that rather than considering efficiency score as a censoring mechanism, as implied in a tobit model, observed efficiency scores are products of the way the scores are defined. Furthermore, the tobit model is originally devised for censored dependent variables that are by nature limited to the so-called ‘corner solution’ variables. Since efficiency scores do not generally take on values of zero, the tobit model is not a plausible specification for conditional mean of a variable like second stage regression for efficiency defined on the interval $[0,1]$ (Ramalho et al., 2010). To avoid the problems associated with using linear and tobit models for second stage regressions, Ramalho et al., (2010) demonstrate that using fractional regression models (FRM) is the most natural way of modelling bounded, proportional variables like efficiency scores.

The FRM provides several alternative functional forms for dealing with the typical asymmetric nature of efficiency scores and can be estimated by quasi-maximum likelihood (QML) approach. This does not require assumptions about the conditional distribution of efficiency scores or heteroscedasticity patterns. Ramalho et al., (2010) indicate that in the FRM framework, a single model is employed to explain efficiency scores of all households, including those that are fully efficient. But where there are relatively high proportion of fully efficient households, a two-sided model is employed to explain separately, first, why some firms are efficient while others are not, and then the relative efficiency of inefficient firms. We follow the approach by Ramalho et al. (2010) and treat efficiency scores as descriptive measures of the relative environmental efficiency of the sampled households. We employ alternative models including FRM logit, probit, log-logistic (loglog) and complementary log-logistic (cloglog) for the second stage estimation, and then test for the appropriate functional form. This generalisation contrasts with the studies by Hoff, (2007) and McDonald, (2009) who employed only a logit FRM.

4.6 Empirical Results

4.6.1 Production frontier

Table 4.2 presents estimates of the deterministic component of six separate SPF models with columns (1) and (2) for pooled sample, (3) and (4) for adopters and (5) and (6) for non-adopters. The pooled sample case gives an indication of technology heterogeneity and include technology and non-technology corrected models. The group sample estimates comprise of with and without selectivity-corrected term models. While the non-selectivity-corrected model accounts for only observable biases, the selectivity- corrected model corrects for both observable and unobservable biases. Before discussing the estimates, we first test for inefficiency and selectivity. The likelihood ratio test of the null hypothesis of no technical inefficiency effects, given the specifications of the SPF model, yields a $\chi^2=3.05$ against a critical value of $\sigma_u = 0$. Thus, the null hypothesis is rejected suggesting that most of the farmers are producing below the production frontier⁵².

In the selectivity-corrected model estimates, the coefficient for the selectivity term (ρ) for adopters and non-adopters are significant at conventional level. This suggests that estimating the SPF model without accounting for selection bias in this will lead to biased technical and environmental efficiency scores (Bravo-Ureta et al., 2012; Villano et. A. 2015). These estimates further show that adoption of CA technology may have different effects for adopters and non-adopters. The same signs (negative), suggests that farmers with above-average yields and net returns have a higher probability of adopting the CA technology (Abdulai and Binder, 2006).

Table 4.2 presents estimates of the deterministic component of six separate SPF models with columns (1) and (2) for pooled sample, (3) and (4) for adopters and (5) and (6) for non-adopters. The pooled sample case, gives an indication of technology heterogeneity and include technology and non-technology corrected models. The group sample estimates comprise of with and without selectivity-corrected term models.

⁵² We used Stata frontier program for the estimates in Table 2.

As indicated earlier, the reported coefficients of the first-order terms are elasticities. The reported partial elasticities for most of the variables in the selectivity-corrected models for adopters and non-adopters are lower compared to those of the conventional models, suggesting that sample selection bias tends to overestimate average partial elasticities (Villano et al., 2015). The first-order term estimates indicate positive and significant effects of land, seeds and nitrogen on maize output, fulfilling the regularity condition of monotonicity. These results are consistent with the meta-frontier estimates of Moreira and Bravo-Ureta (2010) for dairy farms in Argentina, Uruguay and Chile.

The coefficient for the nitrogen surplus variable is however negative and significantly different from zero. Cuesta et al. (2009) also report a negative coefficient for the first-order term of the environmental burden product (sulphur-oxide) for US electricity firms. The estimates of nitrogen in the output and nitrogen surplus are intuitive and have both economic and environmental interpretations. Specifically, while increasing levels of nitrogen uptake by the crop contribute to higher output (or economic returns) and lower environmental burden from nitrogen, increasing levels of nitrogen surplus tend to reduce economic returns and increase potential environmental burden from nitrogen.

In line with Battese et al. (2004), the likelihood-ratio (LR) test of the null hypothesis of homogenous technology is calculated after estimating the stochastic frontier by pooling the data from both technologies. The likelihood ratio statistic is 152.92 and significant at 1% level (using a chi-square distribution with 26 degrees of freedom). The null hypothesis of technology homogeneity is therefore rejected, supporting the use of the meta-frontier (MF) approach in the estimation of technical and environmental efficiency.

Technical and Environmental Efficiency

To compute the meta-frontier estimates, we first estimate individual group frontiers, which is simulated to derive the meta-frontier estimates for the entire sample.

Table 4.1. Descriptive statistics of conservation agriculture technology adopters and non-adopters

Variable	Description of variable	Unmatched sample		Matched sample	
		Adopters	Non-adopters	Adopters	Non-adopters
Gender	(Male=1, 0=Female)	0.72	0.79	0.53	0.51
Education	Number of years of schooling by household head	6.65***	4.91	6.06	5.89
Age	Age of household head in years	46.00	46.11	47.89	45.17
Credit	1 if farmer has access to credit, 0 otherwise	0.98***	0.42	0.78	0.83
Owner	1 if farmer is land owner-operated, 0 otherwise	0.89	0.85	0.67	0.50
Extension	1 if farmer had at least a contact with an extension agent, 0 otherwise	0.97***	0.43	0.67	0.61
Market	Distance to permanent market (km)	5.39	5.85	6.61	6.17
Output	Total maize output in tonnes	8.43***	4.98	6.59	6.24
Land	Farm size in hectares	3.30	3.33	3.03	2.85
Seed	Quantity of seeds planted in kg	59.96	58.65	51.11	48.39
Nitrogen in output	Quantity of nitrogen used up for production in kg	226.57	191.44	138.99	133.23
Nitrogen surplus	Quantity of unused nitrogen in Kg	19.26***	37.92	15.26	17.50
Soil fertility	1= Fertile soils, 0 = Infertile soil	0.53	0.47	0.55	0.55
Season	1= dry season land preparation, 0=rainy season land preparation	0.61	0.566	0.60	0.57
Eastern	1 if farm is located in Eastern province, 0 otherwise	0.25	0.25	0.25	0.22
Western	1 if farm is located in Western province, 0 otherwise	0.29	0.30	0.28	0.28
Southern	1 if farm is located in Southern province, 0 otherwise	0.22	0.24	0.22	0.26
Central	1 if farm is located in Central province, 0 otherwise	0.24	0.21	0.23	0.23
<i>Number of observations</i>		225	182	202	170

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4.2: Translog estimates of conventional and selectivity corrected stochastic production frontier for matched sample

Variable	pooled				Adopters				Non-adopters			
	(1) Coeff.	S. Error	(2) Coeff.	S. Error	(3) Coeff.	S. Error	(4) Coeff.	S. Error	(5) Coeff.	S. Error	(6) Coeff.	S. Error
Constant	1.846***	0.057	1.545***	0.051	1.784***	0.265	1.772***	0.169	1.438***	0.065	1.448***	0.091
Land (x1)	0.662***	0.07	0.694***	0.057	0.884***	0.098	0.881***	0.099	0.498***	0.102	0.500***	0.102
Seed (x2)	0.106	0.074	0.090	0.061	-0.103	0.098	-0.102	0.098	0.212**	0.104	0.212**	0.104
Nitrogen in output	0.696***	0.058	0.429***	0.052	0.535***	0.108	0.546***	0.124	0.549***	0.099	0.542***	0.112
Nitrogen surplus	-0.520***	0.049	-0.280***	0.044	-0.368***	0.085	-0.378***	0.101	-0.302***	0.082	-0.296***	0.094
0.5(x1) ²	-0.245	0.195	-0.181	0.161	-0.209	0.212	-0.215	0.214	-0.068	0.267	-0.070	0.267
0.5(x2) ²	-0.184	0.214	-0.146	0.175	-0.023	0.231	-0.023	0.231	-0.001	0.269	-0.003	0.269
0.5(x3) ²	-0.529**	0.227	-0.311*	0.184	-0.553**	0.242	-0.571	0.261	0.822**	0.406	0.808*	0.417
0.5(x4) ²	-0.509***	0.192	-0.298*	0.157	-0.370**	0.181	-0.385*	0.198	0.430	0.326	0.419	0.336
x1x2	0.238	0.183	0.170	0.151	0.124	0.194	0.122	0.194	0.059	0.252	0.060	0.252
x1x3	0.174	0.128	0.144	0.105	-0.203	0.224	-0.198	0.226	0.134	0.158	0.134	0.158
x1x4	-0.107	0.1	-0.067	0.083	0.256	0.195	0.252	0.196	-0.011	0.119	-0.012	0.119
x2x3	-0.233*	0.128	-0.169	0.105	0.209	0.201	0.205	0.201	-0.317*	0.177	-0.316*	0.177
x2x4	0.101	0.1	0.039	0.082	-0.305*	0.181	-0.306*	0.181	0.089	0.124	0.089	0.124
x3x4	0.522**	0.208	0.314*	0.17	0.464**	0.203	0.480**	0.222	-0.583	0.363	-0.570	0.374
East	-0.025	0.04	-0.016	0.033	-0.049	0.04	-0.049	0.04	0.004	0.05	0.003	0.05
West	0.018	0.037	0.034	0.03	-0.002	0.038	-0.002	0.038	0.066	0.044	0.065	0.044
South	0.002	0.04	0.038	0.033	0.026	0.041	0.025	0.041	0.065	0.049	0.065	0.049
Season	0.008	0.027	0.031	0.022	0.026	0.042	0.026	0.042	0.070*	0.04	0.070*	0.04
Season * x1	0.182*	0.095	0.130*	0.078	0.018	0.109	0.019	0.109	0.351***	0.119	0.349***	0.121
Season * x2	-0.118	0.099	-0.119	0.081	-0.024	0.111	-0.023	0.111	-0.297**	0.12	-0.295**	0.122

Season *	-0.194***	0.069	-0.078	0.058	-0.136	0.121	-0.137	0.122	-0.062	0.103	-0.061	0.103
x3												
Season *	0.115**	0.055	0.035	0.045	0.097	0.101	0.098	0.101	-0.006	0.075	-0.006	0.075
x4												
CA			0.359***	0.026								
ρ							-0.128**	0.053			-0.115**	0.047
Log												
likelihoo	-65.444***		-96.561***		-36.423***		-44.441***		-33.569***			-33.579***
d												
Number of observations				372			202					170

Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively

Results for the group frontiers as well as parameter estimates for the meta-frontiers (quadratic programming) and the simulated standard errors are presented in table 4.3⁵³. The estimates for CA and non-CA technology adopters and the quadratic programming indicate that, the coefficients of all the inputs significantly influence the level of output, hence the tendency to influence technical and environmental efficiency.

For instance, while higher levels of nitrogen utilised to produce output contributes to increased output and technical efficiency, higher levels of nitrogen surplus tend to reduce output and increase environmental inefficiency.

In both the adopters and non-adopters' models, there were no regional fixed effects. The coefficient for the interaction of dry season land preparation and farm size variable in the non-adopters' specification is positive and significantly different from zero. This indicates that preparing more farm land in the dry season has the potential to increase output of non-adopters. This is consistent with Haggblade and Tembo (2003), who indicate that maize yields decline by 1–2% for each day of delay in planting after the onset of the planting rains. It is also in line with the arguments of CA technology proponents in Zambia that, dry season land preparation enables farmers to take advantage of nitrogen flush generated from the sudden rejuvenation of soil organisms that have been dormant in a long dry season. The negative impact of seed and dry season land preparation variable is consistent with crop agronomy that relevant amount of moisture is required to support germination and hence maize yields.

As indicated previously, the meta-frontier function is used in the estimation of meta-technology ratio, as well as technical and environmental efficiency for CA and non-CA technologies. The parameters of the MF are used in the estimation of MTR and technical and environmental efficiency.

⁵³ Group frontiers and the meta-frontier were estimated using Ox version 7.01 (Doornik, J. A., 1994-2013).

Table 4.3: Technical Efficiency Stochastic Frontier Estimates

Variable	CA adopter		CA non-adopters		Meta (Quadratic programming)	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. errors
Production frontier model						
Constant	1.779***	0.080	1.315***	0.083	1.910***	0.129
Land (ln x1)	0.873***	0.097	0.514***	0.107	0.542***	0.1
Seed (ln x2)	0.093	0.098	0.181***	0.092	0.240**	0.114
Nitrogen in output (ln x3)	0.568***	0.127	0.598***	0.121	0.299***	0.117
Nitrogen surplus (ln x4)	-0.402***	0.105	-0.340***	0.098	-0.293***	0.107
0.5 (ln x1) ²	-0.23	0.316	-0.200	0.248	-0.216	0.263
0.5 (ln x2) ²	-0.117	0.253	-0.058	0.251	0.243	0.633
0.5 (ln x3) ²	-0.242	0.454	0.890**	0.397	0.847*	0.496
0.5(ln x4) ²	-0.044	0.440	0.462	0.304	-0.469	0.467
ln x1 * ln x2	0.173	0.264	0.157	0.23	-0.265	0.379
ln x1 * ln x3	-0.267	0.238	0.205	0.148	0.050	0.366
ln x1 * ln x4	0.284	0.192	-0.052	0.099	0.535*	0.288
ln x2 * ln x3	0.303	0.241	-0.428***	0.142	-0.626***	0.199
ln x2 * ln x4	-0.347*	0.198	0.165*	0.097	-0.785***	0.249
ln x3 * ln x4	0.129	0.456	-0.629*	0.346	0.152	0.33
East	-0.060	0.04	0.001	0.048	-0.063	0.06

West	-0.005	0.036	0.069	0.04	0.196	0.129
South	0.025	0.039	0.057	0.053	0.104	0.079
Season	0.019	0.035	0.046	0.04	0.031	0.066
Season * ln x1	0.060	0.139	0.331***	0.119	0.607***	0.193
Season * ln x2	-0.058	0.134	-0.266**	0.115	0.192	0.289
Season * ln x3	-0.114	0.102	-0.084	0.1	-0.593**	0.241
Season * ln x4	0.073	0.085	0.008	0.07	0.184	0.165
ρ	-0.170***	0.015	-0.252***	0.122		
Inefficiency model						
Constant	-1.308***	0.309	0.632	0.102		
Age	-0.327	0.212	-0.273	0.338		
Gender	0.232	0.312	-0.434	0.832		
Education	-0.783**	0.382	-0.12	-0.062**		
Credit	-0.554	0.522	-0.285	0.489		
Soil quality	0.408	0.885	0.462	0.493		
Extension	0.300	0.611	0.438	0.518		
Market	0.429**	0.214	0.104	0.135		
Log likelihood	-58.909		-42.515			
Number of observations		202		170		

Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

Table 4.4 reports a summary of technical and environmental efficiency scores for the pooled, CA and non-CA technology group frontiers, respectively. The group-specific inefficiency scores relate to individual group frontiers with no common reference between groups. For a reasonable interpretation and comparison of the differences in efficiencies between CA and non-CA technology farms, we use the meta-technology ratio and meta-frontier scores.

The estimates indicate statistically significant differences in the meta-technology ratio, technical efficiency and environmental efficiency between CA and non-CA technology farms. The reported meta-technology ratios indicate the specific technology related productivity gaps between CA and non-CA technologies relative to the meta-frontier, with a higher score indicating better returns from the technology. The results show an average meta-technology ratio score of about 0.94 for CA farms, ranging from 0.34 to 1.00. On the other hand, an average meta-technology ratio score of 0.76 is reported for non-CA farms, ranging from 0.17 to 1.00.

Table 4.4: Metafrontier Technical and Environmental Efficiency Estimates

	CA Adopters				Non-CA adopters		
	Pooled	Group	MTR	MF	Group	MTR	MF
<i>Technical efficiency</i>							
Mean	0.821	0.854	0.940***	0.803***	0.781	0.759	0.593
Minimum	0.456	0.650	0.337	0.336	0.420	0.174	0.164
Maximum	0.995	0.995	1.000	0.995	0.925	1.000	0.925
SD	0.096	0.520	0.086	0.100	0.084	0.151	0.174
<i>Environmental efficiency</i>							
Mean	0.493	0.548	0.940***	0.515***	0.427	0.759	0.324
Minimum	0.266	0.322	0.337	0.226	0.266	0.174	0.140
Maximum	0.876	0.876	1.000	0.770	0.780	0.818	0.448
SD	0.113	0.082	0.086	0.065	0.127	0.151	0.045

Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

The meta-frontier scores indicate that on average, while CA technology farms are about 80% technically efficient, their non-CA technology counterparts are 59% technically efficient. These findings suggest that with the same level of inputs, the CA technology tends to contribute to increasing average farm output by 19% more than conventional farming. Similarly, while average environmental efficiency for CA farms is about 52% (48 % inefficient), average environmental efficiency for non-CA farms is 32% (68% inefficient). This indicates that CA technology is more likely to contribute to reducing potential environmental degradation and greenhouse gas equivalent from nitrogen sources by 20% more than non-CA technology farms. These differences can be attributed to better production technologies associated with CA technology, including incorporation of fertilisers into the rip lines, minimum tillage and retention of crop cover to conserve soil and water, as well as reduce nitrogen losses resulting from volatilisation, run-off and leaching.

As suggested by Wei, et al. (2010), the estimates can be related to social cost in terms of equivalent impacts of a tonne of carbon dioxide emission into the atmosphere.

The relatively higher environmental efficiency from CA compared to conventional technology indicates that CA technology tends to lower carbon dioxide and greenhouse gas emission equivalence from nitrogen fertilisers, hence CA technology will generate less social cost. Coupled with better technical efficiency, CA technology is likely to enhance the desired prosperity, people and planet synergies of the Sustainable Development Goals (SDGs) of agriculture (UN, 2015).

Determinants of technical and environmental efficiency

The determinants of efficiency indicate the potential sources of efficiency that could enhance policy irrespective of technology. In table 4.5, we present translog maximum likelihood and fraction regression models (FRM) estimates of the determinants of technical inefficiency and environmental efficiency, respectively. The translog maximum likelihood frontier estimates are from a single stage

selectivity corrected pooled sample SPF and inefficiency models. Given that there were no environmentally efficient household at unity in our sample, we use one-part models for our estimation of the determinants of environmental efficiency. The results obtained for the one-part fractional regression models for logit, probit, loglog and cloglog follow the second stages procedure of Ramalho et al. (2010)⁵⁴.

For each FRM, we report the R-squared, and test statistic. The R-squared is calculated as the square of the correlation between the actual and predicted efficiency scores. We find that most of the R-squared values are similar, an evidence that all the competing models fit the data. Consistent with Ramalho et al. (2010), the test statistic results clearly show that, only the cloglog model is not rejected at the 10% level⁵⁵. We therefore select the cloglog model as the most suitable model and for our interpretation of the results. The coefficients are interpreted by their signs, such that, a positive (negative) coefficient for the technical inefficiency results indicate positive (negative) effect on inefficiency, and opposite is for the environmental efficiency determinants. In the interest of brevity, we only discuss the determinants focusing on variables that are statistically significant at conventional levels⁵⁶.

The inefficiency model estimates show that while technical inefficiency is influenced by education, access to credit and distance to markets, environmental efficiency appears to be influenced by age, education, access to extension, access to credit, and distance to markets. The coefficient of the variable education in the technical efficiency (environmental efficiency) model is negative (positive) and significantly different from zero, indicating that higher levels of education have the potential to reduce inefficiency. The result of the technical efficiency model is consistent with finding of other studies like Kibaara (2005) for Kenya, and Ng'ombe for Zambia. The

⁵⁴ The tobit and linear models are available upon request.

⁵⁵ Based on one fitted power of the response index, the RESET test is used in this study (Ramalho et al., 2010).

⁵⁶ Estimates of the deterministic component as in tables 2 to 4 is available upon request.

environmental efficiency model estimate for education concurs with the environmental efficiency findings of Kouser and Qaim (2015) for Pakistan.

The variable age is used as a proxy for experience of the farm household head, especially in the study area where farming is the main source of livelihood for most households. The estimate for age is positive and significantly different from zero for the environmental efficiency model, suggesting that more experienced farmers are environmentally efficient. This is related to the fact that, advancing years of farming experience improves farmers' ability to process relevant farm information for decision making. The results also reveal a negative (positive) and significant relationship between the variable representing access to credit and technical (environmental) inefficiency model, suggesting that liquidity constrained farmers tend to be less efficient.

Table 4.5: Determinants of efficiency

Variable	(1) Technical inefficiency (MLE)		Environmental efficiency							
	Coef.	S. Error	Logit		Probit		Loglog		Cloglog	
			Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Constant	-0.334	0.870	0.007	0.005	0.005	0.003	0.006	0.004	0.005	0.004
Age	-0.022	0.015	0.003**	0.002	0.002**	0.001	0.002**	0.001	0.002**	0.001
Gender	-0.288	0.334	-0.024	0.030	-0.015	0.019	-0.016	0.020	-0.018	0.023
Education	-0.180**	0.087	0.004**	0.002	0.003**	0.001	0.004**	0.002	0.003**	0.001
Extension	-0.214	0.458	0.195***	0.075	0.121***	0.047	0.131**	0.054	0.148***	0.055
Credit	-1.610**	0.584	0.474***	0.073	0.296***	0.045	0.336***	0.052	0.348***	0.053
Soil quality	0.108	0.313	0.001	0.034	0.001	0.021	-0.002	0.025	0.003	0.024
Market	0.033**	0.014	0.374***	0.101	0.234***	0.063	-0.110**	0.055	0.651***	0.070
R-squared			0.454		0.454		0.453		0.456	
Test-statistic			2.887		2.906		3.227		2.641	
P- value			0.089		0.088		0.072		0.140	
Log likelihood	-48.210		-168.094		-168.095		-168.110		-168.080	
Number of observations	372		372		372		372		372	

Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

This finding is in line with the results reported by Ng'ombe and Kalinda (2015), who showed that access to credit reduces farmers' cash constraints for farm input in Zambia, thereby increasing farm efficiency.

Access to extension variable also has positive relationship with environmental efficiency, indicating the significance of information from extension services to improving environmental efficiency. The reported positive (negative) and statistically significant relationship between the distance to market and technical (environmental) inefficiency, suggests that farmers closer to markets tend to be more environmentally efficient. The reason for this could be linked to less transaction cost in acquiring information from input markets on environmentally friendly inputs and acquiring the needed farm implements for soil and water conserving measures.

4.7 Conclusions

In this study, we examined environmental efficiency among maize farmers in Zambia, with particular reference to nitrogen fertilisers. As part of the nitrogen balance sheet generating process, we used a nitrogen index tier zero tool in establishing a nitrogen balance sheet at the farm level, such that the quantity of applied nitrogen fertilisers is split into quantity of nitrogen that yielded the output and quantity of nitrogen surplus. We employed a meta-frontier approach to account for technology differences among farmers practicing conservation agriculture technology and those using conventional farming technology. We accounted for observable and unobservable selection bias, using propensity score matching and Greene's (2010) sample selection stochastic production frontier approach.

The empirical results revealed that CA technology farmers are technically and environmentally more efficient than conventional farming technology farmers, a finding that suggests that CA has the potential to reduce the economic drain and environmental burden that may arise from nitrogen surplus. The meta-frontier estimates also showed that CA technology farms are

more technically and environmentally efficient than the non-CA technology farms. This demonstrates that CA technology has a greater potential in improving farm economic returns in terms of farm output and also reducing environmental burden including non-CO₂ greenhouse gases related to nitrogen losses. Less environmental burden from CA technology is also an indication of less social cost from CA technology in the light of relative carbon dioxide emission (Wei et al, 2010).

The findings also established statistically significant differences in key determinants of technical and environmental efficiency. In particular, we found positive and statistically significant relations between technical efficiency and access to credit, as well as education of the household head and shorter distance to markets. Similarly, environmental efficiency was found to be positively related to access to credit, access to extension services, age, years of education and shorter distances to markets, indicating that there is scope for using policy measures to influence technical and environmental efficiency.

In terms of policy, this study reveals that, policy makers should consider encouraging farm households to adopt conservation agriculture technology, which has the potential to fulfil synergies between reducing social cost, enhancing economic empowerment and reducing environmental pollution. Specifically, encouraging soil and water conservation measures like minimum tillage to reduce disturbance of the soil ecosystem and retaining permanent crop cover to improve soil nutrients and water conservation. Also crop rotation including the use of legumes in the rotation to enhance nitrogen fixation, and timely land preparation to take advantage of nitrogen flush would contribute to improving output and reducing environmental pollution. Moreover, investment in rural infrastructure, including better roads and transport will reduce farm transaction cost and improve the economic well-being of farmers. Improving farmers' access to timely credit packages, including cash and input credit would also contribute to decreasing farm level technical and environmental inefficiency.

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Appendix

4. A1.: Propensity score for CA technology adoption

Variable	Coef.	Std. Err.
Constant	-3.855***	1.150
Age	0.009	0.014
Education	0.112*	0.066
Household size	-0.051	0.093
Credit extension	3.126***	0.396
loan	2.895***	0.425
Season	-0.130	0.341
Market distance	0.326	0.338
Farm size	-0.055	0.054
seed	-0.123	0.095
Machinery	0.012**	0.006
East	-0.802	0.803
West	-0.518	0.584
South	-0.567	0.492
Log likelihood	-0.248	0.505
Pseudo R ²	-37.281***	
Number of observations	0.867	
	407	

Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% respectively.

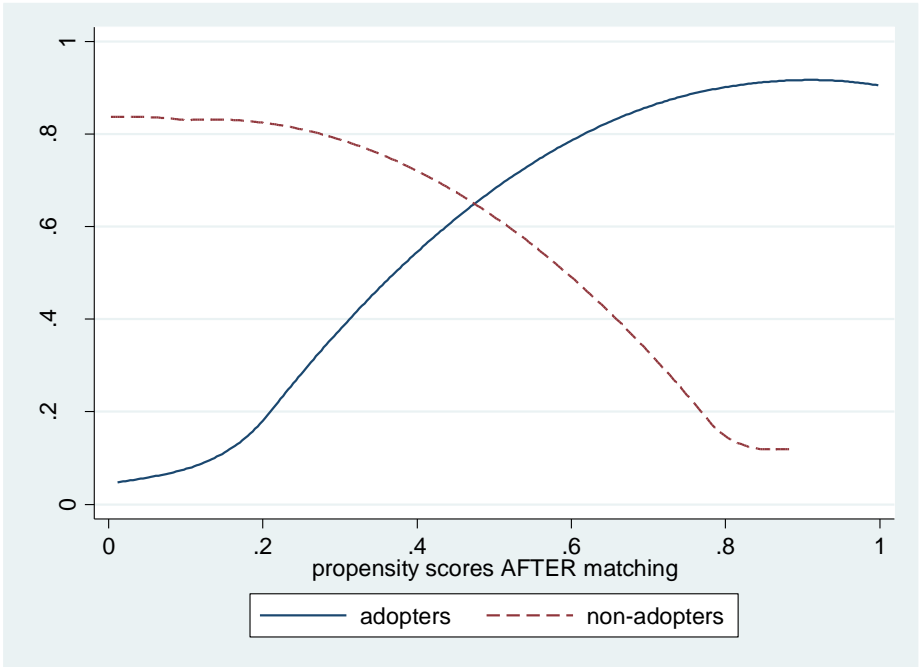


Figure 4. 2: Density of the propensity scores for adopters and non-adopters

Chapter 5

Impact of Technology on Household Welfare: The Case of Conservation Agriculture in Zambia

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Abstract

This paper examines the determinants and impact of conservation agriculture technology adoption on farm household welfare in Zambia. To account for selection bias from both observable and unobservable factors, an endogenous switching regression model is employed to estimate the impact of the technology on continuous outcomes like farm output, throughput accounting ratio, poverty gap, and severity of poverty. A recursive bivariate probit model is however used for the estimation of impact of adoption on a binary outcome like poverty headcount. The empirical findings demonstrate that the adoption of conservation agriculture technology increases maize output and farm throughput accounting ratio and reduces household poverty. Moreover, the results reveal that farmers' years of schooling, social networks, access to credit, extension services and machinery as well as soil quality positively influence adoption of conservation agriculture technology.

Keywords: Impact evaluation, conservation agriculture, household welfare.

5.1 Introduction

In most developing economies, improving the agricultural sector has a direct link to the economic wellbeing of most rural households. Pieces of evidence show that the adoption of agricultural technologies in developing economies contributes to increase in farm productivity and reduces household poverty (e.g. Becerril and Abdulai, 2010; Khonje et al., 2014; Zeng et al., 2015). To this end, conservation agriculture (CA) technology is being promoted by governments and civil society organizations in sub-Saharan Africa (SSA). This is aimed at delivering potential CA related productivity benefits required to ensure sustainable land use, attain food and nutrition security and reduce household poverty (Gowing and Palmer, 2007)⁵⁷.

The Food and Agricultural Organization of the United Nations [FAO] (2010) describes CA technology as a concept for resource-saving agricultural crop production that strives to attain acceptable and sustainable productivity and profits, as well as conserving the natural environment. To harness the desired benefits of CA technology in Zambia, couple of CA technology policy programs have been pursued by the Zambian Ministry of Agriculture (e.g. FNDP, 2006; NAIP, 2014). Although the adoption of CA in Zambia is relatively a success within SSA, like many technologies introduced in the region, CA adoption rate in Zambia can still be considered to be slower than projected (Kassam et al., 2014)⁵⁸.

Bellon et al. (2006) argue that the relative slower rate of adoption of a technology does not rationalize that actual welfare impacts are not realized by participating households. In particular, the Nebraska (2012) and Lusaka (2014) declarations on CA signify that, this technology can be regarded as a means to enhancing food productivity, reducing poverty and mitigating the

⁵⁷ Conservation agriculture relies on the key principles of minimum soil disturbances, retaining permanent crop residue and crop rotation either in sequence or association to enhance synergies.

⁵⁸ It is estimated that only about 200,000 farmers had adopted CA in Zambia by the year 2013 compared to the expected 600,000 by 2015.

consequences of climate change in rural households. Corbeels et al. (2013) note that, in the smallholder context where farmers are resource-poor with short-term planning horizons, CA technology adoption is influenced more by immediate tangible benefits than potential long-term productivity and environmental benefits. It is therefore imperative that this study investigates the adoption and impact of CA technology on tangible household welfare indices including farm output, throughput accounting ratio (TAR) and household poverty.

This study follows the literature on adoption and impact of agricultural technologies, but specifically articulates agricultural policy in line with the impact of CA technology on household welfare (e.g. Rockström et al., 2009; Kazukauskas et al., 2014; Minota and Dewina, 2015). Notably, Rockström et al. (2009) reports yield improvements in the range of 20–120% in smallholder rainfed CA trials in Ethiopia, Kenya, Tanzania and Zimbabwe. Giller et al. (2011) however argue that, on the basis of differential agro-ecological conditions, results from on-station experimental plots may not be the yard stick for the determination of on-farm impact from adoption. Kirkegaard et al. (2014) indicate that on-farm biophysical and socio-economic factors may pose some constraints to adoption and the impact of CA on household welfare, hence the potential impact should be site-specific.

Moreover, in their meta-analysis on CA technology adoption, Knowler and Bradshaw (2007) note that, among several determinants of CA adoption, some regularly assessed variables such as education and farm size seemed to show convergence towards positive and significant influence on adoption. However, incidence of insignificance and even negative correlations were equally reported. These findings reveal the ambiguity in the literature on the adoption and impact of CA technology on household welfare, and support the view that the adoption and impact of CA is location and condition specific.

Using a propensity score matching (PSM) approach, Nkala et al. (2011) found a positive impact of CA technology adoption on the livelihoods of smallholder farmers in Mozambique. The

reliability of empirical estimates from the PSM approach however hinges on the conditional independence assumption that, after controlling for observable characteristics, technology adoption is random and independent of the outcome variables. Yet, as farmers self-select themselves into adoption or non-adoption, selection bias due to unmeasured characteristics may still persist, which could bias the PSM estimates (Smith and Todd, 2005).

This study contributes to the literature by examining the impact of CA technology on farm productivity and household welfare. Specifically, it analyzes the impact of CA technology on maize output, farm throughput accounting ratio and household poverty⁵⁹. To the extent that not all costs may be directly associated with some of the factors of production, the theory of constraints approach is employed to estimate the returns on investment along the throughput accounting ratio (TAR) framework. Following Dercon et al. (2009) and de la Fuente et al. (2015), the cost of basic needs (CBN) approach is employed to determine household poverty status, including poverty headcount, poverty gap and severity of poverty. Recent farm household survey data collected from maize farmers in the Central, Eastern, Southern and Western provinces of Zambia are used for the empirical estimation. The study accounts for selection bias due to both observable and unobservable factor using an endogenous switching regression (ESR) model approach (Lokshin and Sajaia, 2004) for continuous outcomes like output, TAR, poverty gap and severity of poverty. A recursive bivariate probit (RBP) model is employed for the estimation of the impact of a binary outcome variable like poverty headcount (Heckman, 1978).

The rest of the paper is organized as follows. In the next section, conservation agriculture technology in Zambia is discussed. Sections 3 presents the data and the description of the variables employed in the empirical strategy presented in section 5. The conceptual framework and empirical

⁵⁹ Alternative to traditional returns on investment based on cost accounting, throughput accounting ratio is termed as returns on investment based on bottleneck to enterprises (Performance management, 2011).

results are discussed in sections 4 and 6, respectively, whilst the final section highlights the main conclusions and policy implications of the study.

5.2 Conservation Agriculture Technology in Zambia

The Ministry of Agriculture and Livestock (MAL), the Zambian National Farmers Union (ZNFU) and non-governmental organizations are the main CA technology stakeholders in Zambia. In 1999, there was a pronouncement to incorporate CA technology into Zambian agricultural policy. This was aimed at facilitating soil fertility, crop productivity, household incomes and food and nutrition security improvement, mitigating adverse impacts of climate change and incidence of labor constraints as well as diversifying crop production.

In line with CA global principles, the ZNFU considers CA as an integrated technology with three main linked principles; minimum tillage, maintenance of permanent or semi-permanent organic soil cover, and diversification of crop species, grown either in sequence or associations to coincide in time and space to enhance synergies. This entails localizing tillage and application of farm inputs including fertilizers in permanent rip lines or planting stations, ensuring adequate weed control, retaining crop residues after harvest and inter-cropping or rotating crops with nitrogen fixing legumes. The ZNFU also promotes the cropping of complementary perennials such as *Faidherbia albida* (a leguminous tree) and live fences.

Furthermore, completing land preparation before the onset of rains for planting to take advantage of nitrogen flush and reduce average waiting time to planting is considered as a critical CA requirement in Zambia. Haggblade and Tembo (2003) indicate that maize yields decline by 1–2% for each day delayed in planting after the first possible planting date. CA technology therefore ensures that these losses are reduced to a minimum and contribute to mitigating food and nutrition insecurity in SSA (Kuntashula et al., 2014).

5.3 Data and description of variables

The data used in this study are drawn from a recent farm household survey conducted between August and November, 2013 in the Central, Eastern, Western and Southern provinces of Zambia. These provinces contribute more than 60% to maize production in Zambia and considered the prominent CA technology provinces (Crop Forecast Surveys, 2010-2011). A multistage sampling technique was employed to select 408 farm households across 12 districts in these provinces. In the first stage, all four provinces were purposively selected, such that there would be equal opportunity for all CA technology farmers in these provinces to be included in the sample. Each province became a stratum, and in consultation with farmers and extension agents, and also given that there were no differences in the estimated number of adopters in all provinces, three districts each were randomly selected per province. In each district, five agricultural camps⁶⁰ were then randomly drawn, within which three farmer groups were randomly selected. Individual CA adopters and their non-adopter counterparts were then randomly selected from the groups.

Enumerators who spoke both the local language and English were hired and supervised to interview the selected farmers, using a detailed structured questionnaire. The survey gathered information on household characteristics, input quantities and prices, output quantities and prices, as well as social and institutional characteristics. Focus group discussions and meetings were held with informed officials from the Ministry of Agriculture, ZNFU and FAO to obtain additional information. Feder and Umali (1993) argue that while components of an agricultural package may complement each other, some of them can be adopted independently. Farmers may therefore adopt the complete package or subsets of the package can be adopted individually. This is similar to Burton et al. (2003) who defined an adopter as a farmer who uses a technology on all or part of the farm. In

⁶⁰ Agricultural camp in Zambia is a management unit of agricultural camp officer comprising a catchment area of up to eight different zones of different villages.

this study, a farmer who practiced one or more of the global CA principles; minimum tillage, crop rotation and retention of crop cover, is termed an adopter, while a non-adopter is one who did not practice any of the CA principles. With this description, 183 non-adopters and 225 adopters of the CA technology were drawn, comprising 92, 101, 95, and 120 farmers from the Central, Eastern, Southern and Western provinces, respectively.

Table 5.1 presents the definition of variables and mean differences between adopters and non-adopters in the sample. A number of price related variables are computed and included in the empirical model. The income variable which proxies the returns to farm activity is measured as total income from maize farm output. The cost incurred to realizing the income is the sum of annual rent of land, price of seed, labor expenditure, land preparation expenditure and other direct expenses. Land preparation is considered as a fundamental principle in CA technology, hence expenditure on land preparation is included in the model. This is computed as the sum of the cost of hiring animal and mechanical power for land preparation per hectare of maize. Wage expenditure includes hired and family labor valued at opportunity cost. To account for differential cost of fertilizers to adopters and non-adopters, fertilizer expenditure is included in the empirical specification.

In line with Goldratt's idea of theory of constraints (TOC), it can be argued that farmers in Zambia optimize their utility by maximizing farm output and throughput as well as reducing poverty. Throughput is the rate at which a system generates income from sales (Goldratt, 2002). In throughput estimation, only cost of materials directly identifiable to the output are relevant costs (Drucker, 1990). Particularly in Zambia, about 84% of the land mass is held under customary tenure system and most farmers do not pay land rent or taxes (USAID, 2010). Coupled with the fact that most family households supply family labor to their farm business, the major bottleneck to the farm business is material cost including capital, seed, fertilizers and other direct costs. Throughput

accounting ratio (TAR) is measured as the ratio of throughput to total cost per hectare⁶¹.

Age of household head is used as a proxy for farm household farming experience, especially in the study area where the agricultural sector is the major employer of the labor force. Additional years of schooling is expected to influence farmer's ability to gather and analyze relevant data for informed farm decisions (Huffman 2001). The education variable in this study is measured as the number of years of schooling by the household head.

Access to extension services is an indicator of farmers' level of exposure to institutional structures and access to information on farm practices and inputs, and measured as the number of extension contacts over the last three years.

⁶¹ Throughput is the difference between total income and direct material cost (i.e. sum of money price of seed, land preparation expenditure and other direct material cost).

Table 5.1: Variable names, descriptions and descriptive statistics of adopters and non-adopters

Variable	Description of variable	Adopters	Non-adopters	Difference
Income	Total maize farm income (ZMW)	10963.06	6295.04	4668.02***
Cost	Total maize cost of production (ZWM)	5168.91	4490.23	678.68
Wage expenditure	Wage expenditure rate per hectare (ZMW)	153.96	158.96	-5.01**
Land prep. expenditure	Tractor, oxen and manual cost of land preparation (ZMW per hectare)	175.53	178.80	-3.27
Other costs	Sum of the total cost of fertilizer, herbicide, lime and pesticide (ZMW per hectare)	863.75	606.19	257.56***
Throughput accounting ratio	Ratio of throughput to cost per hectare (per ZWM)	1.05	0.48	0.57***
Fertilizer expenditure	Cost of fertilizer per hectare (ZMW)	750.57	565.93	184.64***
Output	Maize output (tons per hectare)	2.86	1.63	1.23***
Education	Household head 's schooling (year)	6.65	4.91	1.74***
Age	Age of household head in years	46.00	46.12	-0.11
Access to credit	1 if farmer has access to credit, 0 otherwise	0.95	0.11	0.84***
Distance to capital	Distance to permanent source of capital (km)	5.582	5.279	0.30
Erosion awareness	1 if farmer is aware of erosion, 0 otherwise	0.90	0.20	0.70***
Market distance	Distance to nearest permanent market (km)	4.27	8.24	-3.97**
Association	1 if a member of farmer association, 0 otherwise	0.716	0.213	0.503***
Extension contacts	Number of extension contacts by household head in last three years	4.72	4.01	0.72***
Networks	Number of family and friends household head discusses farm business with	5.39	5.84	-0.45
Land	Total land holding under farmer's control in hectares	7.17	7.00	0.17
Farm size	Farm size in hectare	3.37	3.36	0.01
Machinery	1 if the farmer owns a tractor or Magoye ripper, 0 otherwise	0.70	0.03	0.67***
Perception	1 if the farmer perceives CA as easy to accomplish, 0 otherwise	0.70	0.05	0.64***
Soil quality	1 if soil quality is good, 0 otherwise	0.26	0.01	0.25***
Poverty headcount	Percentage of households below the poverty line	0.80	0.92	-0.12***
Poverty gap	The gap between poor households from the poverty line	0.49	0.65	-0.16***
Severity of poverty	Poverty gap squared	0.34	0.50	-0.16***
Eastern	1 if farm is located in Eastern province, 0 otherwise	0.25	0.25	0.00
Western	1 if farm is located in Western province, 0 otherwise	0.29	0.30	-0.01
Southern	1 if farm is located in Southern province, 0 otherwise	0.22	0.25	-0.03
Central	1 if farm is located in Central province, 0 otherwise	0.24	0.21	0.03
<i>Number of observations</i>		225	183	

Note: Coefficients followed by ** and *** indicate significance at the 5% and 1% levels, respectively.

Access to credit is used in this study to capture the extent to which farmers are liquidity constrained. The variable is measured in relation to whether the farmer obtained credit in the production season, and or tried to access additional credit than what was made available. Farmers who required credit and could not access it and those who received credit, but were denied additional credit are regarded to be liquidity constrained. Abdulai and Huffman (2014) demonstrate that possession of machinery impacts on adoption of soil conservation measures in Northern Ghana. As CA is a soil and water conservation measure, a variable machinery is included in the empirical specification, and denotes whether a farmer owns a tractor and or Magoye ripper⁶².

A variable on the distance to permanent market of the farmer is included to capture the impact of input and output markets on adoption. It is hypothesized that the farther the distance to markets, the higher the transaction cost in sourcing inputs and output market information, and hence a lower incentive to adoption. Land holding is an indicator of the level of household resource endowment, with larger land holding indicating more household resource endowment. Land holding is measured as the total cultivated and uncultivated land under the control of the household head. Gould et al. (1989) indicate that awareness of soil erosion or other soil problems by farm operators is a prerequisite to adoption of CA technology. Erosion awareness and soil quality are included as potential variables influencing adoption of CA technology. Also the influence of social network is considered to influence adoption. Bandiera and Rasul (2006) indicate positive impact of social network on adoption, suggesting that network of farmer' neighbors strongly determine their adoption decision making process. The number of farmers' family and friends with whom farmers discuss farm business with and farmers' membership of an association are used to capture the effects of learning from social networks.

Given that CA technology only contributes to household income, and given that farm income

⁶² The Magoye ripper is a Zambian innovation which was developed in 1996 at Zambian Ministry of Agriculture and Cooperatives research station of Magoye (Dutch funding).

could contribute to household investment in other non-farm income sources, which determine the purchasing power of households, household per capita income (PCI) is used as a measure of poverty status of farm household. Household PCI is computed on a pro rata basis over a period of seven active months of farming in Zambia (November to May every year). To the extent that there are huge disparities in the cost of living across provinces in Zambia, provincial basic needs basket (BNB) data of Jesuit Centre for Theological Reflection (JCTR) is used in determining household poverty status⁶³. The advantage of the JCTR measure compared to other indices including normal household expenditure is that, it accounts for both expenditure and value of home-produced food. In the JCTR BNB framework, average monthly basic needs basket for a family of 5 from October, 2012 to September, 2013 for the Central province (Kabwe), Eastern province (Chipata), Southern province (Monze) and Western province (Mongu) for 2012/2013 were ZMW 2344.09 (\$436.52), 2089.23 (\$389.06), 2081.35(\$387.59) and 1633.19(\$304.13), respectively⁶⁴. The JCTR BNB data is collected in the last week of the month, thus reflecting actual expenditure.

Poverty indices are measured using Foster et al. (1984) poverty indices expressed as:

$$p_n = \frac{1}{N} \sum_{i=1}^P \left(\frac{l - K_i}{l} \right)^s \quad (1)$$

where p_n is the poverty index, N is the total sample, P is the number of poor households, l is the poverty line, K_i is household's PCI and s is the poverty scale⁶⁵. In this study, a household's poverty line is determined using its provincial BNB. A household whose PCI is less than its provincial BNB is considered to be poor. Poverty headcount index is a measure of the proportion of households who are counted as poor relative to the poverty line. The headcount index only indicates poor and non-

⁶³ Jesuit Centre for Theological Reflection (JCTR) is a prominent local non-state actor that has single-handedly brought cost of basic household need in Zambia to the limelight since 1991 through its monthly provincial surveys on costs of living across Zambia under the basic needs basket (BNB) framework.

⁶⁴ At the time of survey, 1. U.S. dollar was ZMW 5.37.

⁶⁵ At poverty headcount; $s = 0$, poverty gap; $s = 1$, whilst at poverty severity; $s = 2$.

poor household, and hence does not change if households below the poverty line become poorer. To measure the extent to which households are poor a poverty gap index is computed. Poverty gap index indicates the extent to which average household income falls short from the poverty line. The poverty gap index is expressed as a percentage of the poverty line. Here, the non-poor have zero poverty gap. To determine the degree of income inequality or poverty severity among the poor, a squared poverty gap index is used.

The *t*-test values indicating the differences between adopters and non-adopters in Table 5.1 suggest that, there are statistically significant differences between adopters and non-adopters of the CA technology with respect to some household and farm-level characteristics. In particular, while adopters obtained about 2.86 tons of maize output per hectare and ZMW 1.05 TAR per ZMW, non-adopters obtained just 1.63 tons of maize output per hectare and ZMW 0.48 TAR per ZMW. Moreover, adopters and non-adopters differ significantly in household income, money wage and other direct expenses. Also while adopters reported about seven years of completed schooling, non-adopters reported about five years of completed schooling. Furthermore, there are significant differences between household head's access to credit, ownership of machinery, soil quality, and perception about CA. More so, adopters reported lower levels of poverty in relation to poverty headcount, poverty gap, and severity of poverty compared to non-adopters. Although the reported differences for output, TAR and the poverty indices in Table 5.1 could be interpreted as impacts, this may not really hold when other confounding factors are taken into consideration. This study therefore models the adoption decision in relation to other confounding factors.

5.4 Conceptual framework

Conservation agriculture technology adoption decision

On the assumption that the choice of a given household is binary such that farmers choose to either adopt the CA technology or not, the adoption decision-making process and impact of the CA

technology on farm household welfare can be modelled in an optimization framework. Given that farmers are risk neutral, and evaluate the net welfare associated with adoption and non-adoption of CA, denoted by C_{iC} and C_{iN} respectively. To the extent that only the adoption status is known to the researcher, but the household preferences like net welfare are known to only the farmer, the net welfare of farmer i which is unobserved is represented by $C_i^* = C_{iC} - C_{iN}$. The net welfare from CA adoption can be expressed with respect to a vector of household explanatory variables in a latent variable framework as:

$$C_i^* = X_i' \alpha + \varepsilon_i, C_i = 1[C_i^* > 0] \quad (2)$$

where C_i is a binary variable, with 1 for farmers who adopted the technology, and 0 otherwise, X includes all observable factors that influence CA adoption decision, such as household and farm-level characteristics, α is a vector of parameters to be estimated, and ε , the error term with mean zero and variance σ_ε^2 , capturing measurement errors and unobserved factors.

The probability of adoption is expressed as:

$$\Pr(C = 1) = \Pr(C_i^* > 0) = \Pr(\varepsilon_i > -\alpha'X_i) = 1 - F(-\alpha'X_i) \quad (3)$$

where F is the cumulative distribution function for ε . Assuming a normal distribution, a probit model is used for this study.

Given that farm households maximize their return (welfare) from maize output, the adoption decision with respect to input demand and output supply is expressed as:

$$\pi_{max} = [PQ(V, Z) - MV] \quad (4)$$

where P is output price, Q is the expected levels of output, V is a vector of inputs; Z is a vector of household characteristics and M is a vector of prices for maize input like herbicides and fertilizers. From equation (4) the net return as a function of variable inputs, output prices, household characteristics and CA technology adoption can be expressed as:

$$\pi = \pi(M, P, C, Z) \quad (5)$$

Direct application of Hotelling's Lemma (4) $\left(\frac{\partial \pi(P, V)}{\partial P_i}\right)$ to equation (4) yields the reduced form of the output supply function from the first-order condition and expressed as:

$$Q = Q(M, P, C, Z) \quad (6)$$

Equations (5) and (6) show that farm household welfare depends on input and output prices, CA adoption decision and a vector of household characteristics.

Household impact evaluation and selection bias

This study investigates the impact of CA adoption of farm household welfare, including maize output, TAR and household poverty. Given that these vector of outcomes is a linear function of a vector of farm and household characteristics, the outcome variables can be expressed as:

$$Y_i = Z_i' \beta + C_i \gamma + \mu_i \quad (7)$$

where variable Y_i represents a vector of outcome variables; Z_i is a vector of farm and household characteristics (e.g. landholding, age, education, soil quality, as well as farm input prices); C_i as previously described is an indicator of household CA adoption status; μ_i is a random error term and β and γ are vector of parameters to be estimated.

In impact evaluation, only observed attributes declared by the farmer in the course of the survey are known to the researcher, but unobservable factors like innate technical, social networking, risk and managerial abilities are known to only the farmer. Potential selection bias arises where the undeclared factors, μ in the outcome equation (7), influence on ε in the selection equation (2). This implies the correlation coefficient of the error terms, $\rho = \text{corr}(\varepsilon, u) \neq 0$, hence ordinary least squares (OLS) tend to yield bias estimates. In randomized control trial setting, this selection bias problem is addressed by randomly assigning individuals into treatment (adopters) and control (non-adopters) groups, such that the only differentiating factor among adopters and non-adopters is the technology. In such situations, the control group is a good counterfactual to the

treated group, hence, the impact of the technology is the difference between adopters and non-adopters (Asfaw et al., 2012).

However, in a non-randomized experimental situation like the adoption of CA technology, adoption is not random. Farmers may therefore self-select themselves into adopters and non-adopters based on information at their disposal and their perception about the technology, thus selection bias may occur. The propensity score matching (PSM) approach proposed by Rosenbaum and Robin (1983) is commonly used in impact evaluation of technology on household welfare, in particular when self-selection occurs (e.g. Nkala et al., 2011). As indicated previously a major drawback of the PSM approach is that it only accounts for observable factors. To simultaneously estimate the determinants and impact of adoption, while accounting for both observable and unobservable factors in an efficient manner, an endogenous switching regression (ESR) model approach developed by Lokshin and Saja ia (2004) is employed.

To the extent that the ESR is suitable for continuous expected welfare indices like output, TAR, poverty gap and severity, impact evaluation of adoption on poverty headcount, a binary outcome variable requires a different specification. Since adoption and poverty headcount both have dichotomous dependent variables, seemingly unrelated regression approach cannot directly be applied. Hence, a recursive bivariate probit model (RBP) which accounts for endogeneity and selection bias is used to jointly estimate adoption and impact of CA technology on poverty headcount.

5.5 Empirical specifications

5.1 Endogenous Switching Regression

In the endogenous switching regression (ESR) model framework, a two-stage estimation procedure is estimated simultaneously. The first stage involves estimating the selection equation (2) to determine the factors influencing adoption. In the second stage, the impact of adoption on the

outcome variables is specified for two regimes of adopters and non-adopters of the CA technology as:

$$\text{Regime 1 (adopters): } Y_{iC} = Z_{iC}'\beta + \mu_{iC} \text{ if } C_i = 1 \quad (8a)$$

$$\text{Regime 0 (non – adopters): } Y_{iN} = Z_{iN}'\beta + \mu_{iN} \text{ if } C_i = 0 \quad (8b)$$

where Y_{iC} and Y_{iN} are outcome variables for adopters and non-adopters, respectively; Z is a vector of household endowments and farm-level characteristics; β is a vector of parameters to be estimated and μ is the error term. The structure of the ESR model allows for an overlap of X in equation (2) and Z of equations (8a) and (8b). But for identification purposes, at least one variable in X should not appear in Z , hence the selection equation is estimated using the same variables in the outcome equation in addition to at least an identifying instrument. A valid instrument is expected to influence adoption and not the outcomes. In this study, a variable on household perception about whether CA technology is easy to implement is hypothesized to affect adoption decision but not on the outcome. This considered to be valid and relevant instrument.

To account for selection bias, the variables in Z in equations (8a) and (8b) account for only observable factors. However, the ESR model is able to address selection bias due to unobservable factors within a framework of omitted variable problem. Specifically, Heckman (1979) indicates that the inverse mills ratios or selectivity terms from the selection equation represented by λ_C for adopters and λ_N for nonadopters, and the covariance terms σ_{CN} , $\sigma_{C\varepsilon}$ are plugged into (8a) and (8b) to obtain (9a) and (9b) and specified as:

$$Y_{iC} = Z_{iC}'\beta + \sigma_{C\varepsilon}\lambda_C + \vartheta_{iC} \text{ if } C_i = 1 \quad (9a)$$

$$Y_{iN} = Z_{iN}'\beta + \sigma_{N\varepsilon}\lambda_N + \vartheta_{iN} \text{ if } C_i = 0 \quad (9b)$$

where the selectivity terms λ_C and λ_N correct for selection bias from unobservable factors and ϑ_{iC} and ϑ_{iN} are the error terms with conditional zero means.

Lokshin and Sajaia (2004) argue that, a disadvantage of the two-stage approach is that it generates residuals that are heteroskedastic and cannot be used to obtain consistent standard errors

without cumbersome adjustments. They then proposed a full information maximum likelihood approach, used in this study, as an efficient methodology to simultaneously estimate the outcome and selection equations.

The signs and significance levels of the correlation coefficients of the outcome and selection equations ($\rho = corr(\varepsilon, u)$) have econometric interpretations. Specifically, if either $\rho_{C\varepsilon}(\sigma_{C\varepsilon}/\sigma_C\sigma_\varepsilon)$ or $\rho_{N\varepsilon}(\sigma_{N\varepsilon}/\sigma_C\sigma_\varepsilon)$ is significantly different from zero, there is selection bias from unobservable factors, hence unbiased estimates are only obtained using empirical models like the ESR which account for both observable and unobservable factors. If they report same signs, it indicates that there is hierarchical sorting. This implies adopters have an above average welfare index compared to non-adopters. On the other hand, reported alternate signs indicate that adopters and non-adopters consider their comparative advantage in adoption decision. A positive ρ implies negative selection bias, indicating that farmers with above average outcome like output and TAR are less likely to adopt the technology. On the other hand, a negative ρ implies positive selection bias suggesting that farmers with below average outcome of the welfare indices are less likely to adopt the technology.

In addition to estimating factors that influence adoption, the ESR model can also be used to examine the impact of adopting the CA technology on household welfare. The impact of adopting the CA technology on household welfare is examined by comparing the expected welfare of farm households who adopt with expected outcomes of the counterfactual hypothetical cases that adopters did not adopt. The expected values of the outcome Y on adoption and non-adoption can be expressed as in equations (10a) and (10b):

$$E(Y_{iC}|C = 1) = Z' \beta_{iC} - \sigma_{C\varepsilon} \lambda_C \quad (10a)$$

$$E(Y_{iN}|C = 1) = Z' \beta_{iN} - \sigma_{N\varepsilon} \lambda_C \quad (10b)$$

A change in the outcome due to adoption termed the average treatment effect on the treated (ATT), is expressed in equation (11) below as the difference in the expected outcomes from equations (10a)

and (10b) (Lokshin and Sajaia, 2004):

$$ATT = E(Y_{iC}|C = 1) - E(Y_{iN}|C = 1) = Z(\beta_{iC} - \beta_{iN}) + \lambda_C(\sigma_{C\varepsilon} - \sigma_{N\varepsilon}) \quad (11)$$

where σ represents the covariance of the error terms and λ the inverse mills ratios. Thus, the impact of adoption on maize output, TAR, poverty gap and severity can be estimated using the ESR model.

5.2 Recursive Bivariate Probit model

In evaluating the impact of a binary variable on a binary outcome like adoption on poverty headcount, other studies have employed Heckman two-stage selection method to account for observed and unobserved heterogeneity between adopters and non-adopters (e.g. Kuntashula et al., 2014). As indicated previously, Lokshin and Sajaia (2004) argue that, the two-stage approach generates residuals that are heteroskedastic and cannot be used to obtain consistent standard errors without cumbersome adjustments. To overcome this shortcoming, this study uses a recursive bivariate probit model (RBP) to jointly estimate adoption and impact of CA on poverty headcount (Amare et al., 2012; Joshi et al., 2015). The RBP model also consists of a selection equation previously described in equation (2) for the potentially endogenous binary variable and outcome equation, indicated in equation (7) expressed as:

$$C_h^* = X_h' \delta + \varepsilon_h, \quad C_i = 1[C_i^* > 0] \quad (12)$$

$$Y_h = Z_h' \vartheta + C_h' \eta + \mu_h \quad (13)$$

where variable C_h^* is the latent adoption outcome of farm household; X_h includes all factors influencing CA adoption decision, such as household and farm-level characteristics; Y_h represents poverty headcount for household h ; Z_h is a vector of household and farm level characteristics (e.g. landholding, age, education, soil quality, as well as farm input prices); C_h is an indicator of household CA adoption status as indicated previously; μ_h and ε_h are a random error term δ , η and ϑ are parameters to be estimated. The error terms are assumed to follow a bivariate distribution and expressed as (Marra and Radice, 2011):

$$\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \quad (14)$$

where ρ is the correlation coefficient among unobserved explanatory variables in both equations.

As in the ESR model, for identification, it is important that the exclusion restriction on the exogenous variables hold, such that X_h and Z_h must differ in at least by one variable (Maddala, 1983). The bivariate normal cumulative distribution function is specified as:

$$\Phi(X_h, Z_h, \rho) = \frac{e^{-1/2(X_h^2 + Z_h^2 - 2\rho X_h Z_h)/(1-\rho^2)}}{2\pi(1-\rho^2)^{1/2}} \quad (15)$$

A significant ρ indicates correlation of the disturbance terms. The non-linear conditional expectation for estimating the marginal effects is expressed as:

$$E[C_h|Y_h, Z_h] = \frac{\Phi(\vartheta X_h, (2Y_h - 1)\vartheta Z_h, (2Y_h - 1)\rho)}{\Phi[(2Y_h - 1)\vartheta Z_h]} \quad (16)$$

The average treatment effect on the treated (ATT) is estimated as:

$$ATT = E(Y_{hC}|C = 1) - E(Y_{hN}|C = 1) \quad (17)$$

where Y_{hC} is the expected probability of poverty headcount from adoption, and Y_{hN} is the expected probability of poverty headcount outcome in the counterfactual case.

To the extent that potential endogeneity problems may arise in both the ESR and RBP estimation, in particular, as farmers' access to credit and adoption decision may be jointly determined. Failure to account for this potential endogeneity problem could result in bias estimates. As the dependent variable is dichotomous, the two-stage procedure of Blundell and Smith (1989) is employed to account for endogeneity. In the first-stage, the potentially endogenous variable (access to credit) is specified as a function of all other exogenous variables including a set of instruments as in equation (20) below:

$$\Pr[D_i = 1] = \eta'N_i + \tau'I_i + e \quad (18)$$

where D_i is a vector of the potential endogenous variables, N_i is a vector of exogenous variables,

and I_i is a vector of instruments that are correlated with the given endogenous variable, but uncorrelated with the error terms in equation (18). For identification, a suitable strategy is employed to include a variable that strongly influences access to credit in equations (18) but does not influence the welfare outcomes. Distance to source of capital which influences access to credit but not expected welfare is chosen as an instrument in the access to credit specification. In the second stage, the observed values of access to credit and their corresponding residuals from equation (18) are incorporated into the ESR models. This enables consistent estimation of the parameters in the presence of potential endogenous variable in N_i . A simple t -test for the significance of the coefficient vector is a test for the exogeneity of these variables (Wooldridge, 2010).

5.6 Empirical Results

As indicated previously, the full information maximum likelihood approach is employed to jointly estimate the selection and outcome equations in all specifications⁶⁶. Tables 5.2, 5.3, 5.4, 5.5 and 5.6 present the estimates for maize output, TAR, poverty headcount, poverty gap as well as severity of poverty, respectively. In particular, the coefficients of the ESR estimates reported in the second columns of Tables 5.2, 5.3, 5.5 and 5.6 are the selection equations estimates, while the fourth and sixth columns report the impact of adoption on adopters and non-adopters. The RBP estimates of adoption and impact of adoption on poverty headcount is presented Table 5.4⁶⁷. The selection and outcome equations estimates are presented in columns two and four, respectively. Given possible non-independence of error terms across households in the RBP estimation, robust standard errors estimates are presented in columns three and five. As in a normal probit case, marginal effects of the determinants of poverty headcount are reported in column six of Table 5.4 for easy

⁶⁶ The full information maximum likelihood method was estimated using Stata version 12 (StataMP 12).

⁶⁷ The estimate of Hosmer-Lemeshow test was not significantly different from zero indicating that the bivariate probit model was correctly specified.

interpretation of the results. Since it is tedious to decompose total marginal effect into direct and indirect components as described in Greene (1997), only total marginal effect is reported in this study.

Before proceeding to discuss the empirical estimates some other relevant tests in the estimation strategy are highlighted. As indicated in the empirical specification, identification of the model requires that at least one variable in the selection equation should not appear in the outcome equations. In both ESR and RBP specifications, the variable representing perception of the farmer on whether it is difficult to implement the CA technology is used as identifying instrument. It is expected that farmers' perception about the CA technology will influence adoption decision but not directly on output, TAR or poverty status. The credit residual estimates obtained from the first stage estimates of equation (18) are not statistically significant in all specifications, suggesting that the coefficients of the credit variable have been consistently estimated (Wooldridge 2010).

The likelihood ratio tests for joint independence of the equations in ESR and RBP specifications show that the equations are dependent. The correlation coefficient (ρ) in both specifications are significant, indicating that the selection bias due to unobservable factors occurred in adoption. Hence, the use of models like the ESR and RBP which account for both observable and unobservable factors are appropriate in this study (Lokshin and Sajaia, 2004). The negative and significant signs for ρ indicate positive selection bias suggesting that farmers with above-average output, TAR and lower poverty have higher probability of adopting the technology. This result is consistent with earlier studies by Abdulai and Huffman (2014) but contrasts with the result by Kabunga et al. (2012). The log likelihood ratio is significant at 1% indicating that the recursive bivariate regression model is overall a good fit.

Table 5.2: Full Information Maximum Likelihood Estimates of Endogenous Switching Regression Model for adoption and Impact of Adoption on Maize output

	Selection		Adopters		Non-adopters	
	Coefficient	Std Err.	Coefficient	Std Err.	Coefficient	Std Err.
Constant	-8.812***	1.243	1.998***	0.533	1.044***	0.304
Age	-0.002	0.015	0.006	0.004	0.001	0.003
Education	0.295***	0.040	0.015**	0.007	0.015	0.014
Wage expenditure	-0.008	0.007	0.002**	0.001	0.003***	0.001
Land prep. expenditure	-0.007*	0.004	-0.001	0.001	0.002**	0.001
Fertilizer expenditure	0.535	0.704	0.019***	0.004	0.022***	0.003
Access to credit	4.736***	0.681	0.433*	0.250	0.024	0.144
Erosion awareness	3.234***	0.622	-0.062	0.160	0.042	0.090
Machinery ownership	3.483***	0.666	0.030	0.108	0.013	0.178
Land	-0.015	0.037	0.008*	0.005	-0.005	0.005
Extension contacts	0.228***	0.077	0.008**	0.004	0.014	0.015
Networks	0.116*	0.068	0.030***	0.012	0.011***	0.001
Market distance	-0.072*	0.040	-0.021*	0.012	-0.004	0.008
Association	1.462***	0.438	0.083	0.122	0.071	0.088
Soil quality	1.357*	0.800	0.156*	0.088	0.047	0.309
Eastern	-0.812	0.530	-0.117	0.144	-0.061	0.125
Western	-4.277***	0.720	-0.072	0.143	-0.036	0.136
Southern	-4.838***	0.973	0.051	0.158	-0.140	0.144
Credit residual	-0.672	0.558				
Perception	1.223***	0.149				
$\ln\sigma_1$			0.393***	0.047		
ρ_1			-0.175***	0.041		
$\ln\sigma_2$					0.811***	0.052
ρ_2					-0.891	0.637
Log likelihood	-351.810					
			15.050**			
Likelihood ratio of independence: $\chi^2(1)$			*			

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5.3: Full Information Maximum Likelihood Estimates of Endogenous Switching Regression Model for adoption and Impact of Adoption on Throughput Accounting Ratio

	Selection		Adopters		Non-adopters	
	Coefficie nt	Std Err.	Coefficie nt	Std Err.	Coefficie nt	Std Err.
Constant	3.999**	2.011	1.276**	0.616	-1.089***	0.331
Age	-0.018	0.021	-0.001	0.005	-0.003	0.003
Education	0.249**	0.100	0.052**	0.022	0.018	0.016
Wage expenditure	-0.001	0.012	-0.001	0.002	-0.001	0.001
Land pre. expenditure	-0.004	0.004	-0.001*	0.001	0.001**	0.001
Fertilizer expenditure	1.223	0.832	- 0.0917***	0.028	-0.054***	0.014
Access to credit	3.357***	0.921	0.399*	0.225	0.436**	0.193
Erosion awareness	2.212***	0.675	0.196	0.186	-0.106	0.109
Machinery ownership	2.755***	0.772	0.119	0.126	0.256	0.212
Land	0.016	0.027	0.010*	0.006	-0.004	0.005
Extension contacts	0.071**	0.035	0.066***	0.023	-0.001	0.016
Networks	0.078**	0.033	0.024*	0.014	0.014	0.011
Market distance	-0.081*	0.045	0.028**	0.014	-0.003	0.009
Association	0.330***	0.118	0.106**	0.014	-0.006	0.097
Soil quality	1.541	1.263	0.217*	0.102	0.873**	0.360
Eastern	-0.862	0.972	0.090	0.168	-0.086	0.137
Western	-2.646***	0.933	0.013	0.166	-0.180	0.157
southern	-2.654**	1.154	-0.214	0.183	-0.254	0.157
Credit residual	-0.287	0.246				
Perception	1.654***	0.615				
$ln\sigma_1$			0.239***	0.047		
ρ_1			-0.009	0.410		
$ln\sigma_2$					0.740***	0.053
ρ_2					-0.520**	0.215
Log likelihood	-408.641					
Likelihood ratio of independence: $\chi^2(1)$			11.730***			

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5.4: Full Information Maximum Likelihood Estimates of Recursive Bivariate Probit Model for adoption and Impact of Adoption on Poverty Headcount

Total Marginal effect = 0.858

	Selection		Poverty headcount		Marginal effects
	Coefficient	Std. Error	Coefficient	Std. Error	
Constant	-7.6513***	2.5806	3.0258***	1.0036	
CA Adoption			-0.6584**	0.2012	-0.4452
Age	-0.0287*	0.0167	0.0180*	0.0098	0.0012
Education	0.2144***	0.0734	-0.1424***	0.0487	-0.0332
Wage expenditure	0.0022	0.0096	-0.0041	0.0047	-0.0033
Land pre. expenditure	0.0073**	0.0035	0.0003	0.0014	0.0010
Fertilizer expenditure	0.0007	0.0005	0.0001	0.0002	0.0010
Access to credit	4.6085***	0.9962	-1.0624**	0.4247	-0.7701
Erosion awareness	2.6559***	0.4832	-0.8393**	0.3098	-0.5640
Machinery ownership	4.4513***	0.9221	-0.5805**	0.2676	-0.4012
Land	-0.0286	0.0176	-0.0477***	0.0123	-0.0072
Extension contacts	0.0716	0.0973	-0.1731***	0.0418	-0.0020
Networks	0.1721***	0.0580	-0.2417***	0.0391	-0.0362
Market distance	-0.0577**	0.0248	0.0855***	0.0244	0.0211
Association	0.9732**	0.4432	0.4855***	0.2395	0.0930
Soil quality	1.7680**	0.7493	-0.4741**	0.2273	-0.2540
Eastern	-0.3430	0.6508	-0.1375	0.3088	
Western	-2.6636***	0.7853	-0.1878	0.3048	
Southern	-3.6070***	1.2208	-0.2856	0.3763	
Credit residual	0.6789	0.5391			
Perception	0.5239***	0.2336			
ρ	-0.9520***	0.0030			
Log likelihood	-109.313***				

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Determinants of adoption

Given that the empirical results in the selection equation can be interpreted as normal probit coefficients, the results from the selection equations are presented in Tables 5.2, 5.3, 5.4, 5.5 and 5.6 together. Estimates for variables with the same name in the selection equation, representing the probability of adopting CA technology have similar effects on adoption.

As the adoption of a technology like CA sometimes depends on awareness and access to reliable information about the technology, awareness of soil erosion and access to extension are considered important awareness and information variables for CA technology adoption. The coefficient of the variable erosion awareness is positive and significantly different from zero in all specifications, indicating that farmers' awareness or perception of soil problems positively correlates with the adoption of CA technology. This is consistent with the finding by Gould et al. (1989), who emphasize that awareness on the part of farm operator of soil erosion or other soil problems is a prerequisite to adoption of CA practices like no-till.

Also interesting is the effects of the soil quality variable, which is significantly different from zero in the output and poverty gap specification. This finding augments the soil erosion variable result and indicates that CA technology is more likely to be adopted by farmers who aim to retain their soil quality. Also, the extension contacts variable, a proxy for institutional network and access to extension is positive and statistically significant in all specifications, indicating that farmers with more contacts to extension services are more likely to adopt the technology. Genius et al. (2014) also find extension to be a strong determinant of technology adoption. The estimates of farmers' social network variable represented by association membership and network variables, which are proxies for access to information through social networks are positive in all specifications, and statistically significant in Tables 5.2, 5.3, 5.5 and 5.6. This indicates that farmers with access to information from their social networks are more likely to adopt the technology. This result concurs with the results by Khonje et al. (2014) who indicate a strong relationship between technology

adoption decisions and social network for Ethiopia and Zambia, respectively.

Notably, the estimate of the variable education, which is positive and statistically significant in all specifications at conventional levels, suggesting that more educated and informed farmers are more likely to practice CA technology on their farms, a finding that is consistent with the literature that education is important in farmers' decisions to adopt agricultural technologies (e.g. Huffman, 2001; Asfaw et al., 2012). The access to credit variable, an indicator of liquidity constraint is also positive and significantly different from zero, suggesting that liquidity constrained farmers are less likely to adopt the technology and confirming the significance of access to credit in adoption decision process. The results show that shorter distance to market is likely to reduce transaction cost and improve access to market information, thereby influencing early adoption.

The negative and statistically significant estimate of the market variable, a proxy for transaction cost and access to market information is consistent with the findings by Asfaw et al. (2012). In line with Knowler and Bradshaw (2007) who indicated the relevance of financial conditions and operational management variables in CA technology literature, the labor and land preparation expenditure variables are negative in all specifications. The negative and statistical significance of the land preparation expenditure variable in the output, poverty gap and poverty severity specifications indicates that increasing cost of minimum tillage operations relative to conventional land preparation is likely to reduce adoption of CA technology. In the same vain, the negative and statistical significance of the labor variable is an indication that increasing wage expenditure in CA technology operations is more likely to reduce adoption. These results are consistent with economic rationality of households that, rational agents compare the relative cost and benefits among alternatives and chose the relatively lower cost and or higher benefit option.

Table 5: Full Information Maximum Likelihood of Endogenous Switching Regression Model for adoption and Impact of Adoption on Poverty Gap

	Selection		Adopters		Nonadopters	
	Coefficie nt	Std Err.	Coefficie nt	Std Err.	Coefficie nt	Std Err.
Constant	-3.903***	1.022	0.804***	0.197	0.800***	0.234
Age	-0.007	0.018	0.002**	0.001	0.002	0.001
Education	0.148**	0.076	-0.010**	0.005	0.001	0.007
Wage expenditure	-0.013**	0.007	0.001	0.001	-0.002**	0.001
Land pre. expenditure	-0.010***	0.002	0.002	0.002	0.001	0.001
Cost of fertilizer	0.275	0.123	-0.002	0.004	-0.002	0.003
Access to credit	3.790***	1.068	-0.066	0.100	-0.321***	0.071
Erosion awareness	2.130***	0.584	0.044	0.061	0.040	0.044
Machinery ownership	3.257***	0.436	-0.054*	0.031	-0.002	0.085
Land holding	-0.002	0.032	-0.007***	0.002	0.001	0.002
Extension contacts	0.069***	0.018	-0.043***	0.007	-0.061***	0.007
Networks	0.107***	0.048	0.016***	0.005	-0.027***	0.005
Market distance	-0.110***	0.036	-0.005*	0.003	-0.004	0.004
Association	1.216*	0.652	-0.036**	0.017	0.055	0.042
Soil quality	1.672**	0.827	0.011	0.034	0.033	0.151
Eastern	-2.007***	0.491	-0.035	0.055	-0.053	0.054
Western	-3.065	1.387	-0.099*	0.054	-0.033	0.064
southern	-3.229***	0.665	-0.057	0.060	-0.067	0.069
Credit residual	-0.463	0.383				
Perception	1.480**	0.625				
$\ln\sigma_1$			-			
			0.475***	0.047		
ρ_1			-0.421	0.690		
$\ln\sigma_2$					-	
					0.913***	0.053
ρ_2					-0.617***	0.221
Log likelihood	-321.954					
Likelihood ratio of independence: $\chi^2(1)$			4.670***			

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Also interesting is the estimate of the variable machinery ownership, an indicator of farm household resource endowment and access to farm machinery, which is positive and statistically significant in all specifications. In the study area where specialized implements are used for minimum tillage operations of the CA technology, this finding indicates that farmers with better access to farm machinery are more likely to adopt the technology compared to those with poor access to machinery. The empirical results also reveal that location fixed effects may play a significant role in adoption decision. The negative and statistically significant estimates of the Eastern, Western and Southern variables indicate that, farmers in the Central province are more likely to adopt the technology compared to those in the Eastern, Western and Southern provinces. This finding is plausible, especially since the Central province is the most accessible compared to the other provinces in the Zambian landscape.

Impacts of determinants

The estimates in the outcome equations in the columns for adopters and non-adopters in Tables 5.2, 5.3, 5.5 and 5.6 generally show the impact of household and farm-level characteristics on maize output, TAR and the poverty indices for adopters and non-adopters. The marginal effects estimates in Table 5.4 report the effects of these characteristics on poverty headcount. The impact estimates in Tables 5.2, 5.3, 5.4, 5.5 and 5.6 suggest that education influences maize outputs, TAR and poverty among adopters of the technology. The positive and statistically significant coefficients reported in Tables 5.2 and 5.3 indicate that education tends to contribute to increasing output and TAR. Conversely, the negative and statistically significant estimates in Tables 5.4, 5.5 and 5.6 indicate that higher education is more likely to reduce the chances of household being below the poverty line, hence lower poverty headcount, poverty gap and severity of poverty for highly educated farmers.

Table 6: Full Information Maximum Likelihood of Endogenous Switching Regression Model for adoption and Impact of Adoption on Poverty Severity

	Selection		Adopters		Nonadopters	
	Coefficie nt	Std Err.	Coefficie nt	Std Err.	Coefficien t	Std Err.
Constant	-3.536**	1.614	0.755***	0.175	0.609***	0.151
Age	-0.008	0.017	0.002**	0.001	0.002	0.001
Education	0.128*	0.075	-0.005*	0.003	0.003	0.007
Wage expenditure	-0.007	0.010	0.001	0.001	0.002	0.002
Land pre. expenditure	-0.008***	0.003	0.002	0.002	0.001	0.001
Fertilizer expenditure	0.687	0.567	-0.015	0.011	-0.005	0.004
Access to credit	3.537***	1.144	-0.106*	0.059	-0.308***	0.074
Erosion awareness	1.373**	0.646	0.001	0.054	0.037	0.045
Machinery ownership	2.941***	0.748	-0.036	0.036	-0.002	0.089
Land	0.003	0.066	-0.004***	0.002	0.001	0.002
Extension contacts	0.055***	0.016	-0.040***	0.007	-0.064***	0.007
Networks	0.129***	0.048	-0.011***	0.004	-0.025***	0.005
Market distance	-0.077*	0.045	-0.003	0.004	-0.001	0.004
Association	0.826*	0.493	-0.051*	0.030	0.047*	0.026
Soil quality	1.261	1.019	-0.011	0.030	0.063	0.154
Eastern	-1.078	1.168	-0.049	0.049	-0.026	0.062
Western	-2.508	1.831	-0.114**	0.048	-0.037	0.068
Southern	-2.422	1.553	-0.075	0.053	-0.055	0.071
Credit residual	-0.368	0.262				
Perception	1.542***	0.498				
$\ln\sigma_1$			-	0.480		
			0.479***			
				0.30		
ρ_1			-0.609**	4		
$\ln\sigma_1$					-0.514***	0.053
ρ_2					-0.965**	0.332
Log likelihood	-123.558					
Likelihood ratio of independence:	$\chi^2(1)$		22.290***			

Note: Coefficients followed by *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

The results on output and TAR are in line with other findings like Abdulai and Huffman (2014) for Ghana who indicate that, good knowledge and firm understanding of a technology from education may increase the benefits of soil and water conservation technology. Awotide et al. (2013) show that high level of education tends to have a negative impact on poverty in Nigeria which is consistent with the finding of this study. The wage expenditure variable is also positive and statistically different from zero in the output specification for adopters. This finding is consistent with the results by Di Falco et al. (2011) who indicate positive output returns to labor per hectare in Ethiopia.

Although the coefficient for cost of fertilizer in the selection equations are statistically significant, in the output and TAR specification, estimates of the variable for fertilizer expenditure are significantly different from zero. The positive coefficient in the outcome equations of the output specification indicates that fertilizer application tends to increase output of both adopters and non-adopters. The negative coefficients in the TAR outcome specifications indicate that higher expenditure on fertilizers tend to decrease households returns on investment. The estimates for the soil quality variable is positive and statistically significant for adopters in the output and TAR specifications indicating the positive impact of soil quality to farm output and returns on investment. This finding is consistent with the results by Abdulai and Huffman (2014) for soil fertility.

The estimate for the access to credit variable is positive and statistically different from zero for adopters and non-adopters in the output and throughput specifications, but negative and statistically different from zero in the poverty headcount and poverty severity specification for adopters and non-adopters. The results indicate that access to credit is likely to reduce liquidity constraints, hence increase household welfare. The variable for owning farm machinery tends to have negative and significant impacts on poverty headcount and poverty gap, but no significant impact for non-adopters in all specifications. This finding suggest the importance of machinery ownership in poverty reduction. Especially in the study area, owners of machinery like tractor and

ripping implements earn additional income from ripping and hence owning machinery tends to reduce household poverty. The positive and statistically significant coefficient of the association membership and network variables for adoption in the output and throughput specifications suggest a positive impact of social network from family and friends on farm output and household throughput.

The marginal effect estimates of the RBP specification are interpreted as elasticities. For instance, marginal effect of the education variable with negative and statistically significant estimate indicates that additional year of household head's education is more likely to contribute to reduce household poverty by 3.3%. The positive and statistically significant marginal effect estimate of the market distance variable suggests that an additional kilometer of market away from farmers is likely to increase the probability of being poor by 2.1%.

Household welfare impacts

As explained previously, to examine the impact of adoption on household welfare, the average treatments effects (ATT) on the expected outcomes are estimated. Table 5.7 presents the ATT estimates of the ESR specification for output, TAR, poverty gap and poverty severity as well as the RBP specification estimates for poverty headcount. In contrast to the mean differences in Table 5.1, which do not account for confounding factors, these ATT estimates account for other confounding factors including selection bias arising from potential systematic differences between adopters and non-adopters. The results reveal that adoption significantly increases output and TAR and reduces poverty. Specifically, the expected output produced per hectare from adoption is 2.96 tons compared 1.65 tons from non-adoption, representing a causal effect increase in output from adoption by 79%. These findings are consistent with other studies which report that adoption of new agricultural technologies can improve farm productivity (e.g. Di Falco et al., 2011; Abdulai and Huffman, 2014). Similarly, adoption contributes to increase throughput on investment from ZMW 0.47 to ZMW 1.06 per each ZMW invested, a finding consistent with positive returns on

investment results of Kleemann et al. (2014) from the adoption of technology for Ghana.

On the other hand, there is a negative impact of adoption on the poverty indices in all specifications. Specifically, the RBP estimates on the impact of adoption on poverty headcount indicates an increase in the probability of reducing poverty from 96 percent points from non-adoption to 69 percent points from adoption.

Table 5.7: Impact of Conservation agriculture on household welfare

	Adopters	Non-adopters	ATT	t-value
Yield (tons/ha)	2.96	1.65	1.31***	69.02
Throughput accounting ratio (per ZMW)	1.06	0.47	0.59***	25.74
Poverty headcount index (%)	0.69	0.96	-0.27***	-21.65
Poverty gap index (%)	0.52	0.71	-0.19***	-19.06
Poverty severity index (%)	0.65	0.93	-0.28***	-31.11

Note: Coefficients followed by *** indicate significance at the 1% level.

This finding mimics that of Khonje et al. (2014) and Zeng (2015) for technology adoption by maize farmers in Zambia and Ethiopia, respectively. The poverty gap and severity estimates also indicate a reduction in both poverty gap and severity. Specifically, increase in per capita income from adoption tend to reduce poverty gap by 27% and poverty severity by 30% from adoption. Becerril and Abdulai (2010) also reported negative and significant impacts of technology on all poverty indices, supporting the view that agricultural technologies have a major role in poverty reduction policy of developing economies.

5.7 Conclusions

This study used recent data from a cross-section of farm households in Zambia to examine factors influencing the adoption of conservation agriculture technology and the impact of adoption on maize output, throughput accounting ratio (TAR) and poverty among maize farmers. Results from technology mean differences revealed statistically significant differences in output, TAR, poverty

headcount, poverty gap and severity of poverty between adopters and non-adopters. Although these mean differences could be considered as impacts, the mean differences do not account for the effects of other characteristics including factors influencing adoption. Given that farmers self-select themselves into adopters and non-adopters, endogenous switching regression and recursive bivariate probit models are employed to estimate differential adoption and impacts of the technology on continuous outcome variables like output, TAR, poverty gap and severity of poverty and on a discrete poverty headcount variable, respectively.

The empirical findings generally showed that adoption of conservation agriculture technology has a statistically positive influence on maize output and TAR, but a statistically significant negative influence on poverty headcount, poverty gap and severity of poverty. The results also demonstrated that, if the impact of CA technology on these outcomes were estimated without accounting for observable and unobservable factors in the adoption decision process, sample selection bias could have occurred. On factors influencing adoption, the findings indicated that higher education, increasing extension contacts, access to credit, shorter distance to markets, access to machinery, lower wage expenditures and land preparation expenditure had positive and significant influence on adoption. The results also showed that awareness of soil problems like erosion and soil quality had positive and significant effect on adoption of CA technology. Access to information through extension, membership of farmer association and farmer contacts with family and friends as well as shorter distance to market outlets influenced adoption positively. However, while education, access to credit and landholding had positive and statistically significant impacts on output and TAR, they had negative and statistically significant impacts on poverty headcount, poverty gap and severity of poverty.

The findings from this study have policy implications and suggest that CA technology could contribute to enhancing farm productivity and household returns on investment as well as reducing rural poverty. Furthermore, the results suggest that household welfare policy measures such as,

investment in rural education, improving access to agricultural information through improving extension contacts and formation of farmer groups will effectively promote the adoption of new technologies. The positive impacts of access to machinery and access to credit on adoption and household welfare advocates for the incorporation of input credit schemes including farm mechanization in agricultural policy design to enhance technology adoption. This means existing and future programs like the recent FAO and Zambia Ministry of Agriculture collaborations on the Scaling-up of Conservation Agriculture Project (2013-2017) and other initiatives of Zambian National Farmers' Union pay attention to credit and mechanization.

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Chapter 6

Summary and Conclusions

The movement for sustainable agriculture is garnering increasing support and acceptance within mainstream agriculture globally, with the aim of harnessing economic, environmental and social benefits from agricultural systems. In particular, conservation agriculture technology is gaining significance as a sustainable agricultural system in Eastern and Southern Africa, with numerous activities and promotion programs from both government agencies and civil society organizations. To the best of our knowledge, this is the first study that has empirically examined the prospects of conservation agriculture from economic, environmental, social and institutional benefits of sustainability. Firstly, the study has contributed to enrich empirical perspective to efficiency measurement by employing a procedure that accounts for both potentially fully efficient and inefficient farms in a given setting. Secondly, the study examined the main factors that influence instantaneous adoption and the time dimension to the adoption of conservation agriculture, with reference to social and institutional networks and other confounding factors.

Also the study employed a nitrogen balance measurement tool and examined the environmental efficiency of conservation agriculture with reference to the utilization of nitrogen fertilizers among Zambian maize farmers. Furthermore, the study estimated the contribution of conservation agriculture to household welfare indicators, including farm output, throughput accounting ratio and household poverty. This study revealed that, conservation agriculture has a role towards attaining the Sustainable Development Goals (SDGs) in agriculture, as it fulfils synergies in social networking, enhancing economic empowerment and reducing environmental pollution. The following subsections outline detail summary and policy implications of the key findings of this study.

6.1 Allocative and Scale Efficiency among Maize Farmers in Zambia: A Zero Inefficiency Stochastic Frontier Approach

In this chapter, a translog cost frontier approach is employed to estimate and compare efficiency scores from the traditional stochastic frontier (SF) model and the zero-inefficiency stochastic frontier (ZISF) model among maize producing households in Zambia. The ZISF model proved to be a realistic technique for efficiency measurement, by simultaneously accounting for the presence of both fully efficient and inefficient farm sub-samples among the selected household, compared to the SF model which accounts for only inefficient farms. Furthermore, the ZISF provides different options to defining the benchmark farms in a statistically meaningful manner as opposed to the current practice in the SF where farms with the lowest level of inefficiency in the sample are the benchmark. The empirical results also revealed that cost inefficiency could be reduced by improving farmers' access to credit and extension services, providing rural education and by improving roads and transport services. Furthermore, the study demonstrated that scale of operations of maize farmers in Zambia were below optimum, suggesting that increasing farm size and allowing relatively scarce resources (e.g., farm land) to be transferred among farm households could help enhance allocative efficiency.

A finding from the study is that improving farmers' access to education services from the youth and adult literacy program in Zambia will enhance the allocative ability of farmers, and hence help in reducing cost inefficiency. The results also support the widely held view that agricultural extension services play a major role in enhancing farm business efficiency in SSA. Also improving farmers' access to timely and friendly credit packages including cash and input credit could contribute to decrease farm level cost inefficiency. The finding of scale economies indicates that developing land market will be useful in improving efficiency of resource use, as farmers can effectively engage in land transfers to enhance farm efficiency.

6.2 The role of social and institutional networks in promoting the diffusion of Conservation Agriculture in Zambia

This chapter has examined the role of social networks, extension services and risk preferences, as well as other confounding farm and household characteristics in the diffusion of CA technology among farmers in Zambia, using a discrete-time duration model to account for the time path to CA technology adoption. To account for potential endogeneity of sources of information in the duration model, a principal component approach is employed to generate scores for social and institutional network variables. The empirical results suggest that CA technology diffusion is duration dependent with progressive rate of adoption and positively influenced by access to information from institutional networks. In particular, exposure to extension services and social networks such as association involvement, as well as contacts with peers who had adopted the technology influence diffusion. It is also found that farmers are risk averse and tend to consider both absolute and down side risks in the adoption process.

These findings suggest that, the role of extension agents is quite important in promoting the adoption of these technologies. Policy makers and program implementers should therefore support extension agents with the requisite logistics and expertise. Given that there are no natural barriers to information flow amongst farmers and considering the socially interlinked family systems in Zambia, enhancing social networks through the formation of farmers' associations and the promotion of the community lead - farmer extension systems stand a better chance to enhance adoption of the technology. As widely documented in the literature, improving farmers' access to credit is a way of helping them to overcome imperfect financial markets, making it easier for them to adopt new technologies. Hence, policy design should include measures that contribute to enhancing access of farmers' to adequate and timely financial resources.

6.3 Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia

In this chapter, environmental efficiency among maize farmers in Zambia is examined, with particular reference to the utilization of nitrogen fertilizers. A meta-frontier approach was used to account for technology differences among conservation agriculture technology farmers and conventional farming farmers. To account for selection bias from both observable and unobservable factors, propensity score matching and Greene's (2010) sample selectivity correction stochastic production frontier approach is used in the empirical estimation. A nitrogen index tier zero tool is used to establish a nitrogen balance sheet at the farm level, such that the quantity of applied nitrogen fertilizers are split into quantity of nitrogen that yielded the output and quantity of nitrogen surplus. The empirical findings also showed that unobserved selectivity bias existed and was appropriately accounted for.

The CA technology farmers were found to be technically and environmentally more efficient than conventional farming technology farmers, a finding that suggests that CA has the potential to reduce the economic drain and environmental burden that may arise from nitrogen surplus. This demonstrates that CA technology has a greater potential in improving farm economic returns in terms of farm output and also reducing environmental burden in non-CO₂ greenhouse gases related to nitrogen losses. Less environmental burden from CA technology is also an indication of less social cost from CA technology in the light of relative carbon dioxide emission. The results also showed that access to credit, as well as age and increasing level of education of the household head positively influenced technical efficiency. Similarly, environmental efficiency was found to be positively related to access to credit, farming experience, years of education and shorter distances to markets, indicating that there is scope for using policy measures to influence technical and environmental efficiency.

6.4 Impact of Technology on Household Welfare: The Case of Conservation Agriculture in Zambia

In this chapter, factors influencing spontaneous adoption of conservation agriculture technology and the impact of adoption on maize output, throughput accounting ratio and poverty among maize farmers are evaluated. Given that farmers self-select themselves into adoption and nonadoption, endogenous switching regression and recursive bivariate probit models are employed to estimate differential adoption and impacts of the technology on continuous outcome variables like output, throughput accounting ratio, poverty gap and severity of poverty and discrete poverty headcount variable, respectively. The empirical findings generally showed that while adoption of conservation agriculture technology positively influenced on maize output and throughput accounting ratio, it negatively influenced on poverty headcount, poverty gap and severity of poverty. The results further demonstrated that higher education, increasing extension contacts, access to credit, shorter distance to markets, access to machinery, lower labor wages and capital costs had positive and significant influence on adoption. The results also showed that awareness of soil problems like erosion and soil quality had positive and significant effect on adoption of CA technology.

The findings from this chapter suggest that the CA technology could contribute to enhance farm productivity and household returns on investment as well as reducing rural poverty. Furthermore, the results suggest that household welfare policy measures such as, investment in rural education, improving access to agricultural information through improving extension contacts and formation of farmers groups will effectively promote the adoption of new technologies.

6.5 Policy Implications

The findings summarized above have important policy implication in respect of the contribution of technology, especially conservation agriculture technology to production efficiency and household welfare. In particular, the positive impact of conservation agriculture technology on household

technical and environmental efficiency suggests that, policy framework that ensures effective implementation of conservation agriculture technology has the tendency to enhance sustainable agriculture. This requires policy to facilitate site selection and acquisition, improve access to machinery to enhance timely minimum tillage land preparation, promote judicious use of external inputs, retention of permanent crop cover and encouraging the rotation of maize with legumes. The findings demonstrate positive impact of conservation technology on farm output, household throughput accounting ratio and poverty reduction. This implies, policy makers should provide enabling environment for the adoption and diffusion agricultural technologies to improve household incomes, food and nutrition security and reduce poverty. The results further show that policy could improve the adoption and diffusion of technology by taking advantage of the common extended family systems in sub-Saharan Africa to support information flow among neighbors and within farmers' association.

The results also support the widely held view that agricultural extension services play a major role in enhancing information dissemination and improving farm business efficiency in sub-Saharan Africa. Policy that empowers extension agents with the requisite skills and logistics would therefore improve agricultural productivity. Improving farmers' access to education services through youth and adult literacy programs in Zambia will enhance the allocative ability of farmers, and hence help improve productivity and efficiency. Also improving farmers' access to timely and friendly credit packages including cash and input credit would contribute to increase farm level output, improve efficiency and reduce household poverty. Moreover, policy initiatives that will improving roads and transport infrastructure will motivate private sector participation and ensure functioning input and output markets, hence improving cost efficiency. The finding of scale economies indicates that development of a land market will be useful in improving efficiency of resource use, as farmers can effectively engage in land transfers to enhance farm productivity and returns on investment.

Appendices

Appendix 1: Questionnaire



Christian-Albrechts University of Kiel, Germany

The Institute of Food Economics and Consumption Studies

Adoption, Productivity and Efficiency of Conservation Agriculture: Insight from the Zambian National Farmers Union

This questionnaire is purposely for field survey on Conservation Agriculture (farming) in collaboration with the ZNFU. Kindly note that all information provided is for research purposes only and shall be kept strictly confidential. Thank you for participating in this interview.

Survey Identification

Questionnaire number -----

Name of enumerator -----

Date of interview -----

Time started -----

Province/Region -----

District/ Local Government area -----

Name of village/town -----

Language for the interview -----

Socio-demographic characteristics

A/1 name of farmer (optional)..... Tel/ Address.....

A/2 age of the farmerA/3 Gender(1) male (0) female

A/4 Marital status.....(1)Single (2) married (3) Divorced (4) Widowed (5) Separated (6) cohabitant A/5 If married, indicate family kind..... (1) polygamous (2) monogamous (3) other specify A/6 family type..... (1) nuclear (2) extended (3) other (specify)

A/7 level education(1)Nil (2) primary (3) Secondary (4) Tertiary (5) other (specify).....

A/8 Years of Education (years) A/9 Religious affiliation A/10 Relationship with household head(1) head (2) Spouse (3) Child (4) relative (5) In-Laws (6)other(specify).....

A/11 status in the locality..... (1) chief (2) headman/woman (3) member (4) migrant (5) other (specify) ethnic group.....A/7 religion.....

A/12 primary occupation of the farmer.....

A/13 secondary occupation of the farmer.....

A/14 Other occupations of farmer (if any).....

A/15 Indicate total number of household members in their respective as in the table below

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

A/16 Indicate number of household members under your care as in A/15 if different from A/15

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

(B) Conservation agriculture practices

B/1 Are you a ZNFU farmer? (1) yes (2) no

B/2 If yes to B/1, which year did you start conservation farming (CF)?.....(write for the year)

B/3 How did you get to know about CF?.....(1) ZNFU (2) MOAL (3) Colleague farmer (4) family member (5) ASP (6) other (specify).....

B/4 Who mainly influenced your adoption of CF?.....

B/5 why did you adopt CF?(1) I thought it would be profitable (2) was convinced by ZNFU (3) was convinced by government campaign (4) Market access through ZNFU (5) other(specify).....

B/6 If yes to B1, Complete the table below

No.	CF Principles	Minimum tillage	Crop rotation	Permanent cover
1	Indicate the principles you have practiced before			
2	Indicate when you started practicing it			
3	Why do you practice it? (multiple response is allowed)(1) good for root growth (2) reduces yield failure in seasons of poor rains (3) less expensive (4) for good drainage (5) yield enhancing (6) improves soil fertility (7) reduces quantity of fertilizer use (8)reduces total yield loss (9) reduces incidence of pest and diseases (10) other(s) specify			
4	Indicate which principle you have stopped practicing before			
5	If you have stopped practicing it before in which year?			
6	If you stopped practicing it why (multiple response is allowed) (1) labour intensive (2) inadequate labour (3) expensive (4) time consuming (5) animal grazing (6) inadequate quality legume seeds (7) expensive legume seeds (8) other (specify)			
7	Do you plan to restart it in future? (1=yes, 2=no)			
8	If yes, when?			

B/7 Do you know *Faidherbiaalbida*?(1) Yes (2) No

B/8 Do you grow *Faidherbiaalbida* on your farm?.....(1) Yes (2) No

B/9 In which year did you first plant it?

B/10 If yes, why did you plant it? Multiple response is allowed (1=add nutrients to the soil, 2= shade, 3= other farmers do so, 4= ZNFU advised me to do, 5=other (specify))

B/11 Do you practice these other soil conservation measures? (1=yes, 2= no) a. ditches..... b. terracing..... c. Contour farming..... d. other (specify).....

B/12 if yes to B/11, since when? a. ditches..... b. terracing..... c. Contour farming..... d. other (specify).....

B/13 What other CF practices to you do on your farm?

B/14 Please complete the table below based on your land preparation technology

No	Crop production technology	1=Basin 2=hoe	Oxen, 1=ripping, 2=ploughing	Mechanical 1=ripping 2=ploughing
1	Indicate the technology you practiced on your farm			
2	Indicate when you started practicing it			
3	Why do you practice it? (multiple response allowed) (1) precise plant spacing and use of inputs (2) less expensive (3) other farmers use it (4) I started CF with it (5) no access to oxen (6) no access to tractor services (7) higher yielding (8) basin is labour intensive (9) other (specify)			
4	Indicate which technology you have stopped practicing before			
5	If you have stopped practicing before in which year?			
6	If you stopped practicing it why? (multiple responses allowed) (1) labour demanding (2) Inadequate labour (3) expensive (4) time consuming (5) switched to basin (6) switched to oxen (7) switched to mechanized (8) inadequate oxen (9) long waiting time (10) inadequate tractor services (11) no access to oxen services (12) other(specify)			
7	Do you plan to restart it in future? (1=yes, 2= no)			
8	If yes, when?			

B/15 For how long have you being farming on your own?(years)

B/16 for how long have you being farming maize?(years)

B/17 experience in farming the other crops.....(years)

B/18 please indicate your crop production details in the table below starting with the main crop

No.	Crop	Variety(ies)	Years of cropping	Reason for cropping (1)food (2)cash (3)subsidy (4)other(specify)	Was it cropped last season (1=yes, 2=no)	Yield last season	If production is halted why (1)high cost of production (2)low yielding (3)high incidence of pest attack (4)no market for it (5)labour demanding (6)communal reasons (7)no more interested (8)other(specify)	Do you plan to continue production in future	
								1=yes 2=no	when
1									
2									
3									
4									
5									
6									
7									
8									
9									

B/19 when do you prepare your land for planting.....(1) dry season (2) rainy season

B/20 if dry season, how long before the onset of planting rains(weeks)

B/21 if rainy season, how long after the onset of the planting rains(weeks)

B/22 how many seasons do you produce your maize in a year?(1) Major (2) winter (3) both

B/23 in which planting season did you plant the maize in 2012?.....(1) Major (2) winter (3) both

B/24 Do you treat your seeds before planting?(1) Yes (2) No

B/25 If yes, with which product?.....

B/26 for non-adopters, why didn't you adopt?.....(1) I thought it would not be profitable (2) I did not know the technique (3) No access to land (4) No access to information (5) Labour intensive

B/27 Do you plan to start CF in future?..... (1) Yes (2) No

B/28 if yes to B/27, when.....and why.....(1) I think it is profitable (2) I now know the technique (3) I have access to land (4) I have access to information (5) Other (specify).....

(C) Land Information

C/1 Land holding

No.	Land holding	Owner cultivated	Rented out	Borrowed in cultivated	Garden fields	Grazing	Fallow or virgin field
1	How many of them do you have?						
2	What are their sizes (ha)						
3	What is the total size of your current land (ha)						
4	What was the total size of your land before you started CF (ha)						
5	What was the total land you cultivated in 2012						
6	What is the total size of your land under CF(ha)						
7	What is your total size of land under non-CF (ha)						
8	What is the total size of land for other purposes (ha)						
9	If 8 applies to you, indicate purpose						

C/2 Plot characteristics

No.	Plot characteristics	Owner cultivated	Rented out	Borrowed in cultivated	Garden fields	Grazing	Fallow or virgin field
1	Vegetation before you started farming on the plot? (1=forest(>200 trees), 2=semi-forest (200 to 50 trees), 3=savanna(<50 trees))						
2	Current vegetation as in 1 (1+forest, 2=semi forest 3=savanna)						
3	Was the plot uncultivated before you moved in? (1=yes, 2=no)						
4	If yes to 3, for how long before you started cultivating it?						
5	If no to 3, how long was it cultivated before you started cultivating it?						
6	Which crops were grown on the plot before you started using it?						
7	Were there trees on the plot before? (1=yes, 2=no)						
8	If yes to 7, what type of trees?						
9	Have you cut down some of the trees since you started farming on the plot? (1=yes, 2=no)						
10	If yes to 9, approximately how many?						
11	Soil type (1=sand, 2=clay, 3=loam, 4=other (specify))						
12	Have you ever carried out soil test on the plot? (1=yes, 2=no)						
13	If yes to 12, how do you describe the organic matter content (1=good 2=medium, 3= poor)						
14	If yes to 12, how you describe the soil pH? (1=acidic 2=neutral, 3=alkaline)						
15	Soil quality (1=good 2=medium, 3= poor)						
16	Slope of soil(1=flat 2=medium slope, 3= steep slope)						
17	Soil drainage(1=good 2=medium, 3= poor)						
18	Rank the level of erosion of the plot (1=no erosion, 2=minimal erosion, 3=moderate erosion, 4=eroded 5=severe erosion)						

19	If 2-5 in 18, how do you manage it? (1=minimal tillage, 2=mulch or crop cover, 3=alley cropping, 4=contour ploughing, 5=terracing 6=ditches, 7=strip cropping 8=buffer zones 9=other (specify))						
20	How do you describe the annual rainfall condition on the plot (1-5) 1=very minimal ...2=very heavy						
21	Do you practice crop rotation on the plot? (1=yes, 2=no)						
22	If yes, which crops do you rotate with your main crop						
23	Indicate the annual order of crop rotation for at least 4 years						
24	If yes to 21, what is the annual farm size in rotation (ha)						
25	Do you leave crop residue on the farm after harvest? (1=yes, 2=no)						
26	If yes to 25, what is the size of plot under permanent cover (ha)						
27	If yes to 25, is your farm guarded? (1=yes, 2=no)						
28	Is the crop residue has been grazed by neighbouring livestock? 1=yes, 2=no)						
29	Is the crop residue being set on fire annually? (1=yes, 2=no)						
30	If yes by who? (1=self, 2=hunters, 3=neighbours 4=I don't know, 5=others (specify))						
31	Do you use cover crops? (1=yes, 2=no)						
32	If yes to 31, which crops do you use as cover crops?						

C/3 Land Tenure

No.	Land use and Tenancy	Owner cultivated	Rented out	Borrowed in cultivated	Garden fields	Grazing	Fallow or virgin field
1	Which of these land-use types applies to you?						
2	How did you acquire it? (1=purchase, 2=Inheritance, 3=allocated/given, 4=long term lease, 5=fixed annual rent, 6=borrowed in without payment, 7=rented out, 8=walked in, 9=other(specify))						
3	Are you cultivating the plot this year? (1=yes, 2=no)						
4	Did you cultivate the plot in 2012? (1=yes, 2=no)						
5	Who inherits the plot(s) after you?						
6	What is the tenancy situation of the plot? (1=state land titled, 2=state land untitled, 3=former customary titles, 4=customary untitled, 5=Other (specify)						
7	What is the duration of the tenancy agreement? (Years)						
8	How many years more are left?						
9	Do you pay or receive rent on it? (1=yes, 2=no)						
10	If yes to 9, what type of rent? (1) fixed annual rent, (2) annually negotiated rent (3) shared cropping (4) other (specify)						
11	If yes to 9, how much per year? (K)						
12	Do you participate in deciding the rent? (1=yes, 2=no)						
13	If no to 12, who determines the rent?						
14	Have you renewed the contract on the plot before? (1=yes, 2=no)						
15	If yes to 14, how many times?						
16	Have you ever been prevented by the landlord from practicing CF on the plot? (1=yes, 2=no)						
17	Are there some restrictions on the use of the plot? (1=yes, 2=no)						
18	If yes to 17, please specify						
19	Is the landlord living in the community where the plot is located? (1=yes, 2=no)						

Labour use

No.	Labour use information	Family (F)	Hired (H)	F+H	Other (specify)
1	Which type of labour do you use on your farm?				
2	How many are they?				
3	How many of them work on your farm?				
4	How many are permanent?				
5	How many are casual?				
6	How many are female?				
7	How many are male?				
8	What type of wage did you pay? (1=hourly, 2=daily, 3=monthly, 4=other (specify))				
9	Which type of labour did you use in 2012?				
10	What was the average rate in 2012? (K)				
11	Was the wage rate same for male and female? (1=Yes, 2=No)				
12	If no to 11, how much was for male?				
13	If no to 11, how much was for female?				
14	In which year did you started using each labour type?				
15	Why do you use a particular labour type? (1=family labour is in school, 2=I can no longer afford to pay, 3=sick, 4=already have enough labour, 5=my family labour is under aged, 6=other (specify))				
16	Have you ever halted using this labour type? (1=Yes, 2=No)				
17	Why the halt (1=family labour is in school, 2=I can no longer afford to pay, 3=sick, 4=already have enough labour, 5=my family labour is under aged, 6=other (specify))				
18	For the type that does not apply to you now, do you intend using it in future? (1=Yes, 2=No)				
19	If yes to 18, state reason (1=completed schooling, 2= I can afford to pay, 3=I do not have enough labour, 4=my family labour will be of age then, 5=others(specify))				
20	Which operation do you use for the labour type for? (1=all farm operations, 2=land preparation, 3=planting, 4= weeding, 5=fertilizer application, 6=spraying, 7= harvesting, 8=others (specify))				
21	If you don't use a particular type state reason (1=family labour is in school, 2=I can no longer afford to pay, 3=sick, 4=already have enough labour, 5=my family labour is under aged, 6=other (specify))				

Chemical Use

No.	Chemical Use	Herbicides	Fertilizer	Pesticides
1	Do you use chemical(s) on your farm (1=Yes, 2=No)			
2	Name(s) of chemical(s) you are currently			
3	In which year did you start using this chemical?			
4	What is your recommended dosage (lit./kg/ha)			
5	Where do you source it from			
6	Were you using another one before(1=Yes, 2=No)			
7	If yes, why did you stop using it?			
8	Who recommended to you what you are currently using?			
9	When do use it on the farm? (1=pre-planting, 2=at planting, 3=post-planting to harvest, 4=at harvest, 5=post-harvesting)			
10	Who applies it for you on your farm?			
11	If self, are you trained on the use? (1=Yes, 2=No)			
12	If yes to 11, who trained you?			

Livestock and other Assets

F/1 please provide information on ownership of livestock in the table below (table 6)

1	What types of animals do you own? (tick)	Cattle	Sheep	Goat	pigs	chicken	guinea fowls	Others
2	How many did you have before joining ZNFU?							
3	How many do you have now?							
4	On average how many do you acquire in a year							
5	On average how many do you sell a year							
6	On average how many die in a year?							
7	How many do you consume a year?							
8	How many did you have at the end of 2012?							
9	How many more have you acquired this year?							
10	How many were born in 2012?							
11	How many did you sell in 2012?							
12	Do you seek for veterinary services for them? (1=yes, 2=no)							

F/2 please complete the table below on the asset owned your household

No.	which of the assets below do you have?	availability		if yes, please state the number available	year of purchase	cost of purchase	Please indicate source of income for the purchase (1)CF (2) not CF
		Yes	No				
1							
2	Cutlass						
3	Chakka Hoe						
4	Knapsack						
5	Radio						
6	Television						
7	Bicycle						
8	Motorcycle						
9	Car/minitruck						
10	Mobile phone						
11	Bullock						
12	Magoye ripper						
13	Tractor						
14	Mechanized ripper						
15	House						
16	Other(s)						

Social Capital and Networks

G/1 Social Capital from participation in Farmer Based Organization (FBO) Activities

No.	Description	Farmer	Spouse
1	Are you a member of ZNFU farmer organization? (1=yes, 2=no)		
2	If yes to 1, when did you join the ZNFU?		
3	What benefits do you derive from the ZNFU (1) training (2) marketing assistance (3) CA input credit (4) lead farmer training services (5) carbon market (6) social network within the group (7) others (specify)		
4	What is your status in ZNFU?(1) Ordinary member (2) lead farmer (3) field officer (4) other(specify)		
5	Name of ZNFU association farmer belongs		
6	How often do you meet? (1) once a week (2) twice in a month (3) once in a month (4) once every quarter		
7	How often do you attend meetings? (1= very often5=not at all		
8	Current relationship with with this ZNFU farmer group...(1) member (2) not a member (3) old member		
9	Status in farmer group ...(1) executive member (2) non- executive member (3) old executive (4) ordinary member (5) other (specify)		
10	Have you worked with another organization? (1=yes, 2=no)		
11	If yes to 10, indicate name and the year you first started the relationship	Name: Year:	
12	If yes, indicate the type of relationship: multiple response is allowed (1. Ploughing or ripping services 2. Gift of farm inputs 3. Sale of farm produce by institution 4. Reduced transportation cost from bulk purchase of farm inputs 5. Sale of farm inputs by institution 6. Provision of farm equipment 7. Farmer group formation, 8 extension services 9. Credit 10. Other (specify)		
13	Do you still work with them? (1=yes, 2=no)		
14	If yes, indicate relationship if different from above		

G/2 Social Networks

No.	Informal Social Networks	Farmer	Spouse
1	Do you have friends apart from your relatives? (1=yes, 2=no)		
2	If yes to 1, how many times do you visit these friends (in a month)		
3	How many farmers live in a radius of 5km around your home (and your farm)		
4	How many of them do you discuss business with?		
5	How often do you have these discussions (in a month)?		
(B) Networks for specific purposes			
1	Do you have someone who assists you practically in your farming activities (through the ZNFU) 1= yes, 2=no		
2	If yes to 1, who is he/she (1=field officer, 2=farmer coordinator, 3=other (specify)		
3	If yes to 1, how many times does he/she visit you (in a month)		
4	If yes to 1, how many of you does he/she help?		
5	Is there someone who assists you with money in case of need? 1= yes, 2=no		

6	If yes to 5, how many would help you? Differentiate between 1=relatives, 2= friends and neighbours, 3=others (specify) (use the code and state number of individuals for each)		
7	Name the religious network you belong (if any)		
8	Do you have close relation in government?		
9	If yes to 8, indicate exact relationship (1=member of the nuclear family, 2=extended family member, 3=friends and neighbours, 4=other (specify))		
10	Indicate the position		
(C) Information and Networks			
Ci	Community Level		
1	On the average, when you decide to adopt CA how many CA farmers were in your community/village?		
2	On the average, how many do you think are in your community/village now?		
3	How many of them adopted CA through you?		
4	How many are your family members?		
5	How many are your friends and neighbours?		
6	How many are your religious faith (if any)?		
7	How many of your religious faith practice CA?		
8	What is the level of experience of your friends and or neighbours in CA? 1=very bad, 2=bad, 3=average, 4=good, 5=very good		
9	Do you discuss CA with some of them? (1=yes, 2=no)		
10	If yes to 9, how many of them do you discuss CA with?		
11	If yes 9 applies, how many times in a year?		
12	Do members of your group/locality seek your advice on CA? (1=yes, 2=no)		
13	If yes to 12, how many of them do you seek advice from?		
14	How many of them seek your advice on CA?		
15	If so, how many times in a year?		
16	Do you seek advice on CA from other members of your community? (1=yes, 2=no)		
17	If yes to 11, from how many of them?		
18	If so, how many times in a year?		
19	Do you experience new CA adopter in your community often? (1=yes, 2=no)		
20	If yes, on the average how many people in a year?		
21	Do you anticipate a time that there will no longer be new adopters? (1=yes, 2=no)		
22	If yes, how many years from now and why?		
23	Are you aware the government is promoting CA in your community? (1=yes, 2=no)		

Financing farm and household

H/1 what is the average monthly cash income of your household from farming (crops and livestock)

(1)<KR1000 (2) KR1001 - 3000 (3) KR 3001 -5000 (4) KR5001 - 10,000 (5) > KR 10,000

H/2 what is the average monthly cash income of your household from non-farming including other business, donations, gifts and remittances?

(1)<KR100 (2) KR101 - 300 (3) KR 301 -500 (4) KR 501 - 1,000 (5) KR > 1,000

H/3 If you suddenly need money where do you turn to?.....

H/4 what is the average amount of money you can get from this source?.....

H/5 do you source credit to finance your farm operations?..... (1) yes (2) no

H/6 if no, please state the reasons for not sourcing credit?

- H/7 if yes, please indicate name of credit agency.....
- H/8 what are your other sources of finance for your farm operations?.....
- H/9 did you source credit for your farm business in the 2012 season? ----- (1) yes (2) no
- H/10 do you know of other farming credit sources in your locality? ---- (1) yes (2) no
- H/11 if yes please name them.....
- H/12 Have you sourced credit from them before?.....(1) Yes (2) No
- H/13 if yes, do you still source credit from them and why?.....
- H/14 has your loan application ever been rejected? ----- (1) yes (2) no
- H/15 if yes, for what reason?.....
- H/16 did you buy any input on credit during the 2012 season? ----- (1) yes (2) no.
- H/17 if yes list the inputs
- H/18 if yes, what were the terms of the credit?----- (1) repay in cash (2) repay with farm produce (3) repay with cash and farm produce (4) other (specify) -----
- H/19 did you repay with interest.....(1) yes (2) no
- H/20 if yes what was the interest rate(% p.a.)
- H/21 what was the average repayment periodmonths
- H/22 please provide your credit history in the table below (if any)

Source of credit	Year	Amount (K)	Interest rate	Purpose	Repayment Duration	Number of instalments	instalment amount

- H/23 Did you enjoy any input subsidies in 2012? (1) yes (2) No
- H/24 if yes to H/23, on which inputs,
- H/25 if yes to H/23, how much per input?.....

I/1 Maize Crop Budget for 2012

No.	Description	Non-CA			CA		
		Quantity	Unit price	Amount	Quantity	Unit price	Amount
1	Farm size cultivated(ha)						
2	Land preparation						
3	Clearing and stumping						
4	Labour (hours)						
5	Rental services						
6	Ripping, Basins, ploughing						
7	Tractor rental						
8	Oxen rental						
9	Hoe/basin						
10	Other(specify)						
11	Labour						
12	Liming						
13	Lime (bags)						
14	Labour(per bag)						
15	Machinery (if any)						
16	Other rentals(if any)						
17	Planting						

18	Seeds(kg)						
19	Seed treatment						
20	Labour (per 10kg)						
21	Machinery (hrs)						
22	Weed Control						
23	1 st weeding						
24	Herbicides (bottles)						
25	Spraying labour(per ha)						
26	Water (buckets)						
27	Manual weeding labour(per ha)						
28	2 nd Weeding						
29	Herbicides (bottles)						
30	Spraying labour(per ha)						
31	Water (buckets)						
31	Manual weeding labour(per ha)						
32	Fertilizer Application						
33	Basal						
34	Fertilizer (bags)						
35	Labour for application (per ha)						
36	Machinery (hrs)						
37	Top dress						
38	Fertilizer (bags)						
39	Labour for application (per ha)						
40	Machinery (hrs)						
41	Pest and Disease management						
42	Pesticides (bottles)						
43	Spraying labour (hrs)						
44	Water (buckets)						
45	Cost of Implementing Rotation						
46	Cost of maintaining permanent cover						
47	Harvesting and processing						
48	Labour (per ha)						
49	Machinery (hrs)						
50	Gross output at harvest (bags)						
51	Output sold						
52	Output consumed						
53	Output as gift						
54	Packaging (bags)						
55	Transportation (bags)						
56	Other benefits (eg. Carbon credit)						
57							

I/2 Maize production in the first 3 years of CA

Description	Non-CA (if any)			CA		
	1 st CA year	2 nd CA year	3 rd CA year	1 st CA year	2 nd CA year	3 rd CA year
Farm size cultivated						
Labour for land preparation (man-days)						
Labour for planting (man-days)						
Labour for weeding (man-days)						
Labour for fertilizer application (man-days)						
Labour of harvesting (man-days)						
Quantity of seeds planted (kg)						
Quantity of herbicides used (Litres)						
Quantity of fertilizer used (bags)						
Quantity of line used (bags)						
Total output realized (bags)						

I/3 Before adopting CA, what were your expectations? Multiple response is allowed(1) Yield increase (2) increased revenue (3) reduced cost (4) labour savings (5) food security, (6) input subsidy (7) other (specify).....

I/4 what were your specific expectations and what are the actuals?

No.	Description	Expected			Actual		
		Minimum	Average	Maximum	Minimum	Average	Maximum
1	Yield increase (bags)						
2	Cost reduction (K)						
3	Cost increase (if any)						
4	Revenue increase (K)						
5	Profit (K)						

I/5 Before CA

No.	Description	Worse non-CA year			Best Non CA year		
		Minimum	Average	Maximum	Minimum	Average	Maximum
1	Farm size cultivated						
2	Labour for land preparation (man-days)						
3	Labour for planting (man-days)						
4	Labour for weeding (man-days)						
5	Labour for fertilizer application (man-days)						
6	Labour of harvesting (man-days)						
7	Quantity of seeds planted (kg)						
8	Quantity of herbicides used						

	(Litres)						
9	Quantity of fertilizer used (bags)						
10	Quantity of line used (bags)						
11	Total output realized (bags)						

I/6 During years of CA

No.	Description	Worse year of CA			Best year of CA		
		Minimum	Average	Maximum	Minimum	Average	Maximum
1	Farm size cultivated						
2	Labour for land preparation (man-days)						
3	Labour for planting (man-days)						
4	Labour for weeding (man-days)						
5	Labour for fertilizer application (man-days)						
6	Labour of harvesting (man-days)						
7	Quantity of seeds planted (kg)						
8	Quantity of herbicides used (Litres)						
9	Quantity of fertilizer used (bags)						
10	Quantity of line used (bags)						
11	Total output realized (bags)						

(J) Marketing

J/1 what is your percentage distribution of your maize output after harvest?

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

J/2 where do you sell your maize?.....(1) farm gate (2) market (3) MOAL (4) other (specify)

J/3 do you have a market in your community?(1) Yes (2) No

J/4 what is the average distance to the market?.....(Km)

J/5 Do you have a Particular buyer for your maize?(1) Yes (2) No

J/6 If yes, since when?.....

J/7 Do you have a written/verbal contract with your buyer?(1) Yes (2) No

J/8 If yes, what are the terms?.....

J/9 how does the buyer support you?.....(1) supply of seeds (2) provision of training (3) provision of credit service in cash or kind (4) any other please specify

J/10 what other support do you have from your buyers?.....

J/11 kindly provide information on your maize marketing for 2012 season in the table below

Please tick as appropriate	Farm gate	market	MOAL	Other (specify)
----------------------------	-----------	--------	------	-----------------

Quantity sold (kg/bag)				
Price (kg/bag)				

(K) Others

K/1 what is the condition of the time of starting and ending of rainfall in your farm?.....(1) good

(2)average (3) bad

K/2 what is the condition of rain during planting and harvesting season on your farm?.....(1) good

(2)average (3) bad

K/3 what is the condition of the amount of rain you experience in a year on your farm?..... (1) good

(2)average (3) bad

K/4 are you satisfied with the annual distribution of rainfall in your locality.....(1) yes, (2) no

K/5 which are the common pest and disease in your area?.....

K/6 do they affect your CA production (1) yes, (2) no

K/7 if yes, how do you manage it.....

(L) Non-farm Business Activities

	Household member		Farmer	Spouse	Other members
1	Self –employment	Type of business			
		How much time (hrs) is spent on the work each day?			
		How much capital obtained for the business?			
		What was the total cost (K) of the business in 2012			
		What was the total income (K) of the business in 2012			
2	Non-Agricultural wage employment (eg., teacher, driver, security etc)	Actual job			
		Number of working days per month			
		Monthly wage (K)			
3	Off-farm agricultural employment (eg., Hired labour)	Actual Job			
		Number of working hours per month			
		Daily wage (K)			

(M) Training and Extension services

M/1 Have you received farming or business training before (1) yes (2) no

M/2 If yes, please provide information on training in the table below

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

M/3 Kindly provide information about extension visits in the table below

	MAL	ZNFU	Other (specify)
Extension visits (yes or no)			
Frequency of visit*			
Where do you meet**			
Distance extension office from meeting point (Km)			

*(1) weekly (2) monthly (3) once in a 3 months (4) once every 6 months (5) Once a year (6) Never ***(1)

Farm (2) house (3) Lead farmer's farm (4) demonstration farm (5) others, specify

M/4 Have you ever visited any extension office

M/5 If yes, how many visits in 2012?.....

M/6 If yes, specify when and reason for your visit.....

M/7 Rank the level of confidence in the government extension system (1-5), 5 is very confident

M/8 Rank the level of qualification of the government extension officers (1-5) , 5 is very confident ...

M/9 Which of the following the major source of useful information for your farming operations? ... (1) TV (2)

Radio (3) news paper (4) extension agents (5) fellow farmers (6) Farmers' organization (8) others; please specify

(N) Perceived Needs

N/1 Please complete the table below on the constraints faced in your CA operations

Constraint	Very high	High	Low	Very low	None
Land					
Small land size					
Poor property rights (ownership) on land					
Difficulty in getting land to rent					
Difficulty in getting land to buy					
Land Preparation					
Magoye rippers					
Chakka hoes					

Mechanized rippers					
Access to ripping					
Time of ripping					
Others (specify)					
Seed					
Poor quality of seed					
Seed not available					
Price variability					
Other (specify)					
Fertilizer					
High cost					
Not available throughout the year					
Available late in the season					
Long distance to the fertilizer market					
Other (specify)					
Labor for farm business					
Not enough labor					
Labour cost to high					
Seasonal shortage					
Other (specify)					
Equipment & Infrastructure					
Difficult to acquire ripper					
Difficult to acquire planters					
Difficult to maintain equipment					
Poor access to the road					
Other (specify)					
Water management at plot level					
Difficult to access water					
Difficult to manage water					
High cost of water fees					
Other (specify)					
Credit					
Non- availability of credit					

High interest rate charges on credit					
Delays in acquiring credit					
Difficult to repay credit					
Other (specify)					
Post-harvest grain losses due to					
Threshing					
Winnowing					
Storage					
Transport					
Decorticating (removing husks)					
Other (specify)					
Product market					
Long distance to market for maize					
Low prices for maize					
High transport cost					
Lack of market/demand for maize					
Other (specify)					
Extension services					
Unavailability of extension services					
Lack of effectiveness					
Long distance to the extension workers					
Other (specify)					

N/2 what is your general perception about CA.....1= very easy to achieve 5= Very difficult to achieve

N/3 what is your general perception about CA business.....1= Not effective all 5= highly effective

N/4 will you recommend CA to other farmers? (1) Yes (2) no

N/5 Name three most important things you wish to be addressed in the current CA operations (starting with the most crucial)

.....

N/6 Other comments (if any)

Time Ended

Thank You

Appendix 2: Curriculum Vitae

ABDUL NAFEO, Abdulai, born on August 30, 1977, Savelugu, Ghana.

Award: DAAD Scholarship for Doctoral Studies at the University of Kiel; Germany.

Professional Experience

06/2011- 06/2012 Cotton Program Manager, West Africa Fair Fruits, Tamale, Ghana.

06/2010 – 06/2011 Fruit Program Coordinator, West Africa Fair Fruits, Accra, Ghana.

04/2008 – 05/2010 Organic Pineapple Coordinator, West Africa Fair Fruits, Accra, Ghana.

03/2007 – 03/2008 Monitoring and Evaluation Officer, West Africa fair Fruits, Accra, Ghana.

05/2007 – 07/2007 Acting Accountant, West Africa Fair Fruit Project, Accra, Ghana.

10/2006 – 03/2007 Organic Certification Consultant, GIZ, Cape Coast, Ghana.

10/2005 – 09/2006 Assistant Pineapple Agronomist, West Africa Fair Fruit Project, Accra, Ghana.

09/2000 – 09/2002 General Science and Mathematics Teacher of Nanton and Rawdatul-Atfal J.S.S.

Academic Qualifications

10/2012 – 05/2016 PhD fellow, University of Kiel, Germany.

Thesis title: The Contribution of Conservation Agriculture to Production Efficiency and Household Welfare in Zambia.

10/2008 – 12/2010 MPhil Agribusiness, University of Ghana, Legon, Ghana.

Thesis title: Assessing the Prospect of Organic Pineapple Production in the Central and Eastern Regions of Ghana: Financial Viability and Value Addition.

06/2007 – 06/2011 Association of Certified Chartered Accountants (ACCA) – UK
Part II and a paper at the Final level; P1 (Risk, Ethics and Governance).

10/2001 – 06/2005 Bachelor of Science (Agriculture), University of Cape Coast Ghana.

Thesis title: assessing the Status of Guinea Fowl Production in the Savelugu-Nanton District of Northern Ghana.

09/1997 – 06/2000 3-Year Teachers Certificate 'A', Bagabaga Training College, Tamale, Ghana.