ISBN: 978-82-575-1414-3
ISSN: 1894-6402

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Philosophiae Doctor (PhD), Thesis 2016:102

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Philosophiae Doctor (PhD)
Thesis 2016:102

Conservation agriculture, livelihoods and deforestation in Zambia

Konserveringslandbruk, levebrød og avskoging i Zambia

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Dedication

To the memory of dad, M.A.N. Long gone, yet gone too soon. Your legacy lives on.

For Mazuba and Ngoza, in the future.

Acknowledgments

Walking the thousand miles PhD journey is only possible with good company. As an African proverb says, 'If you want to go fast, go alone. If you want to go far, go together.' Several individuals and organizations helped me live my PhD dreams. I am grateful to the Norwegian Agency for Development Cooperation (Norad) for financing my PhD studies through the Center for International Forestry Research (CIFOR). I thank CIFOR for giving me space to stay ahead of the curve when deciding my research focus. In this regard, I thank Dr. Lou Verchot and Dr. Christopher Martius. Thank you Levania Santoso and team for all the help. I am grateful to Dr. Davison Gumbo for all the support and for facilitating fieldwork in Zambia.

To my PhD advisor, Professor Arild Angelsen, thank you for your tireless and timeless advice not just on my PhD work, but life in general. Your impressions on my professional and personal life are indelible. For this, I will forever be grateful. Your persistent questions *'what is new/additional'* challenged me to dig deeper and, in retrospect, worked through several *questions* about *questions*. Your open door policy ensured that my PhD work was punctuated with refreshing dinners, watching soccer and 'julegaver' over the years. True to the words of Dr. Lou Verchot, you have been the best PhD advisor I could possibly have.

I thank Professor Ragnar Øygard for his leadership in the department. I am grateful to Professors Stein Holden, Knut Einar Rosendahl, Kyree Rickertsen, Olvar Bergland, Ståle Navrud, Frode Alpines, Mette Wik and others for different interactions during my PhD studies. I thank Lise Thoen for her excellent coordination of PhD studies, Berit Petterson for keeping the money flowing, and to Reidun Aasheim, Hanne Marie Fisher, Nicha Thonghiang and Silje Sandersen for all the magic.

Further gratitude goes to Professor Thomas Jayne, Dr. Nicole Mason, Dr. Nicholas Sitko and Mr. Brian Mulenga with whom I co-authored some papers. It was a joy to work with you all. A special thank you to Dr. Gelson Tembo and Dr. Antony Chapoto for all the support and encouragements throughout my studies. I thank the Indaba Agricultural Policy Research Institute for providing part of the data used in the thesis.

Several colleagues and friends made the long PhD journey memorable and endurable. Thank you Thabbie Chilongo for being a wonderful coach early into my PhD. To PhDers in the department, I drew comfort from interacting and sharing similar PhD wows - 'things are not working, so - so, could be better' - not least because we were in 'the valley of stuff' together, but because every cloud has a silver lining. I am grateful to Livingstone, Alam, Øyvind, Muuz, Habtamu and several others. The PhD trips and retreats were refreshing and KREM discussions enlightening. Special thank you to Amare Teklay, the office mate with whom I shared the highs and lows of PhD life. From midnight frantic efforts to beat assignment deadlines in McDonalds in Warsaw to the stunning scenery in Bergen, from four awesome months in Gothenburg and Stockholm to the awe in Bogor, we have been through it together. Your calmness and attention to detail is inspiring. Thank you for the time we spent together. To colleagues from the 2014 PhD specialization classes at Gothenburg University (funding from SIDA gratefully acknowledged), the system is now stable. Thank you all for networks forged. I am grateful to families of Roselyne Alphonce, Doreen Auma and Alfred Obia who made us feel at home in Skogveien. Special thank you to the family of Dr. Byman Hamududu in Hamar, our second - second home away from home. We appreciate the close fellowship, God bless.

I thank all immediate and extended family members for being supportive during my PhD studies. To my mother and mother in-law, the times you visited us will remain some of our happiest memories of Norway. To my wife – Mulenga, the hero of our family, thank you so much for your unwavering love, support and prayers. Your ability to see the bigger picture is fascinating. To our children Mazuba and Ngoza, I love you both more than you can imagine. Mazuba (M.A.N.H), managing your school runs always reminded me that I needed to complete my school and give you space. Ngoza, taking time off my PhD work to welcome you into this world will remain one of the proudest memories in my life. Your innocent smiles were a constant reminder that after all, I was not just a PhD; I am a dad. I always looked forward to getting back home to unwind in your company after long days in the office. Even though my PhD journey was sometimes dreary, you all made it worthwhile. As Abraham Lincoln once said, 'We can complain because rose bushes have thorns, or rejoice because thorn bushes have roses', I am glad to earn the PhD with you. Now, dad is home.

Finally and not least, I thank God Almighty for His mercies and blessings upon my life and family. Completing the PhD is but just one of the many blessings for which I am grateful. In the words of Karl Paul Reinhold Niebuhr, 'Lord grant me the serenity to accept the things I cannot change, the courage to change the things I can, and the wisdom to know the difference'.

Hambulo Ngoma
Ås, October 2016

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2. Does minimum tillage with planting basins or ripping raise maize yields? Meso-panel data evidence from Zambia, (with Nicole M. Mason and Nicholas J. Sitko), Published in *Agriculture, Ecosystem and Environment 2015: 212, 21-29.*
3. Does minimum tillage improve livelihood outcomes of smallholder farmers? A micro-econometric analysis from Zambia.
4. Can conservation agriculture save tropical forests? The case of minimum tillage in Zambia, (with Arild Angelsen).

Summary

Conservation agriculture (CA) practices such as minimum tillage have been promoted for about two decades as a way to conserve soils and increase agricultural productivity and farm incomes in sub-Saharan Africa, including Zambia. As an integral component of Climate Smart Agriculture, which aims to enhance agricultural productivity and climate change adaptation and mitigation, CA is central to poverty reduction efforts since the majority of rural households in sub-Saharan Africa depend on rainfed agriculture for their livelihoods. However, such multiple objectives associated with CA makes objective assessments of its uptake and impacts difficult. This thesis focuses on minimum tillage, the main component of CA, and addresses four questions on uptake, and impacts on maize yields, livelihoods and deforestation.

First, in the backdrop of policy levers to scale up promotion of minimum tillage, albeit immense debates on the extent of its adoption and benefits for smallholders in sub-Saharan Africa, paper one asks: Do current promotion approaches work and how does uptake respond to rainfall variability? What are the recent trends in the uptake of minimum tillage? Results from nationally representative household survey data spanning five years and spatial rainfall data suggest that the uptake of minimum tillage is lower than generally believed. Low seasonal rainfall increases uptake, while being in districts where minimum tillage has been promoted for about a decade increases uptake for some, but not all minimum tillage principles. These results question one-size-fits-all promotion approaches: financial, labor and information barriers constrain uptake.

Second, given the importance of meeting household food and income security for rural households, papers two and three use household survey data to assess the effects of adopting minimum tillage on maize yield and household incomes. Minimum tillage practices confer positive yield gains over medium - to long-term, compared to their conventional tillage counterparts only with timely field operations and planting. There are significant yield penalties for delayed field operations in implementing minimum tillage. Moreover, results suggest no significant short-term gains in household income (welfare), crop income and crop revenue from adopting minimum tillage.

Lastly, paper four assesses the effects of minimum tillage on cropland expansion (deforestation) using household survey data. The paper addresses the potential role of minimum tillage to mitigate climate change in smallholder agriculture. Overall, minimum tillage does not reduce cropland expansion among households in the sample. It is negatively correlated with expansion among households who already expanded. However, higher yield and labor availability stimulate expansion. This suggests that the net effect of minimum tillage on cropland expansion is indeterminate. Thus, minimum tillage on its own maybe a risky strategy for reduced cropland expansion.

Overall, results suggest that the uptake of minimum tillage (as the main tillage) by smallholder farmers in Zambia is low. Although minimum tillage has the potential to raise maize yield contingent on timely field operations over medium - to long-term, these gains may not be large enough to enhance smallholder welfare in the short-term. Thus, yield increases are insufficient from a livelihoods perspective. Moreover, minimum tillage in itself may not reduce cropland expansion. Key policy challenges include adapting minimum tillage to local contexts, addressing barriers to uptake and combining minimum tillage with policies to control cropland expansion in order to make win-win outcomes probable.

Sammendrag

Konserveringslandbruk (KL), inkludert redusert jordbearbeiding, har vært fremmet i omlag to tiår som et virkemiddel for å bevare jordsmonn og øke produktiviteten i landbruket og bønders inntekter i Afrika sør for Sahara, inkludert Zambia. KL er endel av klimasmart landbruk, som har som mål økt produktivitet, tilpasning til klimaendringer og reduksjon i klimagassutslipp. KL er sentralt i fattigdomsreduksjon siden de fleste rurale husholdninger i Afrika sør for Sahara har landbruk som sitt viktigste levebrød. Ulike målsettinger knyttet til KL gjør objektive vurderinger av opptak og effekter vanskelige. Denne avhandlingen fokuserer på redusert jordbearbeiding, den viktigste komponenten i KL, og svarer på fire spørsmål om opptak og effekter på maisavlinger, levekår og avskoging.

På bakgrunn av ulike politiske tiltak for å promotere redusert jordbearbeiding, og omfattende debatter om omfanget av opptak og gevinstene for småbrukere i Afrika sør for Sahara, stiller første artikkelen spørsmålet: Hvor effektiv er den nåværende promoteringen, og hvordan varierer opptak med variasjon i nedbør? Hvilke trender er det i opptak av redusert jordbearbeiding? Resultater fra nasjonalt representative husholdningsundersøkelser og nedbørsdata over fem år tyder på at opptaket av redusert jordbearbeiding er lavere enn generelt antatt. Samtidig finner artikkelen at lite nedbør øker opptaket. I distrikter hvor redusert jordbearbeiding har blitt fremmet i et tiår øker opptaket for noen, men ikke alle, prinsippene for redusert jordbearbeiding. Disse resultatene stiller spørsmål ved 'one-size-fits-all' tilnærminger, og opptak begrenses av finansielle, arbeids- og informasjonsbeskrankinger.

Gitt viktigheten av å møte husholdningenes mat- og inntektsbehov undersøker de to neste artiklene, ved hjelp av hjelp av omfattende husholdningsdata, effektene av redusert jordbearbeiding på maisavlinger og husholdningenes inntekter. Redusert jordbearbeiding gir muligheter for positive gevinster på mellomlang og lang sikt, sammenlignet med konvensjonelle metoder, forutsatt at plantingen skjer på riktig tidspunkt. Forsinket utplanting kan gi store reduksjoner i avlingene. Videre viser resultatene ingen signifikante kortsiktige gevinster i totalinntekt (velferd), jordbruksinntekt og total verdi av jordbruksproduksjonen.

Den siste artikkelen vurderer, ved hjelp av husholdningsdata, effekten av redusert jordbearbeiding på ekspansjon av dyrket mark og på avskoging. Artikkelen tar utgangspunkt i hvordan redusert jordbearbeiding kan begrense klimautslippene fra småskala landbruk. Samlet sett fører redusert jordbearbeiding ikke til redusert arealekspansjon blant husholdningene i utvalget, selv om man finner en negativ korrelasjon mellom redusert jordbearbeiding og nivået på ekspansjonen blant husholdninger som ekspanderer. Høyere avlinger og god tilgang på arbeidskraft stimulerer ekspansjon. Nettoeffekten av redusert jordbearbeiding på arealekspansjonen er derfor usikker. Derfor vil satsing på kun redusert jordbearbeiding være en risikabel strategi for redusert avskoging.

Samlet sett tyder resultatene i avhandlingen på at opptaket av redusert jordbearbeiding blant småbønder i Zambia er lavt. Selv om redusert jordbearbeiding har potensiale til å heve maisavlingene på mellomlang og land sikt, dersom dyrkingen skjer på rett tidspunkt i sesongen, så er ikke disse gevinstene tilstrekkelige til å forbedre småbøndenes velferd på kort sikt. Videre er redusert jordbearbeiding i seg selv ikke tilstrekkelig til å redusere ekspansjonen av dyrket mark. Viktige politikkutfordringer inkluderer bedre tilpasning av redusert jordbearbeiding til lokale forhold, adressering av barrierer for opptak, og kombinering av redusert jordbearbeiding med virkemidler som begrenser ekspansjon av jordbruksarealer og avskoging. Dette vil gjøre vinn-vinn utfall mer sannsynlige.

Introduction

Conservation agriculture, livelihoods and deforestation in Zambia

Hambulo Ngoma

1 Introduction

1.1 The multiple challenges of climate change

Climate change and rural livelihoods are interlinked. Rural households in sub-Saharan Africa, including Zambia are more exposed (more likely to be affected) and vulnerable (lose more when affected) to the shocks of climate change because of their dependence on rainfed agriculture (Hallegatte et al., 2016). Low adaptive and coping capacities limit the extent to which these households can adequately manage climate shocks, which in turn worsens their vulnerability. This makes climate change one of the major threats to poverty alleviation in sub-Saharan Africa.

The challenge for the region, therefore, is how to attain the win-win outcomes of reduced poverty and a stable climate. Agriculture provides an entry point: it is important for macroeconomic reasons - it contributes about 20% to Gross Domestic Product (GDP)- and for microeconomic reasons - it provides for livelihoods of nearly 60% of households in sub-Saharan Africa (IMF, 2012).

Climate change has both direct and indirect impacts on the livelihoods of rural households in sub-Saharan Africa (Porter et al., 2014). Two direct impact pathways include the likely negative effects of climate change on crop yields (and therefore agricultural income, food security and the poor's ability to escape poverty), and its negative effects on household asset stock accumulation and returns on assets. Indirectly, climate change affects output prices, wages, off-farm employment and alternative livelihood opportunities, and food systems (Olsson et al., 2014; Porter et al., 2014).[1] These effects will vary depending on whether an area receives more or less rainfall, becomes hotter or drier and due to differences in initial conditions (Angelsen and Dokken, 2015). Uncertainties on the impacts of climate change should amplify rather than dampen the need to increase adaptive and coping capabilities of households (Angelsen and Dokken, 2015).

The net impacts of climate change are, therefore, highly variable and context specific. For example, net sellers of agricultural output and farm workers may benefit from an increase in output prices caused by extreme weather events, but net buyers stand to lose. Climate change also affects the behavior of rural households such that they may opt for less risky and low yielding livelihood strategies or asset accumulation pathways, which in turn perpetuate their poverty and vulnerability.

Despite the climate challenges, rainfed-farming systems in sub-Saharan Africa face an urgent need to raise productivity in order to meet rising food demands driven by population and income growth and to engineer the escape from poverty of the majority smallholders in the region. Therefore, addressing climate change and poverty should go in tandem: it is neither possible to eradicate poverty without accounting for climate change and its impacts on people nor to stabilize climate change without recognizing that ending poverty is important (Hallegatte et al., 2016).

[1] Food systems refer to the whole range of processes and infrastructure involved in satisfying people's food security requirements (Porter et al., 2014).

1.2 The conservation agriculture debates

Conservation agriculture (CA) has three principles: reduced soil disturbance or minimum tillage (MT), *in-situ* crop residue retention and crop rotation. MT is a tillage system with reduced soil disturbance concentrated only in planting stations and it has three main variants - ripping, planting basins and zero-tillage. Rip lines are made with ox or tractor-drawn rippers, planting basins are made with hand-hoes, and zero-tillage is based on handheld or mechanized direct planters. Residue retention entails leaving at least 30% of crop residues to serve as mulch or cover crop. Crop rotation involves planting cereals and nitrogen-fixing legumes in succession on the same plot to maintain or improve soil fertility (Haggblade and Tembo, 2003).

Although initially promoted as a means to address declining soil productivity and droughts, CA has evolved over time to include multiple benefits such as sustainable intensification, climate change adaptation and mitigation, and biodiversity conservation (Baudron et al., 2009; Govaerts et al., 2009; IPCC, 2014a; Thierfelder and Wall, 2010). Thus, CA is multifaceted as a farming system, and broad-based as a development tool that may help achieve several objectives if it works, but this has also generated immense debates on the performance of the technologies.

Despite almost two decades of actively promoting CA and in some cases providing subsidies, there are disagreements on the extent of its uptake and impacts on productivity and welfare among smallholder farmers in sub-Saharan Africa (Andersson and D'Souza, 2014; Giller et al., 2009). This has led to questions on the compatibility of CA with smallholder farmers in the region (Giller et al., 2009) and on the potential disconnect between the agronomic rationale for CA on the one hand, and CA outcomes in smallholder farm systems on the other (Ngoma et al., 2015, pp 21).[2]

Debates on uptake and impacts of CA on productivity, livelihoods and mitigation (hereafter the CA debates) can be grouped into researcher and farmer domains (Feder et al., 1985; Foster and Rosenzweig, 2010). From a researcher's perspective, these debates may be driven by complexities of untangling the CA concept or they may relate to more fundamental issues such as defining adoption and when a farmer qualifies as an adopter. Is it when they use one, two, or all the three core principles of CA, over what period? For example, should CA adoption be defined as the use of minimum tillage and crop rotation and residue retention or simply minimum tillage or crop rotation or residue retention? How adoption is defined matters: it influences adoption estimates and can confound impact assessments. In a review of CA adoption studies in sub-Saharan Africa, Andersson and D'Souza (2014) found that the inconsistent definition of adoption is one of the main reasons for disagreements on the uptake and performance of CA principles among smallholder farmers in sub-Saharan Africa.

A related dimension is adoption intensity: should the intensity or depth of adoption matter? What is the reference point and is there a minimum threshold for adoption? Does a hectare of minimum tillage count the same as two three-meter rip lines or five planting basins in the backyard? It is important that the definitions and baselines are similar and presumably from comparable datasets in order to compare adoption and impact assessments across time and space. This also brings out an epistemological question: How do we know what we know regarding adoption and what is the source of the data? Is the data reliable and based on sound scientific methods that are verifiable? With its multiple objectives, the narratives around CA embody some knowledge politics on generation and interpretation of

[2] An extended online discussion following Giller et al. (2009) is here `https://conservationag.wordpress.com/2009/12/01/ken-gillers-paper-on-conservation-agriculture/`.

data (Whitfield et al., 2015). This thesis does not dwell further on the knowledge politics or the political economy of conservation agriculture.

The CA debates on yield effects are driven by the fact that most of the evidence so far draws from experimental studies with low external validity (Ngoma et al., 2015). Most of the impact assessments of CA on welfare are based on methods that do not account for unobserved heterogeneity and therefore to do not measure causal impacts (paper three). Despite inconclusive evidence on the potential for CA to mitigate climate change through soil carbon sequestration (Powlson et al., 2014, 2016), the unidirectional focus on this pathway has left other potential mitigation pathways (e.g., the effects of CA on cropland expansion) less well-understood (paper four).

Adverse selection and incentive problems could also explain the CA debates. Adverse selection may manifest where the wrong farmers (project-dependent) are targeted by CA projects as beneficiaries. Such farmers may pretend to adopt some components of CA for as long as they receive project benefits (e.g., input vouchers) but they still maintain most of their cultivated land under conventional tillage or are quick to revert to conventional methods as they await the next project (Ngoma et al., 2016). This leads to problems of inclusion and exclusion: deserving farmers are excluded and those who are not supposed to be in the program are included. Incentive problems arise where adoption estimates are intentionally over-reported (i.e., impressionistic) to impress funding agencies or serve other interests.

The CA debates also relate to different factors from the farmers' perspectives. The arduousness and labor intensity of some CA principles (e.g., basins) constrain adoption (Ngoma et al., 2016; Thierfelder et al., 2015). The high discount rates by smallholder farmers imply that they may find CA incompatible since its larger benefits accrue in the medium to long-term (Giller et al., 2009). Although CA is generally considered risk reducing, risk averse farmers may not adopt it because they may be unwilling to take on risk.

Ambiguity aversion may strengthen this effect if the likelihood of positive benefits from CA is unknown. Ambiguity averse farmers may not adopt the 'unfamiliar' CA principles because of uncertain outcomes and instead, choose the familiar conventional tillage even if it yields lower benefits. How information problems and farmer attitudes towards risk and uncertainty influence CA uptake remains under-researched.

It is, however, a puzzle that even after several years of promoting CA and given that it presumably addresses the core problems facing smallholder agriculture - namely low productivity and climate change, its uptake does not spread like wildfire.

The issues above are only partially addressed in existing CA literature on sub-Saharan Africa. The results on the extent of adoption and impacts on productivity and livelihoods are mixed and context specific (Andersson and D'Souza, 2014; Andersson and Giller, 2012; Giller et al., 2009; Mazvimavi, 2011) and impacts on deforestation under-researched. This suggests a need for a more nuanced analysis of CA principles in the region.

This thesis contributes to filling this gap and addresses some of the salient issues raised above. Using cases from Zambia and focusing on the main CA principle of minimum tillage, this research is composed of four independent papers on uptake (paper one) and impacts of minimum tillage on yield (paper two), livelihoods (paper three) and cropland expansion (paper four).

1.3 Thesis objectives, research questions and significance

Overall, this research sought to determine factors influencing uptake and impacts of minimum tillage on household objectives related to food security, livelihoods and global concerns of deforestation. In assessing this objective, we address the following interrelated questions: 1) How does minimum tillage uptake respond to exposure to long-term promotion activities and rainfall variability? 2) Does minimum tillage raise maize yields? 3) Does minimum tillage improve livelihood outcomes for smallholder farmers? 4) Does minimum tillage reduce cropland expansion into forests?

By addressing the above questions, this research contributes to filling an important gap on understanding the extent to which the main CA principle of minimum tillage is used by smallholder farmers and its impacts on maize yields, household welfare and deforestation. Reliance on small cross-sectional samples often drawn from project sites has obscured a good understanding of the true extent of adoption, while the use of non-rigorous impact assessment methods yields misleading results. This research addresses these issues by using large household survey data spanning 4-5 years to assess uptake and impacts on productivity and applies rigorous impact assessment methods that account for counterfactual outcomes. Results from this research are relevant for national governments, development cooperators and other stakeholders interested in scaling up adoption of conservation agriculture principles in sub-Saharan Africa.

Apart from highlighting the most recent trends in uptake at national level as well as in districts where promotion has been concentrated for more than a decade, results highlight barriers to uptake and conditions under which positive outcomes are more likely. By providing an explicit (perhaps, the first formal) direct link between conservation agriculture principles and cropland expansion (deforestation), these results are relevant for climate change mitigation. Instead of using satellite imagery, which often makes it difficult to distinguish between different - yet similar - land uses (e.g., grassland and fallow) and to link changes in forest cover to household adoption of minimum tillage, the use of household survey data asking about cropland expansion and an explicit theoretical model of expansion is a novelty of this research. Application of instrumental variable methods in the empirical estimation is a contribution not only to literature on adoption but also to deforestation literature in general where weaker identification strategies are commonly used (Villoria et al., 2014).

Table 1 presents a snapshot of the thesis. It highlights the research questions, hypotheses, theoretical frameworks, data, empirical methods and the key findings for each paper.

Table 1: A snapshot of the thesis

Paper	Research question	Hypotheses	Theory	Data	Empirical methods	Key findings
I	How does the uptake of minimum tillage respond to rainfall variability and promotion?	1) Low seasonal rainfall does not increase uptake of minimum tillage. 2) Being in districts where promotion has been concentrated for at least 10 years does not increase uptake.	Random utility model	Nationally representative crop forecast survey data, 2010-2014	Double Hurdle models implemented via control function approach.	1) Low seasonal rainfall increases uptake of minimum tillage. 2) Being in districts where promotion is concentrated only increases uptake of ripping and not basin tillage.
II	Does minimum tillage raise maize yields?	Ripping and basin tillage do not raise maize yield.	Production function framework	Nationally representative crop forecast survey data, 2008-2011	Correlated random effects model	1) Ripping and basin tillage raise yields if tillage (planting) is done in the rainy season, with fertilizers and improved seed, inter alia. 2) The average gains are higher from ripping than basins, relative to their conventional tillage systems. 3) There are significant yield loses for delayed tillage (planting).
III	Does minimum tillage improve farmer welfare?	Minimum tillage does not improve household and crop income in the short-term	Random utility model	Primary data, 2014	Endogenous switching regression and counterfactual analysis	1) Minimum tillage does not improve farmer welfare in the short-term. 2) Endowment heterogeneity account for most of the differences in outcomes by adoption status.
IV	Does minimum tillage reduce cropland expansion (deforestation)?	1) Minimum tillage does not reduce cropland expansion into forests. 2)Crop yield does not increase expansion.	Agricultural household model (Chayanovian model)	Primary data, 2014	Double Hurdle and two stage least squares (2SLS) models	1) Minimum tillage does not reduce expansion. 2) Crop yield and labor availability stimulate expansion.

2 Conservation agriculture and deforestation

2.1 Conservation agriculture as response to climate change

CA or more broadly Climate Smart Agriculture (CSA) is back in the limelight as countries make voluntary pledges through their Intended Nationally Determined Contributions (INDCs) to reduce emissions and contribute towards the 2015 United Nations Framework Convention on Climate Change (UNFCCC) Paris agreement to limit the global temperature rise to below 2°C relative to the pre-industrial levels. CSA aims to concurrently address climate change and food security by (1) improving agricultural productivity, (2) increasing the resilience of farming systems to climate change, and (3) mitigating greenhouse gas (GHG) emissions (Rosenstock et al., 2015).

The focus on reducing agricultural emissions in INDCs is unsurprising given that these account for 5-5.8GtCO_2 e/year or about 11% of global anthropogenic GHGs (IPCC, 2014b). Moreover, developing countries contribute about 35% of all agricultural emissions (Wollenberg et al., 2016). Agricultural expansion-led deforestation accounts for a large share of agricultural emissions (Carter et al., 2015). CSA can address agricultural emission through reduced tillage and forest emissions if it reduces expansion. Thus, CSA may play an important role in the global climate mitigation efforts (Richards et al., 2015).

However, the science on the potential for specific CSA principles such as no-till or CA in general to sequester soil carbon is far from conclusive (Powlson et al., 2016; VandenBygaart, 2016). A key question addressed in paper four is whether there are other potential ways CSA principles may contribute to mitigation other than through soil carbon sequestration.

2.2 The promotion of conservation agriculture in Zambia

Following a decade long research and development phase, the core CA principles of minimum tillage, *in-situ* crop residue retention and crop rotation were formally introduced to smallholder farmers in Zambia in the 1990s. The successes of CA in reversing soil productivity losses, raising crop yields and reducing input (fuel, labor, fertilizer) costs mostly among commercial farmers in the US, Brazil and Zimbabwe influenced its initial promotion for smallholder farmers in Zambia (Haggblade and Tembo, 2003). At the time, smallholder crop yields were plummeting due to the removal of fertilizer subsidies under the structural adjustment programs and because of declining soil productivity caused by intensive tillage and soil acidification (Arslan et al., 2014; Haggblade and Tembo, 2003; Holden, 2001). This worsened food insecurity and poverty. Since then, CA has been widely recognized as the main priority for agricultural development and it is prominent in government policy documents including the National Agricultural Policy (NAP) and the National Agricultural Investment Plan (NAIP) (GRZ, 2013).

The promotion of CA in Zambia is mainly through project-based interventions led by the Ministry of Agriculture, the Conservation Farming Unit, other government agencies and development cooperators. The main goals of promoting CA are to improve agricultural productivity, reduce poverty and build resilient farming systems. Different donors including international development agencies such as the Food and Agriculture Organization of the United Nations (FAO), the United States Agency for International Development (USAID), the Swedish International Development Agency (SIDA), the Norwegian Agency for Development Cooperation (Norad) and the European Union (EU) fund CA projects in Zambia (Mazvimavi, 2011).

CA promotion among smallholder farmers follows the lead farmer model or own farmer facilitation (Mazvimavi, 2011). This is an extension provision approach where CA promoters select lead farmers who are respectable members in their communities to serve as agents of change. Lead farmers are trained in the use of different CA principles and are expected to train and provide extension services to follower farmers in their respective villages. CA promoters provide training materials and transport to lead farmers to facilitate extension provision.

In addition to lead farmers, CA promoters also use farmer field schools conducted through learning by observation, demonstration plots and field visits. Farmer field schools use demonstration plots either on-station or on-farm, and field days to provide CA trainings and demonstrate its benefits. Although CA is currently promoted in most provinces, it has been promoted the longest (for more than 10 years) and is perhaps most suitable agronomically in the low rainfall agro-regions 1, 2a and 2b covering parts of Central, Eastern, Lusaka, Southern and Western provinces (Figure 1).[3]

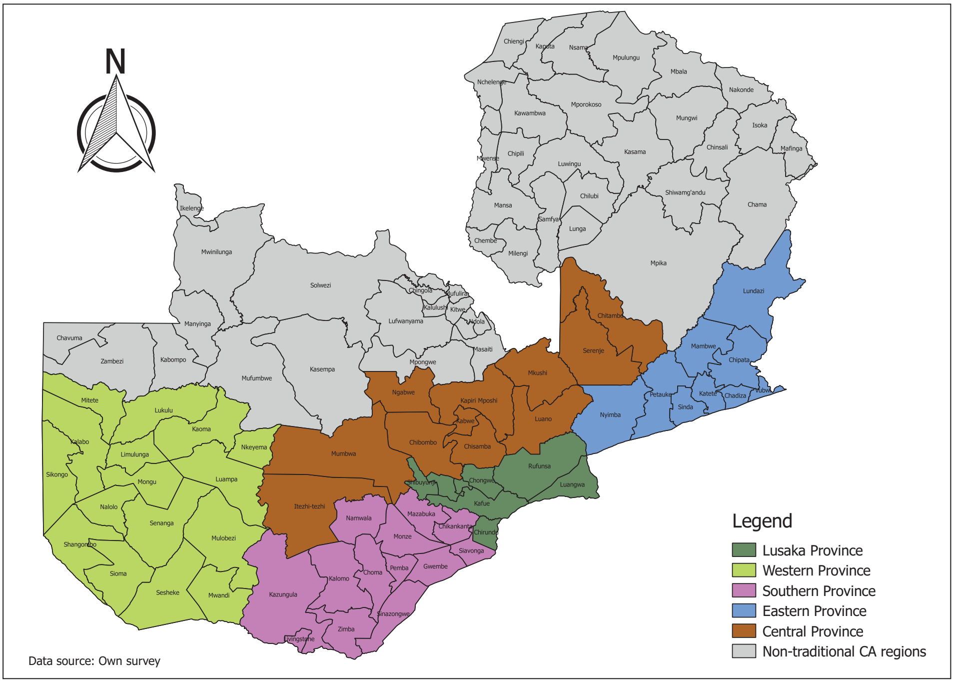

Figure 1: Spatial location of long-term promotion areas for conservation agriculture in Zambia.

2.3 Deforestation in Zambia

Zambia's forest cover remains relatively high at approximately 50 million hectares (ha) or 60-65% of the total land area (FAO, 2015; Kalinda et al., 2013). Recent estimates suggest an increase in deforestation over the last two decades. Using data from the global forest

[3] Agro-regions 1 and 2 receive < 800 mm and 800 - 1000 mm of rainfall per year, respectively. CA is currently promoted in parts of Northern, Luapula and Copperbelt provinces, which mostly lie in region 3 with more than 1000 mm annual rainfall.

resources assessment (FRA) and the forestry department, Mulenga et al. (2015) show that the forest cover reduced from about 70% in 1990 to about 65% in 2015 (Figure 2). This translates to an estimated annual deforestation rate of 0.33% or 167,000 ha.

Zambia has been implementing various activities to address forest loss and to contribute to global efforts to mitigate climate change under the auspices of the United Nations program on Reducing Emissions from Deforestation and forest Degradation (UN-REDD) and through bilateral and project initiatives (Day et al., 2014; Mulenga et al., 2015). Zambia is also among several countries that have already submitted INDCs to the UNFCCC and voluntarily commit to reduce emissions over the next 1-2 decades.

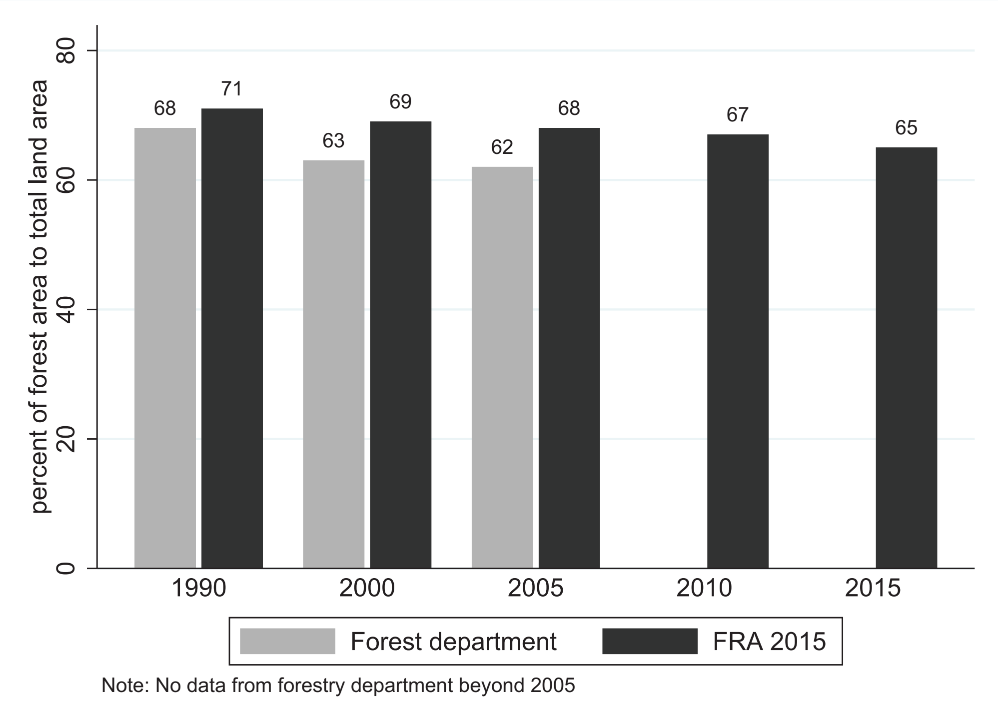

Figure 2: Forest Cover Trends in Zambia, 1990-2015.
Adapted from Mulenga et al. (2015)

Like in several other tropical countries, the main drivers of deforestation in Zambia originate from outside the forest sector. Agricultural land expansion, wood fuel extraction, infrastructure and mining developments, and urbanization are the main drivers of deforestation in Zambia (Day et al., 2014; Vinya et al., 2011). The nexuses between agriculture and forest sectors suggest that the two can no longer be their own silos: country INDCs submitted to the UNFCCC reflect this by including both agriculture and forest as priority sectors for emission reduction (Richards et al., 2015).

However, some specific issues remain poorly addressed. While most INDCs mention CSA, not all are specific enough: what CSA measures are planned? What is their mitigation potential? What are the national circumstances regarding uptake and acceptability? CSA has two potential mitigation channels: soil carbon sequestration and avoided deforestation. Given the inconclusive evidence on the former (Powlson et al., 2014), paper four assesses the potential for minimum tillage to reduce cropland expansion into forests and provides an explicit link between CA and deforestation.

3 Conceptual framework

The overarching conceptual framework for the thesis uses the livelihood framework (LF) as developed by Ellis (2000), *inter alia*. The LF has been widely used to assess the economics of rural livelihoods, including income diversification and poverty reduction (Ellis, 2000; Reardon and Vosti, 1995), poverty-environmental linkages (Reardon and Vosti, 1995) and agricultural land expansion/deforestation (Babigumira et al., 2014). At the core of this framework is an understanding that given contextual factors; the asset stock controlled by rural households influences their livelihood strategies and outcomes.[4] Specific choices and actions taken by households using their assets (e.g., improved land management) define livelihood strategies.

Asset portfolios and contextual factors are relevant to understand household decision-making. Assets are the basis upon which rural households are able to produce and engage in markets (Babigumira et al., 2014) and can be natural (land, forest, water, and biodiversity), physical (productive farm equipment, buildings, roads), human (education, skills and health), financial (savings, credit, insurance and remittances) or social (networks, membership in associations). Contextual factors such as (a) social relations, e.g., gender and group membership, (b) institutions, e.g., rules that influence access to resources including extension, (c) population trajectories, and (d) shocks, e.g., idiosyncratic (such as household labor shortage), covariate (such as droughts or floods) directly influence how these assets lead to *what* livelihood strategies and outcomes. In the balance, the combinations of assets, institutions and shocks determine the production relations (Binswanger and Rosenzweig, 1986) and livelihoods for households dependent on rainfed agriculture.

While paying attention to other asset types, we mainly focus on natural and physical assets (i.e., land, forest and productive assets), and how these combine with other assets to generate realizable livelihood strategies at farm level. Land is the cradle of production and the main source of livelihoods for agricultural dependent rural households. Forest resources play a crucial safety net role at the local level but are also important for the global efforts to mitigate climate change. The stock of productive assets combined with land and forests, and other assets directly determine the choice of livelihood strategies and their outcomes.

At conceptual level, the LF provides a basis for analyzing multiple influences on livelihoods, while recognizing the role of contextual variables. Different models have been used to develop and test specific hypotheses and theories drawn from key relations within the LF (Babigumira et al., 2014). An example of such models is the agricultural household model, which has been widely used to analyze the economic behavior of rural households (De Janvry et al., 1991; Singh et al., 1986). It has also been applied to deforestation and agricultural land expansion (Alix-Garcia et al., 2012; Angelsen, 1999; Maertens et al., 2006; Pagiola and Holden, 2001; Shively and Pagiola, 2004).

Agricultural household models can be separable (recursive) or non- separable. Household production decisions are independent (separable) from consumption decisions if markets are perfect. This means that households can be modeled as pure profit maximizers. Household decisions on production and consumption are not separable if markets are missing

[4] Livelihoods refer to the means of living or the ensemble or opportunity set of capabilities, assets, and activities that are required to make a living (Ellis, 2000).

or imperfect.[5] Non-separable agricultural household models, also known as Chayanovian models, are characterized by endogenous, household-specific prices for factors with imperfect markets. In these models, household demographics as well as market prices and wages affect production decisions.

This thesis recognizes that farmers are - largely - rational agents given their preferences, resource constraints and limited information. This means that farmers consistently choose livelihood strategies to maximize desired objectives, given the constraints they face, e.g., imperfect labor, credit and output markets (De Janvry et al., 1991). Among other things, pervasive market imperfections imply that households can only work at certain times and may not access credit. This influences their behavior towards asset accumulation, choice of farming practices, labor allocation and land use decisions in general. Market imperfections also lead households to heavily discount the future such that they may ignore long-term land management decisions such as conservation agriculture (Holden, 2001). In the tradition of Singh et al. (1986), we develop a simple Chayanovian model of cropland expansion in paper four to assess how land management choices affect cropland expansion.

Figure 3 presents a framework for conceptualizing how land management decisions (livelihood strategies) by rural households interact with conditioning factors (assets, institutions and shocks) to determine livelihood outcomes and global climate benefits. Although the linkages in the Figure are neither axiomatic nor exhaustive, it places the four papers in this thesis into a unified perspective from livelihood strategy choices to livelihood outcomes and shows the issues covered in each paper.

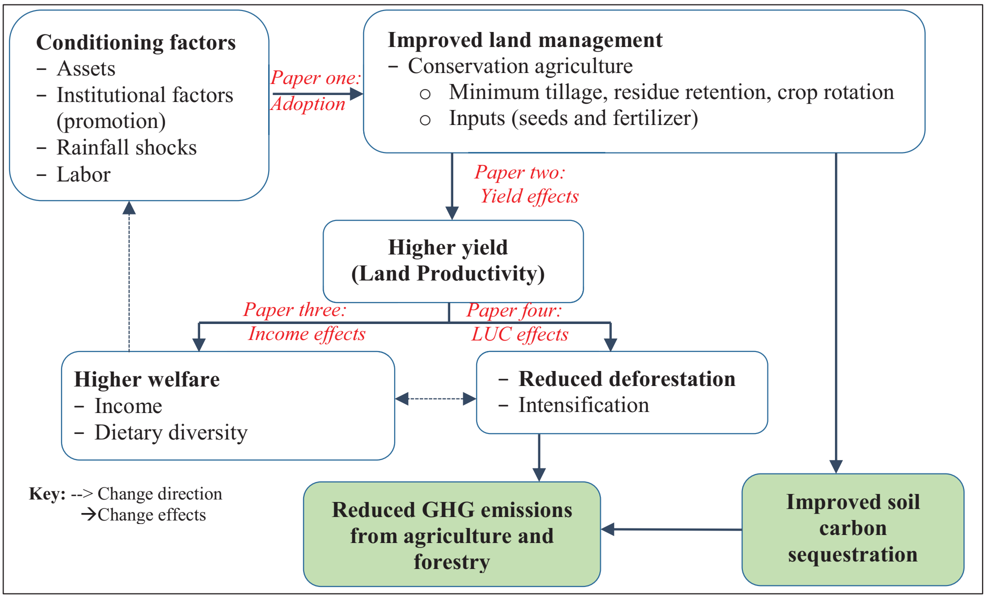

Figure 3: Land management, conditioning factors and livelihood outcomes: a schematic overview of papers in the thesis.

[5] A market fails when the cost of transaction through market exchange creates disutility greater than the utility gain it produces, with the result that the market is not used (De Janvry et al., 1991, pp. 48).

Land management is the central theme in rural livelihoods and in this thesis. If managed well, land resources generate better livelihoods; otherwise poor land management such as extensification into the marginal lands may lead to vicious cycles of immiseration of rural households (Reardon and Vosti, 1995). The main land management option considered here is minimum tillage – the main and necessary component of conservation agriculture.

At the outset, farmers need to adopt minimum tillage for it to be useful as a land management option that can potentially deliver better livelihood outcomes and climate benefits. The asset stocks (e.g., land holding), institutional arrangements (e.g., access to promotion), climate shocks (e.g., low rainfall), and farm and household characteristics (e.g., demographics, labor availability) - the conditioning factors in Figure 3 - constrain adoption decisions at household level.

Smallholder farmers in sub-Saharan Africa may be reluctant to adopt minimum tillage due to resource constraints related to labor, capital and information. These resource constraints do not only influence uptake, they have the potential to drive different productivity and welfare effects of minimum tillage across different households. For example, although minimum tillage may raise productivity, this may not translate into higher household income because of its higher production costs in the short-term. Thus, it is feasible that the productivity effects of minimum tillage are different from its welfare effects. These effects may vary across households depending, e.g., on labor scarcity.

Paper one connects the top two elements in the Figure and assesses the uptake (adoption) of minimum tillage over the period 2010 to 2014 in Zambia. The paper tests the hypotheses that promotion and rainfall variability do not increase minimum tillage uptake. The theoretical framework is based on the random utility model which links discrete choices (whether to use minimum tillage or not) to utility maximizing behavior. Although there are no universally accepted drivers of the adoption of conservation agriculture (Knowler and Bradshaw, 2007), paper one includes several household and farm characteristics (the conditioning factors in the Figure) relevant for the case of Zambia.

While the potential climate benefits of adaptation and mitigation associated with CA are important, we argue that its effects on livelihoods may take precedence for poor smallholder farmers with high discount rates and - for mitigation - due to its public good nature. As such, paper two assesses the effects of minimum tillage on maize yield – the staple crop in Zambia. Whether minimum tillage can achieve higher food production and security is a fundamental question that links it to the broader sustainable development agenda of ending hunger by using sustainable food production systems and resilient agricultural practices. Although yield may not be an aim in itself, it is of utmost importance for both food and income security in Zambia and this partly explains its central position in Figure 3. Paper two uses a simple production function framework to assess the effects of minimum tillage on maize yield in Zambia.

As Figure 3 shows, minimum tillage directly affects household incomes and cropland expansion decisions through its yield effects. Paper 3 assesses the impacts of minimum tillage on farmer welfare measured by household and crop incomes. The paper combines utility maximizing behavior and a counterfactual or treatment effects framework of Heckman et al. (2001).

CA practices such as minimum tillage may contribute to reduced emissions from agriculture through soil carbon sequestration (IPCC, 2014a; UNEP, 2013) or through their direct -yield- effects on deforestation. While the science is inconclusive on the former pathway, little is known about the latter, and this is the focus in paper four. The paper assesses the land use change (LUC) effects of minimum tillage on cropland expansion (deforestation) using a Chayanovian model with an imperfect labor market.

Given the foregoing and as Figure 3 shows, land management options such as CA principles have the potential to deliver local livelihood outcomes (the central parts in Figure 3) and global climate benefits of reduced GHG emissions. An often-encountered question in development discussions is which of the two should be given priority. For example, there are questions on whether CA extension messages should focus on the livelihood outcomes and consider environmental benefits as co-benefits or vice versa. In reality, however, such questions present a false choice: livelihood outcomes have implications for the environment and environmental benefits have implications for livelihoods, suggesting that the two should be addressed together as in Figure 3 and in the thesis. For both livelihoods and environmental benefits to be realizable, adoption of improved land management options such as CA takes precedence.

4 Data and methods

4.1 Context and data sources

The data used in the thesis were collected from smallholder farmers in Zambia.[6] As of 2015, there was an estimated 1.5 million smallholder farmers, producing about 3.5 million metric tons of maize - the staple crop (Chapoto and Mbata, 2016). Zambia is a landlocked country in Southern Africa located 15° S and 30° E, and covers some 753,000 km^2. Its topography is largely plateau with an average elevation of 1,138 m above sea level. The country has a unimodal rainy season spanning November to March, with annual rainfall of more than 1000 mm in the high-rainfall areas in the north and less than 800 mm in the south. Smallholder farmers who mainly practice rainfed farming dominate Zambia's agricultural sector.

The data came from two sources: papers one and two use secondary data from crop forecast surveys, while papers three and four use primary data. Crop forecast surveys are the largest annual surveys of smallholder farmers conducted by the Ministry of Agriculture and the Central Statistical Office in Zambia. These surveys are statistically representative at district, province and national level. With annual samples of approximately 13,600 farm households, these data provide the most comprehensive and widest coverage of smallholder farmers in the country. Figure 4 gives the extent of coverage by annual crop forecast surveys in Zambia.

[6] In the Zambian context, smallholders are farm households who cultivate less than 20 hectares annually.

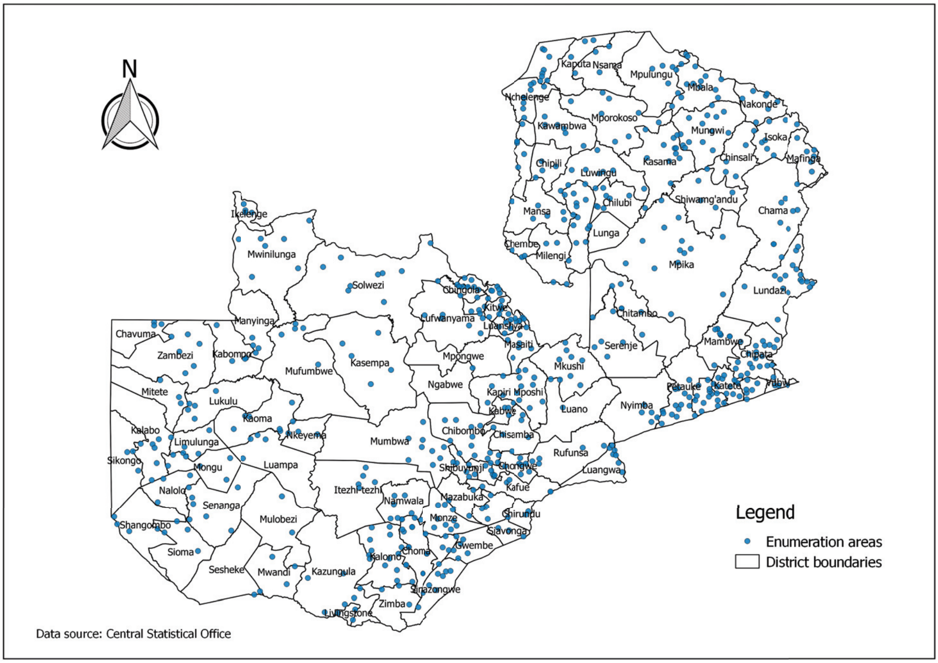

Figure 4: Spatial location of survey areas covered by the annual crop forecast data used in papers one and two.

The primary data used in papers three and four were collected from an intensive household survey conducted in three rural districts of Zambia in 2014. The sample for the survey was selected via three stages. First, Mumbwa, Nyimba and Mpika districts were purposively selected to represent areas where conservation agriculture has been actively promoted, areas with active forest conservation interventions and for prevalence of shifting cultivation systems (Mpika). Second, 10 villages were randomly sampled per district using the most recent village lists and third, 12-15 households were randomly selected from village registers for interviews. In total, 120 households in each of Mpika and Nyimba districts, and 128 from Mumbwa district were interviewed for an aggregate sample of 368 households. Mpika district is located about 650 km north of the capital Lusaka (located in south central), while Mumbwa and Nyimba districts are located 160 km west, and about 340 km east of Lusaka, respectively (Figure 5).

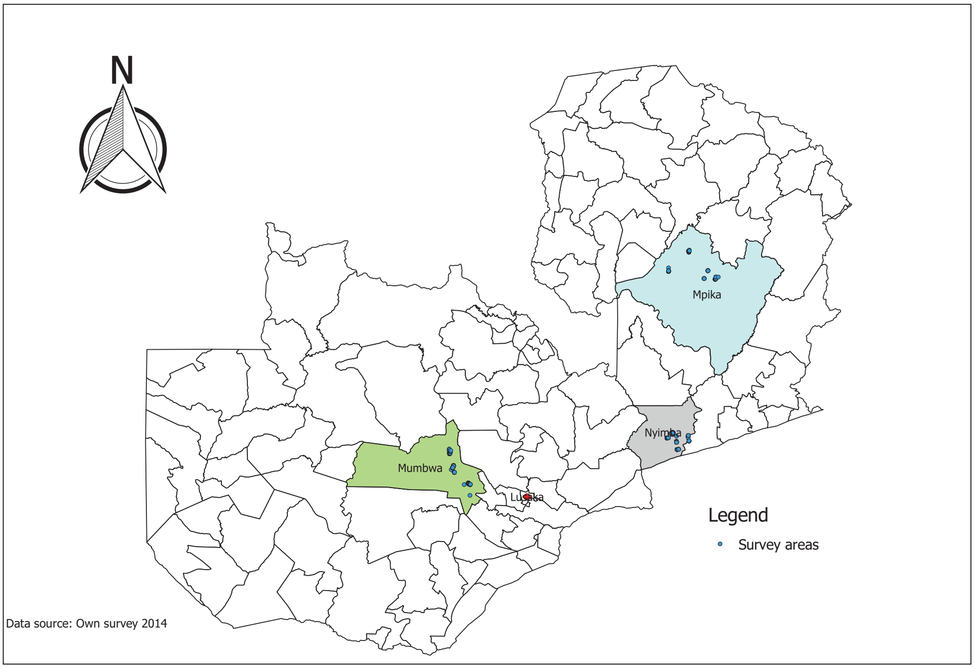

Figure 5: Spatial location of survey areas for data used in papers three and four.

Data collection in the two surveys used semi-structured questionnaires administered by enumerators through face-to-face interviews. Both surveys trained enumerators extensively before going to the field. Each enumerator had a reference manual for use in the field. One supervisor led a team of enumerators during fieldwork. The team leaders reported to a quality assurance team. Supervisors were responsible for overseeing sampling and enumeration, and to check all completed questionnaires for consistency and completeness.

The crop forecast surveys use scientifically robust sampling and survey administration procedures. They collect data on smallholder crop production from demographics, tillage methods, inputs (seed and fertilizer types and quantities), crop management etc. See papers one and two for details.

The household survey from 2014 collected detailed information on demographics, agricultural (including tillage methods) and off-farm activities, yield, labor and other input use, assets, cropland expansion decisions and sources of income. A detailed questionnaire, designed in line with national agricultural survey instruments in Zambia, but with additional sections on labor, cropland expansion and climate change mitigation was used in the survey (included in the appendix). Six enumerators were involved in data collection after successfully undergoing five-days of intensive training and questionnaire pre-testing with farmers from outside the sample. Data entry and processing was done using the Census and Survey Processing (CSpro) software.[7]

[7] http://www.census.gov/population/international/software/cspro/.

4.2 Definitions

How CA and its related concepts are defined can confound uptake estimates and impact assessments. On *uptake*, we clearly distinguish between minimum tillage and the full conservation agriculture package in paper one. This is important to avoid overestimating uptake of the full conservation agriculture package when in fact we only measure some components of it. We also distinguish between *use* and *adoption* in paper one: the former includes testing or experimentation phases, which may or may not lead to adoption, while the latter refers to sustained use of technologies over the long-term and require panel data to measure it appropriately. A related issue concerns how to classify a farmer as an adopter. How much minimum tillage should a farmer practice to qualify as an adopter? We only considered farmers who used minimum tillage as the main tillage on at least one plot as 'users'.

Measuring minimum tillage uptake is also problematic because it is not always reducible to a binary variable. Farmers may experiment with a certain aspect of minimum tillage on a small corner of their field even while most of the field employs conventional tillage methods. Therefore, a question asking about whether minimum tillage methods were used on that field would presumably yield a different response than a question asking about the main minimum tillage method used on that field. The data used here asked the latter question.[8]

We refer to one agricultural season as a *short-term* perspective, while *medium-* to *long-term* refers to multiple agricultural seasons spanning four years or more. By these definitions, papers one and two give medium to long-term perspectives on uptake and impacts of minimum tillage on maize yield. Paper one uses data spanning five agricultural seasons to assess uptake and paper two uses data for four seasons. These data are statistically representative from the lowest administrative units to the national level. These data allow computation of appropriate sampling weights to extrapolate and infer findings to the entire smallholder farmer population in Zambia, including in districts where promotion has been concentrated the longest. Because papers three and four address different questions for which available secondary data were inadequate; these papers use primary data for one agricultural season, and hence they give short-term perspectives.

4.3 Estimation strategies

Several empirical challenges are eminent when using observation cross-sectional data. This subsection briefly discusses the major ones, and how they were addressed. More details are provided in the individual papers. The following discussion draws mainly from Wooldridge (2010).

Sample selection bias

Sample selection bias occurs due to nonrandom samples such that if the reasons for the nonrandomness are systematic, outcomes may be confounded. It may also occur from a random sample when some observations for the outcome variable are systematically missing. For example, we would only observe how much land is under minimum tillage among farmers who adopted. Self-selectivity bias is a specific form of sample selection that arises in cases where participants are not randomly selected into treatment such that if the reasons for self-selecting are systematic, this again may confound and induce bias in the outcomes of

[8] Thus, studies should state clearly how information is gathered in survey-based approaches for readers to be able to assess how results may be influenced by how questions were asked - framing effects.

interest. Because our datasets are from random samples, the main issue dealt with was self-selectivity bias.

Self-selection was mainly encountered in estimating the welfare impacts of minimum tillage in paper three. The paper applies an endogenous regression framework of Maddala (1983) to account for self-selection. For robust identification, access to minimum tillage was used as the exclusion restriction, which was omitted from the outcome equation but included in the selection equation. Intuitively, access to minimum tillage extension does not directly affect household incomes except through minimum tillage.

Missing data: counterfactual outcomes

Another empirical challenge encountered is the typical missing data problem in counterfactual analysis. To assess the causal impacts of minimum tillage on household welfare requires knowledge of outcomes for adopters (non-adopters) with and without adoption. However, we only observe each group in one state of the world at any one point in time: that is we cannot observe what adopters would have earned had they not adopted, while at the same time observing their earnings from adoption. As mentioned earlier, paper three applies an endogenous regression framework of Maddala (1983) and follows Heckman et al. (2001) and Di Falco et al. (2011) in predicting actual and counterfactual outcomes. The predicted outcomes are then used to estimate the average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU). The ATT and ATU measure the impacts of adopting minimum tillage on adopters and non-adopters, respectively. The paper extends average impact assessment by assessing the distribution of the impacts across farm size and asset value quartiles and by using the Blinder-Oaxaca (Blinder, 1973; Oaxaca, 1973) decomposition techniques.

Corner solution outcomes

Corner solution outcomes arise from instances where the outcome variable has large pile-ups at specific values. For example, a large number of farmers may optimally decide not to adopt minimum tillage and therefore, the amount of land under minimum tillage will be zero. For those that adopt, the distribution of land under minimum tillage is assumed continuous.[9]

Only a small proportion of the samples used minimum tillage in paper one and expanded cropland in paper four. Although the Tobit model is the workhorse for corner solution outcomes with pile-ups at zero (Tobin, 1958; Wooldridge, 2010), we used alternative methods. Papers one and four apply double hurdle models to address corner solution outcomes because, unlike Tobit, double hurdle allows the same or different factors to influence participation and extent of participation differently (Cragg, 1971; Wooldridge, 2010). Unlike Heckman models, where zero outcomes are truncated (Heckman, 1979), double hurdle considers zero outcome values as optimal choices. This is a reasonable proposition for minimum tillage since it has been promoted for a long time and for cropland expansion since households can optimally decide not to expand.[10]

[9] Contrast this to censored data, in which case the full range of a response variable is not observed.

[10] Although the econometric models for corner solution outcomes and censored data are similar, their application is different (Wooldridge, 2010, pp. 668).

Measurement error

Measurement error is another common challenge in household survey data. Measurement error in the dependent variable if uncorrelated to explanatory variables is less of a problem than measurement error in the explanatory variables (Wooldridge, 2010). If present, measurement errors lead to endogeneity bias. Measurement errors arise from various sources including human error during recording responses and data entry, the order of questions, length of recall periods and the level of data disaggregation, respondent and enumerator fatigue, and the interview environment - for example presence of another household member. The data used in all papers were meticulously collected to minimize measurement errors by using data collection and management methods that have been tried and tested over the years (data section), and by ensuring that all enumerators are well trained on the survey instrument and are not overloaded in terms of the number of interviews per day. In addition, the surveys collected data in disaggregated ways in keeping with the principle of decomposition.

Omitted variable bias

Omitted variable bias arises when an important covariate in regression frameworks is left out, such that the omitted variable captured in the error term of the outcome equation is correlated with other explanatory variables and leads to endogeneity bias. This violates the zero conditional mean assumption, which states that the error term has an expected value of zero given any value of the explanatory variable. This could occur because some regressors (observed or otherwise) are jointly determined with the outcome or due to measurement error or self-selectivity bias.

Endogeneity bias

Endogeneity is said to occur when an explanatory variable is correlated to the disturbance or error term. This violates the zero conditional mean assumption and leads to inconsistent estimates. As discussed before, omitted variables, self-selection or measurement error lead to endogeneity bias. Thus, addressing different forms of endogeneity biases was the main empirical challenge in all the papers.

The scope of the potential endogeneity biases faced in each paper varied greatly and as such, we used different empirical strategies based on instrumental variable methods. Briefly, this involves specifying an exclusion restriction criterion such that there is a variable - an instrument - significantly correlated to the endogenous variable (relevant) (to account for omitted variables or unobserved heterogeneity) but exogenous to the outcome of interest. Identifying such variables is a nontrivial task in empirical work. However, several econometrics tools can be used to test for endogeneity, significant correlations between the instrument and the endogenous variable and for insignificance of instruments in the main outcome equation. The actual implementation of instrumental variable methods varied across the papers from control function approaches, two stage least squares to endogenous switching regression frameworks as briefly discussed.

Paper one used the control function approach of Wooldridge (2010) to address the potential endogeneity of the location of minimum tillage promotion programs to farmer uptake decisions. This involves estimating reduced form regressions of the endogenous variable using all exogenous variables and instrumental variables and then, computing generalized residuals, which are included in the main double hurdle regressions to test and control for endogeneity. The binary nature of both the endogenous variable and the instrument necessitated this approach. Paper four instead uses the classic two-stage least squares methods to test for endogeneity because all the potentially endogenous variables were continuous. Paper three used the endogenous switching regression framework to control for self-selection bias. We also used district and year fixed effects to account for time-invariant spatio-temporal aspects of unobservables.

Paper two used panel data methods to account for unobservables or omitted variables that may cause endogeneity bias. The main concern here was the presence of unobservables such as business acumen or intrinsic motivation to work hard. That would influence maize yield even without adopting minimum tillage, or would influence both adoption of minimum tillage and maize yield. The paper used panel data at enumeration area level and applied panel data methods to control for community-level or high order time-invariant unobserved heterogeneity. In particular, we used the Mundlak - Chamberlain device or the Correlated Random Effects (CRE) approach (Chamberlain, 1984; Mundlak, 1978; Wooldridge, 2010) and included enumeration area averages of all time varying regressors as additional covariates in the main regressions. Unlike standard fixed and random effects models, CRE retains time-invariant regressors and allows correlations between unobserved heterogeneity and explanatory variables, respectively.

5 Main findings

This section presents brief summaries of the main findings. It highlights the main question(s) within the broad context of the knowledge gaps in literature and presents the key findings for each paper, elaborate discussions of the results are in the individual papers.

5.1 How does minimum tillage uptake respond to rainfall variability and promotion? (Paper I)

Given the current impetus to scale up Climate Smart Agriculture (CSA) – for which conservation agriculture practices like minimum tillage, are key, paper one asks: Do the current promotion approaches increase the uptake of minimum tillage (defined as planting basins and or ripping) and how does uptake respond to rainfall variability? These are fundamental questions for Zambia and sub-Saharan Africa, where despite decades of actively promoting minimum tillage for smallholders, the extent of its uptake remains debatable and the evidence on its adaptation potential is thin.

Using household survey data that are representative at district and national level for the period 2010 to 2014 and long-term spatial rainfall in Zambia, the paper shows that the uptake of minimum tillage as the main tillage is partial and lower than is generally believed. On average, less than 10% of all smallholder farmers used minimum tillage as the main tillage per year even in districts with the highest use rates over the study period. Moreover, minimum tillage occupied less than 3% of the total land cultivated by all smallholders, and farmers using minimum tillage techniques devoted only about 58% of their cultivated area to some elements of minimum tillage.

Further, the results suggest that farmers' decisions to use minimum tillage respond to anticipated rainfall variability and the location of minimum tillage promotion programs, inter alia. While the effects of low seasonal rainfall are positive, the effects of promotion are mixed. Low rainfall significantly increased the likelihood of farmers using minimum tillage by 0.05 percentage points and promotion significantly increased the intensity of minimum tillage use on average, but not for all its individual components. Being in districts where minimum tillage has been promoted for at least 10 years significantly increased ripping intensity by 0.01 ha and reduced the intensity of basin tillage by 0.13 ha. These findings call for improved targeting of minimum tillage promotion not just in terms of the suite of technologies promoted but also taking into account resource constraints faced by smallholder farmers.

5.2 Does minimum tillage with planting basins or ripping raise maize yields? (Paper II)

Conservation agriculture practices such as minimum tillage were introduced to smallholder farmers in sub-Saharan Africa under the premise that they could improve crop productivity. However, the question of whether conservation agriculture can achieve higher food production for rural households in the region has remained poorly understood given that the bulk of the evidence so far comes from experimental data, which has low external validity. Paper two estimates the effects of ripping and basin tillage on maize yields under typical smallholder conditions using survey data that are panel at the enumeration area for the period 2008-2011 in Zambia.

The paper suggests that there are positive maize yield gains from ripping and basin tillage relative to plowing and hand hoe, respectively, but only if tillage is done before the rainy season and over medium- to long-term. The yield gains are also different at national level and in lower rainfall agroecological zones (where minimum tillage is best suited agronomically). Relative to their conventional tillage counterparts, ripping tillage conferred average yield increases of 577kg/ha and 821 kg/ha nation-wide and in lower rainfall agroecological zones, respectively, while basins posited average gains of 191 - 194 kg/ha. However, there are significant yield penalties for late tillage (and planting) averaging 168 - 179 kg/ha lower for basin tillage. As expected, hybrid seed and inorganic fertilizers increase maize yield and low rainfall reduces it.

These results suggest that ripping may be a better option, albeit the modest gains, and highlight the value of dis-aggregating minimum tillage into its individual components. These findings reinforce the importance of early land preparation (and planting) to maize productivity and highlight the overall potential significance of minimum tillage to improving smallholder productivity in Zambia and the region.

5.3 Does minimum tillage improve livelihood outcomes of smallholder farmers? (Paper III)

Given that the majority of rural households rely on rainfed agriculture as the main source of employment, conservation agriculture practices such as minimum tillage (MT) may play a crucial role in the efforts to reduce poverty if they can increase household incomes in sub-Saharan Africa. However, the lack of robust evidence on the impacts of minimum tillage on livelihoods has led to questions on its suitability and relevance for smallholder farmers in the region. This paper assesses the causal impacts of adopting minimum tillage on household and crop incomes using cross-sectional data from 751 plots for the 2013/2014 agricultural season in Zambia.

The results suggest that adopting MT did not significantly affect household and crop incomes in the short-term. However, adopters had higher incomes on average, and non-adopters would have earned higher incomes had they adopted MT. Additional costs of implementing minimum tillage and its low adoption intensity, which imply that it may not be the dominate tillage method could explain these results. This implies that the modest yield benefits from minimum tillage (even when they occur) are not large enough to offset the costs of implementing minimum tillage, and to improve farmer welfare significantly, at least in the short-run - which these data capture.[11] Thus, yield gains alone are insufficient from a livelihoods perspective.

Similar results were obtained across farm size and asset quartiles. The Blinder-Oaxaca decomposition results suggest that differences in incomes between adopters and non-adopters (although not attributable to adoption) are largely driven by differences in magnitudes of explanatory variables (the endowment effect) rather than their relative returns. This means that differences in the observed characteristics such as education level, landholding, asset holdings etc., and not their relative returns explain much of the differences in household incomes between adopters and non-adopters.

The findings in this paper and in paper two may appear contradictory. This is because paper three suggests that minimum tillage has no significant impact on household income, while paper two show that minimum tillage has positive yield effects. These results are in line with *a priori* expectations and show that the time horizon matters. Recall from section

[11] The impact assessment in this paper is limited to the short-term due to data limitations. See full paper for details.

4.2 that paper two has a medium to long-term horizon covering four agricultural seasons, while paper three only covers one season and hence, it has a short-term perspective.[12] The yield gains in paper two are modest at less than one metric ton, suggesting that such gains may not be large enough to affect household incomes significantly, at least in the short-term. Jaleta et al. (2016) found similar results in a recent study in Ethiopia.

5.4 Can minimum tillage save tropical forests? (Paper IV)

Global efforts to mitigate climate change received a renewed boost in the wake of the 2015 Paris agreement, which aims to limit global temperatures rise to below 2°C relative to the pre-industrial levels. As national governments, voluntarily commit to reduce emissions through Intended Nationally Determined Contributions (INDCs): Agriculture and forest are the key priority sectors for mitigation in low, and a few middle-income countries and Climate Smart Agriculture (CSA) is the main avenue. However, evidence on the potential for CSA to sequester soil carbon is inconclusive. Are there alternative potential mitigation pathways?

Paper four addresses this question by focusing on minimum tillage (MT) and asks: Can MT reduce cropland expansion into forests? The paper develops a Chayanovian agricultural household model with an imperfect labor market for a representative farmer who maximizes utility by trading off consumption and leisure. The empirical analysis is based on household survey data for the 2013/2014 agricultural season, collected from 30 villages randomly selected from three rural districts in Zambia.

The paper shows that about 19% of the sampled smallholder households expanded cropland into forests, clearing an average of 0.14 ha over a year, and that overall, minimum tillage does not significantly affect cropland expansion among all smallholders in the sample. However, minimum tillage is negatively correlated with expansion among households who already expanded. This suggests that, through its labor effects, minimum tillage has the potential to reduce expansion among households who already expanded. Because crop yield stimulates expansion, the net effects of minimum tillage on cropland expansion are indeterminate.

Using improved inputs (inorganic fertilizers and hybrid seed), shadow wage, education level of household head and labor availability (adult equivalents) stimulate expansion but age of the household head and secure land tenure reduce it among households who already expanded. Overall, labor availability stimulate expansion, while age of the household head reduce it among all households in the sample. These findings are largely in line with *a priori* expectations: factors that increase agricultural rent and relax labor constraints are expansionary. This implies that policies aimed to improve agricultural productivity may exacerbate deforestation without concomitant forest conservation measures such as direct control of cropland expansion into forests.

6 Limitations

Some caveats are in order when interpreting results in this thesis. While all papers attempt to use instrumental variables and in particular papers two and three use high-order panel data and simultaneous equation methods, respectively, to address unobservables that may jointly affect adoption decisions and respective outcomes, the use of household-level cross

[12] The research question in paper three could not be answered with the large data from paper two.

section data may not fully address endogeneity biases. Further, the use of one-time cross section survey data, which does not account for the dynamic and long-term impacts of minimum tillage on soil biophysical and chemical properties and the learning effects from repeated use of minimum tillage by farmers, makes results in papers three and four short-term. The lack of longitudinal data relevant for the research questions addressed in these papers at the time, justify use of cross-sectional data. Moreover, instrumental variable methods used address statistical endogeneity. Therefore, while the findings may not be entirely causal in light of the foregoing shortcomings - they are sufficient to demonstrate salient features affecting the uptake of minimum tillage and its impacts on livelihoods and deforestation given the methods applied. These findings could also serve as important benchmarks for future research in most of these uncharted areas.

7 Overall conclusions and policy implications

Climate change, population growth and the rise in average incomes work in tandem to exert enormous pressure on smallholder rainfed farming systems in sub-Saharan Africa. Smallholders - who produce most of the staple foods - need to raise agricultural productivity and yet, climate variability increasingly make it difficult to achieve this goal. Throughout the region, smallholder farmers have to reconcile productivity growth and climate resilience in order to meet rising food demands, while at the same time adapt to and mitigate current and future climate change. Reconciling agricultural productivity growth and climate resilience in rainfed farming systems is perhaps one of the most pressing contemporary development challenges in SSA because agriculture remains a strategic and important economic sector providing for livelihoods.

The suite of farming practices under conservation agriculture or more broadly Climate Smart Agriculture are promoted as potential solutions that can - among other things - improve agricultural productivity, raise farm incomes and help smallholders adapt to and mitigate climate change. Despite nearly two decades of actively promoting these farming practices for smallholders in sub-Saharan Africa, there are disagreements on the extent of uptake and impacts on productivity and livelihoods. This thesis focuses on minimum tillage - the main component of conservation agriculture - and provides a nuanced assessment on uptake and impacts on maize yield, livelihoods and deforestation in Zambia. The thesis draws the following general conclusions and implications.

1. The uptake of minimum tillage seems lower than is generally believed, at less than 10% even in districts with the highest uptake over the period 2010 - 2014 in Zambia. Major barriers to uptake include financial and labor constraints. One-size-fits-all promotion approaches do not seem to increase uptake of all minimum tillage principles but low seasonal rainfall does. This implies that future promotion should be targeted in terms of both the technology mix and farmer needs. There is need for more research (e.g., behavioral economics) to better understand the behavioral aspects that hinder adoption and to develop long-term panel studies that would better capture the adoption dynamics.
2. Minimum tillage increases maize yields in the medium- to long-term. The gains depend, however, on timely field operations like early planting, fertilizer application, weed control and good rainfall. The yield effects are also different across the minimum tillage principles and contexts. Identifying what works in different locations and including those in the extension messages to farmers will be key to raise productivity.

Significant yield penalties for late field operations remain a key message to farmers, extension agents and policy makers.

3. Adopting minimum tillage does not increase household and crop incomes in the short-term. This suggests that modest yield gains, which are sometimes tenable, may not be large enough to significantly increase household welfare or cover the additional costs of implementing minimum tillage in the short-term. Thus, from a livelihoods perspective, yield alone is insufficient. Given that minimum tillage is often only partially adopted, these findings pose some policy challenges on the scope - if any - for smart short-term palliatives to encourage uptake and on adapting minimum tillage to local contexts to make it more beneficial for smallholder farmers.
4. Minimum tillage alone has limited impact on reduced cropland expansion. Since higher crop yield and labor availability are expansionary, the net effect of minimum tillage on expansion will be context specific. Nevertheless, given the dual challenge facing African agriculture of both raising yield and farm incomes, while adapting to and mitigating climate change, conservation agriculture practices such as minimum tillage could be part of the overall policy package. Focusing solely on conservation agriculture practices such as minimum tillage would be a risky climate strategy.

After all this, a key policy relevant question remains; for whom and when is minimum tillage beneficial, and under what conditions? Minimum tillage appears beneficial for managing rainfall variability - particularly rainfall stress - both in the short- and long-term. The effects of promotion, i.e., being in promotion districts on uptake are variable. Because minimum tillage constitutes distinct tillage practices with different characteristics (e.g., labor and capital requirements) entails that such uniqueness should be taken into account when designing promotion because farmers consider the individual minimum tillage components differently. Further, farmer characteristics, in particular cash, credit and labor constraints condition uptake. Adopting minimum tillage is a risky venture - more so for poor households dependent on rainfed farming systems and living close to the subsistence level, preventing them from embarking on less well-known production technologies.[13] Therefore designing smart short-term subsidies to relax resource constraints and incentivize uptake without creating dependence remains a sticky policy challenge.

Timely field operations - land preparation and planting, inorganic fertilizers and good rainfall as well as good crop husbandry - are indispensable for positive yield effects from minimum tillage. This call for improvements in agro-dealer supply chains to not only make the requisite inputs and implements accessible on time, but also affordable. Irrigation development is an alternative for management of water stress. The different yield effects among minimum tillage principles relative to their conventional agriculture counterparts echo the need to rethink the mix of technologies promoted in different contexts. Since the yield gains are not particularly large, partial application coupled with high implementation costs imply that minimum tillage will have minimal effects, if any, on household income (welfare) - especially in the short-term. Unless mechanisms are put in place to insulate farmers from these short-term low productivity risks, their high discounting and risk aversion will almost always drive them to no - or partial adoption.

The overall effects of minimum tillage on deforestation appear ambiguous. The profitability of agriculture stimulates expansion, but the demands of more labor for expansion raises the opportunity cost of labor, dampening or even reversing the outcome. On the one hand, the net effects also depend on how adopting minimum tillage affects factor intensi-

[13] Its risk reducing effects requires more research.

ties, especially labor, but also presence of off-farm activities that take up free labor. In both instances, the results would be positive. On the other hand, the overall effects depend on output prices and general market access conditions, as well as household characteristics and preferences. The effects of output prices depend on whether the commodity in question is local - (local supply and demand influence prices strongly) - or if integrated in global markets, in which case prices are given. Presence of government price control policies add another layer of complexities such that in the balance, agricultural technologies like minimum tillage would appear more likely to lead to win-win outcomes only if they are combined with conservation policies such as direct control of expansion into high-carbon habitats such as forests.

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Paper I

Minimum tillage uptake and uptake intensity by smallholder farmers in Zambia

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Accepted for publication, forthcoming in *African Journal of Agricultural and Resource Economics, 2016:11*(4).

Abstract

Minimum tillage has been promoted for about two decades as a way to conserve soils and increase agricultural productivity in Zambia and sub-Saharan Africa. However, the extent of its uptake by smallholder farmers remains debatable. This paper assesses factors influencing uptake and uptake intensity of minimum tillage using large household survey data for the period 2010 – 2014 in Zambia. We apply double hurdle models to account for corner solution outcomes resulting from limited uptake of minimum tillage. Less than 5% and 10% of smallholders used minimum tillage per year as the main tillage method at national level and in the top 10 districts with highest use rates, respectively. Low seasonal rainfall and being in districts where minimum tillage has been promoted for over 10 years increase the likelihood of minimum tillage uptake and uptake-intensity, but not for all its components. These results have implications for targeting future minimum tillage promotion programs.

Keywords: Conservation agriculture, minimum tillage, adoption, Zambia

1. Introduction

Conservation agriculture has been actively promoted as a viable means for smallholder farmers in sub-Saharan Africa to raise agricultural productivity, stabilize crop yields under variable rainfall conditions and adapt agriculture to climate change (IPCC 2014; Thierfelder et al. 2015). Despite almost two decades of promoting its core principles of minimum tillage, in-situ residue retention and crop rotation, their often claimed high adoption and diffusion is contested (Andersson & D'Souza 2014; Giller et al. 2009). Debates on the extent of adoption of conservation agriculture principles have led to questions on their suitability for smallholders in the region (Andersson & D'Souza 2014; Giller et al. 2009), and on the relevance of blanket salesmanship or one-size-fits-all promotion approaches (Andersson & Giller 2012). In part, inconsistent definitions of adoption (or the lack of it), the lack of comparable adoption estimates across countries and time, and the lack of sufficient details on adoption figures drive the adoption debates.

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[1] We acknowledge funding from FSRP III and the CIFOR/NMBU-REDD+ project. We are grateful for comments from the editor, two anonymous reviewers, and Arild Angelsen. Usual disclaimers apply.

There are large variations in existing adoption estimates for conservation agriculture principles in sub-Saharan Africa and most studies neither define adoption consistently nor provide sufficient details on their estimates (Andersson & D'Souza 2014). For example, recent estimates from Zambia ranged from 2% to 71% across different years between 2008 and 2012 (see Ngoma et al. (2014) for details). A similar picture of wide varying adoption estimates emerge at regional level (Andersson & D'Souza 2014; Mazvimavi & Twomlow 2009). Understanding why adoption estimates vary so much in the same countries or regions and over the same periods is a fundamental question and one that cross section data as in this study may not fully answer. However, this paper addresses two critical issues that may be limiting better understanding of the true extent of minimum tillage uptake among smallholders in sub-Saharan Africa. First, we distinguish between conservation agriculture and minimum tillage and focus on the latter, and between adoption and use. Adoption is the sustained use of technologies over time and requires panel data to measure it while technology use includes incentivized testing and experimentation phases, which may or may not lead to adoption. Second, we use survey data that is statistically representative at national and district level to compute weighted minimum tillage uptake or use rates even in districts where minimum tillage has been promoted for over a decade. This paper makes two main contributions to debates on the uptake of conservation agriculture in sub-Saharan Africa. First, we highlight trends and spatial patterns in the use of minimum tillage as the main tillage by smallholder farmers from 2010 to 2014 in Zambia. Second, we test the influence of being in promotion areas and seasonal rainfall on uptake decisions and account for the potential endogeneity of the location of programs promoting minimum tillage on farmer uptake decisions. We return to this issue in the methods section.

We define minimum tillage as use of either ripping or basins, or both.[2] Minimum tillage is the basis for, and the main component of conservation agriculture. Its core principles of planting basins and ripping minimize soil disturbance by only tilling in permanent planting stations. Planting basins are made with hand hoes while rip lines are made with animal draft or mechanical-drawn rippers. In this study, a smallholder household used ripping or planting basins only if they reported these practices as the main tillage method on at least one plot for any field crop. We focus on minimum tillage use for any field crop in order to capture all farmers using minimum tillage.

We measure promotion with a dummy variable (= 1) if a households is in a district where minimum tillage has been promoted for at least 10 years prior to the survey year and rainfall variability with deviations from long-term rainfall. The promotion of conservation agriculture for smallholders started in the mid-1990s in Zambia and initially targeted low rainfall and agriculturally important agro-ecological regions 1, 2a and 2b located in parts of Central, Eastern, Lusaka, Southern and Western provinces (Haggblade & Tembo 2003). These agro-regions were facing declining land productivity caused by hardpans and excessive use of government subsidized inorganic fertilizers in the 1980s. Moreover, these areas were more accessible. The Ministry of Agriculture, non-government organizations and private companies promote conservation agriculture using lead farmers, demonstration plots, and farmer training in Zambia. Although promotion targets specific areas, selection of beneficiaries is not random since each farmer chooses whether to use conservation agriculture or not. Overall, 55% of all smallholders accessed conservation agriculture extension services in 2011 (CSO/MAL/IAPRI 2012). See Arslan et al. (2014) and Whitfield et al. (2015) for detailed historical perspectives on conservation agriculture in Zambia.

[2] We exclude zero tillage, because it was likely confounded by traditional farming practices in surveys prior to 2012.

2. Context, data and sampling

This study used the crop forecast survey data collected by the Ministry of Agriculture and the Central Statistical Office. The crop forecast survey data are representative of small- and medium-scale farming (also called the smallholder sector) conditions at the national, provincial, and district levels and therefore have the best statistical representation of minimum tillage use rates as main tillage among smallholder farmers in Zambia, including within districts where minimum tillage has been most actively promoted. Crop forecast surveys ask about the main tillage method used on each plot for each farmer[3] and use standard enumeration areas as primary sampling units. In total 680 standard enumeration areas are sampled using probability proportional to size sampling with 20 households selected for interviews from each sampled enumeration area. This results in annual samples of about 13,600 households with about 90% coverage. See GRZ (2011) for details on sampling procedures for crop forecast surveys.

This study used data from about 61,000 smallholder households who cultivated field crops over the period 2010 - 2014. These are independent cross sectional surveys pooled over the five years in the analysis. Enumerators conduct face-to-face interviews using structured questionnaires to collect crop forecast survey data. The enumerators are trained enough to be able to capture exact tillage methods reported by farmers and their field reference manuals have detailed explanations on all tillage methods including pictures. Figure 1 shows the extent of coverage by crop forecast surveys in Zambia.

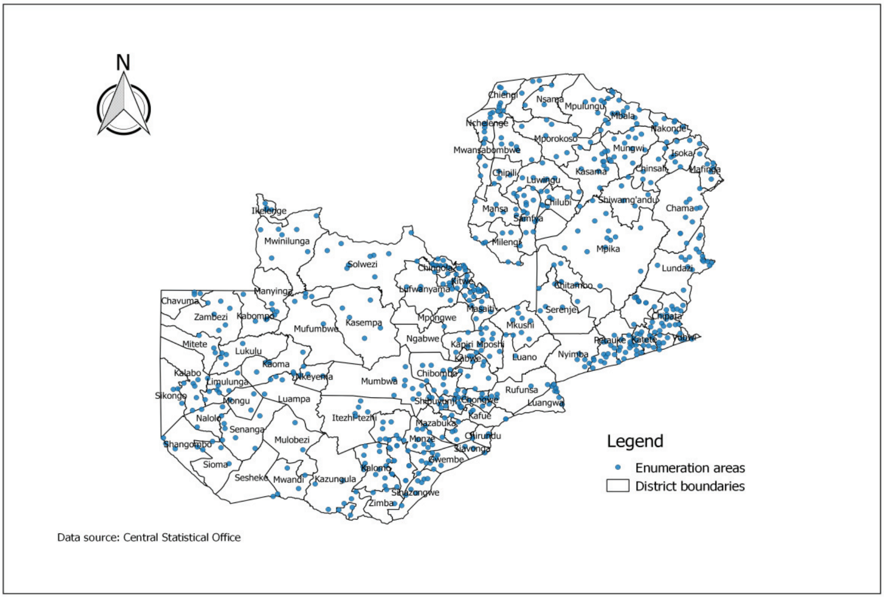

Figure 1: Spatial location of enumeration areas and extent of coverage by crop forecast surveys in Zambia
Source: Author compilations

[3] This includes farmers who used minimum tillage as the main tillage for at least one plot but excludes all those who only partly used it. Therefore, asking if a plot used minimum tillage is different from asking if minimum tillage was the main tillage method.

Regarding our models identifying household use of minimum tillage practices, it is important to note that the crop forecast surveys are production-oriented and do not capture all household socio-economic and demographic variables. Nevertheless, we control for the main determinants of technology adoption used in the literature.

We also used dekad (10-day period) spatial rainfall data from the Climate Hazards Group Infrared Precipitation with Station database (CHIRPS). CHIRPS is a quasi-global spatial database (50'S-50'N) with 0.05' resolution (Funk et al. 2014). We merged the spatial rainfall data with household data at the standard enumeration area level.[4] We supplemented these data with two complimentary sets of focus group discussions held to understand district and household level factors influencing variable minimum tillage use rates from farmers' perspectives. In total, 126 smallholders from Chama, Chipata, Choma, Chongwe and Petauke districts participated in focus group discussions in January 2013 and in August 2014.

3. Methods

3.1. Theoretical framework

Although promoted as part of the conservation agriculture principles, the components of minimum tillage (planting basins and ripping) are distinct tillage options available to smallholder farmers. Smallholders face discrete investment choices when they consider whether to use minimum tillage or not (extensive margin), and continuous land allocation decisions regarding how much land to allocate to minimum tillage (intensive margin). Assuming that farmers derive utility (or profits) from their tillage choices, we can use utility or profit maximization to evaluate their tillage choices. This analysis lends itself to the random utility theory, which links discrete choices to utility maximizing behavior based on the assumption of rational preferences (Train 2002).

Consider a rational risk-averse farmer i faced with a choice of tillage method from J options (includes minimum tillage (MT) and other conventional tillage options). Assume this farmer obtains utility U_{iMT} from choosing MT- the j^{th} option, where $j = 1, \ldots, J$. The decision rule is that the farmer chooses the tillage option that provides the greatest utility: i.e. the farmer will choose MT if and only if $U_{iMT} > U_{ik}$ for $k \neq MT$. However, we cannot observe utility save for some tillage attributes S_{iMT}, and a vector of factors $\boldsymbol{X}_i$ influencing farmers' choices. Following Train (2002), we can define an indirect utility function for the choice of MT tillage as $V_{iMT} = V(S_{iMT}, \boldsymbol{X}_i)$ to relate the observed factors to farmer utility. Since we cannot observe U_{iMT}; $V_{iMT} \neq U_{iMT}$. Assuming that utility is additive separable, we can decompose it as $U_{iMT} = V_{iMT} + \varepsilon_{iMT}$, where ε_{iMT} captures other factors affecting utility from minimum tillage use but are not included in V_{iMT}. Because ε_{ij} is unknown for all J, it is treated as random with a joint density $f(\varepsilon_i) = (\varepsilon_{ij}, .., \varepsilon_{iMT}, \ldots, \varepsilon_{iJ})$. The probability that farmer i chooses minimum tillage is given by;

$$\begin{aligned} P_{iMT} &= \Pr\left(U_{iMT} > U_{ik}, \forall_{k \neq MT}\right) \\ &= \Pr\left(V_{iMT} + \varepsilon_{iMT} > V_{ik} + \varepsilon_{ik}, \forall_{k \neq MT}\right) \\ &= \Pr\left(\varepsilon_{ik} - \varepsilon_{iMT} < V_{ik} - V_{iMT}, \forall_{k \neq MT}\right) \\ &= \int \left(\varepsilon_{ik} - \varepsilon_{iMT} < V_{ik} - V_{iMT}, \forall_{k \neq MT}\right) f\left(\varepsilon_i\right) d\varepsilon_i. \end{aligned} \tag{1}$$

[4] Since household coordinates were not collected then.

Different assumptions on the distribution of the density $f(\varepsilon_i)$ lead to a wide choice of limited dependent variable models to estimate equation (1). We use a double hurdle model, which assumes that $f(\varepsilon_i)$ has a truncated normal distribution.

3.2. Empirical model

Since the main interest of this paper is to model farmer decisions regarding minimum tillage use and use-intensity, (how much land is cultivated under each MT option), corner solution models are appropriate to estimate equation (1) to account for a large proportion of valid zero responses because most farmers in the sample did not use minimum tillage. The Tobit model is an option, however, its major limitation is the assumption that the same factors determine minimum tillage use and use-intensity decisions, and that these factors have equal coefficients and the same signs across the two decision levels. We used the double hurdle model which relaxes the Tobit assumption by allowing different or the same factors to affect minimum tillage use and use-intensity differently (Wooldridge 2010).

The first stage in estimating double hurdle models is a binary probit model of minimum tillage use. The second stage is a truncated normal regression for minimum tillage use-intensity (cultivated land under minimum tillage) among users only. The specific explanatory variables (in Table 1 and described in section 3.4) were selected based on previous studies on adoption of conservation agriculture (Andersson & D'Souza 2014; Arslan et al. 2014; Haggblade & Tembo 2003), and on results from our focus group discussions.

We specified the two equations in the double hurdle as;

$$\Pr(MT_{ij}=1)=\beta_0+Dpromo\beta_1+\boldsymbol{rainfall\beta}_2+land\beta_3+\boldsymbol{X}_1\boldsymbol{\beta}_4+\boldsymbol{X}_2\boldsymbol{\beta}_5+\boldsymbol{year\beta}_6+\varepsilon \qquad (2)$$

And,

$$MTland_{ij}\,|\,MTland_{ij}>0=\beta_0+Dpromo\beta_1+\boldsymbol{rainfall\beta}_2+land\beta_3+\boldsymbol{X}_1\boldsymbol{\beta}_4+\boldsymbol{X}_2\boldsymbol{\beta}_5+\boldsymbol{year\beta}_6+\mu. \qquad (3)$$

where $MT_{ij}=1$ if farmer i used minimum tillage option j, j=basins, ripping, or both (minimum tillage). On average, 3%, 1% and 4% of the sample used basins and ripping or minimum tillage, respectively, over the 5-year period considered in this paper. $MTland_{ij}$ is land area under basins, ripping or minimum tillage for household i, which averaged 0.02, 0.03 and 0.05 hectares (ha) per farm household, respectively. We estimate one model for the combined effects on minimum tillage and two other models for ripping and planting basins separately, since these are distinct principles. *Dpromo* is a dummy capturing minimum tillage promotion districts, ***rainfall*** is a vector of rainfall variability measures, *land* is total landholding size, $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ are vectors of demographic and agro-ecological variables, ***year*** is a vector of dummies for survey years, and ε and μ are error terms in the participation and the intensity of use equations, respectively. The $\boldsymbol{\beta}$'s are model parameters. Section 3.4 gives further details on these variables.

3.3. Empirical strategy: Dealing with the endogeneity of minimum tillage promotion

A priori, we would expect minimum tillage use to be positively related to the location of major minimum tillage promotion programs. Therefore, there may be program placement effects such that minimum tillage programs choose to operate in particular areas based on some unobservable criteria. If these unobservables (not captured in survey data) are correlated with farmer decisions to use minimum tillage, then including a right-hand side variable (*Dpromo*) that specifies whether major minimum tillage promotion programs were operating in the area would result in endogeneity bias of the estimates since program placement and minimum tillage use decisions at farm level will be jointly determined.

We used the control function approach of Wooldridge (2010) to address this potential endogeneity problem and used distance from the homestead to the nearest district business center (*dboma*) as an instrumental variable. A similar instrument was used in Abdulai & Huffman (2014).

Theoretically, distance to the nearest district business center (where most district administrative offices, development project offices, and agro-dealers within a district are located) directly influences farmers' exposure to minimum tillage promotion programs but not necessarily their individual farm level decision to use a given practice. This is because households closer to district business centers are likely to access more information on conservation agriculture from several sources including agro-dealers selling and advertising conservation agriculture equipment and other inputs. Such households are also more likely to be within the promotion areas. As a first step, we estimate a reduced form equation of the endogenous variable, *Dpromo* as a function of the instrumental variable - *dboma* and all exogenous variables in equations 2 and 3;

$$Dpromo = \beta_0 + \boldsymbol{rainfall\beta}_1 + land\beta_2 + \boldsymbol{X}_1\boldsymbol{\beta}_3 + \boldsymbol{X}_2\boldsymbol{\beta}_4 + \boldsymbol{year\beta}_6 + dboma\alpha + \eta, \qquad (4)$$

where η is the error term, α is the parameter associated with the instrumental variable and should be significant for *dboma* to be a relevant instrument. All other variables are as described above. We then computed generalized residuals, which were included as additional regressors in the final models. The significance of the parameter on the residuals both tests and corrects for endogeneity (Wooldridge 2010). We estimate the double hurdle models simultaneously using maximum likelihood estimation with Burke (2009)'s *craggit* command in Stata with bootstrapped standard errors.

3.4. Variables and hypotheses

Table 1 gives the summary statistics for variables used in the regressions. *Dpromo* is a dummy *=1* if a household is in a district where minimum tillage has been consistently promoted for at least 10 years preceding the survey year. This variable was constructed based on information from the Conservation Farming Unit and literature on minimum tillage promotion in Zambia, see (Haggblade & Tembo 2003; Ngoma et al. 2014). It includes 17 districts covered by several conservation agriculture promoters in Zambia and comprises about 39% of the sample. A priori, we expected farmers in these areas to be more likely to use minimum tillage. ***Rainfall*** is a vector of rainfall variability measures; the standard precipitation index (SPI), and rainfall stress periods computed at period *t-1* from spatial growing season (November-March) rainfall data.[5] Following Patel et al. (2007), $SPI_i = (R_{t-1} - \mu)/\sigma$, where R_{t-1} is the rainfall record for the previous growing season, μ and σ are the 10 year average rainfall and standard deviation of rainfall, respectively, and *i* is the current year. A negative and positive SPI indicates a drought (lower than average rainfall) and above average rainfall (floods), respectively, with more negative or positive values showing severity. Rainfall stress is the number of 20-day periods within a growing season with less than 40mm of rain. A priori, we expect rain stress to have positive effects on minimum tillage use. We might expect high SPI to affect minimum tillage use negatively due to flooding and waterlogging. These rainfall variability measures also capture the effects of covariate production risk.

Land is total landholding, which averaged 4.3 ha in the entire sample, and 4.7 and 3.6 ha among ripping and planting basin users, respectively and used as a proxy for wealth. The vector $\boldsymbol{X}_1$ captures household demographics – the sex and education level of the household head, the number of adults aged 15-65 years and age of the household head (44 years on average). We hypothesized that male-headed households, more education and high labor availability facilitated minimum tillage use but age reduced it. About 79% of the sample were male headed and household heads spent an average of 6.2 years in school. The number of adults per household (3.11 on average) is a proxy for household labor availability. Other labor indicators in $\boldsymbol{X}_1$ are dummies = 1 if the household head is monogamously married (71%) or

[5] Computed at t-1 to approximate anticipated rainfall in the following season.

polygamously married (8%). We hypothesized that polygamously married heads might have more family labor available than monogamously married heads.

X_2 is a vector of agro-ecological region dummies = *1* if a household is in agro-ecological regions 1, 2a, 2b or 3.[6] We hypothesized that households in lower rainfall agro-ecological regions 1, 2a, and 2b were more likely to use minimum tillage than those in region 3. ***X_2*** also includes eight provincial dummies to account for the effects of spatial location. ***Year*** is a vector of year dummies to control for year-specific effects. Other variables are quadratic terms for age, education, number of adults and landholding size to check for quadratic effects and an interaction term between agro-region 2a and negative SPI.

Table 1: Definitions and summary statistics of dependent and explanatory variables used in regression models

Variable Name	Description	Mean	Std. Dev
Dependent variables			
MT	Minimum tillage (yes=1)	0.04	0.19
MT_ripping	Ripping (yes=1)	0.01	0.12
MT_basins	Planting basins (yes=1)	0.03	0.16
MTland	Size of land under minimum tillage (ha)	0.05	0.44
MTland_ripping	Size of land under ripping (ha)	0.03	0.36
MTland_basins	Size of land under basins (ha)	0.02	0.23
Explanatory variables			
sex_hh	Male headed household (yes=1)	0.79	0.41
age_hh	Age of household head (years)	44.24	14.70
age2	Age of household head squared	2173	1476
edu_hh	Education of household head (years)	6.20	3.83
edu2	Education squared	53.11	56.76
p_married	Polygamous married (yes=1)	0.08	0.27
m_married	Monogamous married (yes=1)	0.71	0.45
adults	Number of adults, 14-65 years	3.11	1.81
adults2	Number of adults squared	12.97	17.50
land_size	Land holding size (ha)	4.27	11.07
land2	Land holding size squared	141	5873
rain_st	Rainfall season stress periods (#)	0.59	0.74
spirain	Standard precipitation index	0.06	1.06
aer1	Agro-region 1 (yes=1)	0.22	0.41
aer2a	Agro-region 2a (yes=1)	0.27	0.44
aer2b	Agro-region 2b (yes=1)	0.15	0.36
aer 3	Agro-region 3 (yes=1)	0.36	0.48
aer2aspi	In agro-region 2a and experienced negative spi (drought)	-0.10	0.30
Dpromo	MT promoted at least 10 years(yes=1)	0.39	0.49
dboma	Distance from homestead to nearest main town (km)	34.76	27.35

[6] Regions 1, 2 and 3 receive < 800 mm, 800-1,000 mm and >1,000 mm of rain.

Source: Crop forecast surveys 2010-2014, author computations

4. Results and discussions

4.1. How do minimum tillage users compare to non-users?

As a first step, we compared minimum tillage users and non-users on key variables. Results (available from authors) suggest statistically significant differences in terms of exposure to rainfall variability, incidences of droughts or floods and household labor availability. A larger proportion of minimum tillage users were located in areas that experienced more rainfall stress and droughts (as indicated by the negative standard precipitation index). Of all farm households who used minimum tillage, a higher proportion were in the low-rainfall agro-ecological regions 2a and 1, and minimum tillage users had fewer adult household members at 3.31 on average compared to 3.41 among non-users.

4.2. Minimum tillage uptake by smallholders: 2010 to 2014

About 61,000 farmers or 4.40% of the smallholders in Zambia used minimum tillage (basins and, or ripping) as the main tillage method for any field crop in 2014 compared to about 3.55% in 2010 (Table 2). About 2.41% of smallholders used planting basins in 2010 and 3.00% in 2014 while about 1.14% and 1.42% used ripping in 2010 and 2014, respectively. On average, less than 10% of smallholder farmers used minimum tillage per year in promotion and top ten districts (with highest use rates) (Tables 2). However, a larger proportion of farmers used minimum tillage in promotion districts than in non-promotion districts over the study period (Table 2), suggesting a positive effect of promotion. See Figure 2 for the spatial distribution of the five-year average uptake rates across districts.

Table 2: Proportion of smallholder farmers using minimum tillage and its components as main tillage at national level, in promotion and non-promotion districts, and in the top 10 districts, 2010-2014

	Percent of smallholders farmers									
	National level			Promotion districts			Non-promotion districts			Top 10 districts*
Year	MT	Planting Basins	Ripping	MT	Planting Basins	Ripping	MT	Planting Basins	Ripping	MT
2010	3.55	2.41	1.14	5.33	3.49	1.84	2.37	1.67	0.69	7.39
2011	3.11	2.34	0.77	4.19	3.34	0.85	2.37	1.67	0.70	6.49
2012	3.88	2.97	0.91	5.44	3.72	1.72	2.75	2.44	0.32	8.22
2013	3.25	2.30	0.96	4.37	2.58	1.80	2.44	2.04	0.40	5.92
2014	4.40	2.98	1.42	6.19	3.81	2.38	3.11	2.36	0.76	9.26

Notes: MT is minimum tillage, * ranked by percent MT use rate.

Source: Crop forecast surveys 2010-2014, author computations

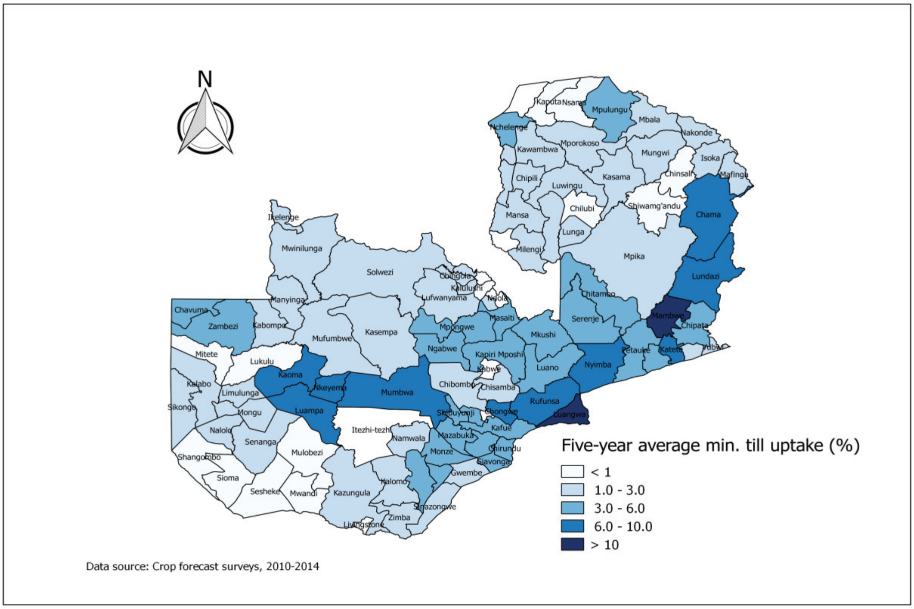

Figure 2: Spatial distribution of district level minimum tillage uptake by smallholder farmers in Zambia, 2010-2014.
Source: Authors compilations

However, there were large variations in uptake rates by district and by year, posting about 30 and 19-percentage point increase and decrease in districts with the highest positive and negative changes, respectively, between 2010 and 2014 (Figure 3). Section 4.3 explores plausible reasons for these variations in minimum tillage uptake.

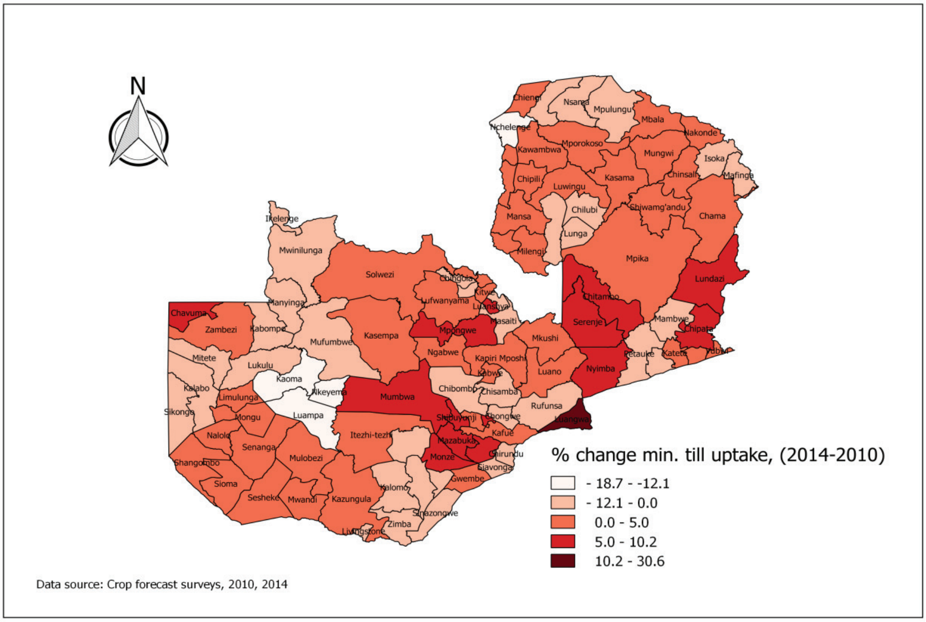

Figure 3: Change in district level minimum tillage uptake rates by smallholder farmers in Zambia, 2010-2014
Source: Authors compilations

Further, the use of minimum tillage remains partial with an uptake intensity of about 58% among users and only about 2.5% in the whole sample on average and over the study period. Of the 2.1 million hectares cultivated by smallholder farmers in 2014, only about 2.8%, 1.49% and 1.35% was under minimum tillage, ripping and basins, respectively (Table 3).

Table 3: Proportion of land cultivated under minimum tillage by smallholder farmers in Zambia, 2010-2014

	Cultivated land under (ha)				% of cultivated land under		
Year	Total	Planting Basins	Ripping	Minimum Tillage	Planting Basins	Ripping	Minimum Tillage
2010	1,935,204	22,260	16,157	38,417	1.15	0.83	1.99
2011	1,973,337	24,573	14,901	39,474	1.25	0.76	2.00
2012	2,051,925	27,809	19,021	46,830	1.36	0.93	2.28
2013	2,048,082	25,218	20,796	46,015	1.23	1.02	2.25
2014	2,173,374	29,251	32,333	61,584	1.35	1.49	2.83

Source: Crop forecast surveys 2010-2014, author computations

4.3. Why does minimum tillage use vary across years? Insights from focus group discussions

The focus group discussions suggested that the number of projects promoting minimum tillage at any given time influences uptake rates. Although this effect is positive, it is only temporal in some instances and hence the variations in uptake rates across years. In the context of our findings in Table 2, the higher use rates in 2010 and 2012 coincide with a time when there were several projects promoting minimum tillage. However, other projects were scaling down over the same period and this partly explains the decline in minimum tillage uptake in 2011 and 2013.[7] The combined effects of old projects and new ones like the Conservation Agriculture Scaling Up project could explain the surge in uptake rates in 2014. See Whitfield et al. (2015) for an overview of conservation agriculture projects in Zambia. Other than capacity development, some projects provide start-up support in terms of inputs and implements. However, farmers explained that such support is usually too small in value and over a short period (lasting no longer than two years) for farmers to be able to finance their future conservation agriculture activities. This partly explains the perplexing tendency where some farmers only implement conservation agriculture with project support. However, this does not preclude dependence.

The focus group discussions also revealed that inter-household differences in resource endowments explain why some farmers use minimum tillage practices only with project support. High labor requirements associated with minimum tillage (especially basins), resource constraints faced by smallholders, and distortionary project effects were identified as the main factors impeding uptake of minimum tillage. Farmers explained that it is easier for wealthier farmers to finance their minimum tillage activities such as buying requisite implements, inputs and herbicides. Commenting on household resource constraints, one participant said, “We have received enough training in conservation agriculture and we keep wondering whether training alone would enable Us to overcome the costs associated with implementing conservation agriculture”. Another participant added, “Continuous training in conservation agriculture without adequate start-up support is like fishing with a hook but without a bait”. In addition to higher cash outlays, the focus group discussions suggested that minimum tillage requires more labor for land preparation and weeding compared to conventional tillage.

4.4. Empirical results

Table 4 presents national level estimates for determinants of minimum tillage use and use intensity in Zambia.[8] Columns 1, 2 and 3 show participation, conditional and overall (unconditional) average partial effects (APEs), respectively for the minimum tillage model, while columns 4 and 5 show the overall APEs for basins and ripping models. We find weak evidence (significant at 10%) suggesting that being in promotion areas is endogenous to basin tillage uptake but not ripping, and minimum tillage in general. [9] See estimates for *residuals* in Table 4. Consequently, we dropped the residual terms in minimum tillage and ripping models. The

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[7] E.g. FISRI and CASSP projects.

[8] As robustness checks, we estimated basin models without the IV, national models on a sub-sample of households in the top 10 districts and with Tobit model. The main results are robust to alternative estimations.

[9] The IV-*dboma* was relevant ($\chi^2 = 14.66; p=0.00$) and excludable by the instrument falsification test of Di Falco et al. (2011) ($\chi^2 = 1.79; p=0.41$) - full results available from authors.

estimation is clustered at the standard enumeration area level to account for intra-group correlations.

Table 4: Double hurdle results of factors influencing uptake and uptake intensity of minimum tillage by smallholder farmers in Zambia, 2010-2014.

	(1)	(2)	(3)	(4)	(5)
	Participation APEs (=1 if MT)	Conditional APEs (ha under MT)	Unconditional APEs (ha under MT)	Unconditional APEs (ha under basins)	Unconditional APEs (ha under ripping)
Promotion district [dpromo] (yes=1)	-0.003	0.235**	0.006***	-0.134***	0.009*
	(0.004)	(0.103)	(0.002)	(0.031)	(0.006)
Std. Precipitation index [spirain]	-0.005***	-0.049	-0.009***	-0.004***	-0.009***
	(0.002)	(0.069)	(0.003)	(0.002)	(0.003)
Rain stress [rain_st]	0.005**	-0.091	0.002	0.008***	0.001
	(0.002)	(0.063)	(0.005)	(0.002)	(0.002)
In agro-region 2a and drought [aer2spi]	0.007	-0.125	0.003	0.008*	0.007
	(0.006)	(0.147)	(0.009)	(0.004)	(0.007)
Agro-region 1 [aer1] (yes=1)	0.020*	1.077**	0.071***	0.077***	0.120***
	(0.011)	(0.471)	(0.003)	(0.020)	(0.032)
Agro-region [aer2a] 2a (yes=1)	0.038***	0.964**	0.088***	0.115***	0.129***
	(0.011)	(0.459)	(0.005)	(0.026)	(0.031)
Agro-region [aer2b] 2b (yes=1)	0.021**	0.479	0.047***	-0.005	0.097***
	(0.009)	(0.437)	(0.010)	(0.005)	(0.027)
Male headed hh [sex_hh] (yes=1)	0.005	0.146	0.013*	0.001	0.011
	(0.004)	(0.175)	(0.008)	(0.004)	(0.009)
Age hh head [age_hh]	-0.001	-0.020	-0.002*	-0.001*	-2.5E-04
	(0.000)	(0.016)	(0.001)	(0.000)	(0.001)
Age squared [age2]	6.3E-06	1.4E-04	1.5E-05	7.3E-06*	2.2E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education hh head [edu_hh]	3.3E-04	-0.023	-0.001	-0.002***	0.001
	(0.001)	(0.020)	(0.002)	(0.001)	(0.001)
Education squared [edu2]	- 9.4E-06	1.4E-04	-9.0E-07	1.2E-04***	-1.1E-04
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Polygamously married [p_married]	-0.001	-0.051	-0.003	0.003	-0.005
	(0.005)	(0.186)	(0.013)	(0.005)	(0.009)
Monogamously married [m_married]	-0.006	-0.022	-0.008	0.003	-0.007
	(0.005)	(0.184)	(0.013)	(0.004)	(0.010)
# adults 14-65 years [adults]	0.001	-0.106*	-0.003**	1.8E-04	-0.001
	(0.002)	(0.063)	(0.001)	(0.002)	(0.004)
# adults squared [adults2]	2.0E-04	0.016***	4.6E-04**	-2.5E-05	1.9E-04
	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Land size [land_size]	-6.7E-06	0.008	3.4E-04	3.2E-04	2.6E-04
	(0.000)	(0.008)	(0.001)	(0.000)	(0.000)
Land squared [land2]	-9.2E-09	-5.6E-05	-2.4E-06	-1.2E-06	-1.4E-06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residuals from first stage IV estimation	-	-	-	0.075***	-
	-	-	-	(0.018)	-
Province fixed effects	*Yes*	*Yes*	*yes*	*Yes*	*yes*
Year fixed effects	*Yes*	*Yes*	*yes*	*yes*	*Yes*
Joint prov. LR test		*58.70****		*242.37****	*239.98****
Joint year LR test		20.93***		*36.78****	*45.91****

Observations	60,958	2,397	60,958	60,958	60,958
Mean of dependent variable	0.04	1.23	0.05	0.02	0.03

Notes: Robust standard errors in parenthesis;***, **, * significant at 1%, 5% and 10% respectively; base agro-region, year and province are region-3, 2010, and Western. MT is minimum tillage. Full results for basin and ripping model are available from authors. Variable names are in square brackets.
Source: Crop forecast surveys 2010-2014, author computations

4.4.1. Effects of promotion and seasonal rainfall on minimum tillage uptake

Consistent with a priori expectations, we find strong correlations between farmer tillage choices and rainfall variability and minimum tillage promotion (Table 4). All else constant, an additional rainfall stress period increases the likelihood of minimum tillage uptake by 0.05 percentage points while incidences of floods (above average rainfall) reduce the likelihood of minimum tillage uptake by a similar margin and uptake intensity by 0.01 ha. These results are statistically significant at 1-5%. Being in minimum tillage promotion areas increased minimum tillage and ripping uptake intensity by about 0.01ha and these results are significant at 1% and 10% levels of significance. Moreover, the effects are larger at 0.24 ha among farmers already using minimum tillage (Table 4). However, being in promotion areas reduces basin uptake intensity by 0.13 ha.

Our findings of strong correlations between minimum tillage choices and rainfall variability indicate that farmers appreciate minimum tillage as a way of adapting to droughts, suggesting that minimum tillage maybe a viable option for smallholders to adapt to low rainfall in Zambia. However, the negative results on basin tillage could be because of its arduousness (Rusinamhodzi 2015), which constrains uptake (Thierfelder et al. 2015). This is line with descriptive results in Table 3, which show that as of 2014, there was more land under ripping than basins in Zambia. In the context of scaling-up uptake, the mixed effects of being in promotion areas on uptake suggest a need for future promotion to review the mix of principles promoted to identify what works in particular areas and to adapt interventions.

4.4.2. Other drivers of minimum tillage uptake and uptake-intensity

In line with a priori expectations, farmers in agro-ecological regions 1, 2a and 2b (relative to region 3) are 2- 4 percentage points more likely to use minimum tillage, and the marginal effects on uptake intensity are larger for ripping than basins (Table 4). These findings corroborate results from Nyamangara et al. (2014) and Thierfelder et al. (2015), which suggest that conservation agriculture principles are more beneficial in low rainfall environments. Further, older household heads and the number of adults reduce the intensity of minimum tillage uptake, and there are significant provincial and year effects on minimum tillage choices (Table 4).

The foregoing empirical results confirm and contradict some of the popular beliefs in conservation agriculture literature. For example, our finding that the number of adults (labor availability) negatively affects the likelihood of minimum tillage uptake is counterintuitive. On one hand, this may indicate binding labor constraints and on the other hand, may reflect the drudgery of family labor use in minimum tillage or that family labor has high opportunity costs. Focus group discussions revealed that it is often difficult to hire in labor for labor-intensive minimum tillage practices like planting basins, as the drudgery involved scares away would be workers even when a higher wage is offered. By extension, this suggests that adult family members would opt to work off farm. Therefore and in line with Vaiknoras et al. (2015), if realized, labor saving from adopting minimum tillage may increase its uptake.

5. Conclusion and implications

This study used national household survey data and spatial rainfall data to assess trends in the uptake of minimum tillage, and factors influencing uptake and uptake-intensity among smallholders for the period 2010 to 2014 in Zambia. On average, the uptake of minimum tillage as the main tillage is lower than is generally believed, at less than 5% and 10% on average and per year, at national level and in the top 10 districts with highest use rates. These results are consistent with concerns stated in the 2013 Nebraska declaration on conservation agriculture, which highlight low uptake of conservation agricultural principles among smallholders in sub-Saharan Africa (Stevenson et al. 2014). Despite the low and variable minimum tillage uptake rates across years, the trend is positive and increasing over time in Zambia. However, minimum tillage use remains partial at about 3% of all cultivated land by smallholders over the study period, and only about 58% among those using it. Empirical results suggest that rainfall variability and the location of minimum tillage promotion programs affect farmer choices of minimum tillage, inter alia. Anticipation of low rainfall is associated with increased minimum tillage uptake and uptake-intensity and being in promotion areas increased uptake-intensity for some components of minimum tillage.

Two main implications follow from these results. First, there is need to tailor future promotion of minimum tillage to the needs of target populations in terms of both the mix of technologies and existing farmer resource constraints. Second, given the growing trend in the use of ripping, and its higher maize yield effects (Ngoma et al. 2015) , mechanized ripping services could be more accessible to farmers, inter alia. Future research could assess ripping service provision, develop long-term panel studies to better capture adoption dynamics and evaluate the impacts of specific promotional programs on uptake.

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Minimum tillage uptake and uptake intensity by smallholder farmers in Zambia

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Supplementary Tables and Figure

Table A1: Reduced form equation results (equation 4), dependent variable: Dpromo (=1)

VARIABLES	Coef	T-statistic	P-value
Dist. to nearest township [dboma] (IV)	**0.001*** **	**3.829**	**0.000**
Male headed hh (yes=1)	-0.014	-0.437	0.662
Age hh head	-0.009***	-2.709	0.007
Age squared	0.000**	2.253	0.024
Education hh head	-0.038***	-6.924	0.000
Education squared	0.002***	5.455	0.000
Monogamously married	0.033	1.029	0.304
Polygamously married	0.209***	5.610	0.000
# adults 14-65 years	0.049***	4.152	0.000
# adults squared	-0.004***	-3.451	0.001
Land size	0.001	1.252	0.210
Land size squared	-0.000	-0.762	0.446
Rain stress	0.296***	24.015	0.000
Std. Precipitation index (SPI)	-0.072***	-7.380	0.000
Agro-region2a (yes=1)	1.610***	87.131	0.000
Agro-region2b(yes=1)	0.224***	10.733	0.000
2011 (yes=1)	-0.246***	-8.744	0.000
2012 (yes=1)	-0.221***	-8.337	0.000
2013 (yes=1)	-0.176***	-6.375	0.000
2014 (yes=1)	-0.348***	-11.798	0.000
In AER2a and drought	0.077***	4.589	0.000
Constant	-0.530***	-6.424	0.000
Observations	60,958		

Notes: ***, **, * significant at 1%, 5% and 10% respectively; base zone and year are agro-ecological zone 1 (800-1000mm rainfall p.a) and 2010. Agro region 3 was dropped. IV refers to instrumental variable. The test for H_0: dboma = 0 has a χ^2 value of 14.66 and is statistically significant at 1%. Thus, the IV is very relevant for the endogenous variable.

Table A2: First stage regression results for planting basin, ripping and minimum tillage models

	Estimated coefficients		
	Planting basin model	Ripping model	Min till model
Residual	0.565*	-0.153	0.191
	(1.671)	(-0.364)	(0.638)
Male headed hh (yes=1)	0.053	0.049	0.063
	(0.899)	(0.647)	(1.222)
Age hh head	-0.011*	0.002	-0.007
	(-1.661)	(0.218)	(-1.179)
Age squared	1.1E-04*	-1.1E-05	7.4E-05
	(1.819)	(-0.145)	(1.365)
Education hh head	-0.012	0.021	0.002
	(-1.173)	(1.470)	(0.249)
Education squared	0.001	-0.001	-5.9E-05
	(0.980)	(-0.937)	(-0.100)
Polygamously married	0.039	-0.052	-0.001
	(0.611)	(-0.612)	(-0.015)
Monogamously married	-0.047	-0.049	-0.060
	(-0.731)	(-0.611)	(-1.076)
# adults 14-65 years	0.048	-0.017	0.017
	(1.617)	(-0.575)	(0.706)
# adults squared	-0.006**	0.002	-0.003
	(-2.100)	(0.692)	(-1.119)
Land size	-0.003	0.004	0.000
	(-1.018)	(1.608)	(0.230)
Land size squared	1.8E-06	-6.4E-06	-7.4E-07
	(0.486)	(-1.195)	(-0.301)
Rain stress	0.074**	0.052	0.076**
	(2.021)	(0.849)	(2.044)
Std. Precipitation index	-0.045*	-0.129***	-0.072***
	(-1.714)	(-2.900)	(-2.670)
In AEZ 2a and drought	0.150*	0.042	0.097
	(1.728)	(0.399)	(1.246)
Agro-region 1(yes=1)	0.551	0.688	0.428
	(1.474)	(1.395)	(1.250)
Agro-region 2a (yes=1)	1.002**	0.792	0.716
	(2.005)	(1.221)	(1.571)
Agro-region 2b (yes=1)	0.025	0.808***	0.254**
	(0.270)	(4.432)	(2.516)
Promotion district (yes=1)	-1.129*	0.418	-0.363
	(-1.931)	(0.570)	(-0.691)
Constant	-1.838***	-3.970***	-2.182***
	(-8.530)	(-12.789)	(-10.570)
Observations	60,958	60,958	60,958

Notes: ***, **, * significant at 1%, 5% and 10% respectively; base zone, year and province are agro-ecological zone 3 (>1000mm rainfall p.a), 2010 and Western; Z-statistics are in parentheses; residual is from the first stage estimations, its significance confirms endogeneity (Wooldridge 2010).

Table A3. Double hurdle results of factors influencing use of planting basins and ripping (as main tillage), and the amount of land cultivated under each MT practice by smallholder farmers in Zambia, 2010-2014.

	(1)	(2)	(3)	(4)	(5)	(6)
	------Planting Basins APEs------			-------Ripping APEs------		
Variable	Participation APEs (=1 if used basins)	Conditional APEs (ha under basins)	Unconditional APEs (ha under basins)	Participation APEs (=1 if used ripping)	Conditional APEs (ha under ripping)	Unconditional APEs (ha under ripping)
Dpromotion (yes=1)	-0.065**	-3.044***	-0.134***	0.005***	-0.064	0.009*
	(0.026)	(0.917)	(0.031)	(0.002)	(0.236)	(0.006)
Residuals	0.033**	1.818***	0.075***	-	-	-
	(0.015)	(0.540)	(0.018)	-	-	-
Std. Precip. Index (SPI)	-0.003**	-0.072	-0.004***	-0.005***	0.007	-0.009***
	(0.001)	(0.050)	(0.002)	(0.001)	(0.143)	(0.003)
Rain stress	0.004***	0.151**	0.008***	0.002*	-0.0057	0.001
	(0.002)	(0.063)	(0.002)	(0.001)	(0.003)	(0.002)
In AER2a&negSPI	0.009***	0.013	0.008*	0.002	0.211	0.007
	(0.003)	(0.133)	(0.004)	(0.003)	(0.332)	(0.007)
Agro-region 1 (yes=1)	0.032**	1.922***	0.077***	0.030***	4.224**	0.120***
	(0.016)	(0.590)	(0.020)	(0.006)	(1.743)	(0.032)
Agro-region 2a (yes=1)	0.058***	2.539***	0.115***	0.036***	4.067**	0.129***
	(0.021)	(0.789)	(0.026)	(0.006)	(1.735)	(0.031)
Agro-region 2b (yes=1)	0.002	-0.247	-0.005	0.028***	2.808*	0.097***
	(0.004)	(0.158)	(0.005)	(0.004)	(1.555)	(0.027)
Male headed hh (yes=1)	0.003	-0.064	0.001	0.002	0.512	0.011
	(0.003)	(0.120)	(0.004)	(0.002)	(0.457)	(0.009)
Age hh head	-0.001*	-0.009	-0.001*	7.3E-05	-0.026	-2.5E-04
	(0.000)	(0.011)	(0.000)	(0.000)	(0.038)	(0.001)
Age squared	6.6E-06*	0.0001	7.3E-06*	-6.0E-07	2.1E-04	2.2E-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education hh head	-0.001	-0.060***	-0.002***	0.001	-0.031	0.001
	(0.001)	(0.018)	(0.001)	(0.000)	(0.067)	(0.001)
Education squared	4.0E-05	0.003***	1.2E-04***	-2.7E-05	-0.004	-1.1E-04
	(0.000)	(0.001)	(0.000)	(0.000)	(0.004)	(0.000)
Polygamously married	0.002	0.038	0.003	-0.002	-0.073	-0.005
	(0.004)	(0.116)	(0.005)	(0.003)	(0.435)	(0.009)
Monogamously married	-0.003	0.209*	0.003	-0.002	-0.239	-0.007
	(0.004)	(0.119)	(0.004)	(0.002)	(0.498)	(0.010)
# adults 14-65 years	0.003	-0.081	1.8E-04	-4.5E-04	-0.022	-0.001
	(0.002)	(0.068)	(0.002)	(0.001)	(0.193)	(0.004)
# adults squared	-3.7E-04*	0.011	-2.5E-05	4.7E-05	1.7E-04	1.9E-04
	(0.000)	(0.008)	(0.000)	(0.000)	(0.001)	(0.000)
Land size	-1.4E-04	0.017*	3.2E-04	1.5E-04*	-0.002	2.6E-04
	(0.000)	(0.010)	(0.000)	(0.000)	(0.021)	(0.000)
Land size squared	1.0E-07	-5.1E-05	-1.2E-06	-2.0E-07	-6.2E-05	-1.4E-06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Province fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Joint province dummy LR test	*242.37****			*239.98****		
Joint year dummy LR test	*36.78****			*45.91****		
Bootstrap replications	*200*	*200*	*200*	*200*	*200*	*200*
Observations	60,958	1,641	60,958	60,958	826	60,958

Notes: Bootstrap standard errors in parenthesis;***, **, * significant at 1%, 5% and 10% respectively, base zone, year and province are AER3 (>1000mm rainfall p.a), 2010, and western. APEs refer to average partial effects

Table A4. Double hurdle results for planting basins with and without an instrumental variable

	(1)	(2)	(3)	(4)	(5)	(6)
	------Planting Basins APEs------			-------Basin Model, no IV------		
Variable	Participation APEs (=1 if used basins)	Conditional APEs (ha under basins)	Unconditional APEs (ha under basins)	Participation APEs (=1 if used ripping)	Conditional APEs (ha under ripping)	Unconditional APEs (ha under ripping)
Dpromotion (yes=1)	**-0.065****	**-3.044*****	**-0.134*****	**-0.008****	**0.089**	**-0.0048***
	(0.026)	(0.917)	(0.031)	(0.003)	(0.070)	(0.003)
Residuals	0.033**	1.818***	0.075***	-	-	-
	(0.015)	(0.540)	(0.018)	-	-	-
Std. Precip. Index (SPI)	-0.003**	-0.072	-0.004***	0.002	-0.014	0.0013
	(0.001)	(0.050)	(0.002)	(0.002)	(0.046)	(0.002)
Rain stress	0.004***	0.151**	0.008***	-0.001	0.007	-0.0010
	(0.002)	(0.063)	(0.002)	(0.001)	(0.052)	(0.002)
In AER2a&negSPI	0.009***	0.013	0.008*	0.006	-0.160	0.0012
	(0.003)	(0.133)	(0.004)	(0.005)	(0.127)	(0.005)
Agro-region 1 (yes=1)	0.032**	1.922***	0.077***	-0.000	0.050	0.0009
	(0.016)	(0.590)	(0.020)	(0.008)	(0.179)	(0.005)
Agro-region 2a (yes=1)	0.058***	2.539***	0.115***	0.013*	-0.077	0.0090***
	(0.021)	(0.789)	(0.026)	(0.008)	(0.180)	(0.003)
Agro-region 2b (yes=1)	0.002	-0.247	-0.005	0.001	-0.302*	-0.0072**
	(0.004)	(0.158)	(0.005)	(0.005)	(0.168)	(0.003)
Male headed hh (yes=1)	0.003	-0.064	0.001	0.003	-0.054	0.0015
	(0.003)	(0.120)	(0.004)	(0.003)	(0.122)	(0.004)
Age hh head	-0.001*	-0.009	-0.001*	-0.001*	-0.010	-0.0008*
	(0.000)	(0.011)	(0.000)	(0.000)	(0.010)	(0.000)
Age squared	6.6E-06*	0.0001	7.3E-06*	0.000*	0.000	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education hh head	-0.001	-0.060***	-0.002***	-0.000	-0.047***	-0.0017***
	(0.001)	(0.018)	(0.001)	(0.001)	(0.017)	(0.001)
Education squared	4.0E-05	0.003***	1.2E-04***	0.000	0.003**	0.0001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Polygamously married	0.002	0.038	0.003	0.001	-0.043	0.0000

	(0.004)	(0.116)	(0.005)	(0.004)	(0.119)	(0.004)
Monogamously married	-0.003	0.209*	0.003	-0.004	0.137	0.0001
	(0.004)	(0.119)	(0.004)	(0.004)	(0.121)	(0.005)
# adults 14-65 years	0.003	-0.081	1.8E-04	0.002	-0.101**	-0.0006
	(0.002)	(0.068)	(0.002)	(0.002)	(0.050)	(0.002)
# adults squared	-3.7E-04*	0.011	-2.5E-05	-0.000*	0.014**	0.0001
	(0.000)	(0.008)	(0.000)	(0.000)	(0.005)	(0.000)
Land size	-1.4E-04	0.017*	3.2E-04	-0.000*	0.012*	0.0001
	(0.000)	(0.010)	(0.000)	(0.000)	(0.007)	(0.000)
Land size squared	1.0E-07	-5.1E-05	-1.2E-06	0.000	-0.000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Province fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Year fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Joint province dummy LR test	*242.37****			*239.98****		
Joint year dummy LR test	*36.78****			*45.91****		
Bootstrap replications	*200*	*200*	*200*			
Observations	60,958	1,641	60,958	60,958	1,641	60,958

Being in promotion districts has a negative effect on basin uptake and uptake intensity in models with and without the IV approach. The caveat is that ignoring endogeneity underestimates the effects of promotion and several other variables on basin uptake and uptake intensity.

Table A5. Tobit model versus Double hurdle results for minimum tillage use and use-intensity

	Tobit Model Av. Partial effect (APE)	Double Hurdle Model Overall APE
Promotion district (yes=1)	-0.002	0.006***
	(0.006)	(0.002)
Std. Precipitation index	-0.008***	-0.009***
	(0.003)	(0.003)
Rain stress	0.007**	0.002
	(0.003)	(0.005)
In AER 2a and drought	0.008	0.003
	(0.009)	(0.009)
Agro-region 1(yes=1)	0.033**	0.071***
	(0.016)	(0.003)
Agro-region 2a (yes=1)	0.057***	0.088***
	(0.016)	(0.005)
Agro-region 2b (yes=1)	0.031**	0.047***
	(0.013)	(0.010)
Male headed hh (yes=1)	0.009	0.013*
	(0.007)	(0.008)
Age hh head	-0.001	-0.002*
	(0.001)	(0.001)
Age squared	1.5E-05	1.5E-05
	(0.000)	(0.000)
Education hh head	2.9E-04	-0.001
	(0.001)	(0.002)
Education squared	-1.1E-05	-9.0E-07
	(0.000)	(0.000)

Polygamously married	-0.001	-0.003
	(0.007)	(0.013)
Monogamously married	-0.008	-0.008
	(0.007)	(0.013)
# adults 14-65 years	0.001	-0.003**
	(0.003)	(0.001)
# adults squared	-1.1E-04	4.6E-04**
	(0.000)	(0.000)
Land size	1.4E-05	3.4E-04
	(0.000)	(0.001)
Land size squared	-5.9E-08	-2.4E-06
	(0.000)	(0.000)
Province fixed effects	*yes*	*yes*
Year fixed effects	*yes*	*yes*
Sigma	3.01	16.43
Observations	2,397	60,958

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table A6. Planting basins model testing IV admissibility

	First stage		Second stage	
	Coef.	SE	Coef.	SE
Dist. to nearest township [dboma] (IV)	**0.001**	**0.001**	**-0.005**	**0.015**
Male hh head (yes=1)	0.057	0.059	-0.825	1.942
Age hh head	-0.011*	0.006	-0.152	0.169
Age squared	0.000*	0.000	0.001	0.002
Education hh head	-0.009	0.010	-0.731	0.462
Education squared	0.001	0.001	0.043	0.030
Polygamous married (yes=1)	0.024	0.065	-0.703	1.967
Monogamous married (yes=1)	-0.069	0.064	2.151	2.129
# adults	0.041	0.030	-1.609	1.048
# adults squared	-0.006*	0.003	0.214*	0.124
Land size	-0.004	0.002	0.186	0.135
Land size squared	0.000	0.000	-0.001	0.001
Rain stress	0.028	0.027	-0.215	0.731
Std. Precipitation index	-0.024	0.022	0.121	0.802
Agro-region 1(yes=1)	-0.000	0.128	0.773	2.765
Agro-region 2a(yes=1)	0.231*	0.132	-1.232	3.017
Agro-region 2b(yes=1)	0.022	0.092	-4.774	3.961
Promotion district (yes=1)	-0.141**	0.057	1.361	1.208
In AER 2a and drought	0.110	0.081	-2.541	2.292
sigma		3.256		
Constant	-1.949***	0.211	-7.264	7.190
Observations	60,598		1,641	

*** p<0.01, ** p<0.05, * p<0.1; SE is standard error; the non-significance of the IV suggests that it was fine to exclude it from the main equation in estimating the planting basin model.

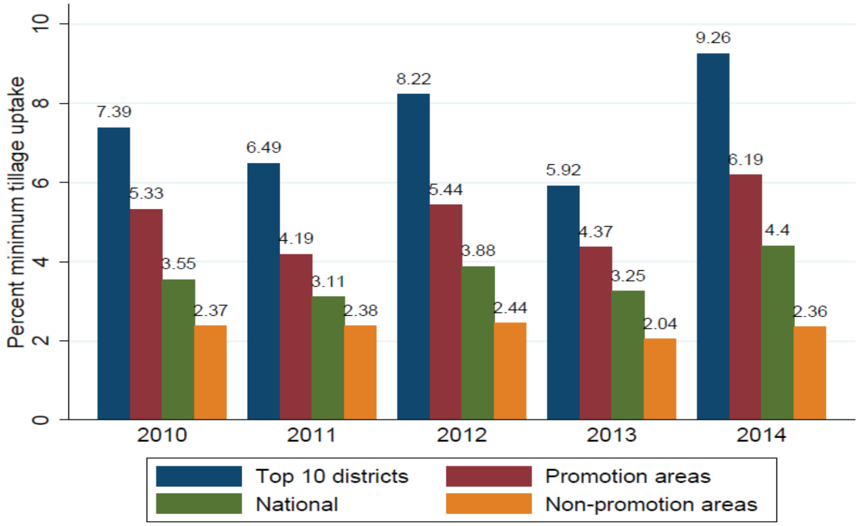

Figure A1: Proportion of smallholder farmers using minimum tillage and its components as main tillage at national level, in promotion and non-promotion districts, and in the top 10 districts, 2010-2014

Paper II

Agriculture, Ecosystems and Environment 212 (2015) 21–29

Contents lists available at ScienceDirect

Agriculture, Ecosystems and Environment

journal homepage: www.elsevier.com/locate/agee

Does minimum tillage with planting basins or ripping raise maize yields? Meso-panel data evidence from Zambia

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ARTICLE INFO

Article history:
Received 4 December 2014
Received in revised form 16 June 2015
Accepted 25 June 2015
Available online 7 July 2015

Keywords:
Conservation agriculture
Minimum tillage
Ripping
Planting basins
Maize yields
Correlated random effects
Zambia

ABSTRACT

Despite nearly two decades of minimum tillage (MT) promotion in Zambia, there is limited empirical evidence on its effect on maize yields under typical smallholder conditions. We use nationally representative survey data from nearly 48,000 smallholder maize plots for the period 2008–2011 to estimate the maize yield effects of the primary MT strategies promoted in Zambia: planting basins and ripping. The estimation approach applies pooled ordinary least squares-correlated random effects to control for time invariant unobserved heterogeneity at the enumeration area level. All else equal, yields on plots tilled with ripping are significantly higher than on conventionally plowed plots if tillage is done before rather than during the rains. The gains average 577 kg/ha nation-wide and 821 kg/ha in agro-ecological zones 1 and 2a (the two zones most suitable for conservation agriculture). Planting basins also have a positive effect on yields, increasing maize yields by 191 kg/ha on average relative to conventional hand-hoe tillage when tillage is done before the onset of the rains. These results suggest that MT with ripping and basin tillage only substantially raises smallholder maize yields relative to conventional tillage when combined with early land preparation.

1. Introduction

Food and agricultural systems in sub-Saharan Africa (SSA) are under mounting pressure. Throughout the region, smallholders must increasingly contend with the interrelated challenges of climate change and variability, declining soil fertility, and increasing land constraints. At the same time, domestic production systems need to sustainably raise crop productivity to meet rising food demand (Deininger, 2013; Laurance et al., 2014). Under these conditions, it is essential to develop strategies that enhance crop yields and the resilience of rain-fed farm systems.

Increasingly, the suite of farm practices that make up conservation agriculture (CA) are being promoted to help farmers in SSA to raise crop productivity and enhance farm system resilience to climate change (Thierfelder and Wall, 2010; Giller et al., 2011; Friedrich et al., 2012; Verhulst et al., 2012; Arslan et al., 2014; Corbeels et al., 2014). Although defined somewhat differently across the region, CA is based on the three core principles of no or minimum tillage, crop residue retention, and crop rotation (Haggblade and Tembo, 2003). Minimum tillage minimizes soil disturbance save for the planting stations. Crop residue retention involves leaving at least 30% of residues *in situ* while crop rotation entail cereal–legume rotations at plot level. Agroforestry is another important aspect of CA in Zambia that involves intercropping cereals with nitrogen-fixing trees or shrubs (*e.g.*, *Sesbania sesban* and *Faidherbia albida*).

However, despite widespread and increasing promotion of CA in SSA (Umar et al., 2011; Grabowski and Kerr, 2013), evidence on its productivity impact among smallholder farmers is mixed (Giller et al., 2009; Andersson and D'Souza, 2014; Brouder and Gomez-Macpherson, 2014).[1] Moreover, smallholder adoption of the full suite of CA practices in SSA is limited (Umar et al., 2011; Grabowski and Kerr, 2013; Andersson and D'Souza, 2014; Arslan et al., 2014).[2] This suggests a potential disconnect between the agronomic rationale for CA on the one hand, and CA outcomes in smallholder farm systems on the other. Theoretically, CA offers a

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[1] CA research and development started in the mid-1980s in Zambia, but it was not until the 1990s that full-scale promotion among smallholder farmers started in the drier agro-ecological zones (AEZs) 1 and 2a.

[2] For example, Arslan et al. (2014) found that only 3% of Zambian smallholder farmers used both minimum tillage and crop rotation in 2008.

http://dx.doi.org/10.1016/j.agee.2015.06.021
0167-8809/

clear pathway to increase agricultural productivity through the optimization of input use, facilitation of early planting through dry season land preparation, reduction of peak season labor demands, and improvement in water harvesting and soil carbon content (Haggblade et al., 2011; Friedrich et al., 2012; Umar et al., 2012; Nyamangara et al., 2014a).[3] However, when integrated into smallholder production systems, the productivity effects of CA practices may be mitigated by higher input use requirements, increased weed pressure, and other crop management challenges faced by smallholders in SSA (Giller et al., 2009; Andersson and Giller, 2012). Moreover, returns to CA may not accrue rapidly enough to sustain smallholder utilization (Giller et al., 2009; Thierfelder et al., 2013; Brouder and Gomez-Macpherson, 2014; Corbeels et al., 2014).

In the context of increased CA promotion and continued uncertainty over the effectiveness of CA practices in smallholder production systems, the paucity of empirical evidence on the productivity effects of CA practices in smallholder production systems is surprising. The current body of evidence on CA in SSA suffers from three primary weaknesses. First, the bulk of the available evidence is drawn from experimental plots or is based on fairly small sample sizes, often from selected sub-segments of the rural population in CA project areas (Haggblade and Tembo, 2003; Rockström et al., 2009; Thierfelder and Wall, 2010; Haggblade et al., 2011; Rusinamhodzi et al., 2011; Umar et al., 2011, 2012; Ngwira et al., 2012, 2013; Thierfelder et al., 2013, 2015; Kuntashula et al., 2014; Nyamangara et al., 2014b; Rusinamhodzi, 2015a).[4] This raises concerns about the generalizability (external validity) of the findings for broader smallholder populations. Second, most analyses rely on bivariate mean comparisons, which are unable to account for differences between adopters and non-adopters that may be correlated with the productivity impacts of and returns to CA (Rusinamhodzi et al., 2011; Umar et al., 2012; Nyamangara et al., 2014b; Thierfelder et al., 2015). Finally, in previous studies where CA practices are included in an econometric framework to control for other factors, they have not been the primary variables of interest and/or endogeneity concerns about the CA practices have not been addressed (Burke, 2012).

In this paper, we seek to address some of these empirical gaps in our understanding of CA effects on smallholder crop productivity. We do so by examining the effects of one core principle of CA, minimum tillage (MT), on maize yields in an econometric framework, using nationally representative survey data from smallholder farm households in Zambia. In particular, the paper estimates the *ceteris paribus* maize yield effects of planting basins and ripping, versus conventional hand hoeing and plowing, respectively. Planting basins and ripping are the primary MT strategies promoted in Zambia.[5] We focus on planting basins and ripping (which we collectively refer to as MT in the paper) because MT is a necessary condition for any CA-based farming system and MT is the CA dimension explicitly captured in the survey data. Further, we focus on maize because it is the main staple food in the region (Rusinamhodzi et al., 2011), and arguably Zambia's most important crop both economically and politically. Moreover, yield is the most important parameter farmers use to evaluate production practices (Rusinamhodzi et al., 2011).

Our approach seeks to compliment previous studies in two main ways. First, we use farm household survey data collected from nearly 48,000 maize plots over the period 2008–2011. This large data set enables us to better assess MT effects under a wide range of actual smallholder conditions. Moreover, because these data are panel at the enumeration area level, we are able to better control for unobserved factors that affect yields and that may be correlated with adoption of MT. Second, we explicitly examine the yield effects of MT practices separately, rather than lumping them together, and are attentive to differences across agro-ecological zones. To our knowledge, this paper offers the most empirically robust analysis of MT effects on crop productivity under typical smallholder conditions in SSA.

The remainder of the paper is organized as follows. The data is described in Section 2 and the methodology is outlined in Section 3. Results are presented and discussed in Sections 4 and 5. Conclusions and policy implications are drawn in Section 6.

2. Data

The Ministry of Agriculture and Livestock (MAL) and the Central Statistical Office in Zambia collect the annual Crop Forecast Survey (CFS) data used in this study. The CFS data are high quality (particularly relative to other crop production data collected by SSA governments) and the surveys are conducted with technical support from Michigan State University and the Indaba Agricultural Policy Research Institute on the survey design, implementation, data entry, and data cleaning. Unlike many countries in SSA, Zambia's production estimates through the CFS are scientifically robust (Jayne and Rashid, 2010), and the CFS collects detailed farm production data.[6] The CFS is the most current and largest smallholder household survey in Zambia. The data are representative (of smallholder farm households) at the national, provincial, and district levels.[7] See GRZ (2011) and Ngoma et al. (2014) for details on the CFS sampling.

We use CFS data from nearly 48,000 maize plots for the period 2008–2011 (*i.e.*, the 2007/08 through 2010/11 agricultural years). During this period, the CFS was conducted in the same standard enumeration areas (SEAs) each year.[8] Data collected in the CFS include basic demographic information (household size, and the gender, age, and marital status of household members) and detailed information on crop production activities (area planted, input use, tillage method, whether land preparation was done before or during the rainy season, *etc.*). In the econometric analysis, we supplement the CFS data with dekadal (10 day period) rainfall data from 36 rainfall stations throughout the country from the Zambia Meteorological Department.

Some caveats with the CFS are in order. First, although the production-oriented CFS captures fairly limited socio-economic and demographic information (*i.e.*, the variables listed in the previous paragraph), it does capture detailed information on the most important maize yield determinants in the Zambian context.[9]

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[3] In particular, early planting facilitated by dry season land preparation improves crop yields (Nafziger, 1994). It also allows crops to benefit from the nitrogen flush in the soil that comes with the first few rains, a phenomenon also known as the "Birch effect" (Birch, 1964; Jarvis et al., 2007).

[4] It is also common under experimental plots for all plots to be planted at the same; a key contribution of the current study is that we consider the benefits of minimum tillage when it is done before *vs.* during the rains. The timing of tillage (and planting) could have major impacts on the yield effects of minimum tillage.

[5] Planting basins and ripping are tillage systems with minimal soil disturbance save for permanent planting stations—basins and rip lines, respectively. Basins are dug using manual labor while rip lines are made by animal draft or mechanical-drawn rippers, ideally soon after harvest when soils are still moist. Further, basins are often dug using Chaka hoes into precise grids of 15,850 basins per hectare (Haggblade and Tembo, 2003). However, some farmers use regular hand hoes to dig planting basins.

[6] This is one strength of the CFS data; as such, it is useful for answering our core research question.

[7] In Zambia, smallholder farm households are defined as those cultivating less than 20 ha of land.

[8] SEAs are the most disaggregated geographic unit in the dataset; each SEA contains approximately 100–150 households or 2–4 villages.

[9] Another general weakness of the CFS data is that it is a multipurpose survey rather than one that is specifically focused on MT. But as explained in the paper, CFS captures detailed production information to analyze MT effects.

Second, the CFS is done before harvest but after the majority of maize plants have reached physiological maturity. CFS production quantities are thus farmers' estimates of how much they expect to harvest (as opposed to recall data on actual quantities harvested). The claim of physiological maturity is based on the dates of CFS data collection, farmers' planting dates, and the length to maturity of maize varieties used by Zambian smallholders. More specifically, the CFS data used in the study were collected during the last two weeks of March and the first week of April each year (see GRZ, 2011).[10] Nearly half (47%) of all Zambian smallholders' maize fields are planted by mid-November, the vast majority (78%) are planted by the second week of December, and nearly all are planted by the end of December (CSO/MACO/FSRP, 2008; CSO/MAL/IAPRI, 2012). The early and medium maturing maize varieties that are prevalent in Zambia reach physiological maturity within 90–120 days (Mubanga, 2014). This information combined suggests that the vast majority of maize fields in Zambia would have reached physiological maturity by the time the CFS data were collected.[11] Additionally, comparisons of farmers' production estimates in the CFS to actual production quantities captured in post-harvest surveys suggest only small and non-systematic differences between expected and actual production (Zulu and Sitko, 2014). Despite all this, the CFS data are well suited to address the core research question of this study: what are the *ceteris paribus* effects of ripping and planting basins on maize yields in Zambia? This is because the CFS data provide the most up-to-date, widest and statistically representative coverage of smallholder farmers at national, provincial, and district levels in Zambia.[12]

We put the CFS data through a series of filters to prepare it for use in the analysis. Starting with 51,156 maize plots in panel SEAs between 2008 and 2011, we dropped 5% of the plots with seed rates exceeding 100 kg/ha. Of these, 0.08% did not report any seed used; 0.7% had yields greater than 8000 kg/ha; 0.4% and 0.1% had basal and/or top dressing application rates exceeding 400 kg/ha each; and two plots that were larger than 20 ha. These cutoff points were determined based on reasonable input use and yield rates in Zambia, and recommendations by MAL (GRZ, Undated).[13] Altogether, these changes resulted in the exclusion of 3197 maize plots (or 6.2% of the original sample), bringing the analytical sample to 47,959 total maize plots. This data filtering is within acceptable levels; for example, Sheahan et al. (2013) excluded 9.7% of maize plots from their original sample after implementing similar cutoffs for a study of the factors affecting maize yields in Kenya.

[10] This gives details about the CFS for 2010/11 season, which is similar to all other CFS surveys.

[11] Agronomists and CFS implementers from MAL also assured us that at least 90% of the maize crop would have reached physiological maturity by the time of the CFS data collection. They also indicated that they have not observed any systematic differences in physiological maturity between MT and non-MT plots at the time of CFS data collection (personal communications with a sales agronomist and a senior economist in MAL, April 2015). Moreover, at this point, farmers would also able to tell if there has been a crop failure.

[12] We use the CFS data instead of the Zambia Supplemental Survey (SS) household panel data because the SS data are more dated than the CFS (they cover the 1999/2000, 2002/03, and 2006/07 agricultural seasons), and unlike the CFS, the SS data are not representative at the district level. There are also major concerns about the quality of the MT data in the SS (personal communication with Steve Haggblade, April 2015). The CFS also better captures changes over time and space in the use of MT in the whole country beyond project sites because the CFS is annual and has a larger sample size (roughly 13,000 households) than the SS (roughly 4300 households). The tradeoff is that while the SS data would allow us to control for time-constant unobserved effects at the household level, the CFS data only allow us to control for such effects at the SEA level.

[13] The recommended maize seeding rate in Zambia is 20 kg/ha, and the recommended fertilizer application rates are 200 kg/ha each of basal and top dressing. Plots larger than 20 ha were excluded because these exceed the definition of a smallholder farmer (*i.e.*, those cultivating less than 20 ha of land).

3. Methodology

3.1. Conceptual framework

The main objective of this paper is to estimate the *ceteris paribus* effects of planting basins and ripping on smallholder maize yields in Zambia. This is accomplished through econometric estimation of a maize production function following Xu et al. (2009) and Burke (2012) for Zambia, and Sheahan et al. (2013) for Kenya. The general production function is specified as:

$$y = f(\boldsymbol{tillage}, \boldsymbol{X}, \boldsymbol{Z}) \tag{1}$$

where y is plot-level maize yield in kg/ha. ***tillage*** is a vector of dummy variables capturing the tillage method used on the plot (*i.e.*, planting basins, ripping, and various conventional tillage methods), and capturing the timing of when tillage was done (*i.e.*, before or during the rainy season). $\boldsymbol{X}$ is a vector of inputs controlled by the farmer (*e.g.*, use of hybrid seed, fertilizer application and seeding rates, labor quantity and quality, *etc.*); and $\boldsymbol{Z}$ is a vector of strictly exogenous yield determinants such as rainfall and other agro-ecological conditions (Burke, 2012). The specific variables included in ***tillage***, $\boldsymbol{X}$, and $\boldsymbol{Z}$ are discussed in detail in the next sub-section. A quadratic functional form is used for the production function in Eq. (1) because it generally approximates well the underlying data generating process of crop yields and is frequently used in analyses of crop yield response in developing countries (Xu et al., 2009; Burke, 2012; Sheahan et al., 2013).

3.2. Empirical model

Bringing Eq. (1) to the data, we specify the empirical model as:

$$y_{sij} = \boldsymbol{tillage}_{sij}\boldsymbol{\beta}_1 + \boldsymbol{X}_{sij}\boldsymbol{\beta}_2 + \boldsymbol{Z}_{sij}\boldsymbol{\beta}_3 + \boldsymbol{year}\boldsymbol{\beta}_4 + c_s + u_{sij}, \tag{2}$$

where y_{sij} is the maize yield in kg/ha in SEA s for household i on plot j.[14] ***tillage***, $\boldsymbol{X}$, and $\boldsymbol{Z}$ are defined as in Eq. (1) above; ***year*** is a vector of year dummies; c_s is unobserved time invariant SEA-level heterogeneity; u_{sij} is the idiosyncratic error term; and the $\boldsymbol{\beta}$s are parameters to be estimated.[15]

The specific explanatory variables included in the empirical models were selected based on previous studies on the determinants of smallholder maize yields in eastern and southern Africa (Xu et al., 2009; Burke, 2012; Sheahan et al., 2013), agronomic principles of maize production in Zambia, and data availability. Table 1 presents summary statistics for the variables used in the regressions. The dependent variable, plot-level maize yield, averaged 1797 kg/ha over the four-year study period.[16]

Included in ***tillage***, the vector of tillage-related variables, are separate dummy variables equal to one if the plot was tilled using planting basins, ripping, plowing, bunding, or ridging, and equal to zero otherwise.[17] The majority of maize plots were tilled using conventional tillage methods: 34%, 33%, and 28% were tilled by hand hoe, plowing, and ridging, respectively. About 2% of plots used bunding, and only 1% of plots each were tilled with ripping and planting basins (Table 1). Also included in ***tillage*** is a dummy equal to one if the plot was tilled before the onset of the rainy

[14] We have excluded time-subscripts to indicate the fact that the data are a panel at the SEA-level and not at the household- or plot-level.

[15] To keep the notation simple, we have also excluded the squared and interaction terms from Eq. (2) but they are included in the estimated models.

[16] Maize yields are in dry grain equivalent terms.

[17] Conventional hand hoe tillage is the base tillage method and therefore excluded from the regressions.

Table 1
Variables used in the econometric analysis.

Variable	Description	Mean	Std. dev.	Percentiles				
				10th	25th	50th	75th	90th
Dependent variable								
yield	Maize yield (kg/ha)	1797	1460	284	690	1420	2556	3904
Explanatory variables								
age_hh	Age of hh head (years)	43.84	14.45	27.00	32.00	41.00	53.00	65.00
sex_hh	Male hh head (=1)	0.79	0.41	0.00	1.00	1.00	1.00	1.00
p_married	Polygamously married (=1)	0.07	0.26	0.00	0.00	0.00	0.00	0.00
m_married	Monogamously married (=1)	0.70	0.46	0.00	0.00	1.00	1.00	1.00
adults	# adults 14–65 years	3.94	2.50	2.00	2.00	3.00	5.00	7.00
b_fert	Used basal fertilizer (=1)	0.43	0.50	0.00	0.00	0.00	1.00	1.00
tp_fert	Used top fertilizer (=1)	0.45	0.50	0.00	0.00	0.00	1.00	1.00
brate	Basal fertilizer rate (kg/ha)	60.50	87.38	0.00	0.00	0.00	100.00	200.00
tprate	Top dressing fertilizer rate (kg/ha)	62.74	87.46	0.00	0.00	0.00	123.46	200.00
seedingrate	Seed rate (kg/ha)	21.06	17.16	4.68	10.00	17.40	25.00	46.40
hyb_seed	Used hybrid seed (=1)	0.45	0.50	0.00	0.00	0.00	1.00	1.00
aez3	AEZ 3 (=1)	0.34	0.47	0.00	0.00	0.00	1.00	1.00
aez2a	AEZ 2a (=1)	0.48	0.50	0.00	0.00	0.00	1.00	1.00
aez2b	AEZ 2b (=1)	0.07	0.25	0.00	0.00	0.00	0.00	0.00
aez1	AEZ 1 (=1)	0.11	0.31	0.00	0.00	0.00	0.00	1.00
rain	Season rainfall (mm)	1020	339	666	792	982	1172	1329
rain_stress	Rainfall season stress periods (#)	1.03	1.24	0.00	0.00	1.00	2.00	3.00
plot_size	Plot size (ha)	0.93	1.05	0.25	0.38	0.60	1.00	2.00
t_till	Tillage before rains (=1)	0.30	0.46	0.00	0.00	0.00	1.00	1.00
bund	Used bunding (=1)	0.02	0.14	0.00	0.00	0.00	0.00	0.00
ridge	Used ridging (=1)	0.28	0.45	0.00	0.00	0.00	1.00	1.00
pl_basins	Used planting basins (=1)	0.01	0.12	0.00	0.00	0.00	0.00	0.00
ripping	Used ripping (=1)	0.01	0.08	0.00	0.00	0.00	0.00	0.00
plow	Used plowing (=1)	0.33	0.47	0.00	0.00	0.00	1.00	1.00
hhoe	Used hand hoe (=1)	0.34	0.46	0.00	0.00	0.00	1.00	1.00

N = 47,959.

season, and equal to zero if it was tilled during the rainy season. Overall, 30% of the plots in the sample were tilled before the rains (Table 1). Among the main tillage methods of interest, 52% and 28% of planting basins and ripped plots, respectively, were tilled before the rains, whereas 43% and 12% of hand hoed and plowed plots, respectively, were tilled before the rains. To capture potential differential effects of tillage method on yields depending on when tillage is done, we interact the tillage method dummies with the tillage-before-the-rains dummy.

Included in $\boldsymbol{X}$, the vector of other yield determinants under the control of the farmer, are basal and top dressing inorganic compound fertilizer application rates (kg/ha), whether hybrid maize seed was used (=1), and the seeding rate for all types of seed (kg/ha).[18] On average, households used 61 kg/ha of basal dressing, 63 kg/ha of top dressing, and 21 kg/ha of maize seed. Overall, basal and/or top dressing fertilizer was used on 46% of the plots in the sample, and hybrid seed was used on 45% of the plots. *A priori*, increases in the fertilizer and seed application rates are expected to increase maize yields up to a point, beyond which decreasing marginal returns are likely to set in. The quadratic functional form allows for such effects. Our models include interactions between basal and top dressing fertilizer to capture the effects of combined fertilizer application.

Also included in $\boldsymbol{X}$ are the area of the plot (ha), and proxies for household labor quantity and quality. These include the number of adults aged 15–65 in the household (3.94 on average), and the age of the household head (44 years on average). Older household heads may have more farming experience but may be less amenable to new management practices such as MT. The labor-related variables also include a dummy equal to one if the household is male-headed (79% of the sample), and dummies for whether the household head is monogamously married (70%) or polygamously married (7%). We hypothesize that households with heads that are polygamously married might have more family labor available for maize production than households with monogamously married heads. Households with married heads might have more family labor available than households with unmarried heads. The CFS data do not consistently capture information on labor input to maize production, so we use the marital status variables and number of adults as proxies.

Included in $\boldsymbol{Z}$, the vector of strictly exogenous yield determinants, are growing season (November–March) rainfall in millimeters and rainfall stress measured as the number of 20-day periods during the growing season with less than 40 mm of rainfall. The former is expected to increase yields up to a point, while the latter is expected to reduce yields. We also control for different soil and rainfall conditions by including dummies for AEZs 2a, 2b, and 3 (with AEZ 1 serving as the base).[19,20] Year dummies (***year*** in Eq. (2)) are included in the empirical model to control for year-specific yield effects.

[18] The fertilizer rates refer to kg of fertilizer aggregated across various types of basal and top dressing fertilizers, respectively. The survey asked farmers, in separate questions, the kg of basal dressing and top dressing applied to each field, and the sizes of each field were also collected. The basal and top dressing application rates in kg/ha, were calculated using these data. These rates are based on compound fertilizers. The survey did not collect the fertilizer type information for the 2008 survey, so we are unable to convert the kg of fertilizer to kg of nutrients.

[19] There are four AEZs in Zambia: AEZ 1 receives less than 800 mm rainfall per year; AEZ 2a has clay soils with 800–1000 mm rainfall per year; AEZ 2b has sandy soils with 800–1000 mm rainfall per year; and AEZ 3 receives more than 1000 mm of rainfall per year.

[20] We also control for soil and other agro-ecological conditions at the SEA-level via the correlated random effects approach, which controls for time-constant unobserved effects in a household's SEA and is discussed further below.

Due to data limitations, we are not able to explicitly control for when plots were planted, the number of times a plot was weeded, whether or not the plot was irrigated, or whether herbicides, lime, or manure, were used on the plot. We are also unable to distinguish between plots that retained crop residues or were in cereal–legume rotation, and those that did not. As the timing of planting and of tillage are highly correlated, the timing of tillage dummy that is included in the models essentially controls for both the timing of tillage and for whether planting was done relatively early or relatively late. The labor quantity-related variables included in the models serve as proxies for the number of weedings. Moreover, data from a cross-sectional, nationally representative survey suggest that crop residue retention, crop rotation, and herbicides were used on only 0.4%, 0.2%, and 0.4%, respectively, of ripped maize plots. Further, these practices were only used on only 0.2%, 0.3% and 0.1%, respectively, of planting basins plots (CSO/MAL/IAPRI, 2012). In addition, ripping and basin tillage were only weakly correlated (rho < 0.20) with use of these practices at plot level (CSO/MAL/IAPRI, 2012). Thus, although these practices may have important effects on yields, their omission should not bias our results because they are largely uncorrelated with the MT variables (or other variables in our models).

We also do not observe in the CFS data the number of years that a given plot has been under planting basins or ripping. Thus, our estimates of the effects of these tillage methods on maize yields should be interpreted as averages for plots currently under the tillage method.

3.3. Estimation strategy

The empirical model is linear in parameters and is estimated via pooled ordinary least squares with standard errors clustered at the SEA level. We estimate models using all observations (national-level model) as well as models using only observations from AEZs 1 and 2a (where CA has been most heavily promoted in Zambia and is arguably most suitable).

The major econometric challenge in estimating the causal effects of planting basins and ripping on maize yields is the potential endogeneity of farmers' tillage method choices. Tillage methods are not randomly assigned to households or plots, and there may be systematic correlation between farmers' use of planting basins and ripping (and other tillage methods and inputs) and unobserved factors affecting maize yields. For example, farmers that are more motivated or progressive, or have greater farming skill or management ability, may be more likely to adopt planting basins or ripping, but would likely have higher yields than other farmers even if they used conventional tillage methods (we use the age and gender of the household head to proxy for these factors).[21] As a second example, use of MT on a given plot could be correlated with unobserved plot-level factors such as soil quality that also affect yields. To address these concerns, we control for as many observed plot- and household-level maize yield determinants as possible given the available data. We take advantage of the SEA-level panel structure of the data to address this potential endogeneity by controlling for time invariant SEA-level heterogeneity (c_s) with a correlated random effects (CRE) approach. We also use an instrumental variables/control function approach to test for remaining endogeneity of planting basins and ripping even after controlling for c_s. These two approaches are described in the next two sub-sections.

[21] Other measures of progressive farmers like wealth would be important but we do not have such variables in our data and hence we use proxies that are commonly used in the literature.

3.3.1. Controlling for SEA-level unobserved heterogeneity using correlated random effects (CRE)

We use a Mundlak–Chamberlain device/CRE approach to control for c_s (Mundlak, 1978; Chamberlain, 1984).[22] For simplicity, let $\boldsymbol{W}_{sij}$ represent all the time-varying covariates in Eq. (2), where s, i, and j index the SEA, household, and plot, respectively. Under the CRE approach, c_s is assumed to be a function of $\overline{\boldsymbol{W}}_s$, the SEA-level averages (across all time periods, households, and plots) of the time-varying covariates, such that:

$$c_s = \psi + \overline{\boldsymbol{W}}_s \xi + a_s \quad (3)$$

where $c_s | \boldsymbol{W}_s \sim Normal(\psi + \overline{\boldsymbol{W}}_s \xi, \sigma_a^2)$, σ_a^2 is the conditional variance of a_s, and ψ and ξ are parameters. Under these assumptions and strict exogeneity, we can control for c_s by including the SEA-level averages, $\overline{\boldsymbol{W}}_s$, as additional regressors in Eq. (2).[23] See Wooldridge (2010) for further details on the use of the CRE approach to control for time invariant unobserved heterogeneity.

3.3.2. Testing for remaining endogeneity of minimum tillage choices

Although the CRE approach controls for correlation between the unobserved time-invariant SEA-level heterogeneity (c_s) and observables affecting maize yields, there could still may be correlation between the farmer's choice of tillage method and timing (***tillage***) or input use decisions ($\boldsymbol{X}$), and the idiosyncratic error term (u_{sij}). This is a common challenge in production function estimation because most right-hand-side variables are choice variables. Some authors fully acknowledge this potential endogeneity, possibly use CRE, and move on (*e.g.*, Xu et al., 2009; Sheahan et al., 2013). Others try to go further and combine the CRE approach with instrumental variables or control function techniques to test and control for the endogeneity of the key covariate(s) of interest (*e.g.*, Burke (2012) for inorganic fertilizer). We attempted to use a control function approach (Wooldridge, 2010) and instrumented for a farmer's use of planting basins with a dummy variable equal to one if the household is in a district where the Conservation Farming Unit (CFU) of the Zambia National Farmers' Union has promoted CA and equal to zero otherwise.[24] We instrumented for ripping using a dummy variable equal to one if the household is in a district where Dunavant Cotton (now NWK Agri-Services Zambia) has promoted CA and equal to zero otherwise. *A priori*, where the CFU and Dunavant choose to promote CA should be exogenous to plot-level yields after controlling for observed input use levels ($\boldsymbol{X}$), other observed factors ($\boldsymbol{Z}$), and SEA-level time invariant unobserved heterogeneity (which would capture things like soil quality, agronomic potential, and agro-ecological conditions in the SEA). CA promotion by CFU and Dunavant is likely to affect a farmer's decision to use planting basins or ripping but is unlikely to be correlated with the idiosyncratic plot-level error term in the yield function. Unfortunately, these instrumental variables (IVs) were only weakly correlated with farmer's use of planting basins and ripping

[22] While a fixed effects (FE) approach would also have been possible, a CRE approach is generally preferred when using meso-panel data with time-varying sampling weights, as in the current application (personal communication, J. Wooldridge, June 2014). Nonetheless, as a robustness check, we estimated the models without sampling weights using both FE and CRE approaches and the results are very similar. Note that both the FE and CRE approaches allow the unobserved time invariant heterogeneity and the observed covariates to be correlated. This is a key difference between the CRE and 'regular' random effects approaches.

[23] As an example, the SEA-level average of the planting basins dummy would be the proportion of maize plots in the SEA under planting basins over the 2008–2011 study period.

[24] Household- or plot-level IVs would have been better but no such IVs are available.

(0.05 < *p* < 0.10); moreover, the control function results suggested that ripping and planting basin use decisions are exogenous to maize yields.[25] As such, and to avoid the bias and inconsistency associated with using weak IVs (Cameron and Trivedi, 2010), we did not pursue this approach further.

4. Results

4.1. Descriptive results

As a prelude to the econometric results of the paper, we used bivariate mean comparisons to test for any systematic differences between MT and non-MT plots in terms of maize yields and the main covariates used in the econometric analysis. Results (in Supplementary Table S1) show no statistically significant difference between yields on MT and non-MT plots.[26] Among the explanatory variables, the only statistically significant difference in means between MT and non-MT plots was for the percentage of male-headed households, which was significantly higher for MT plots (83%) than for non-MT plots (79%).

As a second descriptive approach, we follow Tatwangire (2011) and check for first order stochastic dominance to assess maize yield differences between planting basins and hand-hoed plots, and ripped and plowed plots. Results in Fig. 1 are the cumulative distribution functions (CDFs) for maize yield under each of these tillage methods. The CDFs for ripping and plowing cross at some points, as do the CDFs for planting basins and hand-hoeing. Thus, there is no first order stochastic dominance of conventional *vs.* minimum tillage in either case, *i.e.*, not all farmers would prefer conventional tillage *vs.* its MT variant on the basis of expected yield alone.

Since these descriptive analyses do not control for other factors that could be correlated with both MT adoption and yields, we cannot draw conclusions from them about the causal effects of MT on yields. For this, we turn to the econometric (multivariate) results.

4.2. Econometric results

We estimated three different specifications of the model in Eq. (2). The first specification (spec.1) excludes interaction and squared terms. The second specification (spec.2) includes interactions and squared terms for many of the variables but excludes interactions between the tillage method dummies and fertilizer rates. The third specification (spec.3) is similar to spec.2 but includes tillage–fertilizer interactions. The results are robust to alternative model specifications, so unless otherwise stated, we focus our discussions below on spec.3, the most fully elaborated model. Table 2 shows average partial effects (APEs) from the econometric models while Table S2 in the online Supplementary materials presents the coefficient estimates. Each table reports the results from the national and AEZs 1/2a models.[27]

4.2.1. Effects of planting basins on maize yields

The APEs in Table 2 suggest that, on average, maize yields on plots using planting basins are not statistically different from the yields on plots using conventional hand hoe tillage, *ceteris paribus*.

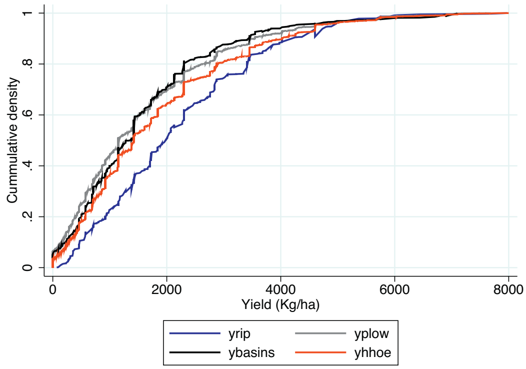

Fig. 1. Cumulative distribution functions of smallholder farmer yields by basin, hand hoe, plow and rip tillage between 2008 and 2011 in Zambia.

Nevertheless, we find positive and significant yield effects when basin tillage is done before the rains (Table S2). For example, the yield boost from planting basins over conventional hand-hoe tillage is 371 kg/ha larger when tillage is done before rather than during the rains. A similar result holds for the AEZs 1/2a model.

The simulated average marginal effect of planting basins on maize yields (compared to conventional hand-hoeing) in panel A of Table 3 suggest average yield gains of 191–194 kg/ha when tillage is done before the rains. This result is significant at the 10% level in the national results but only weakly significant in AEZs 1/2a (*p* = 0.17). However, yields are 179 kg/ha and 168 kg/ha *lower* on average on planting basin plots than on hand-hoed plots in the national-level and AEZs 1/2a models, respectively, when tillage is done *during* the rains (Table 3, panel A).

4.2.2. Effects of ripping on maize yields

The APEs in Table 2 suggest significant and positive ripping effects on maize yields after controlling for other factors. Overall, at national level and in AEZs 1/2a respectively, maize yields on ripped plots are 238 kg/ha and 332 kg/ha higher, on average, than yields on plowed plots (Table 2). However, when disaggregated by timing of tillage, the results in panel B of Table 3 show that yields on ripped fields are 577–821 kg/ha higher on average than on plowed fields when tillage is done before the rains, *ceteris paribus*. This result is highly significant (*p* < 0.01) in both the national and AEZs 1/2a models, and the ripping benefits are larger in AEZs 1 and 2a than for Zambia overall (Table 3). There are no statistically significant differences between yields on ripped and plowed plots when tillage is done during the rainy season.

4.2.3. Other maize yield determinants

Results for other yield determinants in Eq. (2) are generally consistent with *a priori* expectations. Using hybrid maize seed significantly increases maize yields by an average of 146 kg/ha and 135 kg/ha at national level and in AEZs 1/2a, respectively (Table 2). Additionally, maize yield increases by an average of 4 kg/ha and 5 kg/ha per additional kg/ha of basal and top dressing fertilizer, respectively (Table 2). We also find a negative plot size–productivity relationship among smallholder farmers in Zambia. Increasing plot area by one hectare significantly reduces maize yields by an average of 40 and 44 kg/ha at national level and in AEZs 1/2a, respectively. Additionally, all else constant, an increase in the number of rainfall stress periods significantly reduces maize yields by an average of 40 kg/ha at national level.

[25] These results are available from the authors upon request.

[26] Throughout the paper and unless otherwise specified, we use *p* < 0.10 as the cutoff of statistical significance.

[27] Because of the large number of interactions and squared terms included in spec.2 and spec.3, caution must be exercised when interpreting individual coefficient estimates in Table S2. For example, the overall effect of the basal dressing fertilizer application rate on maize yield is the APE reported in Table 2 and not simply the coefficient on brate reported in Table S2.

Table 2
Maize production function average partial effect (APE) estimates (dependent variable: maize yield in kg/ha).

Variables	National			Agro-ecological zones 1 and 2a		
	Spec.1	Spec.2	Spec.3	Spec.1	Spec.2	Spec.3
Planting basins (yes = 1)	−41.417 (69.421)	−109.654 (70.607)	−112.264 (75.249)	−5.561 (74.999)	−83.107 (68.546)	−73.763 (71.244)
Ripping (yes = 1)	186.190* (110.531)	187.298* (107.872)	233.789** (108.591)	276.028** (139.718)	266.637** (134.146)	329.941** (135.323)
Plowing (yes = 1)	−0.212 (29.216)	−6.720 (29.653)	−4.457 (30.078)	5.162 (36.964)	−6.893 (38.343)	−1.808 (39.095)
Bunding (yes = 1)	178.598** (85.104)	144.869 (91.881)	77.369 (92.889)	496.252*** (148.980)	463.384*** (149.626)	459.146*** (140.091)
Ridging (yes = 1)	114.475*** (27.539)	103.386*** (27.959)	98.295*** (27.862)	115.305*** (37.262)	98.279** (38.744)	100.875** (39.837)
Tillage before rains (yes = 1)	−22.486 (21.171)	−24.298 (22.812)	−24.450 (22.732)	36.195 (29.686)	19.623 (33.435)	20.203 (33.374)
Hybrid seed (yes = 1)	180.629*** (22.693)	147.735*** (23.034)	146.055*** (22.985)	158.678*** (29.072)	137.000*** (29.854)	134.754*** (29.824)
Seeding rate (kg/ha)	1.879*** (0.557)	0.691 (0.939)	0.749 (0.935)	1.946*** (0.675)	0.583 (1.172)	0.706 (1.161)
Basal fertilizer rate (kg/ha)	3.128*** (0.328)	4.072*** (0.386)	4.113*** (0.382)	3.180*** (0.383)	3.868*** (0.459)	3.922*** (0.447)
Top dress. fertilizer rate (kg/ha)	4.832*** (0.320)	4.927*** (0.389)	4.822*** (0.387)	4.962*** (0.369)	5.162*** (0.478)	5.047*** (0.470)
Plot size (ha)	−12.730 (9.187)	−39.094*** (13.037)	−39.636*** (12.998)	−13.270 (11.390)	−42.975*** (16.551)	−43.947*** (16.526)
Growing season rainfall (mm)	0.001 (0.106)	−0.008 (0.108)	−0.009 (0.108)	0.014 (0.145)	0.017 (0.147)	0.011 (0.148)
Rainfall season stress periods (#)	−30.277* (15.913)	−40.335** (19.994)	−40.213** (19.917)	9.666 (19.554)	0.146 (23.420)	−1.978 (23.455)
Male head (yes = 1)	37.179 (29.562)	45.866 (29.683)	44.331 (29.664)	17.066 (40.368)	22.335 (40.383)	19.409 (40.330)
Age of hh head (years)	−0.290 (0.550)	0.993 (0.717)	0.970 (0.717)	−0.789 (0.753)	−0.080 (1.010)	−0.151 (1.007)
Polygamously married (yes = 1)	44.937 (39.070)	42.823 (39.117)	41.631 (39.106)	54.684 (48.425)	51.440 (48.439)	50.420 (48.369)
Monogamously married (yes = 1)	20.046 (28.883)	20.514 (29.119)	20.893 (29.056)	31.095 (38.584)	33.561 (38.818)	34.286 (38.711)
Number of adults (15–65 years)	−0.733 (3.995)	−3.044 (5.178)	−2.933 (5.128)	−2.487 (4.914)	−3.984 (6.721)	−3.819 (6.617)
2009 year (yes = 1)	252.316*** (40.945)	237.026*** (40.979)	239.449*** (40.921)	377.950*** (51.572)	367.354*** (52.882)	370.649*** (52.394)
2010 year (yes = 1)	565.090*** (46.990)	541.306*** (48.263)	543.539*** (48.302)	792.754*** (67.339)	779.171*** (70.312)	776.082*** (70.444)
2011 year (yes = 1)	533.487*** (42.154)	519.053*** (41.840)	519.221*** (41.439)	576.920*** (58.691)	577.220*** (58.404)	581.136*** (57.552)
AEZ 2a (yes = 1)	17.997 (50.775)	45.055 (54.239)	59.577 (54.045)			
AEZ 2b (yes = 1)	15.609 (67.342)	15.716 (77.257)	−21.610 (76.277)			
AEZ 3 (yes = 1)	355.503*** (63.136)	345.079*** (65.732)	334.802*** (63.375)			
Observations	47,838	47,838	47,838	25,808	25,808	25,808

Standard errors clustered at the SEA level in parentheses; ***, **, * statistically significant at 1%, 5% and 10%, respectively; base tillage method, base year, and base agro-ecological zone are conventional hand hoe, 2008, and AEZ 1, respectively.

5. Discussion

Our findings that combining MT with early land preparation (early planting) boosts yields are consistent with the CA literature (Haggblade et al., 2011), and with farmer experiences as reported during focus group discussions in Ngoma et al. (2014). The finding that the yield benefits of ripping over plowing (when tillage is done before the rains) are greater in AEZs 1 and 2a (821 kg/ha) than in Zambia overall (577 kg/ha) (Table 3) is consistent with the finding that CA is more beneficial in lower rainfall regions in SSA in general (Rusinamhodzi et al., 2011; Nyamangara et al., 2014b; Rusinamhodzi, 2015a), and in Zambia specifically (Haggblade and Tembo, 2003).[28] Further, our overall findings of higher yield benefits with planting basin and rip tillage before the rainy season is consistent with the notion that early land preparation under MT facilitates early planting which improves yields.

Additionally, our econometric results for ripping corroborate bivariate findings in (Umar et al., 2011, 2012; Thierfelder et al., 2013), who also found positive yield benefits from ripping relative to conventional plowing. However, our results are contrary to those in Nyamangara et al. (2014b) who found no positive yield advantage from ripping on experimental plots in Zimbabwe. Additionally, our positive results for fertilizer application rate and hybrid seed use corroborate those in (Xu et al., 2009; Burke, 2012) for Zambia, and in Sheahan et al. (2013) for Kenya. Moreover, the negative yield effects of increasing rainfall stress and varying tillage yield effects by AEZ bring to light the need to adapt agricultural systems to varying edaphic and climatic conditions as suggested in Chabala et al. (2013) and Rusinamhodzi (2015a). These results also corroborate findings in Lobell et al. (2008) who project that yields in SSA will decline by 30% owing to climate variability.[29]

Our results are somewhat different from those in Haggblade and Tembo (2003), who find positive planting basin effects but no ripping effects on yields. In addition, our econometric results for basin tillage are contrary to Rusinamhodzi (2015b) who found no yield gains under basin tillage. However, these results are in line with Umar et al. (2011) who found higher maize yields on basin plots compared to hand hoe tilled plots.

There are a number of plausible explanations for the different MT yield effects in this paper and others. First, it may be due to omission of key interaction terms of all tillage options, timing of tillage, and fertilizer application rates in Haggblade and Tembo (2003), and the failure to control for other yield determinants in studies that use bivariate mean comparisons. Second, how MT adoption or use is defined, and whether planting basins and ripping are combined into a single "MT" variable or disaggregated, could also explain some of the differences in findings. Third, the different knowledge intensities associated with ripping and basin tillage operations directly influences how well smallholders can use these practices. For example, planting basins have to be dug to specific dimensions using hand hoes and few farmers manage to follow the specifications to the letter as was found in Umar et al. (2012), Haggblade and Tembo (2003) and Ngoma et al. (2014).

Our results of no statistically significant yield benefits from planting basins and ripping if tillage is done during the rainy season could be explained by the following. First, it may be difficult for farmers to dig basins and get rip lines to the required dimensions during the rainy season especially under waterlogged conditions and in clay loamy soils. This directly affects plant populations and input use. Second, basins and ripping tillage done

[28] The planting basins effects in Table 3 for tillage before the rains at national level *vs.* AEZs 1 and 2A are not statistically different from each other.

[29] We tested for interaction effects between minimum tillage methods and the rainfall stress variable but found no statistically significant effects.

Table 3
Average marginal effects on yields of planting basins *vs.* hand hoe tillage, and ripping *vs.* plowing, by timing of tillage (based on spec.3 in Table S2).

Panel A: simulated average yield differences (kg/ha) for planting basins (compared to hand hoe tillage) for tillage done before *vs.* during the rains[a]

	Tillage before the rains		Tillage during the rains	
	Marginal effect	*t*-stat.	Marginal effect	*t*-stat.
National results	191.45*	1.71	−179.25**	−2.21
AEZs 1 and 2a results	194.01	1.42	−168.41*	−1.88

Panel B: simulated average yield differences (kg/ha) for ripping (compared to plowing) for tillage done before *vs.* during the rains, and with average inorganic fertilizer[b]

	Tillage before the rains		Tillage during the rains	
	Marginal effect	*t*-stat.	Marginal effect	*t*-stat.
National results	576.54***	2.96	95.79	0.77
AEZs 1 and 2a results	820.94***	3.30	167.77	1.11

***, **, * statistically significant at 1%, 5% and 10%, respectively.
[a] The planting basins-fertilizer application rate interaction effects are *not* statistically significant in spec.3, and so are set to zero in these simulations.
[b] The ripping-fertilizer application rate interaction effects *are* statistically significant in spec.3; the marginal effects of ripping *vs.* plowing in the table above are evaluated at the average basal and top dressing fertilizer rates in the sample (61 kg/ha basal and 63 kg/ha top dressing in the national model, and 56 and 59 kg/ha, respectively, in the AEZs 1 and 2a models).

after the onset of the rainy season may lead to late planting which negatively affects yields (Nafziger, 1994), and crops cannot benefit from the nitrogen flush in early rains (Birch, 1964; Jarvis et al., 2007). Third, farmers may prefer conventional hand hoe and plow tillage to basins and ripping, respectively, when tillage is done after the onset of the rains because conventional tillage also helps to clear all emerging weeds by complete soil inversion. Fourth, late digging of basins and ripping in the rainy season may be indicative of labor and animal draft power shortages and low management levels overall.[30]

Given the main results of the paper that both ripping and planting basins confer maize yield advantages (if tillage is done before the onset of the rains), it remains unclear why so few farmers are adopting MT in Zambia. This is a critical question, but one that is beyond the scope of this paper. Future research is needed to establish whether the yield gains associated with ripping and planting basins done before the rains are large enough to offset the potentially higher costs associated with MT. It would be also instructive to look at the yield effects of the other CA components not covered in this paper.

6. Conclusions and policy implications

This paper sought to estimate the *ceteris paribus* effects of ripping and basin tillage on maize yields under typical smallholder conditions in Zambia. We controlled for time invariant unobserved heterogeneity at the enumeration area level using the correlated random effects-pooled ordinary least squares estimator applied to nationally representative household survey data. We find positive maize yield gains from ripping and basin tillage relative to plowing and hand hoe, respectively, only if tillage is done before the rainy season. Other important yield determinants include use of hybrid maize seed and application rates for inorganic fertilizer.

On average, rip tillage conferred yield gains of 577–821 kg/ha over conventional plow tillage when tillage was done before the rainy season, and the gains were higher in the lower rainfall agro-ecological zones 1 and 2a. Basins tillage conferred average yield gains of 191–194 kg/ha over conventional hand-hoe tillage when tillage was done before the rainy season. These results reinforce the importance of early land preparation (and planting) to maize productivity and highlight the overall potential significance of minimum tillage to improving smallholder productivity in Zambia and the region.

Given the main findings of the paper that minimum tillage can boost yields over conventional tillage methods *if tillage is done before the onset of the rains*, there is need to emphasize early land preparation and planting in extension messaging about ripping and planting basins, and to demonstrate the potential benefits where the technologies are appropriate. Finally, given the larger yield benefits of ripping over conventional plowing (compared to the yield benefits of planting basins over conventional hand-hoeing), policies and programs to improve the availability and accessibility of rippers and ripping services could play a key role in boosting smallholders' maize yields in Zambia.

[30] We thank an anonymous reviewer for suggesting that we add this fourth factor.

Acknowledgements

The authors are grateful to USAID/Zambia mission through the Food Security Research Project III and Indaba Agricultural Policy Research Institute for financing this study. The first author also acknowledges funding from CIFOR through the REDD+ project at NMBU. We thank two anonymous referees for providing insightful feedback on the manuscript. Further, we wish to thank Arild Angelsen, Steve Haggblade, and Antony Chapoto for incisive comments on an earlier draft. All errors and omissions remain the authors'.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agee.2015.06.021.

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Does minimum tillage with planting basins or ripping raise maize yields? Meso-panel data evidence from Zambia

Hambulo Ngoma, Nicole M. Mason and Nicholas Sitko

Online Appendix Tables

Table S1: Bivariate mean comparisons of key variables between minimum tillage plots and non-minimum tillage plots between 2008 and 2011

		Used minimum tillage on plot		
Variable	**Description**	**No**	**Yes**	**p-value**
yield	Maize yield (Kg/ha)	1796.99	1772.97	0.701
plot_size	Plot size in ha	0.93	0.95	0.568
age_hh	Age of hh head	43.85	43.58	0.685
sex_hh	Male hh *(yes=1)*	0.79	0.83	0.015
adults	Number of adults per hh	3.95	3.81	0.204
p_married	Polygamously married	0.07	0.08	0.416
m_married	Monogamously married	0.70	0.73	0.140
b_fert	Used basal mineral fertlizer	0.43	0.42	0.810
tp_fert	Used top mineral fertilizer	0.45	0.46	0.762
brate	Basal fertilizer rate (kg/ha)	60.50	60.38	0.976
tprate	Top fertilizer rate (kg/ha)	62.70	64.28	0.710
hyb_seed	Used hybrid maize seed	0.45	0.46	0.651
seedingrate	Seeding rate (kg/ha)	21.07	20.75	0.648
rain	Growing season rainfall	1019.83	1052.00	0.110
rain_stress	# of 20 day periods with < 40mm	1.02	1.07	0.431

Source: Authors' computations from CFS 2008-2011

Table S2: Maize production function coefficient estimates (dependent variable: maize yield in kg/ha)

	National			Agro-ecological zones 1 and 2a		
Variables	**Spec.1**	**Spec.2**	**Spec.3**	**Spec.1**	**Spec.2**	**Spec.3**
pl_basins (yes=1)	-41.417	-219.272**	-179.267**	-5.561	-173.561**	-168.406*
	(69.421)	(88.663)	(81.090)	(74.999)	(78.004)	(92.194)
ripping (yes=1)	186.190*	19.951	300.786*	276.028**	64.596	398.131**
	(110.531)	(123.169)	(159.691)	(139.718)	(150.042)	(195.024)
plow (yes=1)	-0.212	-13.468	-13.894	5.162	-3.952	-6.192
	(29.216)	(34.250)	(37.299)	(36.964)	(44.715)	(46.130)
bunding (yes=1)	178.598**	174.062**	206.237**	496.252***	479.996***	476.441***
	(85.104)	(85.666)	(96.982)	(148.980)	(163.688)	(181.034)
ridging (yes=1)	114.475***	92.440***	48.806	115.305***	73.874	17.483
	(27.539)	(32.260)	(36.803)	(37.262)	(45.202)	(48.702)
Tillage before rains (yes=1)	-22.486	-48.624	-50.218*	36.195	-5.798	-7.076
	(21.171)	(29.799)	(29.858)	(29.686)	(44.098)	(44.090)
basins#tillage before rains		369.755***	370.717***		360.296***	362.414***
		(125.448)	(124.623)		(135.027)	(136.802)

ripping#tillage before rains		564.484**	503.349**		804.773***	642.958**
		(238.307)	(219.160)		(302.363)	(280.045)
plowing#tillage before rains		22.761	22.593		-11.713	-10.217
		(59.664)	(59.638)		(75.867)	(75.727)
bunding#tillage before rains		-98.473	-68.607		-66.169	-65.300
		(201.193)	(200.207)		(240.151)	(245.552)
ridging#tillage before rains		36.924	41.291		97.210	108.449
		(44.243)	(44.267)		(66.885)	(66.177)
hybrid seed (yes=1)	180.629***	103.917***	102.729***	158.678***	87.756**	86.129*
	(22.693)	(34.050)	(34.051)	(29.072)	(43.980)	(43.980)
Seeding rate (kg/ha)	1.879***	-3.338**	-3.273**	1.946***	-3.799*	-3.560
	(0.557)	(1.614)	(1.632)	(0.675)	(2.170)	(2.176)
seedingrate#seedingrate		0.014	0.012		0.022	0.019
		(0.019)	(0.019)		(0.025)	(0.025)
hybridseed#c.seedingrate		2.081*	2.057*		2.086	2.060
		(1.164)	(1.167)		(1.352)	(1.352)
basal fert use rate (kg/ha)	3.128***	4.505***	4.518***	3.180***	3.998***	3.490***
	(0.328)	(0.634)	(0.735)	(0.383)	(0.773)	(1.023)
brate#brate		-0.009***	-0.009***		-0.008**	-0.007**
		(0.003)	(0.003)		(0.004)	(0.004)
top fert use rate (kg/ha)	4.832***	4.455***	4.204***	4.962***	4.687***	4.821***
	(0.320)	(0.641)	(0.745)	(0.369)	(0.790)	(1.033)
tprate#tprate		-0.001	0.000		-0.001	0.000
		(0.003)	(0.003)		(0.003)	(0.003)
brate#tprate		0.003	0.002		0.003	0.002
		(0.003)	(0.003)		(0.004)	(0.004)
brate#seedingrate		0.023	0.028*		0.022	0.023
		(0.016)	(0.016)		(0.018)	(0.019)
tprate#seedingrate		0.018	0.014		0.019	0.019
		(0.016)	(0.016)		(0.019)	(0.020)
basins#brate			0.611			2.509
			(1.516)			(1.611)
basins#tprate			-1.273			-2.327
			(1.250)			(1.460)
ripping#brate			6.002**			5.491**
			(2.798)			(2.713)
ripping#tprate			-9.233***			-9.149***
			(2.899)			(2.907)
plowing#brate			-0.774			0.178
			(0.693)			(0.942)
plowing#tprate			0.790			-0.051
			(0.678)			(0.903)
bunding#brate			-1.378			-0.153
			(3.694)			(3.856)
bunding#tprate			-0.401			0.130
			(3.143)			(3.616)
ridge#brate			0.731			2.075*
			(0.743)			(1.162)
ridge#tprate			-0.111			-1.017
			(0.731)			(1.101)

plot size in ha	-12.730	-49.434***	-50.115***	-13.270	-56.414***	-57.530***
	(9.187)	(15.250)	(15.206)	(11.390)	(19.961)	(19.913)
plot size#plot size		5.576***	5.651***		6.294***	6.361***
		(1.548)	(1.550)		(2.013)	(2.006)
Growing season rainfall (mm)	0.001	0.010	0.000	0.014	-0.122	-0.125
	(0.106)	(0.257)	(0.258)	(0.145)	(0.284)	(0.287)
rain#rain		-0.000	-0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
# of 20 day periods with < 40mm rainfall	-30.277*	-49.810	-49.719	9.666	-16.341	-19.754
	(15.913)	(31.428)	(31.270)	(19.554)	(40.564)	(40.365)
rain stress#rain stress		4.623	4.637		5.931	6.394
		(7.388)	(7.354)		(8.368)	(8.304)
Male head (yes=1)	37.179	45.866	44.331	17.066	22.335	19.409
	(29.562)	(29.683)	(29.664)	(40.368)	(40.383)	(40.330)
Age of hh head (years)	-0.290	9.714***	9.548***	-0.789	4.255	3.803
	(0.550)	(3.422)	(3.419)	(0.753)	(4.610)	(4.597)
Age#age		-0.099***	-0.098***		-0.050	-0.045
		(0.033)	(0.033)		(0.044)	(0.044)
Polygamously married (yes=1)	44.937	42.823	41.631	54.684	51.440	50.420
	(39.070)	(39.117)	(39.106)	(48.425)	(48.439)	(48.369)
Monogamously married (yes=1)	20.046	20.514	20.893	31.095	33.561	34.286
	(28.883)	(29.119)	(29.056)	(38.584)	(38.818)	(38.711)
Number of adults (15-65 years)	-0.733	0.828	0.537	-2.487	-3.830	-3.983
	(3.995)	(8.775)	(8.635)	(4.914)	(10.872)	(10.699)
hhsize#hhsize		-0.491	-0.440		-0.019	0.021
		(0.592)	(0.580)		(0.653)	(0.646)
2009.year	252.316***	237.026***	239.449***	377.950***	367.354***	370.649***
	(40.945)	(40.979)	(40.921)	(51.572)	(52.882)	(52.394)
2010.year	565.090***	541.306***	543.539***	792.754***	779.171***	776.082***
	(46.990)	(48.263)	(48.302)	(67.339)	(70.312)	(70.444)
2011.year	533.487***	519.053***	519.221***	576.920***	577.220***	581.136***
	(42.154)	(41.840)	(41.439)	(58.691)	(58.404)	(57.552)
AEZ 2a (yes=1)	17.997	45.055	59.577			
	(50.775)	(54.239)	(54.045)			
AEZ 2b (yes=1)	15.609	15.716	-21.610			
	(67.342)	(77.257)	(76.277)			
AEZ 3 (yes=1)	355.503***	345.079***	334.802***			
	(63.136)	(65.732)	(63.375)			
SEA average	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Constant	1,574.66***	2,142.41***	1,854.86***	1,403.15***	2,121.525*	1,292.151
	(282.170)	(712.453)	(703.859)	(413.908)	(1,095.769)	(1,073.067)
Observations	47,838	47,838	47,838	25,808	25,808	25,808
R-squared	0.376	0.383	0.385	0.352	0.362	0.366
F statistic	148.37	101.14	81.1	78.2	63.86	59.75
p value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors clustered at the SEA level in parentheses; ***, **, * statistically significant at 1%, 5% and 10%, respectively; base tillage method, year, and agro-ecological zone are conventional hand hoe, 2008, and AEZ 1, respectively.

Source: Authors' computations from CFS 2008-2011

Paper III

Does minimum tillage improve livelihood outcomes of smallholder farmers?

A micro-econometric analysis from Zambia

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Abstract

Minimum tillage (MT) is an integral part of Climate Smart Agriculture aimed to raise agricultural productivity, improve farmer livelihoods and build climate resilient farming systems in sub-Saharan Africa. However, low adoption has led to questions on its suitability for smallholder farmers in the region. This paper assesses the impacts of MT on household and farm incomes using an endogenous switching regression (ESR) model, applied to cross sectional data from 751 plots in Zambia. The ESR framework accounts for heterogeneity in the decision to adopt MT or not and consistently predicts actual and counterfactual outcomes. The results suggest that adopting MT did not significantly affect household and farm incomes in the short-term. This can help explain low adoption rates, and lowering implementation costs is needed to spur adoption.

Keywords: Minimum tillage, impact assessment, household income, endogenous switching, Zambia
JEL Classifications: D1, Q12, O33

*I gratefully acknowledge funding from the Norwegian Agency for Development Cooperation [agreement no. GLO-3945 QZA 13/0545; grant on Learning from REDD+ an enhanced Global Comparative Analysis] through the Center for International Forestry Research (CIFOR). I thank Arild Angelsen for comments on the paper, Davison Gumbo of CIFOR Zambia for hosting and facilitating fieldwork and all research assistants. All errors and omissions remain mine.

1 Introduction

Raising agricultural productivity, while both coping with and mitigating current and future climate change, is one of the most pressing development challenges facing sub-Saharan African (SSA). Agriculture is a key economic sector contributing about 20% to Gross Domestic Product (GDP) and employing over 60% of the labor force in the region (IMF, 2012). The high dependence of agriculture on rainfall, however, makes the sector vulnerable to climate variability. In addition to a highly variable climate, smallholders in the region also face declining land productivity. Population and per capita income growth - raising food demand - and food price instability put further pressure on the agricultural sectors in the region. Therefore, raising agricultural productivity and increasing the resilience of rainfed farming systems to climate variability are critical challenges facing smallholder farmers in SSA.

Conservation agriculture (CA) or more broadly Climate Smart Agriculture (CSA) principles aimed to: (1) raise agricultural productivity, (2) improve farmer livelihoods, and (3) build climate resilient farming systems are the main policy response to the dual challenge of smallholder agriculture in the region. In particular, the main CA principles of minimum tillage (MT), *in-situ* crop residue retention and crop rotation are seen as viable options to foster agricultural development and enhance resilience in rainfed farming systems (Arslan et al., 2014; IPCC, 2014; Thierfelder et al., 2015; Thierfelder and Wall, 2010). MT involves reduced or zero mechanical soil disturbance through animal draught or mechanized ripping, zero tillage and/or hand hoe - planting basins. MT aims to improve water and other input use efficiencies by concentrating application to planting stations (Haggblade and Tembo, 2003). Crop rotation requires that cereals and Nitrogen-fixing legumes are planted in succession on the same plot from one year to another in order to maintain or improve soil fertility. Residue retention entails leaving crop residues in the field after harvest to serve as mulch or cover crop for the successive crop.

CA principles including MT are promoted in Zambia using the lead farmer or own farmer facilitation model, combined with training sessions and farmer field schools, e.g., through demonstration plots, field days, exchange visits etc. Development projects and/or government agencies (i.e., MT promoters) train lead farmers and provide them with training materials and transport to enable them train and visit with follower farmers in their villages. On-farm or on-station demonstration plots are used to showcase MT technologies and demonstrate their benefits and also host training sessions and field days.

Despite almost two decades of promoting MT for smallholders, there is limited evidence on its impacts on household and farm incomes in SSA. This has led to questions on its viability (Giller et al., 2009). Except for Jaleta et al. (2016) and Kuntashula et al. (2014), most available studies do not account for counterfactual outcomes, i.e., what adopters (non-adopters) would have earned had they not adopted (adopted), and do not control for unobservables, and therefore do not measure causal impacts. They use mainly gross margin analysis and do not specifically focus on MT, or they fail to define MT consistently.

This paper attempts to contribute towards filling this gap. It assesses the impacts of MT on household and farm incomes under the premise that productivity and income effects are major factors considered by smallholders in their adoption decisions. Improving productivity is important for food security, and income security for poverty eradication. The productivity, adaptation and mitigation potential of MT is discussed elsewhere (Arslan et al., 2015; Jaleta et al., 2016; Ngoma et al., 2015, 2016; Powlson et al., 2014, 2016; UNEP, 2013).

MT is the most prevalent and arguably a necessary (although not sufficient) principle of CA; the other principles (crop rotation and crop residue retention) are complimentary. The current analysis is thus restricted to only MT. A household in this study is considered to use MT if they reported using ripping, planting basins and/or zero tillage as the main tillage on at least one plot.

I consider three measures of livelihood outcomes: household income, crop revenue and crop income, all computed over one agricultural season. These outcome variables are important indicators of rural livelihoods and they are good welfare proxies in the absence of household expenditure data. Household income is computed as the sum of household income from crops, value of livestock owned (sales and subsistence), off farm incomes, remittances and income from non-farming business activities.[1] Crop revenue is gross value from crop sales and subsistence use, while crop income is crop revenue less costs of inputs other than family labor, e.g., seed, fertilizers and hired labor. Crop revenue and crop income are per hectare.

This paper makes three contributions. First, it focuses on MT - the main CA principle in Zambia - and consistently defines adoption or use in assessing the causal impacts on livelihood outcomes.[2] Second, the paper applies a simultaneous equation model with endogenous switching to control for both observable and unobservable farmer heterogeneity that may confound impacts of MT on farm incomes. Third, the paper extends traditional average impact assessment and assesses the distribution of the impacts by asset and farm size quartiles. The paper also decomposes differences in outcomes between adopters and non-adopters to isolate the contributions of endowments and returns to covariates.

The rest of the paper is organized as follows. Section 2 briefly discusses the analytical framework and outlines the estimation strategy. Section 3 presents the data, while sections 4 and 5 present and discuss the results. Section 6 concludes.

2 Methods

2.1 Analytical framework

As rational economic agents, smallholder farmers aim to maximize their well-being given a set of constraints determined by the biophysical environment, institutions and market conditions as well as the information available (De Janvry et al., 1991). They weigh the

[1]Subsistence income accounted for about 49% of household income and it was calculated using observed market prices collected during the survey for the different crops and livestock in the survey villages. The main crops include maize, sunflower, groundnuts, sunflower, soybeans and cotton, and livestock include cattle, pigs, goats and chicken.

[2]For convenience, use and adoption are used synonymously in this paper.

expected or perceived benefits and costs from adopting MT against the benefits and costs from not adopting (business as usual). In doing so, farmers rely on information received from promotion activities and their prior experiences (if any) with MT to learn about its potential yield and income benefits. They also face trade-offs between short-term and long-term benefits. The risk of different options also plays a role, e.g., the potential of MT to stabilize yield under low rainfall.

Smallholder farmers in Zambia operate in an environment with imperfect labor and credit markets. This implies that their production decisions - including on-farm adoption of MT - and their consumption decisions - including how much to work on and off-farm - are interdependent and taken simultaneously (De Janvry et al., 1991).

Household decisions to adopt MT and the resulting effects on welfare must therefore be studied within a utility rather than a profit maximizing framework. Non-separable agricultural household models provide a useful framework for analyzing household behavior when markets are imperfect.

Farmers face both discrete and continuous investment decisions when they decide whether to adopt MT or not and how much land to allocate to it (Feder et al., 1985). Smallholders are endowed with a set of assets or capitals - physical, human, financial, social and natural, and these co-determine the optimal strategy.

The treatment group is composed of farmers who used planting basins, ripping and/or zero tillage (collectively called MT) on at least one plot as the main tillage. These MT principles aim to minimize soil disturbance, improve input use efficiency and augment yield. The control or untreated group comprise all other farmers who used conventional tillage practices such as plowing, ridging and hand hoeing.

How the treatment group, in this case use of MT, is defined is paramount: it can confound impact assessment especially for agricultural technologies with multiple elements such as MT or the full conservation agriculture package for which MT is the main component. Andersson and D'Souza (2014) found that the inconsistent definition of the adoption of conservation agriculture or treatment is a major factor driving disagreements on the performance of the technologies under smallholder conditions in SSA.

Consider then a rational farmer who decides whether to adopt MT or not based on expected benefits or utility. This farmer will only adopt MT if the net benefits (including risk reduction) from adoption outweigh the net benefits of not adopting.[3] Following Alem et al. (2015) and Asfaw et al. (2012), adoption can be modeled more explicitly in a random utility framework, which links discrete adoption decisions to expected benefits of adoption. The rational farmer will, therefore, adopt MT if the utility from adoption (U_1) is greater than the utility from non-adoption (U_0). However, since utility is unobservable, save for whether a farmer adopts MT or not, the farmer will adopt MT (i.e., $MT = 1$) only if $U_1 > U_0$, and will not adopt MT (i.e., $MT = 0$) otherwise. The adoption decision is modeled subject to a number of farm and household characteristics defined in equation (1).

Because farmers are not randomly assigned into MT adoption, a potential selection bias problem arises and should be corrected when assessing impacts of MT on farm incomes. Farmers who self-select into MT adoption might have certain characteristics (observable or non-observable) that may systematically differ from non-adopters (the untreated group). Failure to account for unobservables and using mean differences in farm incomes between MT users and non-users may yield misleading results.

2.2 Estimation strategy

To understand the causal impacts of MT on farm incomes requires estimating what adopters would have earned had they not adopted and what non-adopters would have earned had they adopted. This is a typical missing data problem because we cannot observe farmers in two states of the world at the same time, i.e., we cannot observe what MT farmers would have earned had they not adopted MT (the counterfactual scenario) while at the same time observing their earnings from adoption. Additionally, if sample selection is significant, it ren-

[3]MT is generally considered risk reducing, but due to data limitations, risk is not formally considered in this paper. The effects of risk on technology adoption requires a separate study.

ders simple Ordinary Least Squares (OLS) biased. Moreover, the presence of unobservables influencing self-selection into treatment makes propensity score matching (which matches on observables) less credible, while use of one time cross sectional survey data (as in this study) renders difference-in-difference methods unsuitable.

A suitable empirical strategy that addresses selection bias and can consistently estimate impacts of MT treatment using actual and counterfactual outcomes is the endogenous switching regression (ESR) model (Maddala, 1983). The ESR model uses conditional expectations to estimate counterfactual outcomes while controlling for observed and unobserved heterogeneity (e.g., self-motivation and business acumen of farmers). The application of ESR proceeds in two steps. First, farmer decisions whether to use MT or not are estimated with a probit model. Second, the two main outcome equations are specified as linear regressions for MT users and non-users separately.

To motivate the ESR framework, define a latent variable M_i^* that captures the benefits from adopting MT as;

$$M_i^* = Z\alpha + \varepsilon \quad with \quad MT = \begin{cases} 1 \quad if \quad Z\alpha + \varepsilon > 0 \\ 0 \qquad otherwise \end{cases} \tag{1}$$

where Z is an $n \times J$ matrix of plot level and household characteristics that influence MT adoption, α is a $J \times 1$ vector of parameters to be estimated and ε is an $n \times 1$ vector of normally distributed error terms. Equation (1) is the first stage or the selection equation in the ESR framework. The second stage specifies separate equations for each outcome variable for MT users and non-users;

$$Y_1 = X_1\beta_1 + \varepsilon_1 \quad if\ MT = 1 \tag{2}$$

$$Y_0 = X_0\beta_0 + \varepsilon_0 \quad if\ MT = 0 \tag{3}$$

where y_1 and y_0 are $n \times 1$ vectors of different measures of livelihoods (household income, crop income and crop revenue) for MT users and non-users, respectively. $X_j (j = 1, 0)$ are $n \times k$ matrices of covariates, β_j is a $k \times 1$ vector of model parameters to be estimated and ε_j is an $n \times 1$ vector of normally distributed error terms.

Self-selection into MT user or non-user categories may lead to nonzero covariance in the error terms of the selection equation (1), and outcome equations (2) and (3), i.e., $corr(\varepsilon, \varepsilon_1, \varepsilon_0) = \Sigma$. This is because some unobservables (e.g., business acumen) that may influence adoption may also influence outcomes. The ESR framework assumes that the error terms ε, ε_1 and ε_0 have a trivariate normal distribution with mean zero and a nonzero covariance matrix;

$$corr(\varepsilon, \varepsilon_1, \varepsilon_0) = \Sigma = \begin{pmatrix} \sigma_{\varepsilon}^2 & \sigma_{\varepsilon\varepsilon_1} & \sigma_{\varepsilon\varepsilon_0} \\ \sigma_{\varepsilon_1\varepsilon} & \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1\varepsilon_0} \\ \sigma_{\varepsilon_0\varepsilon} & \sigma_{\varepsilon_0\varepsilon_1} & \sigma_{\varepsilon_0}^2 \end{pmatrix} \tag{4}$$

where σ_{ε}^2, $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_0}^2$are variances of the error terms from equations (1), (2) and (3) respectively, with σ_{ε}^2 from the selection equation normalized to 1. $\sigma_{\varepsilon_1\varepsilon}$ and $\sigma_{\varepsilon_0\varepsilon}$ are covariances between ε and ε_1, and between ε and ε_0 respectively. $\sigma_{\varepsilon_1\varepsilon_0}$ is the covariance between ε_1 and ε_0, which is not defined since the two states y_1 and y_0 are not observable simultaneously. Therefore, in the presence of selection bias, and conditional on MT use, the expected values of the error terms for MT users in equation (2) and non-users in equation (3) are given by;

$$E(\varepsilon_1|MT = 1) = E(\varepsilon_1|\varepsilon > -\alpha Z) \ = \sigma_{\varepsilon_1\varepsilon}\frac{\phi(Z\alpha)}{\Phi(Z\alpha)} = \sigma_{\varepsilon_1\varepsilon}\lambda_1 \tag{5}$$

$$E(\varepsilon_0|MT = 0) = E(\varepsilon_0|\varepsilon \leq -\alpha Z) \ = \sigma_{\varepsilon_0\varepsilon}\frac{-\phi(Z\alpha)}{1 - \Phi(Z\alpha)} = \sigma_{\varepsilon_0\varepsilon}\lambda_0 \tag{6}$$

where ϕ and Φ are probability and cumulative density functions of the standard normal distribution. The ratios $\frac{\phi(.)}{\Phi(.)}$ given by λ_1 and λ_0 for MT users and non-users, respectively, are the inverse mills ratios, which are included in the outcome equations to control for sample selection bias as will be shown below. Significance of the estimated covariances $\hat{\sigma}_{\varepsilon_0 \varepsilon}$ and $\hat{\sigma}_{\varepsilon_1 \varepsilon}$ and the correlation coefficients between the selection and outcome equations would confirm sample selection bias.

Although variables in Z and X, i.e., in the selection and outcome equations may overlap, proper identification requires that at least one variable in Z is omitted from X. For this purpose, I instrument selection into MT with access to MT extension *(MText)* and hence omit this variable from the outcome equations (7) and (8). This and related informational instrumental variables (IVs) are used in Abdulai and Huffman (2014) and Alem et al. (2015). A valid instrument (MT extension) should directly influence MT adoption but not the outcomes (revenue and incomes), except through MT. The test results for IV relevance (presented in the results section) confirm that access to MT extension significantly increased the likelihood of adoption, but it is uncorrelated to the outcomes of interest (Table A1). Thus, the selected IV is relevant and admissible, and therefore, meets the two key criteria for assessing IVs.

2.3 Empirical specification

To bring the above empirical strategy to data, I re-specify the outcome equations to include the inverse mills ratios derived from the selection equation;

$$Y_1 = X_1\beta_1 + \sigma_{\varepsilon_1 \varepsilon}\lambda_1 + \mu_1 \quad if\ MT = 1 \tag{7}$$

$$Y_0 = X_0\beta_0 + \sigma_{\varepsilon_0 \varepsilon}\lambda_0 + \mu_0 \quad if\ MT = 0 \tag{8}$$

All variables are as defined before. Omission of the $\sigma_{\varepsilon j \varepsilon}\lambda_j$ terms in equations (2) and (3) is what makes OLS estimates biased. OLS may also not consistently estimate equations (7) and (8) because the error terms μ_j are heteroskedastic (Maddala, 1983).

I estimated the ESR model using full information maximum likelihood (FIML) with Lokshin and Sajaia (2004)'s *movestay* command in Stata. FIML simultaneously estimates the selection and outcome equations.

2.3.1 Actual and counterfactual outcomes

The ESR model can be used to derive consistent conditional expectations, which are used to compute counterfactual and observed (actual) outcomes for MT users and non-users. Counterfactual outcomes refer to expected outcomes for MT adopters had they not adopted and for non-adopters had they adopted. Conditional expectations for the different outcome scenarios are derived as follows;

$$E(Y_1|MT = 1) = X_1\beta_1 + \sigma_{\varepsilon_1\varepsilon}\lambda_1 \tag{9}$$

$$E(Y_0|MT = 0) = X_0\beta_0 + \sigma_{\varepsilon_0\varepsilon}\lambda_0 \tag{10}$$

$$E(Y_0|MT = 1) = X_1\beta_0 + \sigma_{\varepsilon_0\varepsilon}\lambda_1 \tag{11}$$

$$E(Y_1|MT = 0) = X_0\beta_1 + \sigma_{\varepsilon_1\varepsilon}\lambda_0 \tag{12}$$

Equations (9) and (10) are expected outcomes conditional on MT adoption and non-adoption, respectively. Equation (11) is the expected outcome for non-adopters had they adopted, which is the counterfactual outcome for adopters. Equation (12) is the expected outcome for adopters had they not adopted and also serves as the counterfactual outcome for non-adopters. Following Heckman et al. (2001) and Di Falco et al. (2011), the average treatment effect on the treated (ATT) is the difference between the outcomes in equations (9) and (11). This is the difference between what adopters earned from adoption and what they would have earned had they not adopted;

$$ATT = E(Y_1|MT = 1) - E(Y_0|MT = 1) = X_1(\beta_1 - \beta_0) + \lambda_1(\sigma\varepsilon_1\varepsilon - \sigma\varepsilon_0\varepsilon) \tag{13}$$

ATT captures the effects of MT on farm incomes for households that actually used MT. Similarly, the average treatment effect on the untreated (ATU) for households that did not use MT is the difference between the expected outcomes in equations (12) and (10). This captures the difference between what non-adopters would have earned had they adopted and what they actually earned by not adopting MT;

$$ATU = E(Y_1|MT = 0) - E(Y_0|MT = 0) = X_0(\beta_1 - \beta_0) + \lambda_0(\sigma\varepsilon_1\varepsilon - \sigma\varepsilon_0\varepsilon) \tag{14}$$

All variables are as described before. Following Di Falco et al. (2011), I also compute heterogeneity effects using conditional expected outcomes in equations (9) to (12). This is important since MT users may have had higher farm incomes than non-users even if they did not use MT, due to unobserved factors. For this purpose, a base heterogeneity (BH) effect is defined as the difference between equations (9) and (12) for adopters;

$$BH_1 = E(Y_1|MT = 1) - E(Y_1|MT = 0) = \beta_1(X_1 - X_0) + \sigma\varepsilon_1\varepsilon(\lambda_1 - \lambda_0) \tag{15}$$

And, for non-MT adopters as the difference between equations (11) and (10);

$$BH_2 = E(Y_0|MT = 1) - E(Y_0|MT = 0) = \beta_0(X_1 - X_0) + \sigma\varepsilon_0\varepsilon(\lambda_1 - \lambda_0) \tag{16}$$

To investigate whether the effect of using MT is larger or smaller for farmers that adopted MT had they not adopted, or for farmers that did not adopt MT had they adopted requires computation of transitional heterogeneity (TH) effects. The TH effect is equal to the difference between BH_1 and BH_2 or the difference between ATT and ATU.

2.3.2 Decomposition

I decompose the differences in household and farm incomes (i.e., the outcome variables) between adopters and non-adopters using the Blinder-Oaxaca decomposition approach (Blinder, 1973; Oaxaca, 1973). Decomposition compliments the ESR results by isolating the contributions of differences in magnitudes of covariates (the covariate or endowment effect) and returns to covariates (explanatory variables). The treatment effect from the ESR gives differences in outcome variables by comparing actual and counterfactual outcomes, but it does not parcel out the contributions of differences in levels of endowments and returns to endowments. Decomposition, thus, helps to get a deeper understanding for the causes of the differences, for example, due to differences between adopters and non-adopters in education, plot size, land and livestock endowments.

Following Jann (2008), define the mean differences in outcomes from equations (7) and (8) as;

$$Y_j = \bar{X}_1\hat{\beta}_1 - \bar{X}_0\hat{\beta}_0 \tag{17}$$

where $\bar{X}_i$ and $\hat{\beta}_i (i = 1, 0)$ are mean covariate and parameter values for adopters and non-adopters, respectively, and $j(j = 1, 2, 3)$ indexes the individual outcome variables.

Equation (17) follows from the assumption that $E(u_i) = 0$ in equations (7) and (8), and can be decomposed into the different components that explain variations in Y_j;

$$Y_j = \underbrace{(\bar{X}_1 - \bar{X}_0)\hat{\beta}_0}_{\text{Covariate effect}} + \underbrace{\bar{X}_0(\hat{\beta}_1 - \hat{\beta}_0)}_{\text{Returns to covariate effect}} + \underbrace{(\bar{X}_1 - \bar{X}_0)(\hat{\beta}_1 - \hat{\beta}_0)}_{\text{Interaction effect}} \tag{18}$$

The covariate effect captures the proportion of the outcome differential due to group differences in the explanatory variables (i.e, by adoption status). This part identifies policy options that affect the level of covariates for adopters and non-adopters, e.g., land distribution (Table 1). The returns to covariate effect is the unexplained part that captures the outcome differential due to differences in coefficients. This part identifies policies that influence behavior relative to observed characteristics and measures how outcomes would change if non-adopters had the same rates of return as MT adopters. Following Ainembabazi and Angelsen (2014), policies related to the covariate effects are termed 'X-policies', while those related to returns to covariates are called 'β-policies' in the discussion of results. The third part in equation (18) captures the interaction effects of the first two components.

3 Data collection and descriptive statistics

I use household survey data on 751 plots collected from a random sample of 368 households for the 2013/2014 agricultural season in Zambia. Survey respondents were from Nyimba, Mumbwa and Mpika districts. Nyimba and Mumbwa districts were selected based on their past exposure to MT promotion, while Mpika was selected for being an area outside the main CA promotions regions where zero tillage and shifting cultivation systems are common. Mpika is located about 650 km north of the capital Lusaka, while Nyimba and Mumbwa are about 340 km east and 160 km west, respectively. Figure 1 shows the location of the survey areas.

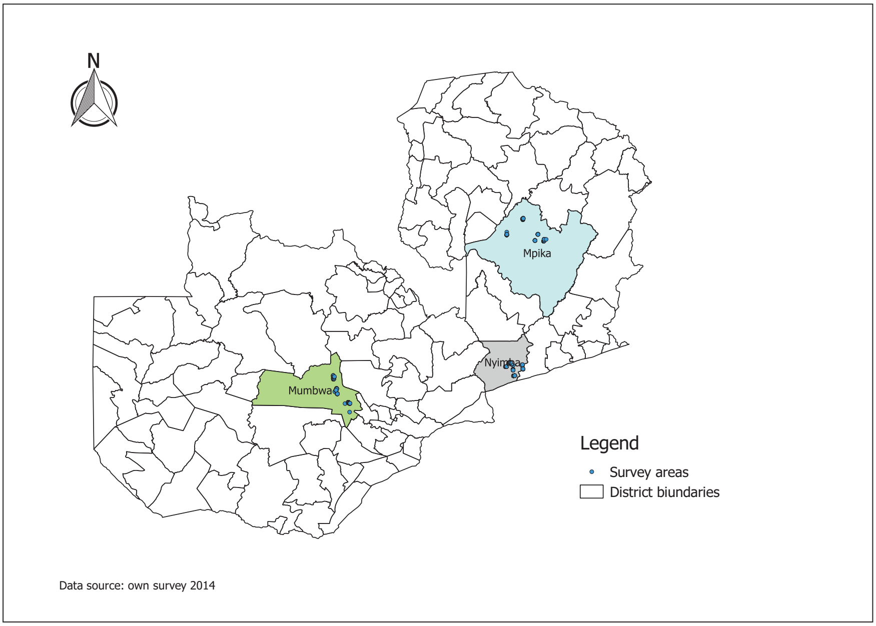


Figure 1: Location of survey districts and villages (green dots on the map).

Ten survey villages were randomly selected from each of the three districts using the most recent national agricultural survey listing of villages. In the final stage, 12 - 15 households were randomly selected from each village for interviews. In total, 120 farm households in each of Mpika and Nyimba districts and 128 households in Mumbwa were interviewed. Mumbwa and Nyimba districts lie within the main areas where government agencies and/or development projects have been promoting MT for almost two decades.

Data were collected using structured questionnaires through face-to-face interviews. The survey collected detailed information on household demographics, agricultural (including tillage methods) and off-farm activities, yield, labor and other input use and costs, asset holdings and sources of income. Overall, 131 (17%) of all plots used MT, while 620 (83%) did not. More specifically, 9% used ripping, 6% used basin tillage and 2% used zero tillage. As expected, the proportion of MT users was highest in Mumbwa followed by Nyimba district.

Table 1 presents summary statistics and mean difference test results between adopter and non-adopter plots for all variables used in the analysis. As alluded to earlier, I use household income, crop revenue and crop income as outcome variables;

$$\begin{aligned}
&Household\ income = \underbrace{crop\ revenue - cost\ of\ crop\ production}_{\text{crop income}} + other\ incomes,\\
&Crop\ revenue = gross\ value\ of\ crops.
\end{aligned}$$

Total household income captures the overall welfare impacts. Crop revenue attaches a monetary value to yield, but it does not take into account costs. To capture the costs elements, therefore, requires crop income. Crop income does not capture the effects of MT on family labor because it only accounts for cash costs for seed, fertilizer and hired labor. Since MT is labor intensive, at least in the short-term, it may absorb family labor and reduce other incomes. This effect can be seen by looking at the total household income. Thus the difference between the impacts of MT on crop revenue and on crop income reflects the costs of implementing MT, while the difference between crop income and household income reflect the effects of MT on household labor. There are no statistically significant differences in these outcome variables between MT and non-MT plots (Table 1).

Explanatory variables are divided into plot and household characteristics. Most of these have been used in assessing impacts of different agricultural technologies on household welfare (Abdulai and Huffman, 2014; Alem et al., 2015; Asfaw et al., 2012; El-Shater et al., 2015; Kassie et al., 2011). Since the paper does not focus on determinants of household incomes per se but rather impacts of MT on household incomes, I do not discuss descriptive statistics in Table 1 for all explanatory variables except for those with significant mean differences. A larger proportion of MT adopters used herbicide and manure than non-adopters. MT adopters applied more fertilizer per ha, had more plots per household and experienced lower seasonal rainfall. Further, MT adopters weeded their plots several times and were closer to input and output sales outlets compared to non-adopters. Additionally, MT adopters had older but less educated household heads, higher livestock units (computed following Jahnke (1982))[4] and adult equivalents. Except for the seasonal rainfall variable, computed from spatial data (Ngoma et al., 2016), all other variables are drawn from the survey described above.

Although this section highlights significant differences between adopter and non-adopter plots, it is misleading to attribute the mean differences to the effects of adoption; bivariate mean comparisons do not take into account self-selection which may confound the results. I turn to this specific issue in the next section.

[4]cattle =0.7, donkey = 0.5, pigs = 0.2, goats =0.1, chicken = 0.01, duck = 0.06.

Table 1: Comparative statistics of key explanatory variables between minimum tillage and non- minimum tillage plots

	Non MT(1)		Used MT(2)			Mean diff. (1-2)
Variable	Mean	SD	Mean	SD	t-stat	Significance
Outcome variables						
Household income	3,290	2,730	3,310	2,929	-0.08	
Crop revenue per ha	2,325	2,500	2,250	2,565	0.31	
Crop income per ha	1,426	2,523	1,207	2,421	0.90	
Independent variables						
Plot characteristics						
Plot size(ha)	1.35	3.5	1.35	2.12	-0.01	
Number of plots	2.56	1.01	3.00	1.21	-4.33	***
Plot fertile (yes = 1)	0.65	0.48	0.65	0.48	-0.10	
Herbicide (yes = 1)	0.14	0.35	0.21	0.41	-1.90	*
Manure (yes = 1)	0.04	0.20	0.12	0.32	-3.30	***
Crop residue (yes = 1)	0.33	0.47	0.37	0.49	-0.89	
Crop rotation (yes = 1)	0.14	0.35	0.16	0.36	-0.50	
Fertilizer rate (Kg/ha)	91.98	173.64	127.18	181.91	-2.08	**
Number weeded	1.48	0.65	1.66	0.82	-2.74	***
Hybrid seed (yes=1)	0.44	0.50	0.49	0.50	-0.93	
Household characteristics						
Age household head (years)	43.95	13.15	47.98	15.49	-3.07	***
Education household head (years)	6.52	3.20	5.87	3.37	2.07	**
Male household head (yes =1)	0.80	0.40	0.76	0.43	1.05	
Head married (yes =1)	0.78	0.42	0.76	0.43	0.46	
Seasonal rainfall (mm)	807.27	65.92	746.31	96.37	6.73	***
Dist. homestead to main market (Km)	25.74	24.13	14.04	14.52	5.31	***
Adult equivalents	5.01	2.00	5.75	2.25	-3.74	***
Tropical livestock units	3.73	6.06	52.85	271.79	-4.51	***
Asset value '000 (ZMW)	2.38	11.20	2.10	3.37	0.28	
Hired labor per ha (number)	1.32	2.93	1.73	3.31	-1.42	
Family labor per ha (number)	12.97	8.60	13.18	7.86	-0.25	
Mumbwa district (yes =1)	0.32	0.47	0.68	0.47	-7.89	***
Nyimba district (yes =1)	0.41	0.49	0.25	0.43	3.34	***
Mpika district (yes =1)	0.27	0.44	0.07	0.26	4.98	***
Member cooperative (yes = 1)	0.54	0.50	0.60	0.49	-1.24	
Relative to headman (yes=1)	0.48	0.50	0.54	0.50	-1.31	
Selection instrument						
MT extension (yes = 1)	0.60	0.49	0.89	0.31	-6.43	***

Notes: SD is the standard deviation; *, **, *** imply statistically significant at 1%, 5% and 10%, respectively; 1USD = 6.22 ZMW; N=751 plots; MT=minimum tillage; negative crop income was recoded to zero before computing household income.

4 Empirical results

Table 2 presents results from three endogenous switching regression models. Column 1 shows results for MT adoption from the selection equation of the household income model. Results for the main outcome equations are given in columns 2 and 3 for household income, 4 and 5 for crop revenue and columns 6 and 7 for crop income. Columns 3, 5 and 7 present results for outcome equations for non-adopters while results in columns 2, 4 and 6 are for outcome equations for adopters. For model diagnostics, wald χ^2 test results reject independence of the selection and outcomes equations for the household income and crop revenue models ($P < 0.5$) and there are significant correlations between error terms in the selection and outcome equations.[5] Thus, it was appropriate to use the endogenous switching regression model.

I follow Di Falco et al. (2011) and check the admissibility of the IV by including it in regressions of outcome equations for non-adopter sub-samples. Results reported in Table A1 (in the appendices) show that the IV was insignificant in all outcome models for non-adopter sub-samples ($P \geq 0.18$), suggesting that it was valid to exclude it from these equations. However, its significance in all selection equations confirms its relevance ($4.5 \leq F \leq 7.85$); see *Min till extension* in Table 2 for an example from the household income model. Estimation was done with standard errors clustered at the village level to account for intra-village correlations.

[5]The crop income model is based on a smaller sub-sample of 565 plots with positive crop incomes only. Observations with negative income were dropped when log-transforming crop income.

Table 2: Parameter estimates of the impact of minimum tillage on livelihood outcomes from endogenous switching regression models

	Household income			Crop revenue		Crop income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	adopt[0/1]	yes	no	yes	no	yes	no
Plot size (ha)	0.010	-0.008	0.035*	-0.040	0.065	-0.054***	-0.072**
	(0.021)	(0.016)	(0.019)	(0.025)	(0.069)	(0.010)	(0.031)
Number of plots per household	0.243***	0.108**	0.085	0.041	-0.011	0.102	-0.008
	(0.089)	(0.052)	(0.089)	(0.110)	(0.193)	(0.083)	(0.137)
Plot fertile (yes=1)	0.174	0.051	0.157	-0.022	-0.219	-0.064	0.586**
	(0.148)	(0.101)	(0.224)	(0.144)	(0.465)	(0.118)	(0.286)
Herbicides applied (yes=1)	-0.042	-0.004	-0.297*	0.126	-0.786*	0.150	0.016
	(0.150)	(0.118)	(0.166)	(0.129)	(0.438)	(0.127)	(0.252)
Manure applied (yes=1)	0.366*	-0.539**	-0.044	-0.907**	-0.374	-1.058***	-0.764
	(0.201)	(0.254)	(0.202)	(0.376)	(0.290)	(0.405)	(0.506)
Crop residue retained (yes=1)	0.278*	-0.056	-0.182	-0.027	-0.009	0.034	0.423*
	(0.153)	(0.092)	(0.201)	(0.166)	(0.308)	(0.109)	(0.246)
Crop rotation (yes=1)	-0.079	0.179*	0.601***	0.241	0.689	-0.211	0.039
	(0.217)	(0.105)	(0.219)	(0.191)	(0.449)	(0.190)	(0.197)
Inorganic fert. rate /100 (Kg/ha)	0.071*	-0.030	-0.022	-0.060	-0.079	-0.060	-0.016
	(0.040)	(0.022)	(0.041)	(0.040)	(0.085)	(0.040)	(0.103)
Number weeded	0.119	0.024	0.005	0.006	0.182	-0.048	-0.105
	(0.092)	(0.046)	(0.117)	(0.099)	(0.271)	(0.082)	(0.129)
Hybrid seed (yes=1)	0.012	0.704***	0.624***	1.460***	0.726**	0.958***	0.230
	(0.126)	(0.123)	(0.181)	(0.220)	(0.365)	(0.179)	(0.269)
Age, hh head	0.001	0.001	-0.014**	0.006	0.005	-0.003	-0.002
	(0.006)	(0.003)	(0.007)	(0.005)	(0.014)	(0.005)	(0.008)
Education, hh head	-0.065*	0.025*	0.040*	0.031	0.031	0.004	-0.035
	(0.034)	(0.014)	(0.022)	(0.023)	(0.045)	(0.023)	(0.046)
Male head (yes=1)	-0.279	0.057	-0.837	-0.073	-0.287	-0.254	-0.159
	(0.336)	(0.147)	(0.761)	(0.245)	(1.047)	(0.198)	(0.563)
Married, hh head (yes=1)	0.439	-0.059	0.959	-0.099	0.737	0.155	1.168*
	(0.300)	(0.125)	(0.724)	(0.216)	(1.039)	(0.190)	(0.616)
Seasonal rainfall/100	-0.284**	0.079*	-0.077	-0.007	-0.017	0.017	-0.653**
	(0.133)	(0.047)	(0.214)	(0.092)	(0.326)	(0.079)	(0.278)
Dist. input output sales	-0.010**	-0.004*	-0.009	-0.010**	-0.026	-0.004	-0.015
	(0.004)	(0.002)	(0.007)	(0.005)	(0.022)	(0.003)	(0.010)
Adult equivalents	0.016	-0.021	-0.002	-0.030	0.137**	-0.074**	0.121**
	(0.036)	(0.025)	(0.030)	(0.044)	(0.063)	(0.034)	(0.048)
Livestock units	0.003	0.008	-0.001***	-0.009	-0.001*	-0.007	0.000
	(0.006)	(0.009)	(0.000)	(0.020)	(0.000)	(0.010)	(0.000)
Log. asset value	-0.168**	0.038	0.042	0.016	-0.173	0.002	-0.339***
	(0.079)	(0.044)	(0.069)	(0.060)	(0.135)	(0.046)	(0.095)
Hired labor per ha	0.026	0.033**	0.057***	0.049**	0.008	0.056**	0.038*
	(0.022)	(0.014)	(0.019)	(0.024)	(0.038)	(0.028)	(0.022)
Family labor per ha	0.009	0.024***	0.017*	0.023**	0.023	0.041***	0.009
	(0.007)	(0.004)	(0.010)	(0.012)	(0.016)	(0.009)	(0.017)
Cooperative member (yes =1)	-0.128	0.036	0.490**	-0.097	0.354	0.322**	0.694***
	(0.164)	(0.100)	(0.193)	(0.168)	(0.373)	(0.159)	(0.252)
Related to headman (yes=1)	0.197	0.094	0.716***	0.153	1.178***	-0.145	0.237
	(0.129)	(0.093)	(0.175)	(0.122)	(0.437)	(0.127)	(0.263)
District fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Min till extension (yes=1)	0.660***	-	-	-	-	-	-
	(0.248)	-	-	-	-	-	-
Constant	1.070	5.653***	6.923***	5.602***	5.364*	6.264***	12.147***
σ_i		0.95	0.78***	1.67****	1.69***	1.26***	0.87
ρ_j		-0.38***	-0.05	-0.22**	-0.07	-0.12	0.15
Wald χ^2 test; ($H_o : \rho_j = 0$)		8.07**		6.05**		1.34	
Number of observations	751	622	129	622	129	479	86

Notes: Robust standard errors in (); *,**,*** significant at 1%, 5% and 10%, σ_i is the square root of the variance in equations (7) and (8); ρ_j is the correlation coefficient for the error terms in equation (1) and equations (7) and (8).

Although not the focus of this paper, results in Table 2 suggest that the number of plots per household, applying manure, inorganic fertilizers, retaining crop residues and access to MT extension increase the likelihood of adopting MT. However, the education level of the household head, high seasonal rainfall and proximity to main input and output markets and households assets reduce the likelihood of adoption. These results corroborate findings in Kuntashula et al. (2014) and Ngoma et al. (2016) for similar technologies in Zambia.

4.1 Does minimum tillage improve livelihood outcomes?

Table 3 presents the main impact assessment results and shows the expected incomes under actual and counterfactual scenarios. Overall, adopting MT did not significantly affect crop revenue and household and crop incomes.[6] Focusing on the first two rows for each outcome variable in Table 3, the main diagonal elements (cells (a, b)) and off diagonal elements (cells (d, c)) in the decision stage columns are actual and counterfactual outcomes, respectively.

The true causal impacts are given by row-wise differences between actual and counterfactual outcomes. The ATT is the difference between how much adopters earned (a) and what non-adopters would have earned had they adopted (c), while the difference between what adopters would have earned had they not adopted (d), and what non-adopters actually earned without adoption (b) gives the ATU. Table 3 presents the ATT, ATU and ATE results in the treatment effects column, while Figure 3 gives the full distributions of the actual and counterfactual incomes for adopters and non-adopters.

[6]I obtained qualitatively similar results from an endogenous treatment effects (ETE) model. The difference between ETE and ESR is subtle, the former uses the control function approach to control for endogeneity while the later uses inverse mills rations to control for selection bias, which may cause endogeneity.

Table 3: Impacts of adopting minimum tillage on household and crop incomes

			Decision stage			
Outcome variable	N	sub-Sample	To adopt	Not to adopt	Treatment effects	
Household income	751	MT adopters	(a) 7.75(0.05)	(c) 7.70(0.02)	ATT	0.05(0.08)
		Non-adopters	(d) 7.68(0.02)	(b) 7.60(0.02)	ATU	0.08(0.03)***
		Het. impacts	(e) 0.07(0.05)	(f) 0.10(0.05)	TH	-0.03(0.01)***
					ATE	0.15(0.06)***
Crop revenue	751	MT adopters	(a) 6.94(0.09)	(c) 6.81(0.09)	ATT	0.13(0.13)
		Non-adopters	(d) 6.90(0.04)	(b) 6.82(0.04)	ATU	0.08(0.05)*
		Het. impacts	(e) 0.04(0.09)	(f) -0.01(0.09)	TH	0.05(0.00)***
					ATE	0.13(0.09)
Crop income	565	MT adopters	(a) 7.03(0.08)	(c) 7.19(0.07)	ATT	-0.16(0.11)
		Non-adopters	(d) 6.98(0.03)	(b) 6.94(0.03)	ATU	0.04(0.04)
		Het. impacts	(e) 0.05 (0.08)	(f) 0.25(0.08)	TH	-0.20(0.00)***
					ATE	0.09(0.08)

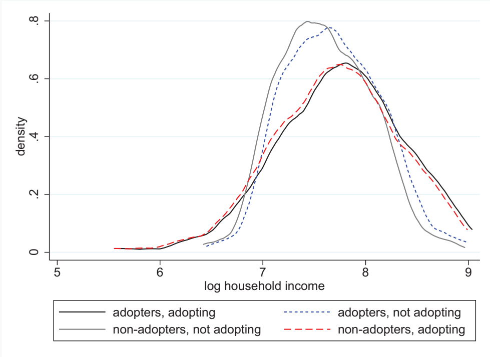
Notes: Standard errors in parenthesis,*,**, *** statistically significant at 1%, 5% and 10%, respectively; ATT (a-c), ATU (d-b) and TH (e-f), respectively, are average treatment effects on the treated, average treatment effects on the untreated and treatment heterogeneity (also =ATT-ATU). These are row-wise differences between 'to adopt' and 'not to adopt' decisions for respective sub-samples. ATE is average treatments effect given by (a-b). The heterogeneous impact is the column wise difference between adopters and non-adopters; Het. is heterogeneous. N is the number of observations.

Although the impact of adopting MT on household income is insignificant for adopters (ATT), results in Table 3 suggest that adopters had 16% higher household income on average (ATE).[7] However, since this is only ATE, the 16% higher income cannot be attributed to adoption because adopters had higher household income on average (Table 1). Thus, considering only the ATE for a random farmer may be misleading because it does not take into account counterfactual outcomes (c) and (d). Results in Table 3 also show that non-adopters would have earned about 8% more household income had they adopted MT.[8] These ATE and ATU results for household income are statistically significant at 1%.

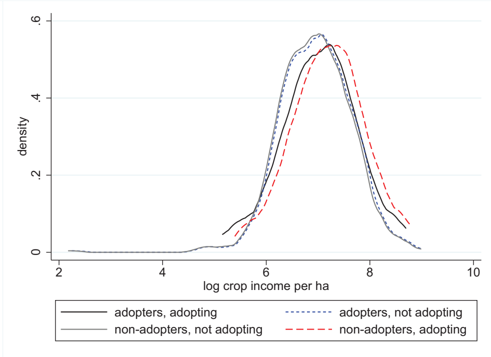
Similarly, the ATT for crop revenue and crop income is insignificant, and so is the ATE. This is in line with results in Table 1 and suggests that on average, MT adopters were not

[7]The percent differences are computed as $100*(e^{ATT}-1)$ for $ATT(U) > 0.05$, since the dependent variables are transformed to natural logs.

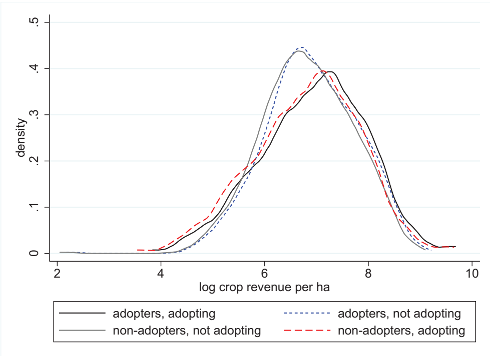
[8]This gain in absolute terms is only about ZMW 275.



(a) Household income



(b) Crop income



(c) Crop revenue

Figure 3: Distribution of actual and counterfactual outcomes of a) household income, b) crop income and c) crop revenue for adopters and non-adopeters.

better than non-adopters were in terms of crop revenue and crop income.

The results in Table 3 also suggest that adopters and non-adopters were systematically different. The transitional heterogeneity (TH) is highly statistically significant at 1% for all outcome variables. It is negative for household and crop income but positive for crop revenue: that is, the (potential) benefits from adoption were lower for household and crop income but higher for crop revenue.

4.2 Distribution of minimum tillage impacts by farm size and household wealth quartiles

Table 4 shows the distributions of the impacts of adopting MT on household income, crop revenue and crop income across farm size and value of household asset quartiles among adopters. I stratified the ATTs by farm size and asset value quartiles in an attempt to isolate the heterogeneity in impacts.

In line with the main results in Table 3, Table 4 shows that adopting MT did not significantly affect household and crop incomes among adopters across all farm size and household asset quartiles.

Table 4: Differential impacts of adopting minimum tillage on a) household income, b) crop revenue and c) crop income stratified by farm size and household asset value

Outcome variable	Stratified by					
(a) Household income	Farm size (ha)			Household asset value (ZMW)		
Quantiles	Obs.	Mean area	ATT	Obs.	Mean asset value	ATT
First	36	0.87	0.05(0.17)	37	183	0.05(0.18)
Second	17	1.83	0.05(0.24)	22	423	0.06(0.15)
Third	40	3.07	0.05(0.11)	30	1,029	0.05(0.16)
Fourth	36	9.55	0.04(0.13)	40	8,249	0.04(0.11)
(b) Crop revenue	Farm size (ha)			Household asset value (ZMW)		
Quantiles	Obs.	Mean area	ATT	Obs.	Mean asset value	ATT
First	36	0.87	0.15(0.25)	37	187	0.13(0.26)
Second	17	1.83	0.15(0.42)	22	423	0.15(0.26)
Third	40	3.07	0.13(0.22)	30	1,029	0.14(0.23)
Fourth	36	9.55	0.10(0.22)	40	8,249	0.11(0.24)
(c) Crop income	Farm size (ha)			Household asset value (ZMW)		
Quantiles	Obs.	Mean area	ATT	Obs.	Mean asset value	ATT
First	25	0.87	-0.19(0.17)	29	187	-0.15(0.19)
Second	13	1.83	-0.17(0.32)	17	423	-0.20(0.21)
Third	24	3.07	-0.17(0.26)	18	1,029	-0.19(0.32)
Fourth	24	9.55	-0.14(0.15)	22	8,249	-0.13(0.17)

Notes: Standard errors in parenthesis; Obs. refer to number of observations; ATT refers to average treatment effects on the treated.

4.3 Decomposition of household and crop incomes

The top panel of Table 5 shows the mean predicted outcomes and their mean differences between adopters and non-adopters, while the lower panel shows the decomposition estimates obtained using equation (18) and the explanatory variables in Table 1. These results suggest that the observed mean differences in household and crop incomes between adopters and non-adopters are largely due to differences in magnitudes of covariates (explanatory variables or endowments) rather than in returns to these covariates. This signals heterogeneity in endowments among households in the sample.

The negative and significant covariate effects for household income (-0.231) and crop income (-0.468) suggest that the mean differences in these outcome variables between adopters and non-adopters would be reduced if the adopters and non-adopters had similar covariates. In other words, if non-adopters had the same number of plots, years of education, assets, experienced similar seasonal rainfall and applied similar quantities of fertilizers and manure (see, Table 2) as adopters; the differences in household and crop incomes between the two groups would diminish. These findings are in line with descriptive results in Table 1, which show significant differences in several characteristics and endowments between adopters and non-adopters.

Table 5: Linear decomposition of the log of household income, crop revenue and crop income by minimum tillage adoption status

	Log household income	Log crop revenue	Log crop income
Mean outcome, non-adopters	7.686	6.904	6.978
Mean outcome, adopters	7.703	6.812	7.195
Mean difference	-0.017	0.092	-0.216*
	(0.114)	(0.182)	(0.128)
Decomposition estimates			
Covariate (endowment) effects	-0.231*	-0.370	-0.468***
	(0.132)	(0.234)	(0.167)
Returns to covariates	0.488	-0.221	-0.418
	(0.586)	(1.075)	(0.501)
Interaction effects	-0.274	0.683	0.670
	(0.617)	(1.107)	(0.489)
Observations	751	751	565

Notes: Robust standard errors in parenthesis; *, *** statistically significant at 1% and 10% , respectively.

5 Discussion

The main results of this paper suggest that adopting MT had no significant effects on household income, crop revenue and crop income in the short-term. These results are in line with Jaleta et al. (2016) who found that adopting MT had no significant impacts on farm incomes in Ethiopia and Kuntashula et al. (2014) who found similar results on maize revenue for smallholder farmers in Zambia. However, results on crop revenue are in contrast to those in El-Shater et al. (2015) who found positive impacts from adopting zero tillage (included MT) among wheat farmers who had more than one year experience using zero tillage in Syria. Therefore, whether farmers have used MT for long or not matters.

Two main features of MT practices may help explain the results of this paper. First, MT does not always lead to immediate yield gains compared with conventional agriculture for an average smallholder farmer (Pannell et al., 2014; Thierfelder et al., 2015) - the main arguments are often the long term effects in terms of reduced land degradation and soil restoration. And, even if it does (Jaleta et al., 2016; Ngoma et al., 2015), the short-term yield gains may be just moderate and not sufficient enough to offset additional input costs (e.g. fertilizers, herbicides, seed, implements, labor) associated with MT for an average farmer. This is in line with Jaleta et al. (2016): despite finding positive yield effects from MT (relative to conventional tillage), these gains were not large enough to cover costs and thereby translate into higher incomes.

The high production costs associated with MT may explain the larger (although insignificant) treatment effects (ATT) for crop revenue relative to crop income in this study. Descriptive results in Table 1 provide a comparative breakdown of the cost elements: a larger proportion of MT plots used herbicides and manure than non-MT plots, used more fertilizer per hectare, were weeded more frequently, and hired more labor per hectare compared with non-MT plots. Figure 4 also confirms these cost differentials. The cost of production and labor input were higher on MT than non-MT plots in the sample: the cumulative density functions of the cost of production and labor input for MT plots are mostly to the right side of those for non-MT plots in Figure 4.

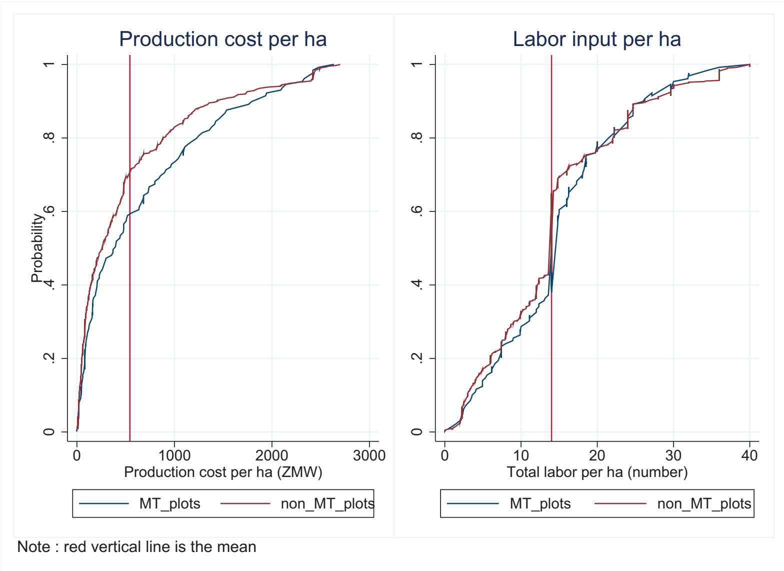


Figure 4: Cumulative distributions of smallholder farmer production cost per hectare (fertilizer, seed and hired labor) and labor quantity by minimum tillage adoption status.

Second, the lags from initial adoption to the time when farmers start realizing positive yield gains may encourage partial application of MT such that a larger portion of cultivated land remains under conventional tillage even among adopters (Ngoma et al., 2016). This may be true for poor farmers who have high discount rates and whose top priority is to meet immediate subsistence needs. Its low adoption intensity may partly explain why results in this paper suggest that MT has no significant impact on household and farm incomes for smallholders in the sample.

Although the ATT results (Table 3) on all outcome variables are insignificant, the differences in magnitudes of the effects might be indicative of three things. First, the ATT on crop revenue is larger than the ATTs on household and crop income. This is expected because crop revenue does not take into account any of the cost elements. Second, the negative ATT on crop income relative to crop revenue suggests, as Figure 4 shows, that MT has higher input costs relative to conventional tillage. Third, the positive and negative ATTs on household income and crop income, respectively, suggest that while MT may be labor intensive, households are still able to allocate labor to other income-generating activities, including to earn off-farm incomes.[9]

Given the limited short-term livelihoods benefits, what policies can then be used to make MT more attractive to smallholder farmers? As earlier defined, two main policy options exist: X-policies lead to changes in observed characteristics (endowments), while the β-policies aim to change returns to explanatory variables. I discuss X-policies only since the magnitudes of covariates or the endowment effect is the most important in this case (Table 5). The X-policies that would raise the benefits (for all outcome variables) of adopting MT for smallholders include: improving farmer education to enable them learn about MT and appreciate its potential benefits, increasing use of hybrid seed, and increasing labor use for timely field operations, e.g., weeding - also possible with herbicides (Table 2). Other important X-policies could focus on promoting farmer organizations such as cooperatives, which facilitate technology transfer and improved market access. The exact policy mix implemented will have to be decided based on their costs and expected benefits.

Some caveats are in order when interpreting results in this paper. First, since it is unknown how long farmers in the sample used MT and results are based only on data from one agricultural season, these results should be interpreted as short-term impacts. These results neither account for the dynamic and long-term impacts of MT on soil biophysical and chemical properties nor the learning effects from repeated use of MT. Second, because production costs were not fully recorded in the survey, the costs reflected in this paper may be underestimated. Third, despite efforts to control for the endogeneity of MT adoption, the use of cross sectional data may not fully account for endogeneity biases. Fourth, results in this paper are drawn from a small sample and do not therefore give a national picture. Nevertheless, if results in this paper are widely applicable, they may partially explain the

[9]Recall that crop income only deducts the costs of hired labor. Therefore, the effect of MT on family labor allocation directly influences household participation in off-farm income generating activities captured in total household income.

perceived low uptake of MT among smallholder farmers in the region.

6 Conclusion

This paper assessed the short-term impacts of adopting minimum tillage on household and crop incomes using plot and household level cross section data for the 2013/2014 agricultural season in Zambia. I applied an endogenous switching regression framework to control for self-selection into adoption, and to generate consistent observed and counterfactual outcomes.

The results suggest that adopting minimum tillage had no significant effects on household and crop incomes. This implies that, while minimum tillage may confer some yield benefits (Jaleta et al., 2016; Ngoma et al., 2015), the gains are not large enough to offset the costs of implementation and translate into higher incomes in the short-term.

These findings suggest that yield alone is insufficient; it may not be the most important variable from a livelihoods perspective. Increased use of complementary inputs such as hybrid seed and raising farmer education are some of the key policy options that can raise the benefits and attractiveness of minimum tillage for smallholder farmers.

Future research could develop longitudinal studies that capture detailed cost profiles of implementing minimum tillage (including hired and family labor) and evaluate impacts on returns to labor and farm profit, and for farmers at different levels of experience with minimum tillage or the full conservation agriculture package.

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Appendices

Table A1: Instrument exclusion tests using the F statistic

Equation	Household income	Crop revenue	Crop income
F statistic (1,27)	0.18	1.85	0.01
$P - value^{*}$	0.67	0.18	0.96

Notes:* The null hypothesis in all equations is that MT extension is insignificant; we fail to reject the null at 1% confidence level in all equations.

Table A2: Correlation matrix for independent variables

	plotsze	nplot	pltfert	herb	manure	cropres	croprot	fertrate	cweedings	hybseed	agehh	eduhh	malehh
plotsze	1.000												
nplot	-0.032	1.000											
pltfert	-0.024	-0.060	1.000										
herb	0.221	0.126	0.061	1.000									
manure	0.048	-0.023	-0.039	0.056	1.000								
cropres	0.058	-0.019	-0.026	-0.010	-0.064	1.000							
croprot	-0.034	-0.028	-0.005	0.007	-0.015	0.300	1.000						
fertrate	0.176	-0.146	0.138	0.166	0.162	0.032	0.056	1.000					
cweedings	0.146	-0.068	0.022	0.058	0.044	-0.029	-0.033	0.062	1.000				
hybseed	0.260	-0.147	0.132	0.094	0.012	-0.021	0.024	0.115	0.004	1.000			
agehh	0.022	-0.027	0.152	0.014	0.118	0.000	0.032	0.123	0.078	0.063	1.000		
eduhh	0.077	0.042	0.232	0.129	-0.013	-0.030	-0.020	0.117	-0.133	0.101	-0.105	1.000	
malehh	0.082	0.084	0.009	0.054	-0.062	0.045	-0.001	-0.045	-0.026	0.013	-0.177	0.132	1.000
married	0.105	0.096	-0.031	0.080	-0.049	-0.006	0.017	-0.027	-0.036	0.008	-0.227	0.152	0.536
rain00	-0.371	-0.113	0.027	-0.276	-0.093	0.037	-0.002	-0.083	-0.129	-0.181	-0.103	-0.076	-0.012
diosales	-0.040	0.054	0.039	0.037	-0.129	0.086	-0.008	-0.112	-0.036	-0.047	-0.200	0.005	0.116
ae	0.147	0.214	0.005	0.198	0.030	-0.047	-0.021	0.092	0.104	0.091	0.252	-0.018	0.180
tlu	0.250	0.317	-0.074	0.220	0.108	-0.010	-0.020	0.038	-0.003	0.017	0.079	0.121	0.147
asset00	0.222	0.311	0.189	0.243	-0.010	-0.059	-0.059	0.150	0.048	0.102	0.091	0.241	0.241
labhire	0.006	-0.082	-0.140	-0.018	0.017	-0.022	-0.043	0.055	0.006	0.019	0.080	-0.024	0.009
famlaba	-0.438	0.055	0.026	-0.135	-0.055	-0.041	0.065	-0.217	-0.075	-0.088	-0.015	-0.021	-0.038
memcoop	0.033	0.215	0.034	0.100	0.082	-0.057	0.008	0.157	0.031	-0.014	0.196	0.054	-0.041
rlthdman	-0.053	0.034	-0.146	-0.087	0.040	0.020	-0.084	-0.100	0.085	-0.086	-0.019	-0.133	0.112
MText	0.081	0.193	-0.024	0.196	0.105	0.031	0.039	0.110	0.086	0.061	0.215	0.186	-0.034

	married	rain00	diosales	ae	tlu	asset00	labhire	famlaba	memcoop	rlthdman	MText
married	1.000										
rain00	-0.029	1.000									
diosales	0.121	0.280	1.000								
ae	0.257	-0.276	-0.035	1.000							
tlu	0.191	-0.465	-0.051	0.331	1.000						
asset00	0.290	-0.355	-0.044	0.451	0.571	1.000					
labhire	-0.025	-0.084	-0.161	0.061	-0.003	0.003	1.000				
famlaba	-0.011	0.131	0.068	-0.003	-0.146	-0.127	-0.183	1.000			
memcoop	-0.016	-0.061	-0.040	0.142	0.261	0.261	0.014	-0.056	1.000		
rlthdman	0.120	0.115	0.030	-0.092	-0.024	-0.159	0.053	0.041	0.014	1.000	
MText	-0.065	-0.388	-0.200	0.161	0.302	0.263	0.066	-0.051	0.302	-0.129	1.000

Paper IV

Can conservation agriculture save tropical forests?
The case of minimum tillage in Zambia

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Abstract

Minimum tillage (MT) is a key component in the promotion of conservation agriculture (CA). This paper asks whether MT reduces cropland expansion and deforestation. We develop a theoretical household model of land expansion, and test hypotheses by estimating a double hurdle model using household survey data from 368 smallholders in rural Zambia. We find that about 19% of the farmers expanded cropland into forests, clearing an average of 0.14 ha over one year. Overall, MT adoption does not reduce cropland expansion among households in our sample, while higher crop yield and labor availability stimulate expansion. Therefore, yield augmenting agricultural technologies (such as MT) may not reduce expansion unless combined with other forest conservation measures.

Keywords: Cropland expansion, deforestation, minimum tillage, double hurdle, Zambia
JEL Classifications: D13, Q12, Q23

*We acknowledge funding from the Norwegian Agency for Development Cooperation [agreement no. GLO-3945 QZA 13/0545; grant on Learning from REDD+ an enhanced Global Comparative Analysis] through the Center for International Forestry Research (CIFOR). We thank Davison Gumbo for hosting and facilitating fieldwork and all research assistants. We are grateful to John Herbert Ainembabazi and for comments from the EAERE 2016 conference in Zurich.

1 Introduction

Smallholder farmers in sub-Saharan Africa (SSA) face an urgent need to raise agricultural productivity to feed a growing population, and - relatedly - increase farm income to reduce poverty. Costly agricultural inputs and constrained access to credit leave area expansion as the main option for many smallholders in the region. Despite its potential to improve both crop yields (Ehui and Hertel, 1989) and production (De Janvry and Sadoulet, 2010) in the short-term, cropland expansion is often unsustainable because farmers face diminishing land productivity and forest loss induces climate risks.

Agricultural land expansion is the main cause of deforestation in tropical countries (Angelsen and Kaimowitz, 2001; Gibbs et al., 2010). Forest loss has contributed about one-third of the accumulated increase in greenhouse gases (GHG), and makes up about one-tenth of the current emissions (IPCC, 2013). Climate change exposes smallholders to higher rainfall variability and other climate related shocks (Hallegatte et al., 2016). This hampers the efforts to reduce poverty in SSA, both due to the direct effects on crop production, and indirectly through destabilizing agricultural markets and higher risks making farmers reluctant to undertake investments in the sector. The dual challenge of smallholder farmers in SSA is, therefore, to intensify agricultural production sustainably while mitigating and adapting to predicted climate change.

Several agricultural technologies have been proposed to meet this dual challenge, based on the assumption that intensifying agriculture would raise productivity and spare nature. These technological options, exemplified by the Asian green revolution of the 20^{th} century, altered factor intensities by increasing use of labor, capital, inorganic fertilizers, improved seeds and tillage. Currently, there is strong political support for climate smart agriculture (CSA) as a major avenue to simultaneously raise smallholder agricultural productivity and enhance climate change adaptation and mitigation in SSA. CSA is a broad-based approach that includes policy reforms to support new technological solutions and farm management practices, which includes conservation agriculture (CA).

CA has three key components: minimum tillage (MT), *in-situ* crop residue retention and crop rotation. It aims to improve agricultural land productivity while delivering adaptation-mitigation co-benefits (IPCC, 2014; Thierfelder et al., 2015; Thierfelder and Wall, 2010; UNEP, 2013).

This paper focuses on household led-cropland expansion and addresses the where, why and how much questions about cropland expansion. We test the effects of CA practices on cropland expansion using a consistent theoretical household model and an empirical analysis based on detailed survey data on farm, household and contextual characteristics. We focus on MT because it is the basis and main component of CA.

Our data are from Zambia, a country which - despite a high forest cover of about 66% (FAO, 2015; Kalinda et al., 2013) - experiences high deforestation driven by household or centrally planned agricultural expansion (e.g., farm blocks), urbanization, new settlements, road development and mining.

The literature suggests two major potential pathways through which MT may contribute to reduced GHG emissions. The first is through improved soil carbon sequestration resulting from reduced tillage and enhanced buildup of soil organic matter (UNEP, 2013). However, a growing evidence base suggesting that MT has limited potential to sequester soil carbon challenges this view (Powlson et al., 2014, 2016; VandenBygaart, 2016). The second pathway links MT to reduced deforestation via its effects on crop yield and household labor allocation. We focus on the second pathway in this paper.

MT improves crop yield by facilitating early planting, buildup of soil organic matter and improved input use efficiency (Haggblade and Tembo, 2003). On one hand, higher yield means the same output can be delivered from less agricultural land, and should therefore take the pressure off forests, sometimes referred to as the Borlaug hypothesis (Angelsen and Kaimowitz, 2001). However, higher yield also provides an incentive to shift resources to a more profitable agricultural sector, including expanding the land area if feasible. Angelsen and Kaimowitz (2001) found that new technologies that raise agricultural productivity might in fact stimulate deforestation by making agriculture more profitable, sometimes referred to as the 'Jevons' paradox. The constant output assumption of the Borlaug hypothesis does not hold.

However, MT is also labor-intensive (Giller et al., 2009; Thierfelder et al., 2015) especially in the initial years of adoption. Labor-intensive technologies absorb family labor (and possibly raise rural wages) and might therefore have a land-sparing effect (Angelsen and Kaimowitz, 2001). As such, it is not readily clear how MT affects deforestation. This depends on the factor intensities and yield impact of the particular MT technology, market conditions, and preferences and farm constraints (Angelsen, 1999). The scale of the analysis also matter. Large-scale adoption provokes general equilibrium effects in the form of lower output prices and higher wages (if labor intensive), which can partly or fully offset the effect of higher profitability (Angelsen and Kaimowitz, 2001).

Most studies on the link between agricultural technologies and deforestation are global or national in scope and apply inadequate econometric methods (Barbier and Burgess, 2001; Gibbs et al., 2010; Phelps et al., 2013; Rudel, 2013; Rudel et al., 2009), making them less informative to local contexts. Others lack explicit theoretical models to guide their empirical analysis, and many focus only on output effects (Balmford et al., 2005; Ewers et al., 2009). Except for Vinya et al. (2011) and Holden (1997), empirical evidence on the nexus between agricultural technologies and deforestation in Zambia remains thin.

This paper adds to the literature in two ways. First, we develop a simple Chayanovian agricultural household model and solve it analytically to guide the empirical estimation. Second, we address data problems by using detailed local context-household survey data from rural Zambia for the empirical analysis and we explicitly test for the potential endogeneity of MT, shadow wages and yield on cropland expansion decisions using instrumental variables.

The rest of the paper is organized as follows. Section 2 briefly reviews existing models of deforestation and presents the theoretical model. Sections 3 and 4 outline the empirical strategy and data sources, while section 5 presents these results. Section 6 discusses the results, and section 7 concludes.

2 Theoretical model

2.1 Economic models of deforestation

Theoretical economic models of deforestation can be classified in two broad categories. The first category applies dynamic optimization to assess optimal land allocation between forest and competing uses (mainly agriculture), possibly also including different sub-sectors of agriculture, e.g., lowland and upland agriculture. With a national or region focus, these models assume that a social planner determines land allocation between competing uses by comparing relative returns over time. Examples include Barbier and Burgess (1997) and Tachibana et al. (2001). In general, these models show that higher agricultural profit stimulate deforestation by favoring conversion of land to agriculture. The idea of an almighty social planner determining land allocation may be far-removed in countries with partly liberalized land markets like Zambia. Yet a market system can mimic some of the characteristics of the optimal solution, but additional features need to be added, e.g., insecure tenure and land claims strengthened by land clearing.

The second category focuses on household level drivers of deforestation and apply different versions of the (mostly) static agricultural household model in the tradition of Singh et al. (1986). These models are again split between recursive and non-recursive models, i.e., based on whether consumption and production decisions can be separated (recursive) or must be taken simultaneously. The former assume that households participate in well-functioning labor, land and output markets, and production decisions are studied within a profit-maximizing framework. Missing or imperfect markets give rise to the non-recursive models, also labeled Chayanovian models. See Angelsen (1999) and Angelsen (2010) for a comparison of different models of deforestation, and Pagiola and Holden (2001), Maertens et al. (2006) and Alix-Garcia et al. (2012) for other applications of agricultural household models on deforestation.

Our theoretical model falls within the second category of deforestation models, i.e., a static model assuming an imperfect labor market (non-recursive model).

2.2 Farm level cropland expansion

We develop a Chayanovian model of cropland expansion for a representative, smallholder farm household in Zambia. We extend existing models of, *inter alia*, Angelsen (1999) and Maertens et al. (2006) by adding a new technology (MT). We assume that land is homogeneous, available and accessible at a cost $d(A - A_0)$. We assume a well-behaved aggregate production function, in which production is a function of family labor (l^a), minimum tillage (M), land area (A) and inputs ($\mathbf{X}$): $Y = f(l^a, M, A; \mathbf{X})$. We consider M a non-essential input. The input vector ($\mathbf{X}$) is assumed fixed, which enables us to solve the model analytically without too much complication. Labor, minimum tillage and land are assumed to be complementary: $f_{l^a}, f_A, f_M > 0$; $f_{l^a l^a}, f_{AA}, f_{MM} < 0$; and $f_{l^a A}, f_{l^a M}, f_{AM} > 0$. Given the complementarity assumption, agricultural land expansion and MT adoption have implications for the demand of family labor.

A representative household maximizes utility $U = U(c, l; \mathbf{h})$ by trading off consumption (c) and leisure time (l). $\mathbf{h}$ is a vector of exogenous household demographics, which we drop in subsequent equations but retain in the empirical estimation. In addition to the land access cost d, we assume an additional convex labor cost of clearing, reflecting, for example, increasing costs with distance from the homestead as crop area expands: $t(A - A_0)^r$, where $t > 0$ and $r > 1$. A is total cultivated land per household and A_0 is the initial stock of land. The difference $A - A_0$ then gives the size of converted land within this period. A representative farm household solves the following problem:

$$\underset{c, l^a, A, M}{Max\, U} = U(c, l; \mathbf{h}) \tag{1}$$

Subject to

$$c = p_y f\left(l^a, M, A; \mathbf{X}\right) - vM - d(A - A_o) - p_x\mathbf{X} + w\bar{l}^o + E \tag{2}$$

$$T = l + t(A - A_o)^r + l^a + \bar{l}^o \tag{3}$$

$$c, A, l^a, M \geq 0,\ r > 1, t > 0, A \geq A_o$$

U is household utility, which has positive but diminishing marginal utilities of consumption and leisure. For simplicity, we assume zero cross partials: $U_c, U_l > 0; U_{cc}, U_{ll} < 0; U_{cl}, U_{cl} = 0$. Equation (2) is the budget constraint. We assume that all income earned by the household is spent on consumption in our single period model. p_y is output price, v is the farm level input and capital costs of implementing MT. p_x is the per unit input cost, which like $\mathbf{X}$ is fixed. E captures all other exogenous income to the household. Equation (3) is the labor constraint; total household time T equals leisure time l plus time spent working on the farm l^a, clearing new agricultural land $t(A - A_o)^r$ and off farm $\bar{l}^o$.

We assume an imperfect labor market in the sense that households can only sell a fixed amount of labor $\bar{l}^o$ at a market wage rate w. This labor market assumption leads to the Chayanovian model with a household specific shadow wage below the market wage (otherwise, the constraint will not be binding, Angelsen (1999)). We assume that output markets are well functioning in the way that farmers can sell (or buy) what they want at a given market price.

We consider the interior solution case where $A - A_0 > 0$ and $M > 0$, and write the Lagrangian for the problem as:[1]

$$\begin{aligned} L = U\left(c, l\right) + \mu\left[c - p_y f\left(l^a, M, A; \mathbf{X}\right) + vM + d(A - A_o) + p_x\mathbf{X} - w\bar{l}^o - E\right] \\ +\lambda[T - l - t(A - A_o)^r - l^a - \bar{l}^o] \end{aligned} \tag{4}$$

The first order conditions (FOCs) are given by

$$\partial L/\partial l^a = \mu[-p_y f_{l^a}] - \lambda = 0 \tag{5}$$

[1]In the empirical estimations, we consider cases where $M = 0$.

$$\partial L/\partial A = \mu[-p_y f_A + d] - \lambda[rt(A - A_o)^{r-1}] = 0 \tag{6}$$

$$\partial L/\partial M = \mu[-p_y f_M + v] = 0 \tag{7}$$

$$\partial L/\partial c = U_c + \mu = 0 \tag{8}$$

$$\partial L/\partial l = U_l - \lambda = 0 \tag{9}$$

Using equations (8) and (9) to eliminate the shadow values of consumption (μ) and labor (λ), the FOCs for the choice variables l^a, M and A are given by:

$$p_y f_{l^a} = z \tag{10}$$

$$p_y f_A = d + zrt(A - A_o)^{r-1} \tag{11}$$

$$p_y f_M = v \tag{12}$$

where,

$$z = \frac{U_l\,(c,l)}{U_c\,(c,l)} \tag{13}$$

Equation (13) defines the shadow wage (z) as the marginal rate of substitution between consumption and leisure. Equation (10) states that the marginal productivity of agricultural labor (or leisure) is equal to z, which is the marginal rate of substitution between consumption and leisure. The marginal productivity condition in equation (11) states that a household will expand cropland (A) until the marginal productivity of land equals the sum of the cash and labor cost of land and expansion. Equation (12) states MT is profitable as long as its marginal benefit is equal to the cost of implementing it.

Since MT (M) and cropland expansion (A) are both endogenous, assessing the impact of MT on expansion cannot readily be seen from the FOCs without further comparative statics. Also, since M is endogenous in the model, the exogenous (policy) variable to investigate in our formulation is the costs of implementing MT, namely v. As seems from equation (2), a policy lowering v will lead to higher adoption of MT.

2.3 Comparative statics

The complete comparative statistics is presented in Appendix A. We used Cramer's rule to assess how changes in exogenous variables affect cropland expansion (A), the key outcome variable of interest. This section only discusses results for the effects of the cost of implementing MT (v) on cropland expansion (A): $\partial A/\partial v$. The full derivation and other variables are discussed in Appendix A.

The impact of changes in (costs of) MT adoption on land expansion is the net of the substitution and income effects. The substitution effect is what a recursive model would give, i.e., by keeping z constant. The income effect is analyzed through changes in z (Angelsen, 1999).

The substitution effect of a change in v on A is as follows: lower (higher) costs of MT adoption increases (reduces) adoption. Higher M increases the marginal productivity of land (and labor), given the complementarity assumption. Expansion becomes more profitable, and the substitution effect only gives that $\partial A/\partial v < 0$.

The income effect is, however, positive. Lower v has several effects on z. First, all inputs remaining constant, it will reduce the costs of production and raise consumption (cf. equation (2)). Higher consumption raises z, cf. equation (A1). Second, the substitution effect gives higher M, A and l^a when v is lowered. The household will produce and work more, and have less leisure. This will trigger an increase in the households shadow wage rate, cf. again equation (A1). Higher opportunity costs of labor will have a negative impact on expansion, i.e., positive impact on $\partial A/\partial v$. We summarize our results, cf. equation (A26) in the following proposition:

> ***Proposition***: The overall effects of lower costs of MT (v) on cropland expansion are indeterminate, *a priori*. The substitution effect is positive, reflecting the higher profitability of land expansion. The income effect is negative, reflecting that higher consumption and less leisure raise the household shadow wage rate, reducing the profitability of land expansion.

We cannot determine the net effect, but can hypothesize how different factors will affect the net result. Household preferences matter, i.e., the responsiveness of the shadow wage to changes in consumption and leisure. Angelsen (1999) shows - using a specific utility function with subsistence levels - that the income effect dominates for poor households (close to that subsistence level). The production technology also matters, e.g., to what extent MT adoption changes the marginal productivity of labor and land. If MT adoption leads to large increases in marginal labor productivity (i.e., is labor intensive), the impact on z can be large, and make the income effect dominate the substitution effect.

3 Empirical strategy

In order to bring the theoretical framework to the data, we can write a parsimonious representation of the reduced form solution as:[2]

$$A^* = A^*(M, y, z; p_y, p_x, x, A_o, \mathbf{h}) + \varepsilon \tag{14}$$

where A^* is the size of expanded cropland, M is the size of land under MT. We use the size of land area under MT (and not a dummy =1 if the household used MT), which also reflects the cost of implementing MT (v). v was not collected during the survey. y is an aggregate crop yield (used as proxy for expected yield), z is the shadow wage, which measures the opportunity cost of labor and p_y is the per kg cost of maize and used as a proxy for output price.

X is now a dummy $= 1$ if a household used inorganic fertilizers and/or hybrid seed, (p_x) is an average per kg input cost of mineral fertilizer and seeds, l^o is a dummy $= 1$ if at least one household member worked off farm and A_o is the initial amount of land (farm size) controlled by the household (net of newly expanded area). $\mathbf{h}$ is a vector of demographics and other exogenous variables such as value of assets, access to subsidy, tenure, distance from

[2]This representation relaxes some assumptions from the theoretical model for example on fixed p_x and $\mathbf{X}$.

homestead to protected forest and location dummies added in the empirical estimation. ε is the error term.

Following from the theoretical model, M, y, and z are endogenous and therefore may be correlated with the error term in equation (14). There are also reasons to suspect that MT is endogenous because farmers who self-select themselves into MT adoption may have unobservable characteristics, which may also influence their expansion decisions. Moreover, since MT affects cropland expansion through yield effects, then MT and yield may be interdependent, and possibly jointly determined with expansion decisions at household level. Subsection 3.1 elaborates how we addressed these endogeneity concerns.

We compute the household specific shadow wage (z) following Jacoby (1993). First, we estimate a Cobb Douglas production function and then use its results (Table A3,appendix B) to compute:

$$z = \beta \frac{\widehat{prod}}{labor} \tag{15}$$

where *labor* is total labor input per household, β is an estimated parameter associated with labor and $\widehat{prod}$ is predicted production (the dependent variable in the Cobb Douglas function).

3.1 Estimation challenges

A natural first step before deciding how to estimate equation (14) is to test for the endogeneity of M, y and z. This can be achieved using the control function approach or the standard two stage least squares (2SLS) method (Wooldridge, 2010). We used 2SLS because all the suspected endogenous variables are continuous and 2SLS provides straight forward post estimation procedures to test for endogeneity and instrument relevance. We estimate one 2SLS model including one suspected endogenous variable at a time, all exogenous variables and instrumental variables (IVs).[3]

We used the following IVs. For MT area, we used access to MT extension (dummy = 1). We would expect access to MT extension to affect farmer decisions to adopt MT, but not their expansion decisions directly. For yield, we used whether the household head is polygamously married (dummy = 1), monogamously married (dummy = 1) and distance from homestead to main feeder road. For the shadow wage, we used whether the household head is polygamously or monogamously married (dummies =1).

Suitable IVs should affect MT area, yield and shadow wages, but not expansion directly. We might argue that our IVs are only indirect measures of the direct factors that affect expansion such as labor availability that we include directly in the main estimations. We formally tested for IV relevance (significant correlations to endogenous variable) and admissibility (insignificance in the expansion equation). Table A1 in appendix B shows that the IVs were relevant in each of their respective first stage equations ($5.24 < F < 9.16$), but they were jointly insignificant in the main expansion equation ($F = 1.47, p = 0.21$), suggesting that the exclusion restrictions were valid.[4] The endogeneity test results for MT, yield and shadow wage show that $p \geq 0.71$. Following (Wooldridge, 2010), we fail to reject the null hypothesis that the (potentially endogenous) variables are exogenous.

Therefore, our empirical estimation proceeded without considering prior endogeneity concerns. From henceforth, M, y and z are now considered exogenous.

The second estimation issue is the censored nature of the outcome variable where only about 19% of all farmers in the sample expanded cropland. Although Heckman and Tobit models are potential options, we used the double hurdle model which relaxes the Tobit assumptions by allowing the same or different factors to affect expansion decisions and extent of expansion differently (Cragg, 1971; Wooldridge, 2010).

[3]If M, y and z are confirmed endogenous after the tests, three stage least squares (3SLS) could be used to account for the multiple endogenous variables (Greene, 2012). However, because of challenges to empirically test for consistency of the error covariance matrix in 3SLS, its use would be questioned. The the final model used is the double hurdle model and not 2SLS because we do not find significant evidence of endogeneity, see section 3.2. We also tested for endogeneity using IV Tobit and arrived at the same conclusion.

[4]We used the Tobit model to test for IV admissibility.

A third challenge concerns how to parcel out the effects of area under MT (our measure of MT effects) from those of crop yield on cropland expansion. Recall from our theoretical discussion that MT affect cropland expansion both through its effects on yield (higher profitability of expansion), but that the demands of more labor also increases the shadow wage, dampening or even reversing the outcome. In an attempt to isolate these two effects, we include MT area and crop yield in separate models. Yield in this case also includes the effects of MT on yield, but the size of area under MT better reflects labor demand related to MT.[5]

3.2 Empirical specification

Following Wooldridge (2010), the first stage of the double hurdle model is a probit model of whether or not households expanded cropland i.e., ($exp > 0$):

$$P(exp > 0|\mathbf{G}) = \Phi(\mathbf{G}\gamma) = \alpha_1 + \mathbf{G}\psi + \epsilon \tag{16}$$

The second stage is a truncated normal regression of area expanded (A^*) conditional on $exp > 0$ and $\mathbf{G}$:

$$E(A^*|exp > 0, \mathbf{G}) = \alpha_2 + \mathbf{G}\beta + \mu \tag{17}$$

exp is a dummy = 1 if a household expanded cropland and A^* is the amount of new cropland in the 2013/2014 season. α_i are the intercept terms. $\mathbf{G}$ is a vector of all exogenous variables defined as before, β and γ are parameters to be estimated while ϵ and μ are error terms from the first stage and second stage respectively. The overall or unconditional

[5]Our data do not allow us to explicitly isolate the contributions of MT to crop yield and to household labor supply and demand. We also tried to use 3SLS, but we dropped it for reasons mentioned earlier.

expected value of $E(A^*)$ is a product of the expected values for equations (16) and (17) and the first derivatives of these equations measure marginal or average partial effects (APEs). Readers are referred to Wooldridge (2010) for a thorough discussion. We estimated the two steps of the double hurdle simultaneously with maximum likelihood following Burke (2009).

4 Data sources

The data used in this study are from an extensive household survey conducted in 2014. Sampling proceeded at three levels. First, we selected Nyimba, Mumbwa and Mpika districts based on exposure to forest conservation interventions, agriculturally productive area and prevalence of shifting cultivation systems. Second, we randomly sampled 10 villages per district using the most recent village lists per district. Third, we used up-to-date village registers obtained from village leaders to select 12-15 households, randomly from each village for interview. This gave sub-samples of 120 from each of Mpika and Nyimba districts, 128 from Mumbwa, and 368 households in total. Figure 1 shows the location of survey areas.

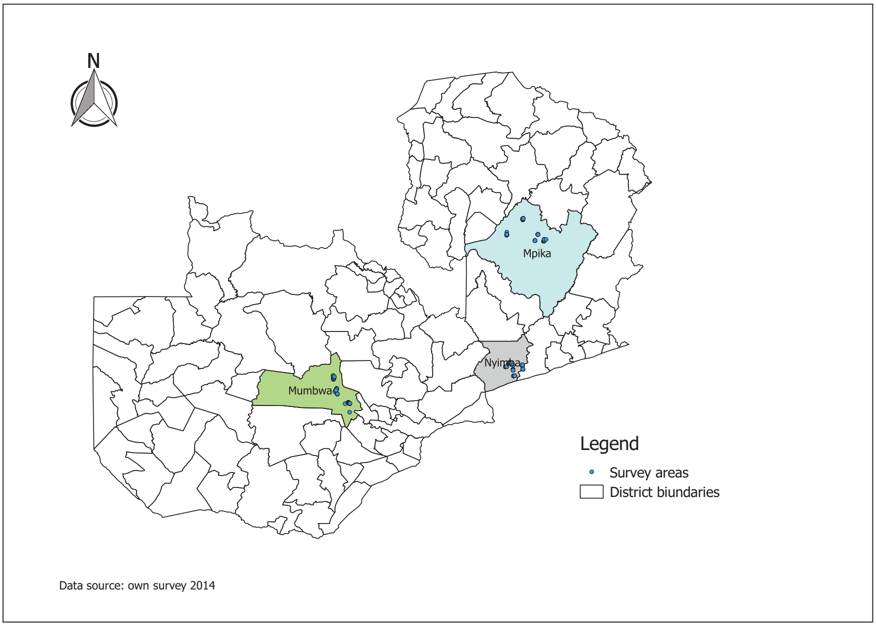

Figure 1: Spatial location of survey areas in Zambia

Data were collected using structured questionnaires and face-to-face interviews. The survey collected detailed information on household demographics, agricultural (including tillage methods) and off-farm activities, yield, labor and other input use, asset holdings and sources of income. Specifically, the survey asked households whether they expanded their cropland in the 2013/2014 season. Those who expanded provided the size of the new (additional) area, reasons for expanding, the main crop(s) grown, where they expanded into, and who among household members made the decision. Similarly, those who did not expand provided reasons.

The main crops grown in the study areas include maize, cotton, groundnuts, sunflower, soybeans, mixed beans and cassava. Table 1 defines the main variables and presents summary statistics.

Table 1: Variables used in regression models and summary statistics

Variables description	Name	Mean	Standard deviation
Dependent variable			
Expanded cropland into 2013/2014 season (yes =1)	$(A > A_0)$	0.19	0.40
Self-reported cropland expansion area (ha)	A^*	0.14	0.39
Potentially endogenous independent variables			
Size of land under minimum tillage (ha)	M	0.13	0.47
Aggregate crop yield (kg/ha)$^+$	y	1,874.76	1,229.54
Shadow wage	z	0.41	0.19
Exogenous Independent variables			
Distance from homestead to protected forest (km)	h	13.50	11.75
Age of household (hh) head (years)	h	45.04	13.89
Male head of hh (yes=1)	h	0.77	0.42
Education, hh head (years)	h	6.37	3.23
Value of household assets (ZMW)*	h	2,236.95	1,383.78
Total land under hh control (net of expansion) (ha)	A_0	4.29	6.93
Adult equivalents	h	4.96	2.01
Household member earned off farm income (yes=1)	l^0	0.09	0.29
Used improved inputs (fertilizer and/or hybrid seed)	x	0.78	0.41
Average per kg fertilizer and seed cost (ZMK/kg)	p_x	4.50	1.41
Average per kg maize price ZMK/kg)	p_y	1.85	0.67
Some plots on title (yes=1)	h	0.04	0.19
Accessed subsidy - FISP (yes=1)	h	0.30	0.46
Mumbwa district (yes=1)		0.37	0.48
Nyimba district (yes=1)		0.34	0.47
Mpika district (yes =1)		0.29	0.46
Instruments (IVs) for 2SLS estimations			
Distance from homestead to main feder road (km)		2.56	7.55
Polygamously married (yes=1)		0.03	0.18
Monogamously married (yes=1)		0.71	0.45
Accessed MT extension (yes =1)		0.59	0.45
Number of observations		350	

Notes: $^+$For all crops, but mainly maize and used as a proxy for expected yield at the time farmers made the decision to expand in the 2013/2014 season. The sample reduced to 350 after dropping 18 households who had zero harvest because they only cultivated cassava during the survey period. *1 USD = 6.2 ZMK at the time of the survey.

5 Results

5.1 Where do smallholders expand cropland and why?

Our first descriptive approach considered situations when cropland expansion led to deforestation. Not all cropland expansion causes deforestation, and we therefore asked respondents who expanded cropland; what land parcels were expanded, what land they expanded into, and - if fallows - how old the fallows were.

Overall, about 24% of the respondents expanded cropland during the survey reference period (i.e., between 2012/2013 and 2013/2014 agricultural seasons). Among these, about 75% and 25% expanded into uncultivated land (forest) and fallows, respectively. When we define deforestation as cropland expansion into virgin forests or fallowed land older than 15 years, we find that only about 19% of the households are involved in cropland expansion that should be considered deforestation (Figure 2).[6] We base our empirical analysis on this second definition of expansion. Of all fallow land brought back into cultivation, only about a quarter had been in fallow for more than 15 years, a sign of shortening fallow periods in the study areas.

There is no significant difference in cropland expansion and extent of expansion between MT adopters (about 23%) and non-adopters (Figure 2). Within each group, about 18-19% of the households expanded their cropping area into forests during the last agricultural season. Among adopters, the average cropland cleared per household was 0.10 ha, while it was about 0.15 ha on average per household among non-adopters. Thus, non-adopters cleared larger parcels on average.

About 79% of all households expanded cropland for maize production. This finding corroborates those in Babigumira et al. (2014), who found that most of the cropland expansion in Africa is for maize production - the staple in many sub-Saharan African countries.

[6]We follow FAO (2015) and define forests as land parcels larger than 0.5 hectares and not in agricultural use, with tree canopy cover of more than 10% and that these trees should reach a minimum height of 5 meters in situ. This definition includes primary and secondary forest, native or exotic, as well as closed and open forest (e.g., woodlands).

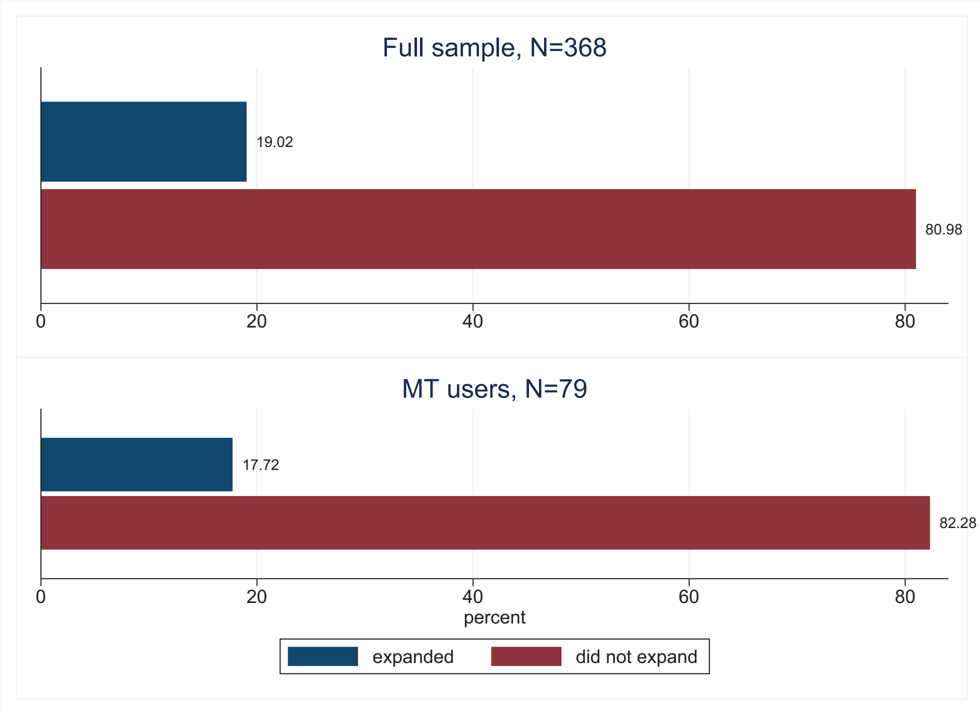

Figure 2: Cropland expansion by smallholder farmers in the full sample and among those using minimum tillage

Most households in the sample stated that they expanded to increase production to meet subsistence requirements (Figure 3). Other reasons included improved market access, declining land productivity, settling in new area (out-migration), improved access to inputs through government subsidies and clearing to secure title.

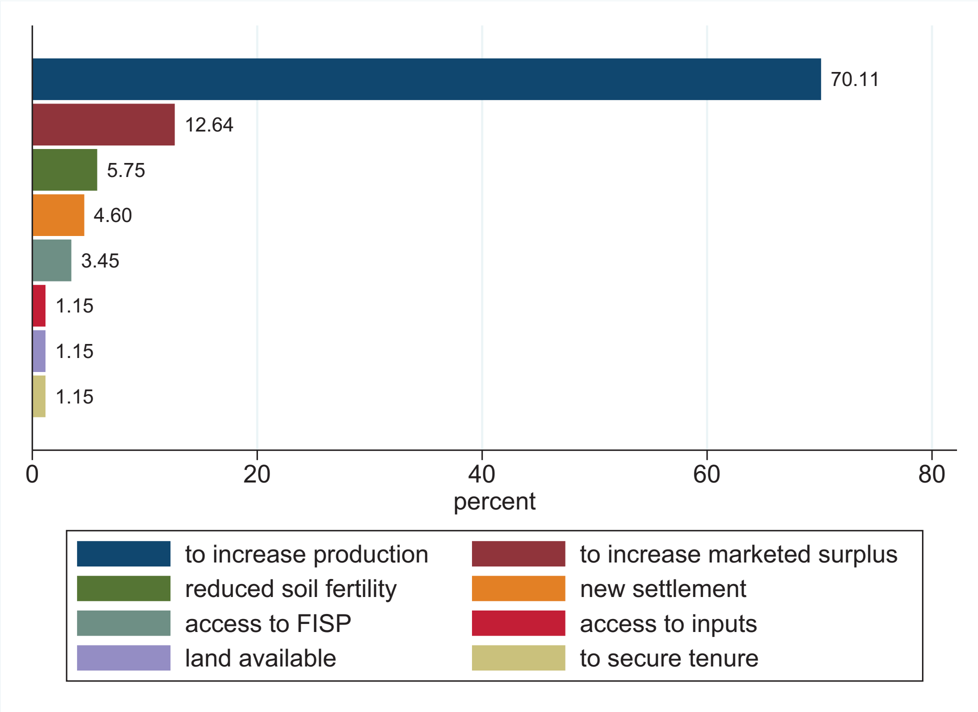

Figure 3: Reasons smallholder farmers expanded cropland into the 2013/2014 season

Among households who did not expand cropland, the majority (68%) stated that they did not expand due to lack of resources (labor and cash) or means to do so. About 21% said there was no land to expand to, and 11% stated that they did not have any need to expand cropland.

5.2 Are households that expanded cropland different from those that did not?

We checked for systematic differences between households that expanded cropland in the 2013/2014 season and those that did not. Table 2 shows, using t-tests, that households who expanded cropland had significantly larger farms (6.0 ha vs. 3.9 ha) before expansion, higher asset endowments and used improved inputs (a possible indicator of better market access).

Among those that expanded, the share of male-headed households is higher (indicating the critical role of access to family (male) labor). At district level, Nyimba had the largest proportion of households who expanded.

Although the differences are insignificant, Table 2 shows that the average crop yield was higher among households who expanded. A larger proportion of households who expanded received input subsidies,[7] and they were on average more educated and had younger household heads.

Table 2: Bivariate mean comparisons of key variables between households who expanded cropland into the 2013/2014 season and those that did not

	Expanded cropland into 2013/14 season			
	No	Yes	T-statistic	
	Mean	Mean	Mean diff.	Significance
Land under MT (yes=1)	0.14	0.13	0.01	
Distance to protected forest (km)	13.63	12.99	0.40	
Shadow wage	0.40	0.43	-1.15	
Yield (kg/ha)	1862.36	1925.27	-0.38	
Adult equivalents	4.9	5.22	-1.20	
Farm size (net of expansion, ha)	3.88	5.99	-2.28	***
Age, head of household	45.48	43.22	1.22	
Male head of household	0.75	0.86	-1.91	*
Education, head of household	6.27	6.77	-1.15	
Value of assets (ZMW'000)	1.37	5.76	-2.38	**
Land on title (yes=1)	0.05	0.01	1.21	
Improved inputs (yes=1)	0.76	0.86	-1.68	*
Subsidy (yes=1)	0.29	0.36	-1.20	
Output price (ZMW/kg)	1.84	1.93	-1.01	
Input price (ZMW/kg)	4.51	4.46	0.29	
off farm work (yes=1)	0.09	0.1	-0.32	
Mumbwa district (yes=1)	0.37	0.35	0.34	
Nyimba district (yes=1)	0.32	0.45	-2.09	**
Mpika district (yes=1)	0.31	0.20	1.81	*

***, **, * significant at 1%, 5% and 10% respectively.

We further explored the bivariate relationships between cropland expansion and key variables: area under MT, farm size, household wealth and yield. For each variable of

[7]The effect of subsidies on expansion requires a separate study.

interest, we estimated a simple bivariate quadratic regression to predict its effects on expansion.[8] Figure 4 suggests a weak relationship between land cultivated under MT (adoption-intensity) and expansion. In line with *a priori* expectations, higher yield, farm size and household wealth are correlated positively and mostly significant with expansion. However, some caveats are in order when interpreting these results because bivariate analysis fails to control for correlations across explanatory variables and their possible endogeneity. This leads us to the econometric analysis of next section.

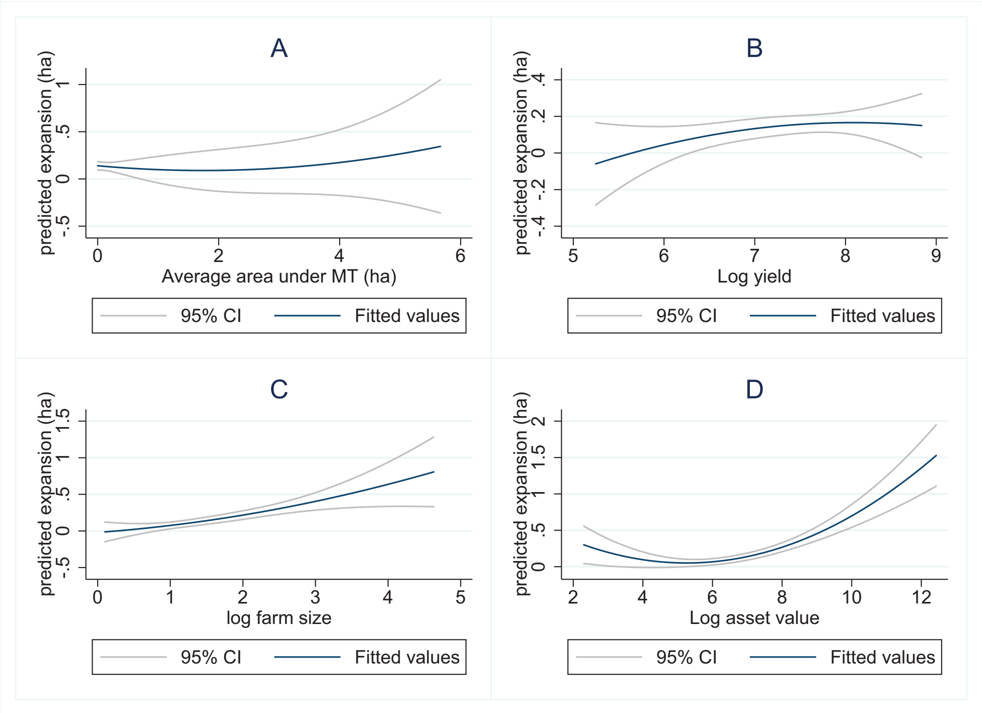

Figure 4: Quadratic predictions of the effects minimum tillage adoption intensity (A) yield (B), farm size (C) and value of household assets (D) on cropland expansion.

[8]We used the *qfitci* command in Stata.

5.3 Econometric results

We estimated several specifications of the double hurdle model. We report results from two specifications with the area under MT and yield variables included separately. These two models better capture and isolate the different channels through which MT may affect expansion, namely through yield and labor effects. Because the results are similar, we will focus mainly on model 1 and only refer to model 2 when necessary. The estimation was done with standard errors clustered at the village level.

As alluded to earlier that could not reject exogeneity, estimation proceeded without correcting for endogeneity. Table 3 presents the average partial effects (APEs) for the probability of expansion, extent of expansion conditional on expansion (i.e., among households who expanded), and the overall effects for the model without yield (model 1) in columns 1-3. The APEs for the model with area under MT (model 2) are given in columns 4-6.

Model 1 shows that the size of area under MT is negatively correlated to the probability and extent of cropland expansion, these results are only significant among households who already expanded (column 2). However, the overall effect is insignificant (columns 3). This is in line with our descriptive results in Table 2 and Figure 4 where the size of land under MT did not seem to be correlated with cropland expansion overall, but it was weakly correlated among adopters. Adopters cleared less cropland than non-adopters. Further, this result is qualitatively in agreement with our theoretical results, which suggest that the overall effects of MT on expansion are indeterminate *a priori*, as labor and yield effects pull in different directions.

Using improved inputs (inorganic fertilizers and hybrid seed) increases the likelihood of expansion by 14 percentage points (columns 1, Table 3), while as expected, age of the household head and input prices reduce the likelihood of expansion by 0.30 and 4.00 percentage points, respectively. These results are statistically significant at 5% level of significance.

Higher crop yield (model 2), shadow wage, education of the household head and adult equivalents are positively correlated with expansion among households who already expanded, and these results are significant at 1-10% (columns 2 and 5). Age of the household head, off-farm work and secure land tenure reduce the extent of expansion among households who already expanded (column 2).

The overall effects suggest that labor availability (adult equivalents) and shadow wage stimulate expansion while age of the household head and having some land on secure tenure could reduce expansion. There are significant location effects: farmers in the more densely populated Mumbwa and Nyimba districts (relative to those in Mpika district) were more likely to expand cropland.

Table 3: Double hurdle average partial effects (APE) of factors influencing cropland expansion

	Model 1			Model 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Probit	Truncreg	Overall	Probit	Truncreg	Overall
MT area	-0.022	-0.453**	-0.101	-	-	-
	(0.059)	(0.201)	(0.072)	-	-	-
Yield (kg/ha) /100	-	-	-	2.20E-04	0.008*	0.002
	-	-	-	(0.002)	(0.004)	(0.002)
Household-Shadow wage	0.132	1.553**	0.382*	0.120	0.287	0.128
	(0.129)	(0.666)	(0.182)	(0.130)	(0.441)	(0.188)
Adult equivalents	0.007	0.124***	0.028**	0.006	0.102***	0.023*
	(0.010)	(0.028)	(0.011)	(0.010)	(0.036)	(0.013)
Farm size (net exp)	0.002	-0.023	-0.003	0.002	-0.023	-0.003
	(0.007)	(0.014)	(0.007)	(0.007)	(0.015)	(0.008)
Age household head	-0.003**	-0.011***	-0.004***	-0.003**	-0.012**	-0.004***
	(0.001)	(0.004)	(0.002)	(0.001)	(0.005)	(0.001)
Male household head (yes = 1)	0.059	0.013	0.040	0.058	-0.030	0.030
	(0.041)	(0.135)	(0.048)	(0.041)	(0.168)	(0.048)
Education household head	0.010	0.022*	0.011*	0.010	0.029**	0.012**
	(0.007)	(0.013)	(0.006)	(0.007)	(0.015)	(0.007)
Asset value (ZMW) /100	0.004	0.012	0.005	0.004	0.012	0.005
	(0.006)	(0.021)	(0.007)	(0.006)	(0.020)	(0.005)
Some land on tenure (yes =1)	-0.081	-0.518***	-0.263**	-0.082	-0.510***	-0.275*
	(0.077)	(0.151)	(0.129)	(0.073)	(0.154)	(0.154)
Improved inputs (yes =1)	0.139**	-0.195	0.068	0.139**	-0.190	0.067
	(0.057)	(0.218)	(0.059)	(0.056)	(0.233)	(0.060)
Govt. input subsidy (yes =1)	0.040	-0.037	0.018	0.038	0.013	0.026
	(0.053)	(0.118)	(0.036)	(0.053)	(0.115)	(0.044)
Output price kg	-0.015	0.033	-0.003	-0.015	0.086	0.007
	(0.032)	(0.083)	(0.031)	(0.034)	(0.094)	(0.031)
Input price kg	-0.036**	0.005	-0.022	-0.037**	-0.032	-0.029
	(0.017)	(0.062)	(0.018)	(0.017)	(0.071)	(0.018)
Off farm income (yes=1)	0.018	-0.030	0.005	0.016	-0.234*	-0.043
	(0.073)	(0.138)	(0.070)	(0.077)	(0.136)	(0.074)
Dist. protected forest (km)	0.001	0.003	0.001	0.001	0.007	0.002
	(0.004)	(0.004)	(0.002)	(0.004)	(0.006)	(0.002)
Mumbwa district (yes =1)	0.066	0.552**	0.138**	0.062	1.000**	0.201**
	(0.097)	(0.245)	(0.066)	(0.096)	(0.480)	(0.081)
Nyimba district (yes =1)	0.231*	0.540**	0.240***	0.231**	0.855**	0.289***
	(0.115)	(0.231)	(0.070)	(0.117)	(0.351)	(0.079)
Log pseudolikelihood		-174.47*			-180.10*	
Observations	350	69	350	350	69	350

Notes: ***, **, * significant at 1%, 5% and 10% respectively. Bootstrapped standard errors in parenthesis (300 replications). APEs refer to average partial effects. Mpika is the base district. Probit, Truncreg and Overall are APEs computed from probit, truncreg and double hurdle models. Margins was used for the first two, while we followed (Burke, 2009) in computing the overall APEs.

6 Discussion

6.1 Minimum tillage and deforestation

The main result of this paper is that higher MT adoption intensity does not significantly reduce cropland expansion overall. An MT adoption intensity of 0.13 ha or about 8% of cultivated land on average per farm household (among all households in the sample) shows that MT is not the dominant tillage method at household level, and this could explain our results. These overall results are in agreement with Byerlee et al. (2014) who conclude that technology-driven intensification alone is unlikely to reduce cropland expansion without improved governance and incentives to preserve nature. They also echo earlier synthesis of case studies on the impacts of improved agricultural technologies on deforestation (Angelsen and Kaimowitz, 2001).

However, MT adoption intensity is negatively correlated with expansion among households who already expanded. We can use our theoretical results and surmise that this captures the effects of MT on labor allocation. MT is labor intensive, at least in the short run, and if labor is the scare resource, then adopting MT may potentially reduce expansion due to the higher demand for labor. The net effects of MT on cropland expansion will depend on whether its yield or labor effects dominate, an issue that would require further investigation. (Note that the yield and labor effects are not equivalent to the substitution and income effects discussed in the theory section.) Because we are not able to fully investigate the labor intensity of MT in our data, this result should be interpreted with caution.

6.2 Other drivers of deforestation

Our finding that a higher opportunity cost of labor stimulates expansion runs counter to economic intuition and to our theoretical results. We find it challenging to provide a rationale for this result. One explanation might, however, be found in the way the shadow wages are calculated, although the model is commonly used. The formula of equation (15) includes total agricultural production; a high shadow wage may therefore reflect that the household has certain characteristics (including unobservables) that increase productivity also from recently cleared land.

The positive and significant effect of adult equivalents on expansion is in line with our *a priori* expectations about the role of access to family labor to facilitate expansion. This result is also in line with Babigumira et al. (2014) who found that households with more male labor were also more likely to expand cropland. The negative correlation between age of the household head and the likelihood, and extent of expansion is line with the life cycle theory and also corroborates findings in Babigumira et al. (2014). Households headed by younger household heads were more likely to expand, both due to higher physical strength and due to the need to invest in more land at early stages in the life of the household.

Results showing that higher yield stimulates cropland expansion (among households who already expanded) support long-standing arguments suggesting that higher crop productivity may stimulate deforestation (Angelsen and Kaimowitz, 2001; Balmford et al., 2005; Rudel et al., 2009). Thus technological-driven intensification on its own may stimulate expansion if market conditions are favorable (Byerlee et al., 2014).

The negative effect of seed and fertilizer prices on the probability of cropland expansion highlight the importance of market factors as suggested in Babigumira et al. (2014). Our result that proximity to protected forests does not influence expansion decisions reinforces the need to improve local forest management institutions given that these are generally weak in Zambia (Mulenga et al., 2015).

Tenure security may have contradictory effects on cropland expansion. It can make investments in existing land more secure, and help making intensification more attractive relative to expansion. If, however, farmers clear forests to claim tenure rights and titles, more secure tenure can spur forest clearing (Angelsen, 1999). We find that secure land tenure reduce cropland expansion, suggesting that the first effect is stronger. This is in line with our findings that only 1% of respondents cleared forests to secure title. It is also in line with other studies suggesting that secure tenure facilitates farm level investments in land improvements in Ethiopia (Deininger and Jin, 2006), Kenya (Kabubo-Mariara, 2007), Zambia (Smith, 2004) and Africa, in general (Place, 2009) - which in turn would reduce the need for expansion - at least in the short run. This finding is also in agreement with Place and Otsuka (2000) who found that conversion of forested land to agriculture was highest under customary (insecure) tenure in Uganda. However, because we measure tenure as a dummy, and we do not investigate further its potential endogeneity, caution is needed when interpreting these results.

Finally, our findings suggesting that farmers in Mumbwa and Nyimba districts were more likely to expand relative to those in Mpika district highlight differing land pressures across the districts: the population density in Mpika is 5 person/km^2 compared to 10 and 8 in Mumbwa and Nyimba, respectively. Only 19% of the respondents expanded cropland, highlighting that increasing land scarcity in Zambia is setting constraints to farmers' options (Chamberlin et al., 2014).

7 Conclusion

This paper assessed the effects of minimum tillage and other proximate factors on cropland expansion. We developed a theoretical non-separable household model with limited off farm work opportunities and tested hypotheses using household survey data for the 2013/2014 agricultural season in Zambia. Future research should assess the effects of the full conservation agriculture package on deforestation, and develop long-term panel data sets to assess its effects on labor allocation and productivity, and cropland expansion.

About one-fifth of smallholder households in our sample expanded cropland into forests, clearing an average of 0.14 ha over one year. Its low adoption intensity, averaging 0.13 ha or about 8% of cultivated land on average per farm household (among all households in the sample) however, suggest that it is not the dominant tillage method at household level.

Minimum tillage is both yield augmenting and labor intensive, its net effects on expansion are ambiguous, *a priori*.

We do not find evidence of lower expansion due to the adoption of minimum tillage practices overall, but among a smaller subset of households who already expanded. The yield enhancing effect might, under the 'right' conditions lead to more forest encroachment. Thus, we conclude in line with Byerlee et al. (2014) that policies aimed to improve agricultural yields such as minimum tillage may require concomitant forest conservation measures such as direct control of cropland expansion into forests or payments for environmental services to prevent and possibly reduce cropland expansion.

Given the dual challenge facing African agriculture of both raising yield and farm incomes, while adapting to and mitigating climate change, conservation agriculture practices such as minimum tillage could be part of the overall policy package.

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Appendix A: Proof of proposition

Appendix A provides proofs for the proposition using the first order conditions (FOCs) in equations (10) - (12). Because household behavior in our theoretical model is reflected through changes in the shadow wage (z) as given by equation (13), we first define the marginal effects of changes in leisure (l) and consumption (c) on shadow wages (z) and then move on to show all the second order derivations used in the comparative analysis. The final step involves the actual comparative statics using Cramer's rule.

Define the marginal effects of l and c on z as:

$$\begin{aligned}
\frac{\partial z}{\partial l} = z_l &= \frac{\left(\frac{\partial^2 U_l}{\partial l^2} \times \frac{\partial U}{\partial c}\right) - \left(\frac{\partial U}{\partial l} \times \frac{\partial^2 U_c}{\partial l}\right)}{{U_c}^2} \\
&= \frac{U_{ll}U_c - U_{cl}U_l}{{U_c}^2} = \frac{U_{ll}U_c}{{U_c}^2} = \frac{U_{ll}}{U_c} < 0, \\
\frac{\partial z}{\partial c} = z_c &= \frac{\left(\frac{\partial^2 U_l}{\partial c} \times \frac{\partial U}{\partial c}\right) - \left(\frac{\partial U}{\partial l} \times \frac{\partial^2 U_c}{\partial c^2}\right)}{{U_c}^2} \\
&= \frac{U_{lc}U_c - U_{cc}U_l}{{U_c}^2} = -\frac{U_{cc}U_l}{{U_c}^2} > 0.
\end{aligned} \tag{A1}$$

Since $U_{lc}, U_{cl} = 0; U_{ll}, U_{cc} < 0$. Thus, z decreases with more leisure but increases with more consumption due to diminishing marginal utility, (cf. equation (13)).

Before we implement the derivations, we can re-write the FOCs in equations (10) - (12) in their complete form as:[9]

$$\begin{aligned}
&L_{l^a} : p_y f_{l^a}(l^a, A, M) - \frac{U_l\left(c, l\right)}{U_c\left(c, l\right)} = 0 \\
&\quad p_y f_{l^a}(l^a, A, M) - \frac{U_l\left(p_y f\left(l^a, A, M\right) - vM - d(A - A_0) - p_x \mathbf{X} + E, l\right)}{U_c\left(p_y f\left(l^a, A, M\right) - vM - d(A - A_0) - p_x \mathbf{X} + E, l\right)} = 0
\end{aligned} \tag{A2}$$

$$L_A : p_y f_A(l^a, A, M) - d - \frac{U_l\left(c, l\right)}{U_c\left(c, l\right)}[rt(A - A_o)^{r-1}] = 0 \tag{A3}$$

$$L_M : p_y f_M(l^a, A, M) - v = 0 \tag{A4}$$

where $l = T - t(A - A_o)^{r-1} - l^a - \bar{l^o}$.

To simplify notation in the following derivations, we drop the a superscript in l^a and use m instead of M from henceforth. We implement the derivations using one FOC at a time for the variables of interest l, A, M, p_y, A_o and v. Similar results can be obtained by total differentiation.

[9]Note that the FOCs can also be obtained by substituting equations (2) and (3) into equation (1).

Differentiating equation (A2) with respect to l, A, M, p_y, A_o, v and using results in (A1) to simplify yields:

$$
\begin{aligned}
\frac{\partial^2 L_l}{\partial L_l^2} &= p_y f_{l_l} - \left[-\frac{U_{lc} p_y f_l U_c - U_{cl} U_l}{U_c^2} - \frac{U_{ll} U_c - U_{cc} p_y f_l U_l}{U_c^2} \right] \\
&= p_y f_{l_l} - \left[-\frac{\left(U_{lc} p_y f_l - U_{ll}\right) U_c}{U_c^2} - \frac{\left(U_{cc} p_y f_l - U_{cl}\right) U_l}{U_c^2} \right] \\
&= p_y f_{l_l} + \frac{U_{ll} U_c}{U_c^2} + \frac{U_{cc} U_l}{U_c^2} p_y f_l \\
&= p_y f_{l_l} + \frac{U_{ll}}{U_c} + \frac{U_{cc} U_l}{U_c^2} p_y f_l \\
&= p_y f_{l_l} + z_l - z_c p_y f_l = p_y f_{l_l} + z_{l^a}
\end{aligned} \tag{A5}
$$

$$
\begin{aligned}
\frac{\partial^2 L_l}{\partial L_l \partial A} &= p_y f_{l_A} - \left[-\frac{U_{ll} tr (A - A_o)^{r-1} U_c}{U_c^2} - \frac{U_{cc} \left(p_y f_A - d\right) U_l}{U_c^2} \right] \\
&= p_y f_{l_A} + \frac{U_{cc} U_l}{U_c^2} \left(p_y f_A - d\right) + \frac{U_{ll} U_l}{U_c^2} (tr (A - A_o)^{r-1}) \\
&= p_y f_{l_A} + z_c \left(p_y f_A - d\right) + z_l (tr (A - A_o)^{r-1}) \\
&= p_y f_{l_A} - z_A
\end{aligned} \tag{A6}
$$

where $z_A = z_c \left(p_y f_A - d\right) + z_l (tr (A - A_o)^{r-1})$

$$
\begin{aligned}
\frac{\partial^2 L_l}{\partial L_l \partial m} &= p_y f_{lm} - \left[\frac{U_{lc} \left(p_y f_m - v\right) U_c - U_{cc} \left(p_y f_m - v\right) U_l}{U_c^2} \right] \\
&= p_y f_{lm} - \left[\frac{\cancel{U_{lc} p_y f_m U_c} - U_{cc} U_l \left(p_y f_m - v\right)}{U_c^2} \right] \\
&= p_y f_{lm} + \frac{U_{cc} U_l}{U_c^2} \left(p_y f_m - v\right) \\
&= p_y f_{lm} + z_c \left(p_y f_m - v\right) = p_y f_{lm}
\end{aligned} \tag{A7}
$$

Since $\left(p_y f_m - v\right) = 0$ by equation (A4).

$$
\begin{aligned}
\frac{\partial^2 L_l}{\partial L_l \partial p_y} &= f_l - \left[\frac{y U_{lc} U_c}{U_c^2} - \frac{U_{cc} U_l y}{U_c^2} \right] \\
&= f_l + \frac{U_{cc} U_l}{U_c^2} y \\
&= f_l - z_c y,
\end{aligned} \tag{A8}
$$

where $y = f(l, A, M)$.

$$
\begin{aligned}
\frac{\partial^2 L_l}{\partial L_l \partial v} &= - \left[\frac{U_{lc} m U_c - U_{cl} U_l}{U_c^2} - \frac{U_{cc} m U_l}{U_c^2} \right] \\
&= - \left[\frac{\cancel{U_{lc} m U_c - U_{cl} U_l}}{U_c^2} - \frac{U_{cc} m U_l}{U_c^2} \right] \\
&= z_c m
\end{aligned} \tag{A9}
$$

$$\begin{aligned}\frac{\partial^2 L_l}{\partial L_l \partial A_0} &= \left[-\frac{\left(U_{ll}\left(tr(A-A_o)^{r-1}\right)\right)U_c}{U_c^2} - \frac{U_{cc}U_l}{U_c^2}\right] \\ &= -\frac{U_{ll}U_c}{U_c^2}\left(tr(A-A_o)^{r-1}\right) \\ &= -z_l\left(tr(A-A_o)^{r-1}\right) - z_c d\end{aligned} \tag{A10}$$

Differentiating equation (A3)with respect to to l, A, M, p_y, A_o, v and using results in (A1) to simplify yields:

$$\frac{\partial^2 L_A}{\partial L_A \partial l} = p_y f_{Al} + (z_l - z_c(p_y f_l))\beta \tag{A11}$$

where $\beta = tr(A-A_o)^{r-1} > 0$.

$$\frac{\partial^2 L_A}{\partial L_A^2} = p_y f_{AA} - z_A \alpha \tag{A12}$$

where Z_A is given in equation (A6) and $\alpha = (r-1)\, rt(A-A_o)^{r-2} > 0$.

$$\frac{\partial^2 L_A}{\partial L_A \partial A_o} = z_{A_o}[(r-1)\, rt(A-A_o)^{r-2}] \tag{A13}$$

Where $z_{A_o} = z_l(rt)(A-A_o)^{r-1} - z_c d$

$$\frac{\partial^2 L_A}{\partial L_A \partial v} = z_c m \beta \tag{A14}$$

where, as before $\beta = tr(A-A_o)^{r-1} > 0$.

$$\frac{\partial^2 L_A}{\partial L_A \partial M} = p_y f_{AM} - z_c\,(p_y f_m - v) = p_y f_{AM} \tag{A15}$$

since $p_y f_m - v = 0$ by equation 8.

$$\frac{\partial^2 L_A}{\partial L_A \partial p_y} = f_A - z_c y \tag{A16}$$

where $y = f(l, A, M)$.

Differentiating equation (A4) with respect to l, A, M, p_y, A_o, v and using results in (A1) to simplify yields:

$$\frac{\partial^2 L_m}{\partial L_m \partial l} = p_y f_{ml} \tag{A17}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial A} = p_y f_{mA} \tag{A18}$$

$$\frac{\partial^2 L_m}{\partial L_m^2} = p_y f_{mm} \tag{A19}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial A_o} = 0 \tag{A20}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial v} = -1 \tag{A21}$$

$$\frac{\partial^2 L_m}{\partial L_m \partial p_y} = f_m \tag{A22}$$

Equations (A5) - (A22) can be combined and arranged into matrix form as

$$\begin{pmatrix} \frac{\partial^2 L_l}{\partial L_l^2} & \frac{\partial^2 L_l}{\partial L_l \partial A} & \frac{\partial^2 L_l}{\partial L_l \partial m} \\ \frac{\partial^2 L_A}{\partial L_A \partial l} & \frac{\partial^2 L_A}{\partial L_A^2} & \frac{\partial^2 L_A}{\partial L_A \partial m} \\ \frac{\partial^2 L_m}{\partial L_m \partial l} & \frac{\partial^2 L_m}{\partial L_m \partial A} & \frac{\partial^2 L_m}{\partial L_m^2} \end{pmatrix} = - \begin{pmatrix} \frac{\partial^2 L_l}{\partial L_l \partial p_y} & \frac{\partial^2 L_l}{\partial L_l \partial A_o} & \frac{\partial^2 L_l}{\partial L_l \partial v} \\ \frac{\partial^2 L_A}{\partial L_A \partial p_y} & \frac{\partial^2 L_A}{\partial L_A \partial A_o} & \frac{\partial^2 L_A}{\partial L_A \partial v} \\ \frac{\partial^2 L_m}{\partial L_m \partial p_y} & \frac{\partial^2 L_m}{\partial L_m \partial A_o} & \frac{\partial^2 L_m}{\partial L_m \partial v} \end{pmatrix} \tag{A23}$$

On the LHS is the coefficient matrix and the parameter matrix is on the RHS. Replacing the actual derivations into equation (A23) and rearranging yields:

$$\begin{gathered} \begin{pmatrix} p_y f_{ll} - z_{l^a} & p_y f_{lA} - z_A & p_y f_{lm} \\ p_y f_{Al} - z_{l^a}\beta & p_y f_{AA} - z_A\alpha & p_y f_{Am} \\ p_y f_{ml} & p_y f_{mA} & p_y f_{mm} \end{pmatrix} \begin{pmatrix} \partial l \\ \partial A \\ \partial m \end{pmatrix} = \\ \begin{pmatrix} -f_l + z_c y & z_l \left(tr(A - A_o)^{r-1} + z_c d \right) & -z_c m \\ -f_A + z_c y & -z_{A_0} (r-1)\, tr(A - A_o)^{r-2} & -z_c m\beta \\ -f_m & 0 & 1 \end{pmatrix} \begin{pmatrix} \partial p_y \\ \partial A_o \\ \partial v \end{pmatrix} \end{gathered} \tag{A24}$$

Expanding the coefficient matrix on the LHS of equation (A24) using column 3, working through the resulting algebra and using earlier definitions for Z_A, β and α to simplify gives the following determinant:

$$|H| = p_y^3 \left[\begin{gathered} \Big(\underbrace{f_{ll} - z_{l^a} p_y^{-1}}_{g} \Big) \Big(\Big(\underbrace{f_{mm} f_{AA} - f_{AM}^2}_{h} \Big) - f_{mm} Z_A \alpha \Big) + \\ \left(-f_{lA} - z_A p_y^{-1} \right) \left(f_{Am} f_{ml} - f_{mm} \left(f_{lA} + z_{l^a} p_y^{-1} \beta \right) \right) \\ - f_{lm} \left(\left(z_l p_y^{-1} \beta \left(f_{mA} \right) + f_{Al} \right) - f_{lm} \Big(\underbrace{f_{AA} - z_A p_y^{-1} \alpha}_{g} \Big) \right) \end{gathered} \right] < 0 \tag{A25}$$

Following definitions in the production function and the differentiation results, it is easy to verify that g terms are negative and the h term is positive. The determinant in equation (A25) is therefore negative.

Since the main interest is to determine the effects of the cost of implementing MT on cropland expansion, the outcome of interest is $\partial A / \partial v$, which can be evaluated using Cramer's rule:

$$\frac{\partial A}{\partial v} = \frac{|H_v|}{|H|} = \frac{\begin{pmatrix} -z_c m & p_y f_{lA} - z_A & p_y f_{lm} \\ -z_c m\beta & p_y f_{AA} - z_A\alpha & p_y f_{Am} \\ 1 & p_y f_{ml} & p_y f_{mm} \end{pmatrix}}{H} \tag{A26}$$

Stating with the substitution effect where z is held constant so that $z_l, z_c = 0$ (Angelsen, 1999): $\frac{\partial A}{\partial v} = \frac{|H_v|}{|H|} < 0$; because $|H|_v > 0$ after dropping all terms with z_l andz_c in equation (A26), but $|H| < 0$ from equation (A25). The income effect is always the opposite to the substitution effect so that $\partial A/\partial v > 0$. Analytical results of the effects of other variables used in the empirical model can be obtained following similar procedures.

Appendix B: Endogeneity tests, robustness checks and production function estimates

Appendix B reports the endogeneity and instrument admissibility test results in Table A1 and A2 report results for the Cobb-Douglas production function. The correlation matrix for explanatory variables is given in Table A3.

Table A1: Instrument relevance and endogeneity tests from 2SLS

	IV relevance test		Endogeneity test	
Endog. var	F-statistic	P-value	F-statistic	P-value
MT area	5.46	0.03	0.50	0.48
Yield	5.24	0.00	0.24	0.89
Shadow wage	9.16	0.00	0.14	0.71

$F = 1.47, p = 0.21$ for the joint F-test for all IVs in the main expansion equation.

Estimation of shadow wages

To estimate household specific shadow wages, we follow Jacoby (1993) and first estimate a Cobb Douglas production function. The dependent variable is aggregate household crop production for all crops grown by households in the sample (e.g., maize, cotton, sunflower, groundnuts, dry beans), while the explanatory variables are also aggregates across crops per household, all transformed into logs. We also include average household age, education and size to control for household specific factors that may influence production.

Homogeneity is imposed by normalizing the explanatory variables using the quantity of seed. Alternative estimations with value of production as the dependent variable and with trans-log did not yield better results. The household specific shadow wage (z) is estimated using equation (15).

Table A2: Cobb Douglas production estimates

	Coefficient	T-statistic
Log land cultivated (ha)	0.544***	4.289
Log fertilizer quantity	0.389***	7.718
Log labor hours	0.292***	5.878
Log number of oxen	0.442	0.480
Average household age	-0.002	-0.372
Average household education	0.039**	2.042
Average household size	-0.021	-1.135
Constant	2.224***	7.073
Observations	350	
R-squared	0.650	

Notes: *,**,*** statistically significant at 1%, 5% and 10%.

Table A3: Correlation matrix for independent variables

	MTarea	yield	s.wage	adulteq.	farmsize	agehh	malehh	eduhh	asset	tenure	imprvd.i	fisp	outputp	inputp	offfarm	d.pforest
MTarea	1.000															
yield	-0.008	1.000														
s.wage	0.078	0.263	1.000													
adulteq.	0.150	0.147	0.047	1.000												
farmsize	0.048	-0.095	0.134	0.105	1.000											
agehh	0.147	0.074	0.010	0.231	0.065	1.000										
malehh	0.045	-0.007	0.015	0.214	0.158	-0.151	1.000									
eduhh	-0.025	0.161	0.152	-0.050	0.116	-0.138	0.095	1.000								
asset	0.123	0.209	0.277	0.427	0.311	0.089	0.234	0.183	1.000							
tenure	0.024	0.139	0.039	0.046	-0.075	0.049	0.043	0.089	0.127	1.000						
imprvd.i	0.066	0.295	0.343	0.242	0.089	0.247	-0.046	0.167	0.301	0.003	1.000					
fisp	0.126	0.126	0.134	0.141	0.026	0.204	-0.022	-0.033	0.140	0.024	0.350	1.000				
outputp	0.152	-0.279	-0.016	0.060	0.238	0.031	0.035	-0.011	0.132	0.020	0.016	0.010	1.000			
inputp	0.178	0.171	0.334	0.168	0.066	0.067	0.026	0.116	0.324	0.084	0.469	-0.040	0.061	1.000		
offfarm	-0.037	0.146	0.058	-0.028	-0.116	-0.093	0.100	0.152	0.004	0.090	0.069	-0.096	-0.104	0.118	1.000	
d.pforest	-0.042	0.056	0.054	0.023	-0.052	-0.044	0.014	0.094	-0.024	-0.222	0.068	0.010	-0.173	-0.062	0.032	1.000

Appendix: Questionnaire for data used in paper III and IV

Center for International Forestry Research

Norwegian University of Life Sciences

Informed Consent Statement

This survey is part of a team effort by the Centre for International Forestry Research (CIFOR) and the School of Economics and Business, Norwegian University of Life Sciences (NMBU) aimed at studying how farm decisions interact with natural resource management and use among smallholder farmers in Zambia. Your help in answering these questions is very much appreciated. Your responses will be kept COMPLETELY CONFIDENTIAL. Feel free not to answer questions that you are not comfortable with. Your responses will be summed together with those of roughly 450 other households and general averages from analysis will be reported. You indicate your voluntary consent by participating in this interview: may we begin? If you have questions about this survey, you may contact the CIFOR regional office in Lusaka on +260 211 265 885. If you have any questions about NMBU, you may contact Prof. Arild Angelsen at +47 6496 5700.

1	Province		**PROV**	
2	District		**DIST**	
3	Village		**VIL**	
4	Sub-village (if applicable)		**sVIL**	
6	Household Serial number		**HH**	
7	Name of household head		**nhHH**	
8	Cell phone number for head of household		**cell**	
9	Name of main respondent (if different from head) *(Enum: respondent must be a household member)*		**RES**	
10	Household GPS location	South	**S_DD**	______.________________
		East	**E_DD**	______.________________
11	Response Status ***1=Complete 2=Refusal 3= Non-contact***		**RSTATUS**	

	Assignment record		**Day**	**Month**	**Year**
12	Enumerator name	Date completed			2014
13	Supervisor name	Date checked			2014
14	Data entry clerk	Date entered			2014

SECTION 1: DEMOGRAPHIC CHARACTERISTICS OF HOUSEHOLD MEMBERS

1.1 Tell us about each member of the household who has lived in this household for the past 1 year since August 2013. *Start with adult members (≥ 12 years). If this household is part of a polygamous family, ask only about the household members at this particular household (i.e. those living under the same roof and share resources).*

Table 1.1 Demographic Characteristics of Household Members
Reference Period: Beginning of Aug 2013 to end of September 2014 *Key variables: VIL, HH, MEM*

ID	Name *(Enumerator: list the head first and then **all** members starting with adults who lived in this household over the last year)*	In which **year** was ...... born?	What is the **sex** of .... ? ***1=male 2=female***	What is the **relationship** of ... to the **current** head ***(see code below)***	*(Ask only if older than 12 years)* What is the **marital status** of ..... ***(see code below)***	Is .... currently **attending formal** school? ***1 = Yes 2 = No***	What is the **highest** level of **formal** education ... completed? ***(see codes below)***
MEM	**NAME**	**D01**	**D02**	**D03**	**D04**	**D05**	**D06**
1	*(head)*			1			
2							
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							

Relationship to head (D03)	**Marital Status (D04)**	**Education levels (DA06)**		
1= head 2= spouse 3= child (own/step) 4= parent / parent-in-law 5= brother / sister 6= other relatives 7= unrelated	1 = never married 2 = monogamously married 3 = polygamously married 4 = divorced 5 = widowed 6 = separated 7 = cohabit	00=None 01=Sub-standard A; 01=Sub-standard B; 02=Standard 1; Grade 2 03=Standard 2; Grade 3 04=Standard 3; Grade 4 05=Standard 4; Grade 5	06=Standard 5; Grade 6 07=Standard 6; Grade 7 08=Form 1; Grade 8 09=Form 2; Grade 9 10=Form 3; Grade 10 11= Form 4; Grade 11 12= Form 5; Grade12	13= Form 6 Lower 14= Form 6 Upper 15= College Student 16=Undergraduate student 17=Certificate/Diploma 18= Bachelors Degree 19= Masters degree & above

SECTION 2: FARM LAND AND USE

2.1 Enumerator: Tell the respondent that we would like to ask some general questions about land use in the area. Remind the respondent that the information he/she shares is strictly confidential, so they can speak freely. Enter -9 or -8 if I don't know or not applicable in 2.1.2 and 2.1.3

2.1.1	Is there **good** arable land in this village close enough to your homestead that you could expand your farm into if you chose to?	*1=Yes* *2=No*	**HHb04**	
2.1.2	What was the average renting price for 1 hectare of arable (good and close-to-homestead) land over the last 12 months? ***ZMW***	**HHb05**		
2.1.3	What was the average selling price for 1 hectare of arable (good and close-to-homestead) land over the last 12 months? ***ZMW***	**HHb06**		

2.1.3 ***Enumerator: Sketch ALL plots for different land uses including cultivated (rented in/borrowed in), rented-out or borrowed-out by the household during the 2013/2014 agricultural season. Include land cultivated, fallow land, virgin land, and all other land owned, borrowed, and rented. After sketching, sequentially number the fields. Label (in words) on the sketch, the land use of each field (land use categories on the left).***

Table 2.1.3 All plots *Key Variables: PROV, DIST, VIL, HH, LUTYPE* ***Reference Period: 2013/2014 agricultural season***

Land use types		**During the 2013/ 2014 agricultural season, did the household have any .....?** *1=Yes* *2=No -> go to next field type*	How **many** ..... did the household have?	*SKETCH <u>ALL THE FIELDS</u> and <u>list crops within each cultivated field</u> & Indicate mono or mixture field*
	lutype	**luse**	**Numlu**	
Cultivated/Cropped land				
Own cropped plots	**1**			
Cropped - rented or borrowed in plots	**2**			
Other land uses				
Fallow plots (natural)	**3**			
Fallow plots (Improved)	**4**			
Rented or borrowed out fields (received cash/in-kind payment)	**5**			
Virgin land (never cultivated)	**6**			
Garden	**7**			
Others (incl. orchards etc.) __________	**8**			

2.2	According to the sketch you indicated that you had ________ plots in the 2013/2014 agricultural season. Please tell us about each of those plots. *Enumerator: –* ***check the sketch and <u>record the number of plots</u>***. ***Number of plots***	**HHb07**	

DIST_____ VIL________HH________

Table 2.2.1 plots *Key Variables: PROV, DIST, VIL, HH, PLOT, F01* ***Reference Period: 2013/2014 agricultural season***

PLOT ID	What is the **land-use** of this plot? *(Enumerator: Transfer land use from the plot sketch)*	What is the **area of this plot**? *(transfer from the sketch)*		What is the **tenure status** of this plot?	When was this plot first cultivated i.e. converted from natural habitat to agricultural land ?	What was the **main crop or use** for this plot in ***the 2011/12 agricultural season*** *(2 seasons ago)*?	What was the **main crop or use** for this plot in ***the 2012/13 agricultural season*** *(1 season ago)*?	What happened to the **crop residue(s)** from this plot from ***the 2012/13 agricultural season***?	What was the **main crop or use** for this plot in ***the 2013/14 agricultural season***	*(Enum: Transfer from the sketch)* *Was this field a mono crop or mixture?*	Did the household irrigate this field?	***Ask only if F01 = 3 or 4***	
	1=own cultivated 2=rented/borrowed in 3=fallow (natural) 4=fallow(improved) 5=rented/borrowed out 6=virgin (forested) land 7=other (specify) __________	Area of plot	Unit *1=lima 2=acre 3=hectare 4=square metre*	*1=state land titled 2=former customary land titled 3=customary no title 4= other (specify)____* ***(If F01 = 5-7 → go to next field)***	*(year)*	***(See code below)***	***(See code below)***	***(See code below)***	***(See code below)***	***1= mono crop 2=mixture***	***1= yes 2=no***	How many years has this plot been left as ……… fallow? ***(See code below)***	On average how many years does it take before you can cultivate fallow fields?
PLOT	**F01**	**F02**	**F03**	**F05**	**FO5a**	**F06**	**F07**	**F08**	**F09**	**F09a**	**F10**	**F12**	**F13**
1													
2													
3													
4													
5													
6													
7													
8													
9													
10													
11													
12													

Codes for F06, F07 & F09:	Codes for F08:	Codes for F12:
1=maize 2= other cereal 3= cotton 4= sunflower 5=groundnut 6=soy beans 7= other crops 8= Cassava 9=Tobacco 10= Mixed beans -8= did not plant	*1=left in field till the following season 2= left in field, burnt or grazed by livestock 3=removed from the field for other uses*	*1 = < 1 years 2 = 1-5 years 3 = 6-10 years 4 = 10-15 years 5 = > 15 years*

Table 2.2.2. Labor requirements for production activities in the 2013/14 season. ***(Enumerator: Ask only if F01 =1 or 2, that's is only for cultivated fields EXCLUDING gardens)*** *Key Variables: PROV, DIST, VIL, HH, PLOTb, FOPER* **Reference period 2013/14 season**

PLOT ID *(Copy from T2.2.1)*	What is the **land-use** of this plot? *(Enumerator: Transfer land use from the plot sketch)*	Did the household hire labor to do ……… on this plot? ***(Enum: Ask this question in a disaggregated way to ensure that you get the required responses. Reference period: 2013/14 season)***						Did the hh use any adult family labor to do ……… on this plot? ***(Enum: Ask this question in a disaggregated way to ensure that you get the required responses. Reference period: 2013/14 season)***					
	1=own cultivated 2=rented/borrowed in		***1=yes 2=no*** *(if no go to next FOPER)*	Number hired	Unit wage	Unit 1=daily 2=monthly	Total days/months per year	***1=yes 2=no*** *(if no go to next FOPER)*	List MEM IDs inolved in this FOPER *Eg 1,2,3,4*	Number of hh MEM involved	Hours workd per day	Number of days worked per month	Total months worked per year
PLOTb	**F01b**	**FOPER**	**F05b**	**F06b**	**F07b**	**F08b**	**F10b**	**F11b**	**F12b**	**F13b**	**F14b**	**F15b**	**F16b**
1		Landprep											
		Weeding											
		Other field ops											
2		Landprep											
		Weeding											
		Other field ops											
3		Landprep											
		Weeding											
		Other field ops											
4		Landprep											
		Weeding											
		Other field ops											
5		Landprep											
		Weeding											
		Other field ops											
6		Landprep											
		Weeding											
		Other field ops											
7		Landprep											
		Weeding											
		Other field ops											
8		Landprep											
		Weeding											
		Other field ops											
9		Landprep											
		Weeding											
		Other field ops											
10		Landprep											
		Weeding											
		Other field ops											

2.3 Land Use

***Enumerator:* Please list below only cultivated fields and gardens from the sketch. Include plots with F01 = 1, 2 from Table 2.2.1**

Table 2.3.1 Farm Land and Use *Key Variables: PROV, DIST, VIL, HH, PLOTID1* ***Reference period: 2013/2014 Agricultural Season***

PLOT ID (*enter appropriate field number from T 2.2.1 F01 = 1, or2)*)	**Main crop** in the **2013/14 season**? *(transfer from question F09 in T2.2.1)*	What was the **main tillage method** used on this plot and the source of power? ***(see codes below)***		**Area** of plot under the **tillage** in **FL03**?	**Unit of area** *1=lima 2=acre 3=hectare 4=square metre*	**When** was the main **tillage** done? ***1=Before the rains 2=During the rainy season***	*Ask If FL04 < F03 from T 2.2.1* **What tillage was used on the remainder of the plot? *(see codes below)***	How many **complete weedings** did you do in this **plot?**	What is the soil fertility of this plot? *1=very fertile 2=fertile 3= not fertile -9= I don't know*	Did you apply ....?			Did you apply basal fertilizer in.....?				Did you apply top dressing fertilizer in.....?				Did this hh access FISP in the 2013/14 season? ***1 = Yes 2 = No***
		MTIL	SOUC							**Herbicide** ***1=Yes 2=No***	**Lime** ***1 = Yes 2 = No***	**Animal/ chicken manure?** ***1 = Yes 2 = No***	***1 = Yes 2 = No*** *If no,go →FL18*	Quantity applied *(kgs)*	***Unit Price***	***Unit (see codes below***	***1 = Yes 2 = No*** *If no, go →FL20*	Quantity applied *(kgs)*	***Unit Price***	***Unit (see codes below***	
PLOTID1	**FL01**	**FL03**	**FLO3a**	**FL04**	**FL05**	**FL06**	**FL07**	**FL09**	**FL09a**	**FL10**	**FL11**	**FL12**	**FL16**	**FL17**	**FL17a**	**FL17b**	**FL18**	**FL19**	**FL19a**	**FL19b**	**FL20**

Main Tillage codes (FL03, FL07)	Source of tillage codes (FL03a)	Unit Codee (FL21, FL15b, FL17b, FL19b, CM10a, CM15a, CM10b, CM15b)		Codes (CM16c, CM16e)
1 = Conventional hand hoeing	1=Manual household labour	1=90kg bag	11=5lt gallon	1=FRA
2 = Planting basins	2=Manual hired labour	2=50kg bag	12=MEDA	2= Private traders within vil
3 = Zero tillage	3=Own animals with HH labour	3=25kg bag	13=bunches	3= Private firms within vil
4= Plowing	4=Own animals with hired labour	4=10kg bag	14=MUCHUMBU	4= Main market at boma
5 = Ripping	5=Hired/borrowed animals with HH labour	5=20lt tin	15=ka B.P.	5= Private traders in boma
6 = Ridging (before planting)	6=Hired/borrowed animals with hired labour	6=90kg bag unshelled	16=crates	6= Private firms in boma
7 = Permanent Bunds	7=Own mechanical with HH labour	7=50kg bag unshelled	17=tonnes	7=Other households
8 = Temporal Bunds	8=Own mechanical with hired labour	8=25kg bag unshelled	18=boxes	8= Others, specify
9 = Mounding	9=Hired/borrowed mechanical with HH labour	9=10 kg bag unshelled	19=number	
	10=Hired/borrowed mechanical with hired labour	10=20lt tin unshelled	20=kilogram	

2.3.2. Crop Management – Planting And Harvesting (all cropped fields in **MONOCROP**)

<u>Enumerator:</u> Transfer field numbers from the Table 2.3.1 for mono-cropped plots-F09a=1 (fields have only one crop). Also, transfer crop and area from the sketch into CROPA, CMO1A CM02A. Ask the following questions for all the fields mono-cropped in the 2013/2014 agricultural season. Calculate the quantity harvested in <u>kgs</u> for seed cotton, tobacco, paprika etc. Make "Comments" regarding actual information for these crops that the respondent gives for quantity and unit harvested so the information can be verified.

Table 2.3.2. Crop Management - Planting and Harvest. *Key Variables: DIST, VIL, HH, PLOTAA, CROPA* ***Reference Period: The 2013/2014 Agricultural Season***

Field ID *Copy from T2.3.1*	Crop Code *Copy from Table 2.2.1 – F09a=1- mono-crop*	***Transfer Area*** *under each crop from the sketch*		What **portion** of the **area planted** was **harvested**?		What **main seed variety** did the hh use for the first planting? ***1=Hybrid 2= OPV 3=Recycled 4= Local***	What **quantity of seed** /planting material did the hh **plant for the first planting**? ***(Enum: if not bought, ask respondent to estimate how much they would have spent if they bought the seed, do not ask for tobacco)***				When did the hh **finish the first planting** this crop?		Did the hh **replant** any part of this plot? ***1=Yes 2=No***	**How much** of this crop did the household produce from this plot in the 2013/14 season? *(Enum: Include quantity sold and retained for home use)*		**Of the total produce from the 2013/14 season, how much was sold?**				**Of the total produce from the 2013/14 season, how much was retained for home use?**	
		Area planted	Unit ***1 = Lima 2 = Acre 3 = Ha 4 = Sq. meters***	Area harvested	Unit ***1 = Lima 2 = Acre 3 = Ha 4 = Sq. meters***		Quantity planted	Unit ***(see codes pg 6)***	Unit Price	Unit ***(see codes pg 5)***	Month 1=jan 2=Feb . . 12=Dec	Week: *Enter 1, 2, 3,or 4 as week ids*		Quantity harvested *(if 0 → go to next field)*	Unit ***(see codes pg 6)***	Quantity sold *(if 0 → go to CM17c)*	Unit ***(see codes pg 6)***	Unit price	Main market ***(see codes pg 6)***	Quantity retained *(if 0 → go to next field)*	Unit ***(see codes pg 6)***
PLOTA	**CROPA**	**CM01A**	**CM02A**	**CM03A**	**CM04A**	**CM08A**	**CM09A**	**CM10A**	**CM10Aa**	**CM10Ab**	**CM11A**	**CM12A**	**CM13A**	**CM14A**	**CM15A**	**CM14c**	**CM15c**	**CM15d**	**CM16c**	**CM17c**	**CM18c**

2.3.3. Crop Management – Planting And Harvesting (all cropped fields in **MIXTURE**)

Enumerator: ***Transfer field numbers from the Table 2.3.1 for mono-cropped plots, F09a=2 (fields have mixture of crops). Also, transfer crop and area from the sketch (page 7) into CROPA, CMO1A CM02A). Ask the following questions for all the fields mixed in 2013/2014 agricultural season Calculate the quantity harvested in kgs for seed cotton, tobacco, paprika etc. Make "Comments" regarding actual information for these crops that the respondent gives for quantity and unit harvested so the information can be verified.***

Field ID *Copy from T2.3.1*	Crop Code *Copy from Table 2.2.1 – F09a=2 mixture*	***Transfer Area*** *under each crop from the sketch*		What **portion** of the **area planted** was **harvested**?		What **main seed variety** did the hh use for the first planting? *1=Hybrid 2= OPV 3=Recycled 4= Local*	What **quantity of seed**, **tubers, or vines** did the hh **plant for the first planting**? ***(Enum: if not bought, ask respondent to estimate how much they would have spent if they bought the seed, do not ask for tobacco)***				When did the hh **finish the first planting** this crop?		Did the hh **replant** any part of this plot? ***1=Yes 2=No***	**How much** of this crop did the household produce from this plot? *(Enum: Include quantity sold and retained for home use)*		**Of the total produce from the 2013/14 season, how much was sold?**				**Of the total produce from the 2013/14 season, how much was retained for home use (incl. produce still in stock)?**	
		Area planted	Unit ***1 = Lima 2 = Acre 3 = Ha 4 = Sq. meters***	Area harvested	Unit ***1 = Lima 2 = Acre 3 = Ha 4 = Sq. meters***		Quantity planted	Unit ***(see codes below)***	Unit Price	Unit ***(see codes pg 6)***	Month 1=jan 2=Feb . . 12=Dec	Week: *Enter 1, 2, 3,or 4 as week ids*		Quantity harvested *(if 0 → go to next field)*	Unit ***(see codes on pg 6)***	Quantity sold *(if 0 → go to CM17e)*	Unit ***(see codes pg 6)***	Unit price	Main market ***(see codes pg 6)***	Quantity retained *(if 0 → go to next field)*	Unit ***(see codes pg 6)***
PLOTB	**CROPB**	**CM01B**	**CM02B**	**CM03B**	**CM04B**	**CM08B**	**CM09B**	**CM10B**	**CM10Ba**	**CM10Bb**	**CM11B**	**CM12B**	**CM13B**	**CM14B**	**CM15B**	**CM14e**	**CM15e**	**CM15f**	**CM16e**	**CM17e**	**CM18e**

DIST_____ VIL________HH________

Table 2.3.3 Crop Management - Planting and Harvest. *Key Variables: DIST, VIL, HH, PLOTB, CROPB* ***Reference Period: The 2013/2014 Agricultural Season***

2.3.4. Farm land expansion

***Enumerator:* Please inform the respondent that we will now talk a bit more about land use decisions on the farm. In particular we are interested to learn about agricultural land expansion**

Table 2.3.4 Farm Land Expansion

Key Variables: PROV, DIST, VIL, HH, E02

Did the household expand the total cropped land from 2012/13 to 2013/14agricultural seasons or open new fields? ***1 = Yes 2 = No*** *(If no, go →HHb09)*	What main land parcel(s) was the cropped land expanded into? List all ***(see codes below)***	What was the size of the new additional plot? Area	Unit *1=lima 2=acre 3=hectare 4=square metre*	***Ask if E02 = 2 or 3*** How old was this fallow at the time you brought it back under cultivation? ***(see code below)***	Who primarily decided on where to expand the cultivated land into? ***(see code below)***	What was the main crops for which the household increased cropped land? ***(see code below***	Why did the household mainly decide to expand area cultivated for this crop in the 2013/14 season?	Why didn't the household expand their cropped land? *1=lack of new land 2=lack of resources 3=current land & production sufficient*	How did this household seek to mainly increase production levels? ***(see code below***	Comparing your total cultivated land now and 5 years ago, has it ……………? 1=increased 2=reduced *3=no change* *(If 2 or 3, go →HHb13)*	What has mainly driven change in the cultivated land area over the last 5 years? ***(see code below)***	What has happened to the total area cultivated under plow tillage by this household over the last 5 years? ***(see code below)***	What has happened to the total area cultivated under hand hoe tillage by this household over the last 5 years? ***(see code below)***	What has happened to the total area cultivated under basins tillage by this household over the last 5 years? ***(see code below)***	What has happened to the total area cultivated under ripping tillage by this household over the last 5 years? ***(see code below)***	Is animal draft power or tractor ripping service accessible in this village? ***1 = Yes 2 = No***	Did this household access animal draft power or tractor ripping services in the 2013/14 season? ***1 = Yes 2 = No***	What are the effects of practicing conservation agriculture on crop land expansion? ***(see code below)***
HHb08	**E02**	**E03**	**E04**	**E05**	**E06**	**E07**	**E08**	**HHb09**	**HHb10**	**HHb11**	**HHb 12**	**HHb 13**	**HHb 14**	**HHb 15**	**HHb 16**	**HHb 17**	**HH17a**	**HHb 18**

Codes for E02

1=virgin land/pristine forest (never cultivated before)
2=fallow land (natural)
3=fallow land (improved)
4=grass land
5=protected area e.g. forest or game reserve
6= dambo/wetland (never cultivated before)

Codes for E05

1 = < 1 years
2 = 1-5 years
3 = 6-10 years
4 = 10-15 years
5 = > 15 years

Codes for E06

1=male hh head
2=spouse of male hh head
3=female hh head
4= spouse of female hh head
5= male adult hh member
6=female adult hh member
7= male child hh member
8= female child adult member

Codes for E07

1=maize
2= other cereal
3= cotton
4= sunflower
5=groundnut
6=soy beans
7= other crops
8= Cassava
9=Tobacco
10= Mixed beans
-8= did not plant

Codes for HHb12, E08

1=to increase production to meet hh consumption needs
2=to increase marketed surplus (improved market access) through FRA
3=to increase marketed surplus (improved market access) through private traders
4=improved accessibility of FISP inputs
5=increased accessibility of farm inputs from private traders
6= availability of good virgin arable land
7= reduced soil productivity
8=to secure land tenure
9=new settlement
10=other, specify_____________

Codes for HHb13, HHb14, HHb15, HHb16

1=increased
2=reduced
3=remained constant
4= did not do this activity

Codes for HHb18

1= reduces the need for land expansion
2= increases the need for land expansion
3= does not have any effects
-9= I don't know

Codes for HHb10

1= increased fertilizer & hybrid seed use
2=increased labor use
4= increased cash outlays
5= increased use of agro- forestry
6= increased use of residues, manure, crop rotation, CA
7=increases area cultivated

SECTION 3: LIVESTOCK OWNERSHIP AND SALES

Enumerator: Tell the respondent that we will now ask about the different livestock ownership and sales over the past one year.

3.1a LIVESTOCK SALES FROM OWN PRODUCTION *Reference period Past 1 year*

Did the household own and raise …… during the past 1 year? (includes aquaculture)				*(Ask if LV1 = 1)* Did the household sale/barter any ….. during the past 1 year?				Did the household use any……... for home consumption during the past 1 year?		*Enum: Ask these questions in disaggregated way. Ask the number/quantity sold and unit price and then compute the values in LV8a, LV9a, LV10a* Did the household sale any milk over the last 1 year? what is the estimated value		Did the household sale any hides (animal skins) over the last 1 year? what is the estimated value		Did the household sale any eggs over the last 1 year? what is the estimated value	
		1=yes 2= no *(if no, go to next lvstck)*	Num lvstck	1=yes 2= no *(if no, go to LV6)*	Numl sold	Unit price	Market type *(see codes below)*	1=yes 2= no *(if no, go to next LVSTCK)*	Numl Cons.	1=yes 2= no *(if no, go to LV9)* 1=yes 2= no	Value (ZMK)	1=yes 2= no *(if no, go to LV10)* 1=yes 2= no	Value (ZMK)	1=yes 2= no 1=yes 2= no	Value (ZMK)
LVSTCK		LV1	LV2	LV3	LV4	LV5	LV5a	LV6	LV7	LV8	LV8a	LV9	LV9a	LV10	LV10a
Total Cattle	01														
Cows/Heifers	02														
Bulls	03														
Oxen/Tollies/Steers	04														
Calves	05														
Pigs	06														
Goats/sheep	07														
Donkeys	08														
Village Chickens	09														
Guinea Fowls	10														
Ducks & Geese	11														
Fish in ponds	12														

Codes for LV5a

1=FRA
2=Private traders withn vil
3=Private firms within vil
4= Main market at boma
5= Private traders in Boma
6= Private firms in Boma
7= Other households within vil
8= Other, specify____________

3.2 OFF FARM INCOME SOURCES AND REMITTANCES

We would like to talk about all **ADULT** household members who have earned income from **SALARIED EMPLOYMENT OR INFORMAL WAGE LABOUR ACTIVITIES OR PENSIONS OR FORMAL AND INFORMAL BUSINESS ACTIVITIES** over the past 1 year. These activities include all formal salaried employment and all casual labor for which members were paid cash or an in-kind wage, including agricultural and non-agricultural labor. Include also the value of any pensions, business activities (*except those involving forest and non-timber forest products*) or food aid for work received over the past 1 year.

Reference period Past 1 year

3.2.1 Over the past **1 year**, did any **adult** member(s) of the household work for a **wage or salary** outside your farm**?** *1=Yes 2=No (if no, go →3.2.3)*	FI05	

Enum: List below all adult household members who earned income from a wage or salary outside the farm and ask about the incomes earned

Did any adult hh member earn a wage or salary from….? **1=yes** **2=No** **(if no, go to next WACT)**		***Enum: Ask about each adult MEM who earned income from this WACT and transfer MEM ids from T1.1***	***(Ask if WACT = 2, 3, or 4)*** **What was ……'s monthly salary over the past 1 year?**	***Enum: Ask if WACT = 1, 5, 6 or 7. Ensure you ask these questions in disaggregated way so that you capture appropriate responses*** What was the daily/monthly pay for …….. in WACT……?		
				Wage	**1=per day** **2= per month**	**Total days/months worked per year**
WACT	**WS01**	**WS02**	**WS03**	**WS04**	**WS04a**	**WS04b**
FES						
FEF						
CVLS						
PRF						
PRS						
PEN						
other						

WACT codes

1= farm employment -seasonal **(FES)**
2=farm employment fulltime **(FEF)**
3=civil servant (fulltime) **(CVLS)**
4=Private firm (not farm) fulltime **(PRF)**
5= Private firm (not farm) seasonal **(PRS)**
6= Pension **(PEN)**
7= Other

3.2.3 Did any **adult** member(s) of the household operate any **business activity** (formal and informal) besides **farming** over the past 1 year? ***1=Yes*** ***2=No*** *(if no, go →3.2.3)*	**FI06**	
Enum: List below all adult household members who earned income from business activities, the types of business and the incomes earned		

MEM	**BACT** *See codes→*	Estimated costs of running the business *(per year)* **CBACT**	Total estimated incomes *(per year)* **IBACT**

BACT codes

1=input/output trading for crops and livestock (not from own production)

2=service provision e.g. maintenance, repair, transport, etc

3=Other trading

4= Other, specify

3.2.5 Over the past 1 year , did **any** household member **receive cash** or **any other gifts** from another household/relative(s), government, NGO, organization (including food relief, food for work) e.g for marriage dowry/lobola, damage/fine payments, and elopement fees etc ***1=Yes*** ***2=No*** *(if no, → skip to next section)*	**FI08**	
3.2.6 What was the **total income (value)** from cash or gifts received by **all** household members over the past 1 year? *(ZMW)*	**FI09**	

3.3 INCOME FROM FOREST AND NON-FOREST PRODUCTS

We would like to talk about all household members who earned income from selling forest and non-timber forest products over the last one year.

Table 3.3.1: FP/NTFP Products *Key variables: PROV, DIST, VIL, HH, FORES* ***Reference period (last one year)***

Forest Resources (FP/NFP)			Did any **member** of this **household collect/harvest** … for **home** use /**consumption** and/or **sale over the last 1 year**? ***(Enum: Please ask about the other category also)*** ***1=Yes*** ***2=NO → go to next product***	Who primarily carried out this activity? *(See codes below)*	What was the **total quantity** of the … collected/harvested by the household for home use or consumption **over the last 1 year**? *(if hh did not do this activity, enter 0 in Qty. and go → FP04)*		What was the **total quantity** of the … collected/harvested by the household for sale **over the last 1 year**? *(if hh did not do this activity, enter 0 in Qty. and go → next FORES)*			
					Quantity for home use	**Unit**	***Quantity sold***	**Unit Price**	**Unit**	**Market type**
FP/ NTFP	**FORES**		**FP01**	**FP02**	**FP03**	**FP03a**	**FP04**	**FP04a**	**FP04b**	**FP05**
FP	Poles and timber	1								
	Firewood from felled trees (excluding charcoal)	2								
	Charcoal from felled trees	3								
NTFP	Fish from lakes/rivers/streams (excluding fish ponds)	4								
	Edible ants and caterpillars	5								
	Wild fruits	7								
	Wild honey	8								
	Wild mushrooms	9								
	Firewood from dead wood (excluding charcoal)	10								
	Charcoal from dead wood	11								
	Wild animals (e.g. rodents, small game, other)	12								
	Thatching/fencing grass	13								
	Other, specify________									

Unit Code (FP03, FP04b)			**Codes (FP02)**	**Codes (FP05)**
1=90kg bag	10=20lt tin unshelled	9=10 kg bag unshelled	1=Male adults	1= main village markets
2=50kg bag	11=5lt gallon	18=boxes	2=Female adults	2=main market at boma/district
3=25kg bag	12=MEDA	19=number	3=female children	3=Roadside markets within
4=10kg bag	13=bunches	20=kilogram	4=male children	4=
5=20lt tin	14=MUCHUMBU	21=Oxcart/sledge	5=both male & female adults	
6=90kg bag unshlled	15=ka B.P.	8=25kg bag unshelled	6=both male and female	
7=50kg bag unshelled	16=crates	17=tonnes		

SECTION 5. HOUSEHOLD ASSETS / IMPLEMENTS

5.1 Please tell us about the type and number of assets or implements owned by the household.

Table5.1 Assets *Key Variables: PROV, DIST, VIL, HH, ASSET* ***Reference period: 1st Oct 2013***

Type of Assets	Asset code	Did the hh **own** .... as at 1st Oct 2013? *1 = Yes* *2 = No→> go to next asset*	How **many**...... did the hh have in **working condition as at 1st Oct 2013?** ***(Enter "0" if none)***	If the hh were to have **sold all of these**...... how much would they have **fetched in total in Oct 2013**? ***(Enter the total value in ZMW)***
	ASSET	**AST01**	**AST02**	**AST03**
Ox-drawn plough	1			
Disc plough	2			
Harrows	3			
Cultivators	4			
Rippers	5			
Ridger/ weeder	6			
Planter	7			
Tractors	8			
Hand driven tractor	9			
Ox carts	10			
Wheel barrow	11			
Hand hoes	12			
Chaka hoes	13			
Motorized water pumps	14			
Other irrigation equipment	15			
Trucks/lorries	16			
Pick-ups/ vans/cars	17			
Trailer	18			
Motorcycle	19			
Bicycles	20			
Boats/canoes	21			
Motorized hammer mills	22			
Hand hammer mills	23			
Rump presses/oil expellers	24			

Type of Assets	Asset code	Did the hh **own** .... as at 1st May 2013? *1 = Yes* *2 = No→> go to next asset*	How **many**...... did the hh have in ***working* condition as at 1st Oct 2013?** ***(Enter "0" if none)***	If the hh were to have **sold all of these**...... how much would they have **fetched in total in Oct 2013**? ***(Enter the total value in ZMW)***
	ASSET	**AST01**	**AST02**	**AST03**
Knapsack sprayer	25			
Boom sprayer	26			
Hand-operated maize sheller	27			
Motorized maize sheller	28			
Hand-operated groundnut sheller	29			
Motorized groundnut sheller	30			
Standard well (protected)	31			
Borehole	32			
Solar panel	33			
Generator	34			
Cell phone	35			
Radio	36			
TV	36			

SECTION 6. DISTANCES TO KEY AGRICULTURAL SERVICES

6.1 We will now ask about distances to key agricultural services.

Table 12.5 Distances to key agricultural services *Key variables: PROV, DIST, VIL, HH, KEYSERV* *Reference period: now*

From the household, how far is it to the NEAREST ………?		Distance in Km *(1 mile=1.6 Kilometers)* ***(Enumerator: if do not know enter -9)***	How much **time** is required to **reach this destination** using the **most common mode of transport**, (include walking as mode)	
			Time	Unit: *1=minutes 2=hours*
	KEYSERV	**KS01**	**KS02**	**KS03**
Boma	1			
Tarmac/tarred road	2			
Main road usable year round/ feeder road	3			
Main input/output sales outlet	4			
Main FISP input collection point	5			
Agricultural camp extension officer	6			
Other source of general extension advice	7			
Extension info on conservation agriculture	8			
Protected forest reserve	9			
Game management reserve	10			
Food reserve agency (FRA) depot	11			

6.2 kinship ties to traditional local authorities and social capital

Enumerator: Please tell the respondent that we will now talk about other general issues relating to this household and this village? Enter -8 if not applicable

6.2.1	Is the **head** of this household related to the **headman** in this village/area**?** ***1=Yes 2=No*** *(if no, go →6-2-3)*	**K01**	
6.2.2	*(If yes)* What exactly is the **relationship** of the **headman** to the **head** of the household? ***(see codes below)***	**K02**	
6.2.3	Is the **spouse** of this household related to the **headman** in this village/area**?** ***1=Yes 2=No*** *(if no, go →6.2.5)*	**K03**	
6.2.4	*(If yes)* What exactly is the **relationship** of the **headman** to the **spouse** of the household? ***(see codes below)***	**K04**	
6.2.5	Is the **head** of this household related to the **chief** in this village/area**?** ***1=Yes 2=No*** *(if no, go →6.2.7)*	**K05**	
6.2.6	*(If yes)* What exactly is the **relationship** of the **chief** to the **head** of the household? ***(see codes below)***	**K06**	
6.2.7	Is the **spouse** of this household related to the **chief** in this village/area**?** ***1=Yes 2=No***	**K07**	
6.2-8	Is there currently a **member of Parliament** (MP) **from** this ward? ***1=Yes 2=No***	**K08**	
6.2.9	Is anyone in this household a member of a **farmer cooperative, group or association**? ***1=Yes 2=No***	**K09**	

Codes for relationship of chief or headman to head or spouse – K01 – K07			
1= Spouse *2= Child (own/step)* *3= Parent / Parent-in-law*	*4= Brother / Sister*	*5= Other relatives*	*6= headman/chief*

SECTION 7:

QUESTIONS ABOUT AGRICULTURAL/FOREST INFORMATION

7.1 Please tell us about the **services you received** from **organizations, private agents or individual farmers**.

Table 7.1 Advice Provision *Key Variables: PROV, DIST, VIL, HH, SRCODE* ***Reference Period: since January 2013***

Type of Advice	SRCODE	Has the hh...? *1 = Yes* *2 = No---> go to next service*	Who was the **most** **important supplier or organizer** of this advice? *(see code below)*	**How** did the hh **receive** this **advice**? *1=Informal conversation* *2=Radio program* *3=Pamphlet/newspaper* *4=Workshop/training program* *5=Field Day* *6 =Demonstration plot* *7=Visit* *8=Meeting* *9 =Other (specify)________*	Did the hh **use** this **advice** in the **2013/2014** season? *1=Yes* *2=partly* *3=no*
	SRCODE	**SR01**	**SR02**	**SR03**	**SR04**
Received any advice to **plant hybrid maize** seed?	1				
Received any advice to **apply basal & top dressing** fertilizer?	2				
Received any advice on **practicing minimum tillage using planting basins**?	3				
Received any advice on **practicing minimum tillage using ripping**?	4				
Received any advice on **practicing minimum tillage using zero tillage**?	5				
Received any advice to **leave crop residues in the field**?	6				
Received any advice on **nitrogen-fixing crop rotation**?	7				
Received any advice on **crop diversification**?	8				
Received any advice on **adapting to and mitigation of climate change in agriculture**?	9				
Received any advice on the **potential of conservation agriculture for adapting to climate change?**	10				
Received any advice on **the potential of forests for climate change mitigation?**	11				

Provider of Information (SR02)
1=MAL extension agent 2=non-MAL NGO extension agents (project extension agents) 3=ZNFU 4= Forestry department 5=MELNR 6=Forestry project agents; 7= other farmers

SECTION 8. HOUSEHOLD KNOWLEDGE OF AND INVOLVEMENT IN REDD+

Enumerator: *Please tell the respondent that we will now talk about general themes relating to forest resources and climate change mitigation in this village. We will specifically talk about the role of forests in climate change mitigation and climate change mitigation programs such as reducing emissions from deforestation and degradation plus conservation (REDD+)*

HHRK1	Do forests have any role in climate change regulation?? ***1=Yes; 2=No (enter -9 if I don't know, skip to HHRK3 if no)***		
HHRK2	What is the role of forests in reducing chances of climate change? ***1= increases carbon sequestration (storage of carbon in trees); 2=reduces rainfall variability; 3=increase local rainfall; 4=stabilizes temperature - 9 =I don't know***		
HHRK3	Are you aware of any programs/projects about the importance of preserving forests and the possibility of earning extra income by preserving forests in this area? ***1=Yes; 2=No (enter -9 if I don't know, skip to HHRK5 if no***		
HHRK4	Is any member of this household participating in such programs/projects? ***1=Yes 2=No***		
HHRK5	If there is or were to be a REDD+ project in this area, how would you hope that it would benefit your household? ***(Enum: Please ask this as open ended question, and select appropriate responses below. Please probe to get more responses.)***		***1=Yes -8 =does not apply***
	We hope it would improve our incomes	**HHRK5a**	
	We hope it would adequately compensate us for lost forest income	**HHRK5b**	
	We hope it would provide (sufficient) alternative/supplementary income	**HHRK5c**	
	We hope it would successfully protect area forests	**HHRK5d**	
	We hope it would stop the plans of big companies that want to convert our forests	**HHRK5e**	
	We hope it would help reduce the threats from climate change	**HHRK5f**	
	*Other (specify)*____		

Enumerator: *Please tell the respondent that we will now talk about their willingness to participate in REDD+ activities. To do this, we will use one hypothetical scenario that would help the respondents think through the subsequent questions. Please read the scenarios as presented and ask the follow up questions as given.*

Hypothetical Scenario

Over the last few decades, global climate has changed dramatically. This can be seen from increased incidences of droughts, rainfall variability and increasing temperature. The main cause of climate change is emissions of greenhouses gases (GHGs) like carbon dioxide, methane and nitrous oxide from human activities. Some of the human activities responsible for emission of GHGs include use of fuels for cars and in industrial production, and forest degradation and deforestation. In turn, the impacts of climate change are felt in all economic sectors of the world but especially in agriculture and in the developing world, where the capacity to adapt is lowest. In order to reduce the future consequences of climate change, efforts aimed at reducing emissions or increasing removals of GHGs are increasingly being promoted around the world. One such initiative is the reducing emissions from deforestation and degradation plus conservation (REDD+). REDD+ is mechanism that develops policies and programs aimed at averting conversion of forest to alternative uses and promote sustainable management of forests to enhance carbon stocks. This is done by facilitating development of forest management policies at local levels and also by designing performance based incentives to forest owners. One proposal is that, based on verifiable emission reductions, forest owners can qualify to receive monetary payments for conserving forests. This is because their forests play a critical role of carbon sequestration.

Enum: Pose and ask the respondents if anything is unclear? Explain where you can and tell them you are not sure if in doubt.

REDD+ activities are implemented through projects at the local level and among other things aim to compensate forest owners for the environmental services provided by forests. There may be or may not be any such projects in this area yet, but there places within Zambia and elsewhere in the world where such activities are taking place and may soon be expanded to this area. With this background, please help us answer the following questions.

Table 8.2 REDD+ awareness and willingness to participate *Key Variables: PROV, DIST, VIL, HH*

HHR01	Has anyone in this household cleared any forest for agricultural purposes over the past 5 years? ***1=Yes 2=No***		
HHR02	Will you expand your area of agricultural land over the next 5 years by clearing forests? ***1=definitely, yes 2= Probably, yes 3= not sure 4= probably, no 5= definitely, no (If no, go→HHR04)***		
HHR03	By how much on average do think you will expand your agricultural land over the next 5 years? **Unit codes:** *1=lima 2=acre 3=hectare 4=square metre*	**Area HHR03a**	
		Unit HHR03b	
HHR04	Would you be willing to enter an agreement where you are paid for *not* clearing any more forests for agricultural purposes in the future? ***1=Yes 2=No -9 I don't Know (If no, go→HHR06)***		
HHR05	What is the minimum annual payment per hectare that you can accept to enter such a contract not to expand your agricultural activities by clearing forests? ZMW		

HHR06	If a Mr Mbewe, a farmer in this area can clear 1 hectare of forest to grow crops, how much do you think he can accept to be paid per year so that he does not clear this additional 1 hectare of forest?	
HHR07	Imagine that clearing of forest for whatever reasons is forbidden in this village and that each time a farmer wants to clear a forest, she has to pay to do so. What is the maximum amount you would be willing to pay per year to get permission to clear an additional hectare of forest land? ***Enum: Probe to get ZMW value per hectare***	
Enum: Look at the response to question HHR05 to set the referendum price (REFP) and write it on the payment card provided. Then ask the following questions. Remember, this is ZMW per hectare and show it to the respondent.t. If the respondent does not know in HHR05, use the value in HHb06. If there is I don't know in HHb06, use K 600 per hectare. When changing the referendum price, always change the amount by 50%, except when HHR08b=2)		
HHR08a	If a REDD+ project offered you [***HHR08a.1*** ……………………….*ZMW*] would you accept not to clear an additional hectare of forest for agricultural production per year? ***1=Yes 2=No*** ***Enum: Offer a lower amount if yes, and a higher amount if no, and record exact new amounts in the next question under HHR08b.1***	
HHR08b	What if the project offered you [***HHR08b.1*** ……………………….*ZMW] (new figure from HHR08a*), would you accept this and not clear an additional hectare of forest for agricultural production per year? ***1=Yes 2=No*** ***End interview if yes: if no, offer a new amount that is 100% higher and go to HHR08c and record new figure u under HHR08c.1***	
HHR08c	What if the project offered you [***HHR08c.1*** ……………………….*ZMW] (new figure from HHR08b*), would you accept this and not clear an additional hectare of forest for agricultural production per year? ***1=Yes 2=No -8 Not applicable*** ***If no, end interview.***	

END OF INTERVIEW, THANK THE RESPONDENT!!!!

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Hambulo Ngoma was born on 19 March 1982 in Monze district, Zambia. He holds a BSc. Degree in Agricultural Economics from the University of Zambia (2008) and an MSc. Degree in Agricultural and Applied Economics from University of Malawi (2012). Prior to enrolling for the PhD program in August 2013, Hambulo worked primarily in research and development facilitation in Zambia where he garnered a wealth of experience in applied agricultural policy research, project management and development facilitation around sub-Saharan Africa.

Sustained policy support towards conservation agriculture despite debates on the extent of its adoption and benefits for smallholders in sub-Saharan Africa motivated his PhD work. In particular, his thesis assesses linkages between livelihoods, agricultural practices and land use among smallholders in Zambia.

The thesis uses a variety of methods applied to household survey data and spatial rainfall data to understand levers and barriers to uptake of, and to tease out the impacts of minimum tillage on yield, livelihoods and deforestation. The main results suggest a lower uptake of minimum tillage - the main component of conservation agriculture - than is generally believed and that the current promotion approaches work for some but not all principles of minimum tillage. Minimum tillage seems a viable option to raise maize productivity with timely field operations but it has limited effects on cropland expansion (given its low adoption-intensity) and household income (welfare) in the short-term. Providing short-term palliatives to potential adopters, adapting minimum tillage principles to local contexts and combining them with other policy measures for forest conservation as well as improved and targeted promotion, remain key policy challenges in sub-Saharan Africa.

Hambulo is incoming research fellow and in-country coordinator for the Michigan State University-led Feed the Future Innovation Lab for Food Security Policy hosted by the Indaba Agricultural Policy Research Institute in Lusaka, Zambia.

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