Feed the Future Innovation Lab for Food Security Policy

Research Paper 164 December 2019

Zambia Buyin

SWITCHING UP CLIMATE-SMART AGRICULTURE ADOPTION: DO 'GREEN' SUBSIDIES, INSURANCE, RISK AVERSION AND IMPATIENCE MATTER?

By

Hambulo Ngoma, Nicole M. Mason-Wardell, Paul C. Samboko, and Peter Hangoma

Food Security Policy *Research Papers*

This *Research Paper* series is designed to timely disseminate research and policy analytical outputs generated by the USAID funded Feed the Future Innovation Lab for Food Security Policy (FSP) and its Associate Awards. The FSP project is managed by the Food Security Group (FSG) of the Department of Agricultural, Food, and Resource Economics (AFRE) at Michigan State University (MSU), and implemented in partnership with the International Food Policy Research Institute (IFPRI) and the University of Pretoria (UP). Together, the MSU-IFPRI-UP consortium works with governments, researchers and private sector stakeholders in Feed the Future focus countries in Africa and Asia to increase agricultural productivity, improve dietary diversity and build greater resilience to challenges like climate change that affect livelihoods.

The papers are aimed at researchers, policy makers, donor agencies, educators, and international development practitioners. Selected papers will be translated into French, Portuguese, or other languages.

Copies of all FSP Research Papers and Policy Briefs are freely downloadable in pdf format from the following Web site: https://www.canr.msu.edu/fsp/publications/

Copies of all FSP papers and briefs are also submitted to the USAID Development Experience Clearing House (DEC) at: http://dec.usaid.gov/

AUTHORS

Hambulo Ngoma is Research Fellow at Indaba Agricultural Policy Research Institute (IAPRI)

Nicole M. Mason-Wardell is Associate Professor, Department of Agricultural, Food, and Resource Economics, Michigan State University

Paul C. Samboko, Research Associate respectively at Indaba Agricultural Policy Research Institute (IAPRI)

Peter Hangoma,s lecturer, Department of Economics, and Head of the Department of Health Policy and Management, University of Zambia.

Acknowledgments

We wish to acknowledge the financial and substantive support of the Swedish International Development Agency (SIDA) and of the American People provided to the Feed the Future Innovation Lab for Food Security Policy [grant number AID-OAA-L-13-00001 (Zambia buy-in)] through the United States Agency for International Development (USAID). This work was also supported by the US Department of Agriculture (USDA) National Institute of Food and Agriculture and Michigan AgBioResearch [project number MICL02501]. We would further like to acknowledge the technical and capacity building support provided by Michigan State University through its researchers through the financial support from the USAID-funded Zambia buy-in to the Feed the Future Innovation Lab for Food Security Policy (FSP). Special thanks also goes to Patricia Johannes of MSU for editorial and document preparation assistance. The contents are the sole responsibility of the authors and do not necessarily reflect the views of SIDA, USAID, USDA, the United States Government, MSU, or Michigan AgBioResearch.

The authors are also grateful to the Ministry of Agriculture for field guidance and to Kenny Hatontola, Eric Chikwalila, and Bernadette Njala for proving excellent research assistance in conducting the experiments.

This Paper is also published as IAPRI Working Paper No. 146, November 2018.

This study is made possible by the generous support of the American people provided to the Feed the Future Innovation Lab for Food Security Policy (FSP) through the United States Agency for International Development (USAID) under Cooperative Agreement No. AID-OAA-L-13-00001 (Zambia Buy-In). Additional funding support was also provided by the Swedish International Development Agency (SIDA) and the USAID Mission to Zambia. The contents are the sole responsibility of the authors and do not necessarily reflect the views of USAID, the United States Government, SIDA, or MSU.

Published by the Department of Agricultural, Food, and Resource Economics, Michigan State University, Justin S. Morrill Hall of Agriculture, 446 West Circle Dr., Room 202, East Lansing, Michigan 48824, USA.

EXECUTIVE SUMMARY

Climate-smart agriculture (CSA) is an important component of policy options designed to sustainably increase agricultural productivity, build resilience to climate risks, and mitigate climate change in Sub-Saharan Africa. However, the uptake of common CSA practices such as conservation agriculture remains low and material constraint explanations (e.g., credit, market, labor, information) for this low uptake remain inadequate and unclear. Could behavioral traits or risk preferences play a role?

We test the hypothesis that innate behavioral traits such as risk and time preferences play a role in CSA adoption and test whether adoption can be nudged using insurance and *green* subsidies. To do so, we use a series of incentivized field experiments with 323 randomly selected farmers in Zambia. We first conducted two games with each participant to elicit risk and time preference parameters. We then conducted three adoption games. In the first (base) game, participants decided whether to adopt CSA (conservation agriculture in this case) or conventional agriculture under various payoff scenarios. Returns to CSA and conventional agriculture varied depending on seasonal rainfall, and the *realized* seasonal rainfall was determined through a lottery (with a 25% chance of good rainfall) after participants had selected their preferred farming option (CSA or conventional agriculture).

In the subsequent two games, we changed the payoff structures by augmenting CSA with rainfall insurance and a green subsidy, respectively. The green subsidy is an add-on incentive for farmers that adopt CSA. We compare adoption behavior under the base scenario to the CSA plus insurance scenario and the CSA plus subsidy scenario. We also use the elicited preference parameters from the time and risk preferences games to analyze their role in participants' adoption decisions.

Overall, we find that the majority of participants in our experiments are risk-averse and impatient, and that a larger proportion of women were more risk-averse and impatient than men. Risk aversion and impatience were negatively correlated with the likelihood of adopting CSA. Time and risk preferences were associated with the likelihood of switching adoption between the base and follow-on (augmented) games. For example, an increase in risk aversion increased the likelihood of switching from conservation agriculture in base games to conservation agriculture with insurance in follow-on games.

Introducing insurance and green subsidies increased the level of adoption by 10 and 8 percentage points and the probability of adoption by approximately 6 – 12 percentage points. Whether these switch-up levels are high enough is an empirical question, but suggest that insurance and green subsidies are unlikely the panacea. Thus, although monetary returns matter in CSA adoption, non-pecuniary factors such as risk and time preferences also matter. These behavioral traits could partly explain the perceived low adoption of CSA practices such as conservation agriculture. Several factors including uninsured basis risk, trust in and how well farmers understand insurance and subsidy incentives, knowledge of the technology, and subjective perceptions of its riskiness influence adoption choices. Access to extension and subjective risk perceptions were stronger determinants of adoption in real life.

Given our findings that more risk-averse individuals are less likely to adopt CSA, a practice that is intended to be risk-reducing, a key policy implication is the need for a retooling of both public and private extension services to better demonstrate and educate farmers on the risk-reducing effects of CSA practices such as conservation agriculture. Moreover, if insurance and subsidies are to be used successfully to nudge adoption, extension will need to educate farmers on the structure of and mechanisms for payouts. This is important to build trust in the incentive systems.

CONTENTS

LIST OF TABLES

TABLE **PAGE**

LIST OF FIGURES

FIGURE **PAGE**

LIST OF ACRONYMS

CA	Conservation Agriculture
CSA	Climate-Smart Agriculture
CFU	Conservation Farming Unit
CVA	Conventional Agriculture
e-FISP	Farmer Input Support Program
EUT	Expected Utility Theory
FAO	Food and Agriculture Organization of the United Nations
FE	Future Equivalent
FFEs	Framed Field Experiments
FSP	Feed the Future Innovation Lab for Food Security Policy (FSP)
GHG	Greenhouse Gases
GRZ	Government of the Republic of Zambia
IFPRI	International Food Policy Research Institute
MSU	Michigan State University
MT	Minimum Tillage
OLS	Ordinary Least Squares
PT	Prospect Theory
SE	Standard Errors
SIDA	Swedish International Development Agency (SIDA)
SSA	Sub-Saharan Africa
USAID	United States Agency for International Development
US$	U.S. Dollar
ZMW	Zambian Kwacha

1. INTRODUCTION

Agricultural production systems require urgent transformation to respond to increasing food demands and the adverse effects of climate change. This is most profound in Sub-Saharan Africa (SSA) where a growing population, estimated to reach 2.2 billion by 2050 and higher average incomes are increasing food demand and giving rise to new consumption patterns (Canning, Sangeeta, and Abdo 2015). These changes are adding further strain on rainfed farming systems in the region. It is argued that these mega-trends characterize an agricultural time bomb whose epicenter is in the tropics and whose detonation will have far-reaching implications for livelihoods and biodiversity conservation (Laurance, Sayer, and Cassman 2014).

Agriculture production will need to increase by 60 – 80% in order to meet the projected three-fold rise in cereal demand in SSA by 2050 (Lipper et al. 2014; van Ittersum et al. 2016). Achieving these large production gains will require a combination of yield increases through sustainable agricultural intensification, irrigation, agricultural research and development, and supportive policies (Lipper et al. 2014; van Ittersum et al. 2016). Such a shift will require transforming agricultural development away from business-as-usual approaches such as farm blocks, which invariably increase the agricultural carbon footprint and often have irreversible environmental costs (Laurance et al. 2015). In fact, most of the current growth in agricultural production in SSA is driven by expanding cultivated area into forested landscapes (Jones and Franks 2015). Yet, forest loss induces climate change, which disproportionately affects smallholder farmers who depend on rain-fed agriculture, further constraining growth in agricultural production.

While it is generally accepted in development practice that agriculture needs to be more climate-smart in order to sustainably increase productivity to reduce poverty, food, and nutrition insecurity in the face of climate change, it is less clear how to do so. Nonetheless, climate-smart agriculture (CSA) is widely considered a necessary condition (IPCC 2014; Thierfelder et al. 2017). CSA is any suite of agricultural technologies, practices, or policies that aim to: 1) raise agricultural productivity and household incomes; 2) enhance climate change adaptation and resilience; and 3) reduce greenhouse gas (GHG) emissions from agriculture (FAO 2013). In this paper, we focus on conservation agriculture (CA), which is the most common type of CSA in Zambia (CIAT and WorldBank 2017) and is part of national policy in several SSA countries including Kenya, Malawi, Mozambique, Lesotho, Tanzania, Zambia, and Zimbabwe (Giller et al. 2015).

In Zambia, the Ministry of Agriculture and other key stakeholders such as the Conservation Farming Unit (CFU) and FAO have been promoting CA among smallholder farmers for more than two decades (Ngoma et al. 2016). The core practice of CA is minimum tillage (MT), implemented via planting basins, ripping, or zero tillage. In its full suite, CA involves MT, crop residue retention, and crop rotation of cereals with legumes; partial CA involves MT alone or MT with one but not both of the latter two practices. In our experiment, we focus on full suite CA adoption and supporting policy frameworks.

It has been shown that CA can be climate smart (Thierfelder et al. 2017; Ngoma et al. forthcoming), increases productivity in the medium- to long-term (Jaleta et al. 2016; Thierfelder et al. 2016; Ngoma 2018), and has positive welfare effects (Abdulai 2016; Jaleta et al. 2016; Ng'ombe, Kalinda, and Tembo 2017; Tambo and Mockshell 2018). However, its adoption—though on the rise—remains low and it is still unclear what could explain these low levels of adoption if indeed CA confers the above-mentioned benefits. The usual *Homo economicus* explanations based on material determinants—credit, inputs/tools, market, labor, and information constraints—and cultural norms do not tell the whole story (Grabowski et al. 2014; Ngoma et al. 2016; Zulu-Mbata, Chapoto, and Hichaambwa 2016). Even when these are addressed through freebies (incentives) or tailored market-based training programs, adoption is not sustained. Is there a possibility that there are other factors that explain CSA adoption? Could behavioral traits or risk preferences play a role? Could providing insurance or subsidies help to increase uptake?

In this paper, we examine the effects of farmers' risk and time preferences on CSA practice adoption (using the example of CA) and test whether bundling CSA with insurance or *green* subsidies can switch up, nudge, or incentivize adoption via framed field experiments (FFEs).[1] We hypothesize that smallholder farmers' risk and time preferences and their subjective perceptions of the riskiness of CA could provide more insights as to why adoption is (s)low. Further, we hypothesize, as Duflo, Kremer, and Robinson (2011) did for inorganic fertilizer, that nudging farmers to adopt CSA might provide useful insights into the levers of adoption.

We measure farmers' risk and time preferences following the experimental designs of Sutter et al. (2013), which is a simplified version of the Holt and Laury (2002) multiple price list approach. We then use the elicited risk and time preference parameters as covariates in adoption models based on adoption in FFEs and real-life adoption during the 2017/2018 farming season (based on farmer recall data).

Our FFEs consisted of three adoption games. In the first adoption game, all participants chose between CA and conventional or traditional agriculture (as defined below) at the start of the farming season. We denoted this as the base game. Returns to CA and conventional agriculture differ depending on whether the rainfall is *good* or *bad*. In the second adoption game, about half of the participants played the game with CA bundled with insurance, while the other half played the third adoption game where CA was bundled with green subsidies.

We framed conventional or traditional agriculture as the common farming systems involving complete soil inversion and used pictures of hand hoes and ploughs; for CA we used pictures of rip lines, zero tillage, planting basins, and maize fields under CA. Because the relative returns might differ by crop, we limited the framing to a one-hectare plot of maize. The payoff structure differentiated by whether rainfall is good or bad (explained in detail later) was based on actual maize gross margins per hectare for CA and conventional agriculture computed from a survey of roughly 2,500 Zambian smallholder farmers in Zulu-Mbata et al. (2016).

Insurance was framed as a type of rainfall insurance that covers farmers from weather-related production losses. We use rainfall insurance because rainfall risk (indicated by droughts and floods) is among the most important risks facing the agricultural sector in Zambia (Braimoh et al. 2018) and SSA in general (Holden and Quiggin 2017). Because it is observable, rainfall avoids the usual problems of moral hazard and adverse selection in insurance and works well as a mechanism to trigger payment (Karlan et al. 2014). Lastly, we framed green subsidies as an add-on incentive to the current flexible electronic voucher-based Farmer Input Support Program (e-FISP) for adopting CA, which could allow recipients to redeem a larger cash value for CA-relevant inputs and implements such as rippers, jab planters and Chaka hoes, herbicides, insecticides, etc.

We add to the literature in a number of ways. First, and to the best of our knowledge, this is the first paper to assess the role of risk and time preference in the adoption of CA and whether introducing insurance and a green subsidy can nudge farmers to switch their adoption choices from conventional to CA or from CA to CA with insurance or a green subsidy in SSA. We call the latter effect adoption

[1] Bundling in this case implies promoting CA together with insurance and/or green subsidies, respectively.

switching. Second, in the first application of its kind in SSA, we use an FFE to test novel ideas on nudging farmers with rainfall insurance and green subsidies as a means to incentivize CA adoption. Third, while previous literature recognizes that subjective perceptions of the riskiness of technologies matter (Holden and Quiggin 2017), few controlled for both subjective and objective risk as done in this study. Fourth, we assess how introducing insurance and green subsidies influences farmers' adoption switching behavior. Lastly, unlike other studies that use risk parameters elicited ex-post to explain past adoption, our preference parameters and adoption choices and transitions are all captured contemporaneously. Taken together, our study attempts to shed light on the role of behavioral factors and policy levers in CSA adoption.

We find that the majority of the participants in the experiments are risk-averse and impatient. Preferences are significant factors explaining non-adoption and adoption switching behavior as are subjective perceptions of the riskiness of CA, having CA knowledge, and access to CA extension. Introducing insurance and subsidies in our games increased adoption switching from CA alone to CA with insurance and to CA with subsidy by nearly two-thirds, and from conventional agriculture to CA with insurance and to CA with subsidy by nearly a tenth between base games and subsequent games. Yet, nearly one-fifth of the participants who had chosen CA in base games choose CA without insurance or a subsidy in the subsequent games. Overall, introducing insurance and green subsidies in the second stage of the games increased CA adoption by 6 and 12 percentage points, respectively. When taken together, our results suggest that both risk and time preferences matter for CA adoption and while relevant, insurance and green subsidies are unlikely the panacea.

We briefly review the literature on risk and time preferences, and technology adoption in Section 2 and conceptually link preferences to technology adoption in Section 3. Details on fieldwork, including experimental procedures provided in Section 4 are followed by results in Section 5. We discuss the main results in Section 6 and conclude in Section 7.

2. RISK AND TIME PREFERENCES, AND TECHNOLOGY ADOPTION

Risk aversion and preferences in general have long been thought to influence technology adoption in agriculture (Feder 1980). Here, we restrict ourselves to studies that use experiments to elicit individual risk and time preferences and/or relate these to technology adoption in agriculture. The seminal work by Binswanger (1980) that finds that farmers in India are risk averse and that wealth reduces risk aversion is the genesis. Since then, the application of experimental methods to elicit risk and time preferences and their role in adoption has expanded considerably.

For example, Alem, Eggert, and Ruhinduka (2015) found that risk preferences elicited through experiments did not significantly influence the adoption of the System of Rice Intensification among small-scale farmers in Tanzania. Brick and Visser (2015) conducted framed field experiments to assess the role of risk preferences in the adoption of improved agriculture (framed as improved maize variety seed) versus traditional agriculture (framed as traditional seed). They find that risk-averse farmers are more likely to opt for traditional seed varieties. Providing insurance did not change the choices much and authors conclude that residual production risk and basis risk (not covered in standard crop insurance) matter. Holden and Quiggin (2017) study the role of risk and loss aversion and subjective probability weighting on farmers' decisions to adopt drought tolerant maize as a climate risk-reducing strategy. They find that risk-averse farmers are more likely to adopt drought-tolerant maize and local maize, but are less likely to adopt other improved maize varieties. This suggests that farmer's perceptions of the riskiness of new technologies matter in adoption decisions.

In China, Liu (2013) finds that farmers who are more risk and loss averse tend to adopt BT cotton later than other farmers and Jin, Wang, and Wang (2016) find that risk aversion increases the uptake of weather-index crop insurance. In somewhat different applications, Duflo, Kremer, and Robinson (2008) and Duflo, Kremer, and Robinson (2011) use a series of field trials and field experiments to assess returns to fertilizers and find that small nudges such as offering farmers the opportunity to buy free-delivered fertilizer soon after harvest relative to just before planting season increased fertilizer use.

As can be seen from the foregoing, while field experiments are increasingly used to study preferences and their role in agricultural technology adoption, there is a paucity of literature specific to the CSA addressed in this paper. None of the reviewed literature use preference parameters to study adoption switching in the manner done in our paper. Lastly, none of the reviewed literature use field experiments to study how insurance and green subsidies might incentivize or switch-up the persistently low CA adoption in SSA.

3. CONCEPTUAL FRAMEWORK

Why are some farmers quick to adopt innovations and in turn hasten their escape from poverty? Yet others do not, despite being exposed to those innovations, and holding material constraints constant. Risk and time preferences are likely to play a role. When faced with a choice between a familiar and less risky, low-return technology and a new high-risk, high-return alternative, risk-averse farmers are likely to choose the former even if the returns to the latter are higher. Such choices lead to the risk-induced poverty-trap, where risk-averse farmers choose low-return less-risky strategies only to fall even deeper into poverty (Reardon and Vosti 1995; Brick and Visser 2015). Impatience too could lead farmers to highly discount later returns relative to current returns.

Two broad theoretical approaches have been used to study decisions under risk. The expected utility theory (EUT) postulates that a decision maker will choose an option with a higher expected utility of returns. Just and Zilberman (1988) apply the EUT in agricultural technology adoption and show using a well-behaved utility function that the likelihood of adoption decreases with an increase in risk aversion. They also show that other factors such as whether the technology is risk increasing or risk reducing, and access to credit and wealth matter.

The alternative approach is based on Prospect Theory (PT) developed by Kahneman and Tversky (1979). Unlike EUT, PT suggests that human behavior deviates from the rational economic thinking in several ways. PT suggests that people might be more averse to loss than gains and that people tend to overweight small probabilities and underweight large probabilities. The latter leads to risk aversion in choices involving gains, and risk seeking in choices with actual losses. PT theory is increasingly used in the study of decisions under risk (e.g., Tanaka, Camerer, and Nguyen 2010; Liu 2013; Holden and Quiggin 2017)

EUT is appropriate for the technology we study in this paper for two main reasons. First, because CA is believed to have higher average returns than conventional agriculture (and framed as such in this paper), non-adoption may be driven more by the variance of returns than loss aversion. This assertion somewhat finds support in Holden and Quiggin (2017) where risk aversion rather than loss aversion or nonlinear probability weighting explained much of farmers' decisions to adopt drought-tolerant maize, other improved maize, and local maize in Malawi. Second, because returns to CA take some time to accrue and to a large extent are uncertain, we posit that time and risk preference rather than nonlinear probability weighting is more relevant to explain adoption decisions.

In our games, farmers chose between CA and conventional agriculture at the start of the farming season. CA offers higher but more variable returns regardless of whether rainfall is good or bad and requires investing more time in learning the art. The returns to both CA and conventional agriculture are positively correlated because they both depend on rainfall outcomes.

4. DATA AND METHODS

4.1 Data and Sampling

Fieldwork was conducted in seven villages purposively selected (in consultation with the Ministry of Agriculture) to represent areas where there have been CA interventions in Choma and Kalomo districts. Within each village, a random sample of 50 households was selected from village rosters. One household member (the female or male household head or spouse) was invited to participate in the experiments conducted at the village meeting place or a school nearby. We invited 200 and 150 farmers to participate in the experiments in Choma and Kalomo districts, respectively, for a total sample of 350. About 92% of those invited or 323 farmers participated in the experiments.

4.2 Experimental Design and Procedures

We used a combination of within and between subject experimental designs. All participants played the risk and time preference games. Subsequently, three sets of adoption games were played. The first (base) set of adoption games were played by all participants. Then about half of the participants played the second set of games, which combined CA with insurance while the other half played the third set combining CA with a green subsidy. All games were played with a 25% chance of winning the lottery or that seasonal rainfall would be good.

4.2.1 Risk Preference Games

Our study followed experimental designs in Sutter et al. (2013), which is simple enough for less educated participants to follow and is simpler than the complex price lists used in the original Holt and Laury (2002) designs. Participants in the risk games were confronted with multiple price lists where they had to choose between: (i) a sure amount that monotonically increased by K1 from K1 to K20; and (ii) a gamble with a 25% chance to win K20 and a 75% chance to win nothing.[2] If a participant chose to play the lottery, they blindly drew a ball from a bag containing 15 (75%) yellow balls and five (25%) orange balls. If an orange ball was drawn, they would win the gamble, but they would get nothing if a yellow ball were drawn.

Using decision sheets shown in Appendix A, participants chose between a sure amount (Option 1) and a lottery (Option 2) in 20 rows. The point at which a participant switches from playing the gamble to a sure amount gives an indication of their certainty equivalent (CE). The CE is the payoff amount that would make a participant indifferent between a sure amount and a gamble. Following Sutter et al. (2013), we computed the individual risk preference parameter (θ) as:

$$\theta = 1 - \frac{CE}{L}, \qquad (1)$$

where CE was computed as the midpoint between the two sure amounts where a participant switches from playing the gamble to a sure amount. L is the lottery amount, equal to K20 in our games. We define risk loving as $\theta < 0.5$, risk neutrality as $\theta = 0.5$ and risk aversion as $\theta > 0.5$. CEs for participants who chose the sure amount throughout were computed as the midpoint between the first sure amount, K1, and 0, and as 0 for those who chose the lottery throughout. These are

[2] 1 U.S. dollar (US$) = 9.25 Zambian kwacha (ZMW) at the time of the survey.

simplifications but capture the essence of revealed behavior. Participants revealed that they were risk averse by selecting the sure amount throughout and risk loving by selecting the lottery throughout.

4.2.2 Time Preference Games

Following Sutter et al. (2013), we used decision sheets with 20 rows where participants chose either K10 today or an amount starting from K10 and monotonically increasing by K1 increments up to K29 in two weeks. The point at which a participant switches from the sure amount today to the larger, later payment shows their future equivalent (FE). The FE is a payoff that would make a participant indifferent between a payoff today and a payoff in two weeks.

Following procedures in Sutter et al. we define the FE as the midpoint of the future amount in the row where a participant switched and the row just above. For example, if a participant switched from the current payment to the future payment in row 10 in the decision sheet in appendix B, their future equivalent is 18.5. If a participant selected the current payment throughout, they revealed impatience and we set their FE as the maximum amount in the future payment. Conversely, if a participant opted for the future payoff throughout, they revealed patience and we set their FE to 10, the payoff in the current period.[3] Impatience increases with higher FE. Again, these are simplifications, but more closely reveal the time preferences of participants in our sample. Later payments were made through mobile money two weeks after the games were played. These game procedures were explained to participants prior to the start of the games.

Detailed game instructions (available from the authors upon request) were read out in local language prior to the start of each game. Participants played one practice round and were allowed to ask several questions prior to playing the games. No communication among participants was allowed once games were being played. After both risk and time preference games were played, we randomly selected one game to be played for real money and then randomly selected one row to be paid for in the selected game. To do this, once all participants had made their choices, one participant (selected by the group) tossed a coin to select whether the risk or time preference game is played for real money. The same or another participant then drew a random number from a bag containing 20 numbered balls to determine which row is played for real money. These procedures were explained to the participants prior to the start of the games.

We carefully worded the instructions to avoid multiple switching, which is a common problem in eliciting risk and time preferences using multiple price lists as done in this paper. Following Sutter et al. (2013) and Brick and Visser (2015), we enforced this, so that once a participant switched from one choice to another, our explanations made it apparent that it was illogical for them to switch back and forth.

4.2.3 Adoption Games and Framing

Framing was as described in the introduction. We defined CA adoption as allocating at least 25% of a household's maize area to CA. In the adoption games, which were for 1 ha maize plots, participants wishing to adopt CA in the games committed 0.25 ha of the 1 ha maize plot to CA. Participants in the adoption games were asked to choose between CA and conventional agriculture at the start of the farming season, given the relative returns to each option under good and bad rainfall. Whether realized rainfall is good or bad was only determined after all participants had

[3] Of course, this may not be true all the time; such a choice may reveal some other inconsistent behaviors.

chosen the farming option for a season. The payoffs (returns) for the adoption games were triggered by whether seasonal rainfall is good or bad. As in risk preference games and to represent rainfall variability, there was a 25% chance that the rainfall is good. Payoffs used in these experiments for good rainfall years were based on actual per ha maize gross margins for CA and conventional agriculture computed from a survey of over 2,500 smallholder farmers following a normal rainfall year by (Zulu-Mbata et al. 2016). For bad rainfall years, we assumed that yield under CA declined by 30% compared to a 70% reduction under conventional agriculture. These yield reductions are close to observations from on-station experiments (Mupangwa et al. (2017) and projected maize yield reductions due to climate change in SSA (Lobell et al. 2008).

Base Games: Participants in the base adoption games chose between CA and conventional agriculture at the start of a farming season. With good rainfall, CA offered K23 per hectare against K19 per hectare from conventional agriculture. If rainfall is low, returns were -K2 for conventional agriculture and K12 for CA (Table 1). The loss with low rainfall is much less with CA because minimum tillage has better water retention capabilities. To cover the moral issue of subjecting participants to losses in experiments, each participant received a show-up fee of K5, which was sufficient to cover the anticipated loss from choosing conventional agriculture in a bad rainfall season.

Insurance Games: Participants in the insurance games had a third option in addition to CA and conventional agriculture. Here, farmers had the option to choose CA bundled with insurance. Those who chose CA and insurance needed to buy an insurance policy for K1 to cover themselves from rainfall-related production losses. The cost of insurance in these games (K1 or K100 un-rebased) was equivalent to the weather index insurance premium under e-FISP, and the extent of the cover was limited to 80% of the difference in returns between a good and a bad rainfall season and reflected the fact that insurance cover is not 100%. Farmers who chose CA and insurance would then receive an insurance payout of K8 if rainfall is bad, otherwise, they would receive no insurance payout. The payoffs for conventional agriculture and CA without insurance were exactly as before.

Relative to CA without insurance, the returns to CA with insurance are lower at K22 with good rainfall (because of the K1 paid as an insurance premium) but higher at K20 with low rainfall after accounting for the K8 insurance payout (Table 2 following)

Table 1. Payoffs for the Base Games, Conservation Agriculture versus Conventional Agriculture

	Rainfall	
	Good (Normal)	Bad (Low)
Conventional agriculture	19	-2
Conservation agriculture	23	13

Source: Authors unless otherwise designated.
Notes: The payoffs are based on maize gross margins per ha divided by 100.

Table 2. Payoffs for the Insurance Games

	Rainfall	
	Good (Normal)	Bad (Low)
Conventional agriculture	19	-2
Conservation agriculture	23	13
Conservation agriculture and insurance	22	20

Notes: The payoffs are based on maize gross margins per ha divided by 100.

Subsidy Games: In the subsidy games, the third choice was CA with a green bonus subsidy offered to farmers verified to have adopted CA. We consciously framed this bonus subsidy to be given to eligible farmers for a maximum of three years in the hopes that farmers would have learnt enough about CA to carry on afterwards. Because the exit strategy is known from the start, we assumed that farmers could plan their activities accordingly. In our games, the green subsidy was administered as a top-up of K3 to the current e-FISP for verified CA adopters.[4]

The payoff for CA with a green subsidy is K26 if rainfall is good and K16 if rainfall is bad (Table 3). The gain from CA with a green subsidy is higher if rainfall is good because it is assumed that recipients would be able to buy more inputs or implements than before, which should increase productivity. Again, the payoffs for conventional agriculture and CA without the subsidy remained unchanged as before. While conservation agriculture with the green subsidy has higher payoffs than conservation agriculture without the subsidy in both good and bad rainfall years, we may still observe some participants choosing conservation agriculture without the subsidy if, for example, participants have had negative perceptions of or negative past experiences with the input subsidy program in Zambia.

Once all the participants made their choices in adoption games and rainfall had been determined for each session, we randomly selected one game for payment by tossing a coin. If heads came up, we played the base game for real money, but if tails came up, the second game (insurance or subsidy) was played for real money. These procedures were explained to the participants at the start of the games. Each participant completed one pre-experiment survey to assess pre-experiment knowledge of CA, four experimental sessions, and a post-experiment survey. Each participant took on average 3-3.5 hours to complete all the tasks and earned about K37 (roughly $4).

Table 3. Payoffs for the Subsidy Games

	Rainfall	
	Good (Normal)	Bad (Low)
Conventional agriculture	19	-2
Conservation agriculture	23	13
Conservation agriculture and subsidy	26	16

Notes: The payoffs are based on maize gross margins per ha divided by 100.

[4] Government contributes ZMW 1,700 per farmer and each farmer contributes ZMW 400 in the current e-FISP. The e-FISP allows farmers to redeem a prepaid Visa card (e-voucher) at participating agro-dealers' shops for a diverse range of inputs and implements. This is in contrast to the traditional FISP which restricted farmers to mostly maize seed and fertilizers and which distributed these inputs in-kind to farmers rather than being implemented through e-vouchers redeemable at agro-dealers. The ZMW 300 green incentive proposed is 75% of the farmer contribution and would increase the total subsidy value to ZMW 2,400 from ZMW 2,100.

4.3 Data Analysis

We analyzed the data in two main ways. First, we used graphs to show the distributions of risk and time preferences, adoption choices, and switching behavior. These distributions are segregated by various variables of interest including gender, productive assets, and education. We assessed adoption switching by comparing farming system choices in the base games with choices in the insurance and subsidy games. Understanding these transitions is a first step in assessing if bundling CSAs such as CA with insurance or green subsidies can alter farmer behavior and possibly nudge adoption.

Second, we assess the role of risk and time preferences in CA adoption and adoption switching using multivariate regression frameworks. We take advantage of the fact the participants each played two adoption games (the base game and either the insurance or the subsidy game) and use panel data (random effects (RE)) probit models to both account for unobserved heterogeneity and for efficiency gains in estimating adoption.

We controlled for a number of factors thought to influence both adoption and adoption switching, including wealth, risk aversion, impatience, farmers' perceptions of the riskiness of CA, game order effects (i.e., whether the participant played the 'base' game or with insurance/subsidy game first)[5], pre-experiment knowledge of CA, access to CA extension and other relevant farm and individual characteristics. While it is difficult to assign *a priori* the expected signs of all these variables, we hypothesized that respondents that are risk averse (or impatient) are less likely to adopt CA compared to those that are not risk averse (or not impatient). Risk aversion and impatience are likely to influence adoption switching in complex ways, depending on the switch type. For example, we hypothesized that risk aversion would increase switching from CA to CA with insurance, or to CA with subsidy, impatience would have uncertain effects. We used OLS and Probit models to assess determinants of risk and time preferences and test if our data are consistent with findings elsewhere that females are more risk-averse, see, for example, (Brick, Visser, and Burns 2012; Alem, Eggert, and Ruhinduka 2015).

[5] This was randomized to try to avoid order effects.

5. RESULTS

5.1 Sample Characteristics and Descriptive Statistics

Participants in our experiments were on average risk averse with an average risk parameter of 0.65 and slightly impatient with an average impatience parameter of 23 (Table 4). Participants in our experiments were 44 years old on average, spent two years in school, and had lived for an average of 25 years in their current village. About 40% of the participants were female, the majority (91%) had some knowledge of CA prior to participating in the experiments, and over half (52%) believed that CA reduces production risk. The order in which the four games were played was fairly distributed in the sample with about half of the participants having played risk before time preference games, and insurance/subsidy games before the base adoption games. Table 4 summarizes the rest of the key variables used in the regressions.

5.2 Risk and Time Preferences Distributions

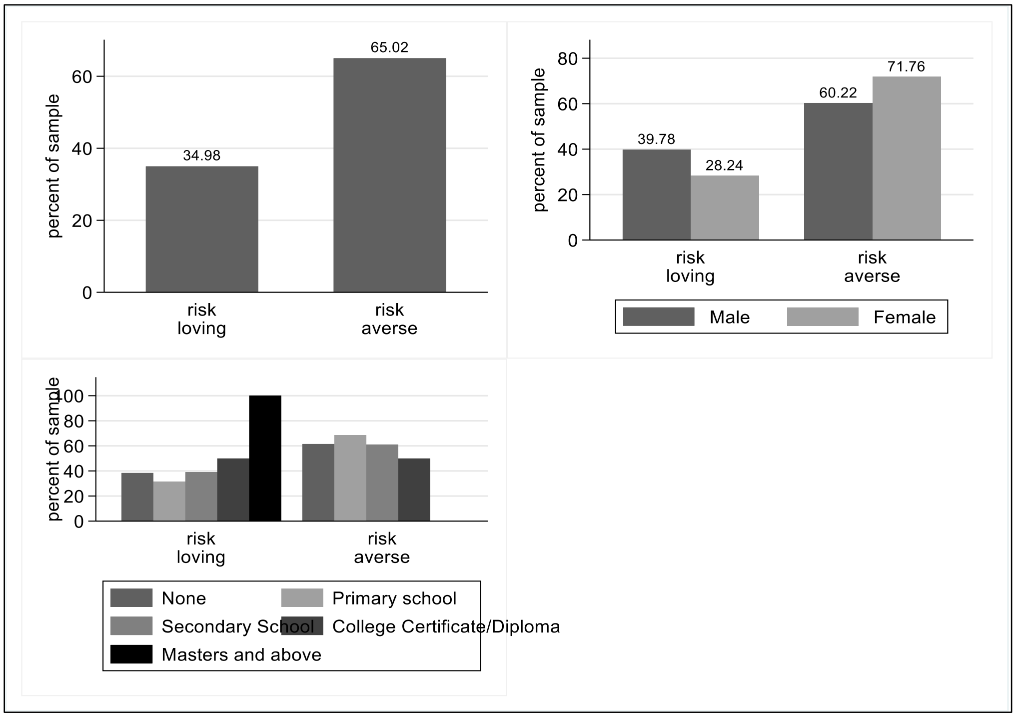
Figures 1 and 2 (following) show the distributions of risk and time preferences among farmers in the full sample and by gender as well as education. The majority (65%) of the participants were risk averse (Figure 1, top left). Females were more risk-averse than males, and farmers appeared more risk loving the higher the level of education (Figure 1, top right and bottom).

Table 4. Summary Statistics of Key Variables Used in the Regressions

Variable	Mean	Standard deviation	Min	Max
Risk averse (yes=1)	0.65	0.48	0.00	1.00
Average risk parameter	0.65	0.34	0	0.98
Impatient (yes=1)	0.52	0.50	0.00	1.00
Average future equivalent	23.45	6.96	10	29
Age	44.26	14.98	18.00	89.00
Female participant (yes =1)	0.41	0.49	0.00	1.00
Education	2.38	0.65	1.00	6.00
Years in village	25.18	17.39	1.00	84.00
Household size	7.67	3.66	0.00	26.00
Risk game first	0.51	0.50	0.00	1.00
Insurance/subsidy game first	0.50	0.50	0.00	1.00
Agric. income level	2.90	1.51	0.00	4.00
Non-agric. income level	1.59	1.74	0.00	4.00
Received CA extension (yes =1)	0.62	0.49	0.00	1.00
Pre-exp. CA knowledge (yes=1)	0.91	0.29	0.00	1.00
CA reduces production risk (yes =1)	0.52	0.50	0.00	1.00
Asset index	0.00	1.80	-3.84	3.35

Notes: N=323; about 55% and 45% of the sample played insurance and subsidy games, respectively.

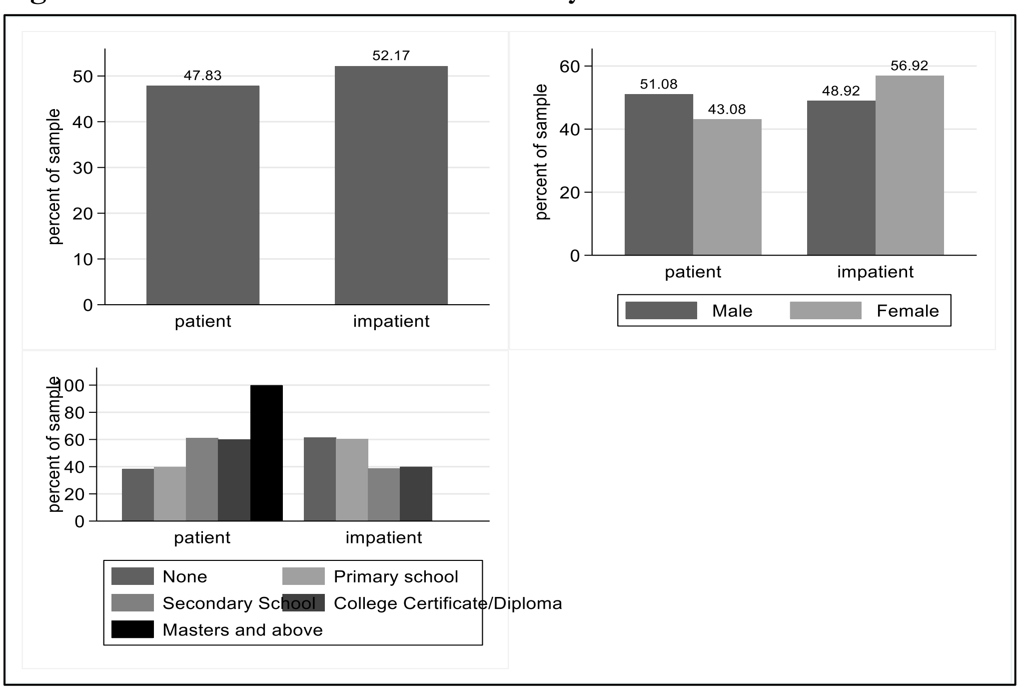
Figure 1. Risk Preference Distributions by Gender and Education



Source: Authors.

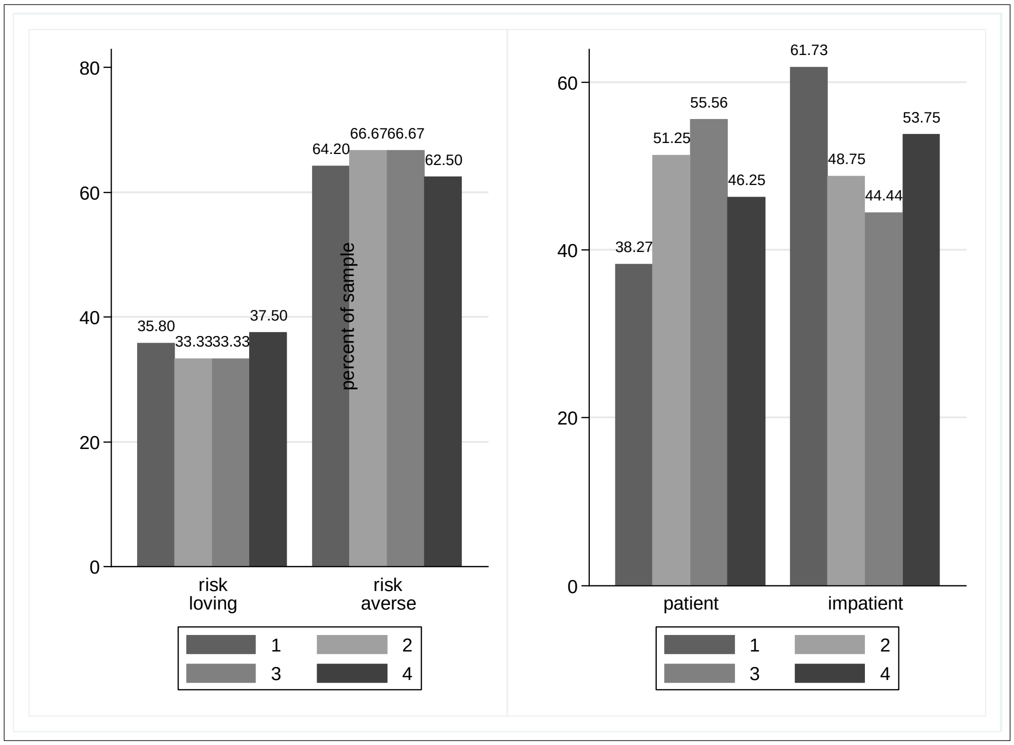
Slightly more than half of the farmers were impatient, and females were more impatient than males (Figure 2). Impatience appeared to wane with increasing education levels.

Figure 2. Time Preference Distributions by Gender and Education



Source: Authors.

Figure 3. Risk and Time Preference Distributions by Asset Quartiles



Source: Authors.
Notes: 1, 2, 3, and 4 show increasing asset quartiles computed using principle components analysis.

Farmers in the wealthiest quartile are slightly less risk averse than their poorer counterparts (Figure 3). This is consistent with the common finding that wealth reduces risk aversion; see for example Binswanger (1980) and Liu (2013). However, the differences between asset quartiles in the proportion of risk averse individuals are small, and we do not find this proportion to be monotonically decreasing as one moves from poorer to richer asset quartiles. We also find that the poorest quartile is the most impatient (Figure 3).

5.3 What Drives Risk and Time Preferences among Farmers?

Since the majority of participants in our games were risk averse and impatient, we assessed and report results on factors influencing risk and time preferences in Table 5 below. Being impatient was positively and significantly correlated with risk aversion for participants in our experiments. High non-agriculture income and being risk-averse were positively and significantly correlated with impatience, while education and wealth (proxied by asset index) were negatively correlated with impatience. These results are robust whether preferences are measured as continuous (columns 2 and 4) or dummy variables (columns 1 and 3).

5.4 CA Adoption Metrics in Experiments

Despite the payoffs of CA dominating conventional agriculture in all our experiments, not all farmers selected CA. In the base experiments, 15% of the farmers still chose conventional agriculture over CA. This may suggest that there are other factors that explain farmers' choice of farming practices beyond pecuniary benefits.

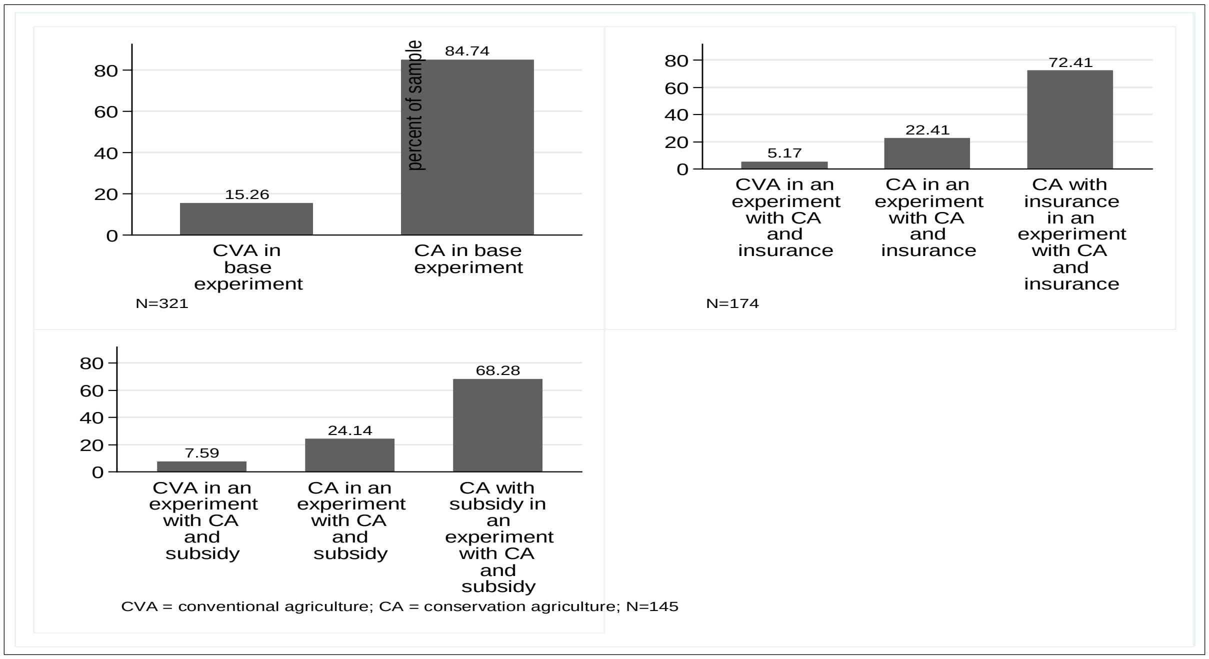
Table 5. Determinants of Risk and Time Preferences

	(1) Risk averse (yes)	(2) Risk parameter (theta)	(3) Impatient (yes)	(4) Future equivalents
Risk averse (yes)	-	-	0.283***	-
	-	-	(4.523)	-
Risk parameter (theta)	-	-	-	7.960***
	-	-	-	(4.054)
Impatient (yes)	0.261***		-	-
	(4.828)		-	-
Future equivalents	-	0.021***	-	-
	-	(7.812)	-	-
Age (years)	-0.002	-0.001	0.002	0.016
	(-0.708)	(-0.859)	(0.670)	(0.456)
Female (yes)	0.091	0.041	0.025	-0.552
	(1.012)	(0.710)	(0.339)	(-0.442)
Education	-0.041	-0.014	-0.112**	-1.139
	(-0.902)	(-0.330)	(-2.040)	(-1.284)
Household size	-0.001	0.002	0.007	-0.031
	(-0.099)	(0.461)	(0.726)	(-0.498)
Risk game first (yes)	0.090	0.034	-0.074	-0.401
	(0.834)	(0.371)	(-0.625)	(-0.319)
Ag. Income level	0.021	0.011	0.001	-0.133
	(1.429)	(0.976)	(0.033)	(-0.595)
Non-ag. Income level	0.008	-0.006	0.008	0.166
	(0.319)	(-0.346)	(0.384)	(0.483)
Asset index	-0.004	0.000	-0.030**	-0.130
	(-0.193)	(0.030)	(-1.974)	(-0.756)
Observations	315	315	315	315
Pseudo (adjusted) R-squared	0.09	(0.18)	0.09	(0.18)

Notes: T-statistics in parenthesis. Columns 1 and 3 were estimated using Probit, and columns 2 and 4 using OLS; the analysis clustered standard errors at village level; *** p<0.01, ** p<0.05, * p<0.1.

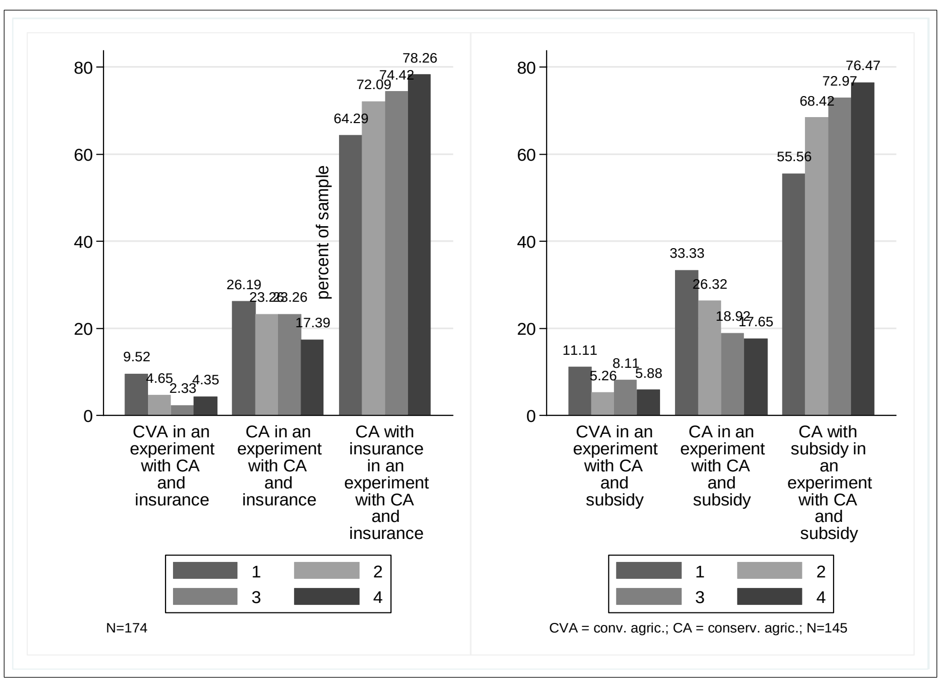
Introducing CA with insurance or CA with a green subsidy as third choices in two separate follow-on games altered farmers' adoption choices in many ways. Overall, with an insurance option, CA uptake increased by 10 percentage points to slightly over 94% (Figure 4). It is noted though that slightly under a quarter of the 94% who chose CA did not opt for insurance. With the subsidy option, CA uptake increased by about 8 percentage points (from 84.7% in the base game to 92.4% in the CA plus subsidy). The choice of either CA with insurance or CA with subsidy increased with asset quartiles (Figure 5), indicating the importance of wealth in adoption decisions.

Figure 4. Adoption of Conservation Agriculture versus Conventional Agriculture in Base Games and in Games with Insurance and Green Subsidies



Source: Authors.

Figure 5. Adoption of Conservation Agriculture versus Conventional Agriculture in Base Games and in Games with Insurance and Green Subsidies by Asset Quartiles



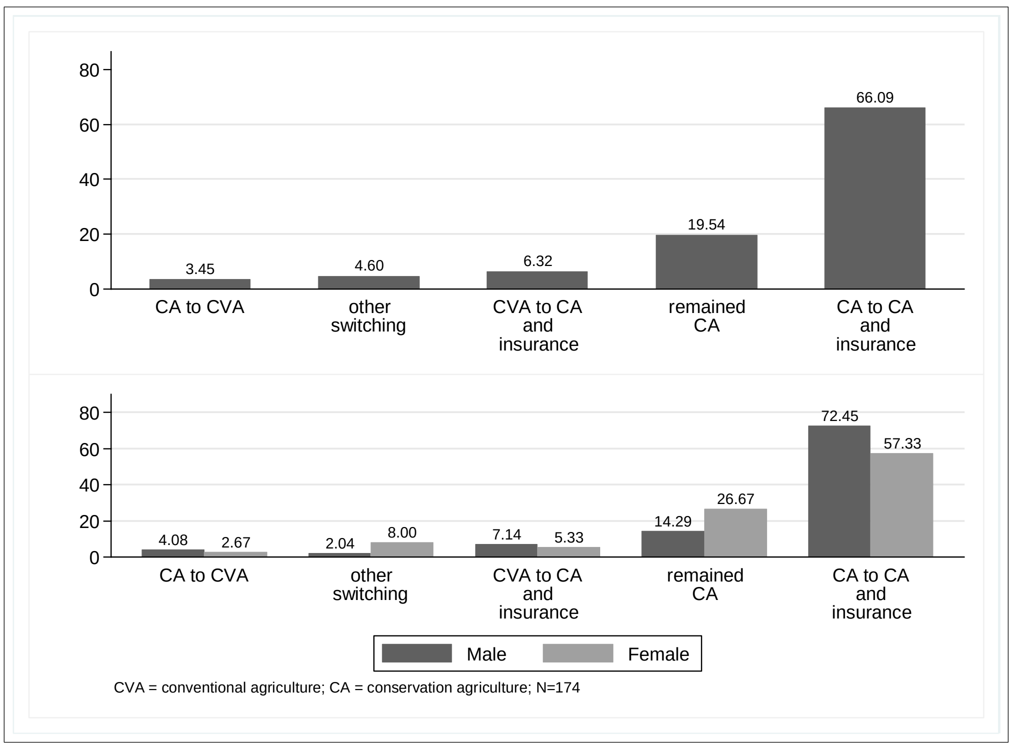
Source: Authors.

5.5 Adoption Switching Transitions

This section provides a detailed assessment of how much farmers switched or changed their farming choices between the base games and those that included insurance or green subsidies. Recall that all participants played the base games and nearly half played each of the insurance and subsidy games. About 66% of the participants switched from CA in the base game to CA with insurance in the insurance games, while 6% switched from conventional to CA with insurance (Figure 6). One-fifth did not switch away from CA only, that is, they chose CA in both base and insurance games, and 3% switched back from CA to conventional agriculture (Figure 6). A larger proportion of female participants chose CA in both base and insurance games than did males but more males switched from CA to CA with insurance in the insurance games (Figure 6).

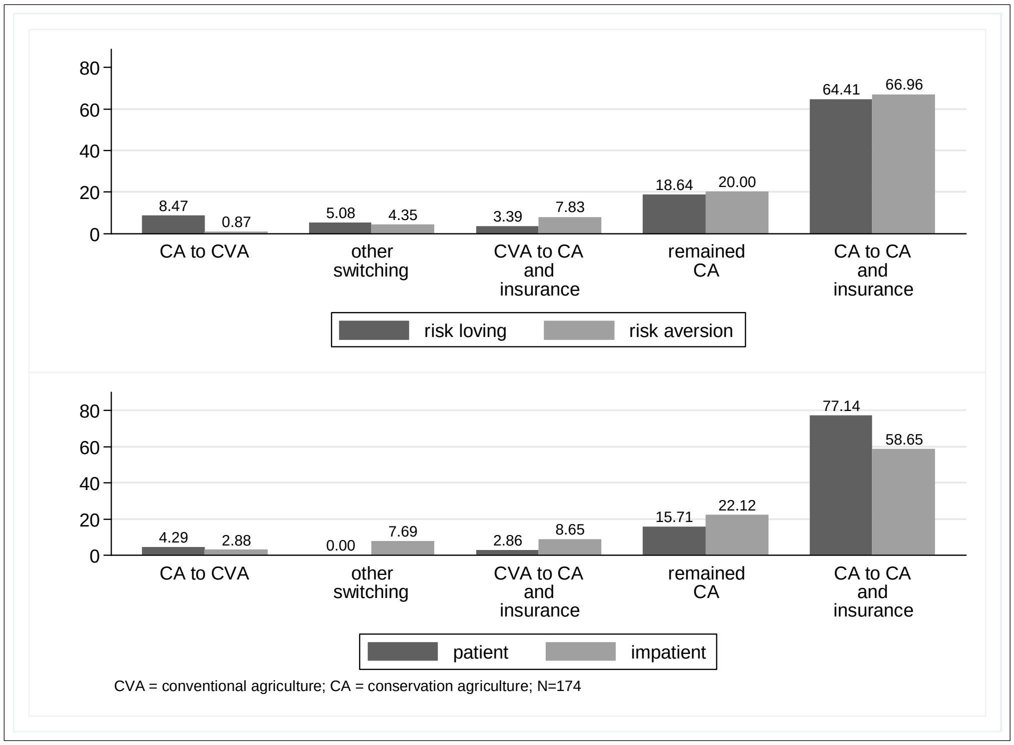
Except for the switch from CA to CA with insurance which was higher among patient participants, the adoption transitions between base and insurance games remained largely unchanged when segregated by risk aversion and impatience (Figure 7).

Figure 6. Adoption Switching between Base Games and Games with Insurance (Top Panel), and by Gender (Lower Panel)



Source: Authors.

Figure 7. Adoption Switching between Base Games and Games with Insurance by Risk (Top Panel) and Time Preferences (Lower Panel)

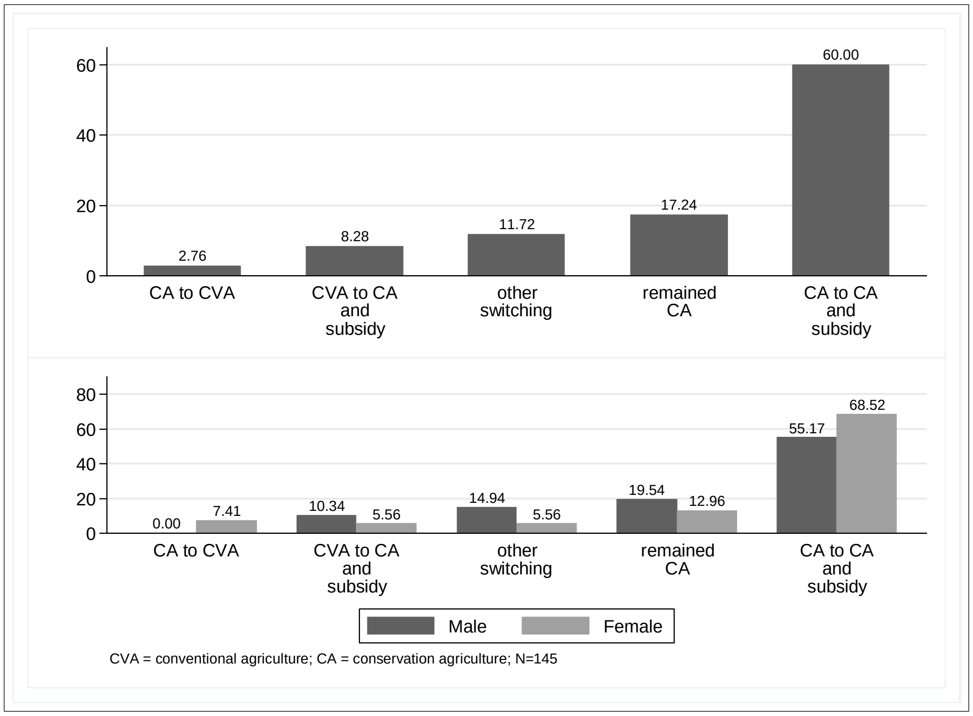


Source: Authors.

We found similar results for adoption switching between base and subsidy games. Overall, 60% and 8% of the participants in the subsidy games switched from CA to CA with subsidy and conventional to CA with subsidy, respectively (Figure 8 below). About 17% of participants chose CA in both base and subsidy games and 3% switched back from CA to conventional agriculture. Figure 8 also shows that a larger proportion of females switched from CA to CA with subsidy between base and subsidy games and the majority of those who made this switch were risk averse and impatient (Figure 9 below).

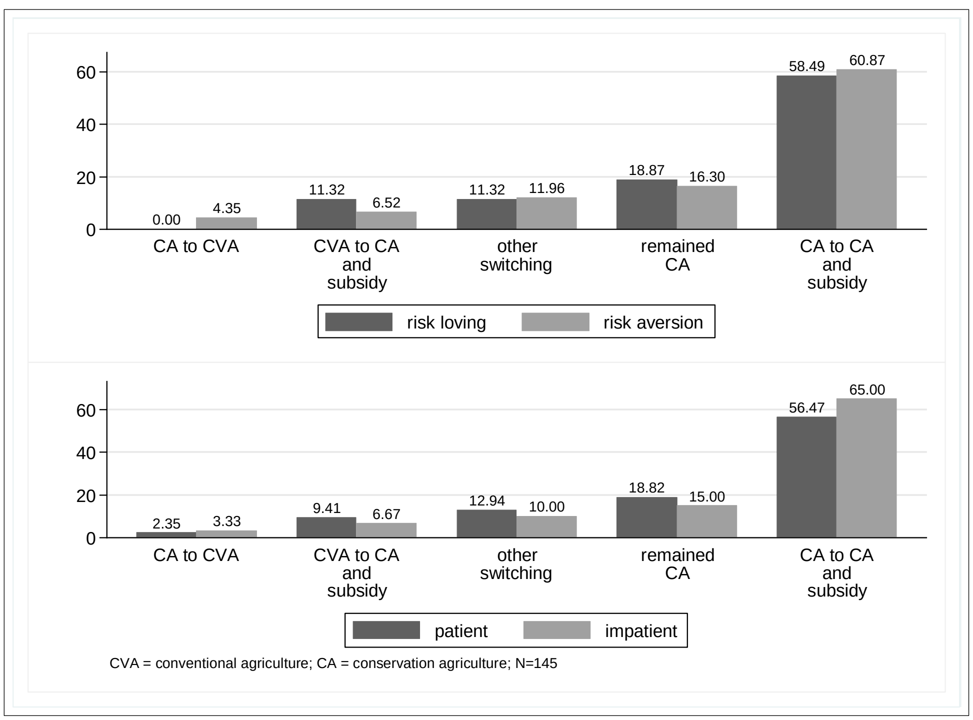
Figures 6 – 9 make apparent that the majority of the adoption switching occurred from CA to CA with insurance and from CA to CA with subsidy between base and subsequent games. These patterns are fairly similar when the results are disaggregated by risk and time preferences or by gender of the participant. However, there are some slight differences in the percentages of participants in each switching category between risk loving/averse and patient/impatient participants (Figures 7 and 9), which may indicate that time and risk preferences influence adoption switching.

Figure 8. Adoption Switching between Base Games and Games with Subsidy (Top Panel), and by Gender (Lower Panel)



Source: Authors.

Figure 9. Adoption Switching between Base Games and Games with Subsidy by Risk (Top Panel) and Time Preferences (Lower Panel)



Source: Authors.

5.6 Risk Aversion, Impatience, and CA Adoption

This section presents results on the role of risk aversion and impatience in the adoption of CSAs such as CA in base games and the adoption of CA in 'real life' during the 2017/2018 season (based on farmer recall). We complement these results and assess the role of risk and time preferences in adoption switching between base games and insurance and subsidy games.

5.6.1 Risk Aversion, Impatience and CSA Adoption in Experiments and Real Life

Because farmers might behave differently in experiments than they would in real life, we assessed whether risk aversion and impatience were correlated to farmers' adoption of CA in the games and in real life during the 2017/2018 farming season. After controlling for pre-experiment knowledge of CA, farmer subjective risk perceptions of CA, household characteristics, order effects and other factors that may influence adoption, we find that risk aversion and impatience are important drives of CA adoption. In our base games, risk aversion and impatience significantly reduced the probability of adopting CA by 7 and 10 percentage points, respectively (column 1, Table 6).

While being impatient was negatively correlated to adoption in the experiments, it was positively correlated to adoption in real life (based on farmer recall data for the previous season). (This last result runs counter to *a priori* expectations and we will return to it in the discussion section). We also found that perceiving CA to reduce production risk and access to CA extension significantly increased the likelihood of adoption in real life by 14 and 38 percentage points (column 2, Table 6). The negative correlations between risk and time preferences are robust even after controlling for actual CA use and even with and without controlling for access to CA extension, and farmers' subjective assessments of the riskiness of CA in columns 3 and 4.

5.6.2 Does Providing Insurance and Green Subsidies Increase Adoption?

While the preceding graphical analysis attempts to show how CSA adoption changed between base games and games with insurance and subsidies, they do not specifically show the effects of insurance and subsidies on adoption. We report these results here. We restricted our analysis to subsamples that chose CA in the base games and/or CA, and/or CA with insurance or subsidy in the subsequent games.

Adoption in this analysis is therefore defined as choosing CA in the base games, and/or CA, and/or CA with insurance/subsidy in the other game. We defined two policy variables to capture the influence of insurance and subsidies on adoption. Whether insurance/subsidy is offered is a dummy = 1 if insurance /subsidy was offered in that session and zero otherwise. These variables were 1 for all follow-on insurance or subsidy games and zero for the base games. Again, because the games were played in two stages, we used Random Effects probit and report the main results in column 4 in Tables 7 and 8 for insurance and green subsidies, respectively.

Table 6. The Role of Risk and Time Preferences in the Adoption of Climate-Smart Agriculture in the Experiments and in Real Life for the 2017/2018 Farming Season

	(1) CA adoption in games	(2) Partial CA use in 2017/2018 season	(3) CA adoption in games	(4) CA adoption in games
Risk averse (yes)	-0.074*	-0.107*	-0.056	-0.077*
	(-1.712)	(-1.678)	(-1.445)	(-1.717)
Impatient (yes)	-0.095**	0.130***	-0.094**	-0.089**
	(-2.289)	(2.871)	(-2.114)	(-2.179)
Used CA in 2017/2018 season	-	-	-	-0.052
	-	-	-	(-1.185)
Age (years)	-0.001	0.001	-0.001	-0.001
	(-0.903)	(0.750)	(-0.543)	(-0.841)
Female (yes)	0.058	0.051	0.064	0.063
	(1.018)	(1.018)	(1.097)	(1.097)
Education	-0.017	-0.022	-0.024	-0.018
	(-0.630)	(-0.611)	(-1.050)	(-0.690)
Household size	-0.001	-0.001	-0.001	-0.001
	(-1.111)	(-0.386)	(-1.341)	(-1.069)
Risk game first (yes)	-0.002	0.010	-0.002	-0.002
	(-0.331)	(1.618)	(-0.359)	(-0.277)
Ag. Income level	-0.102**	-	-0.086**	-0.096**
	(-2.478)	-	(-2.342)	(-2.307)
Non-ag. Income level	0.015	0.007	0.013	0.015
	(1.201)	(0.444)	(0.995)	(1.160)
Asset index	0.001	0.004	0.000	0.001
	(0.071)	(0.365)	(0.009)	(0.110)
Received CA extension (yes)	-0.113***	0.383***	-	-0.095***
	(-3.861)	(4.867)	-	(-3.213)
Pre-exp. CA knowledge (yes)	0.116	-	-	0.124
	(1.236)	-	-	(1.311)
CA is less risky (yes)	0.083**	0.136*	0.052	0.089**
	(2.409)	(1.932)	(1.570)	(2.331)
Asset index	-0.015	0.007	-0.012	-0.015
	(-0.966)	(0.551)	(-0.786)	(-0.911)
Village fixed effects	yes	yes	yes	yes
Observations	309	316	316	309

Notes: The analysis used the Probit model and clustered standard errors at session level and at village level for column 2; *** p<0.01, ** p<0.05, * p<0.1.

Providing insurance and subsidies significantly increased the probability of adopting CA by six and 12 percentage points, respectively (column 4 in Tables 7 and 8). These results are robust across alternative estimators in columns 1, 2, 3, and 5. After controlling for insurance, which presumably covers risk, impatience is the only preference parameter that remains as a significant barrier to adoption (Table 7). However, providing green subsidies, which cover both risk and time preferences, significantly reduced the effects of risk and impatience on adoption (Table 8).

Table 7. Effects of Providing Insurance on Adoption of Climate-Smart Agriculture Both in the Base and Insurance Games

	(1)	(2)	(3)	(4)	(5)
	POLS	Random effects	Pooled Probit	Random effects Probit	Random effects Probit (no preferences)
Insurance offered (yes)	0.065*	0.065*	0.063**	0.063**	0.064**
	(0.033)	(0.033)	(0.027)	(0.027)	(0.027)
Risk averse (yes)	-0.008	-0.008	-0.005	-0.004	-
	(0.024)	(0.024)	(0.021)	(0.021)	-
Impatient (yes)	-0.060*	-0.060**	-0.051**	-0.052**	-
	(0.030)	(0.030)	(0.025)	(0.026)	-
Age (years)	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Female =1	-0.022	-0.022	-0.009	-0.009	-0.014
	(0.047)	(0.047)	(0.038)	(0.038)	(0.037)
Education level (years)	0.009	0.009	0.023	0.023	0.026
	(0.013)	(0.013)	(0.015)	(0.015)	(0.017)
Years lived in village	0.000	0.000	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size (No.)	-0.004	-0.004	-0.003	-0.003	-0.003
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Insurance/subsidy game first	-0.034	-0.034	-0.030	-0.030	-0.014
	(0.034)	(0.034)	(0.030)	(0.030)	(0.028)
Agricultural Income level	-0.004	-0.004	-0.003	-0.002	-0.002
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Non-agricultural Income level	0.020	0.020	0.019**	0.020**	0.019**
	(0.012)	(0.012)	(0.010)	(0.009)	(0.009)
Received CA extension (yes)	-0.052	-0.052*	-0.043**	-0.045**	-0.048***
	(0.030)	(0.030)	(0.020)	(0.020)	(0.018)
	1	2	3	4	5

	POLS	Random effects	Pooled Probit	Random effects Probit	Random effects Probit (no preferences)
Pre-exp. CA knowledge (yes)	0.073	0.073	0.065	0.061	0.077
	(0.063)	(0.063)	(0.064)	(0.065)	(0.068)
CA is risk reducing (yes)	0.022	0.022	0.027	0.028	0.033
	(0.031)	(0.031)	(0.033)	(0.033)	(0.032)
Asset index	-0.012	-0.012*	-0.011**	-0.012**	-0.011**
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)
Village fixed effects	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	340	340	340	340	340

Notes: Standard errors in parentheses are clustered at session level; *** p<0.01, ** p<0.05, * p<0.1; About 178 people played the insurance games in the second stage after playing the base games, reducing to 170 after accounting for missing values or 340 over the two rounds of the experiments. The analysis is restricted to this subsample.

Table 8. Effects of Providing Green Subsidies on Adoption of Climate-Smart Agriculture Both in the Base and Subsidy Games

	(1) POLS	(2) Random effects	(3) Pooled Probit	(4) Random effects Probit	(5) Random effects Probit (no preferences)
Subsidy offered (yes)	0.117**	0.117***	0.123***	0.121***	0.119***
	(0.036)	(0.036)	(0.030)	(0.031)	(0.029)
Risk averse (yes)	-0.098	-0.098	-0.087	-0.081	-
	(0.075)	(0.075)	(0.060)	(0.061)	-
Impatient (yes)	-0.024	-0.024	-0.039	-0.034	-
	(0.040)	(0.040)	(0.055)	(0.057)	-
Age (years)	-0.003	-0.003	-0.003*	-0.003	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female =1	0.082	0.082	0.062	0.062	0.059
	(0.067)	(0.067)	(0.058)	(0.061)	(0.069)
Education level (years)	-0.017	-0.017	-0.014	-0.012	-0.017
	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Years lived in village	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household size (No.)	-0.011	-0.011	-0.010	-0.009	-0.008
	(0.013)	(0.013)	(0.010)	(0.011)	(0.011)
Insurance/subsidy game first	-0.200***	-0.200***	-0.196***	-0.189***	-0.161***
	(0.049)	(0.049)	(0.045)	(0.046)	(0.020)
Agricultural Income level	0.008	0.008	0.002	0.004	-0.000
	(0.016)	(0.016)	(0.017)	(0.016)	(0.015)
Non-agricultural Income level	-0.022*	-0.022**	-0.019**	-0.020**	-0.023***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)
Received CA extension (yes)	-0.042	-0.042	-0.055	-0.059	-0.035
	(0.042)	(0.042)	(0.042)	(0.042)	(0.022)

	(1) POLS	(2) Random effects	(3) Pooled Probit	(4) Random effects Probit	(5) Random effects Probit (no preferences)
Pre-exp. CA knowledge (yes)	0.090	0.090	0.045	0.045	0.112
	(0.149)	(0.149)	(0.114)	(0.122)	(0.128)
CA is risk reducing (yes)	0.077	0.077	0.065	0.066	0.055
	(0.052)	(0.052)	(0.046)	(0.047)	(0.039)
Asset index	0.017	0.017	0.018	0.016	0.020
	(0.017)	(0.017)	(0.013)	(0.014)	(0.016)
Village fixed effects	yes	yes	yes	yes	yes
Observations	274	274	274	274	274

Notes: Standard errors in parentheses are clustered at session level; *** p<0.01, ** p<0.05, * p<0.1; About 145 people played the subsidy games in the second stage after playing the base games, reducing to 137 after accounting for missing values or 274 over the two rounds of the experiments. The analysis is restricted to this subsample.

5.6.3 The Role of Risk and Time Preferences in Adoption Switching between the Base and Insurance Games

We assessed whether risk and time preferences influenced adoption switching between games. While the switch from conventional agriculture (CVA) to CA would be most interesting, we are unable to report these because less than 10% of the participants switched from CVA to CA between base and insurance/subsidy games (Figures 6 and 8). We therefore restrict the analysis in this section to switching between CA to CA with insurance or to CA with subsidy or CVA. In each case, participants who chose CA in the base games would either choose CA or CA with insurance or subsidy, or CVA in the follow-on game. Choosing CA in both stages was the base choice in our Multinomial logit regression models used to assess adoption switching. We report the results for insurance games in Table 9 and subsidy games in Table 10. Column 1 shows results for the switch from CA to CVA while column 3 shows results for the switch from CA to CA with insurance or CA with subsidy.

Relative to choosing CA in both games, being risk averse (impatient) increased (reduced) the probability of switching from CA in the base games to CA with insurance (Table 9). Again, this is in line with *a priori* expectations since insurance is risk reducing, but might not directly influence impatience.

Table 9. The Role of Risk and Time Preferences in CSA Adoption Switching between Base and Insurance Games

	(1)	(2)	(3)	(4)
	Switch from CA in first game to CVA in second game	SE	Switch from CA in first game to CA and insurance in second game	SE
Risk averse (yes)	-0.027	0.102	0.200*	0.105
Impatient (yes)	0.145	0.090	-0.196**	0.081
Age (years)	-0.003*	0.002	0.007***	0.002
Female (yes)	0.105	0.069	-0.117	0.074
Education level (years)	-0.005	0.018	0.122***	0.038
Years in village	0.001	0.001	0.004	0.003
Household size (No.)	-0.003	0.010	-0.008	0.011
Insurance/subsidy game first	0.130	0.097	-0.065	0.098
Ag. income level	-0.006	0.011	-0.005	0.011
Non-ag. income level	0.033*	0.019	0.036**	0.017
Received CA extension (yes)	0.047	0.076	0.033	0.072
CA is less risky (yes)	0.002	0.045	-0.054	0.037
Used CA last season (yes)	-0.032	0.050	0.064	0.055
Asset index	0.003	0.018	0.030	0.019
Village fixed effects	*yes*	*yes*	*yes*	*yes*
Observations	154		154	

Notes: Standard errors (SE) are clustered at session level; the analysis using multinomial logit was restricted to a subsample of participants who choose CA in the base games and played the insurance games in the second stage (this explains the smaller sample size); the base category is choosing CA in both base and insurance games; *** p<0.01, ** p<0.05, * p<0.1

Results for adoption switching between base and subsidy games are less intuitive. On preferences, they suggest being impatient reduces the likelihood of switching from CA to CVA relative to choosing CA in both stages. We will return to this finding in the discussions.

Table 10. The Role of Risk and Time Preferences in CSA Adoption Switching Between Base and Subsidy Games

	(1)	(2)	(3)	(4)
	Switch from CA in first game to CVA in second game	SE	Switch from CA in first game to CA and subsidy in second game	SE
Risk averse (yes)	-0.014	0.165	-0.127	0.165
Impatient (yes)	-0.184**	0.088	0.034	0.088
Age (years)	0.004	0.004	-0.004	0.004
Female (yes)	-0.037	0.049	-0.089*	0.049
Education level (years)	-0.029	0.093	0.029	0.093
Years in village	-0.001	0.005	0.001	0.005
Household size (No.)	-0.029***	0.006	0.029***	0.006
Insurance/subsidy game first	0.050	0.077	-0.192**	0.076
Ag. income level	-0.018	0.024	0.018	0.024
Non-ag. income level	-0.047***	0.016	0.047***	0.016
Received CA extension (yes)	-0.118***	0.040	0.118***	0.040
CA is less risky (yes)	0.024	0.067	-0.024	0.067
Used CA last season (yes)	0.115	0.109	-0.230**	0.109
Asset index	-0.006	0.020	0.006	0.020
Village fixed effects	*yes*	*yes*	*yes*	*yes*
Observations	113		113	

Notes: Standard errors (SE) are clustered at session level; the analysis using multinomial logit was restricted to a subsample of participants who choose CA in the base games and played the subsidy games in the second stage (this explains the smaller sample size); the base category is choosing CA in both base and follow up game; *** p<0.01, ** p<0.05, * p<0.1.

6. DISCUSSION

6.1 Are Farmers Risk Averse and Impatient

The main results in this paper suggest that the majority of the participants in our experiments were risk averse and impatient. As in other studies, (Brick, Visser, and Burns 2012; Liu 2013; Sutter et al. 2013; Alem, Eggert, and Ruhinduka 2015), we also found qualitative evidence that female participants were more risk-averse and impatient than their male counterparts. For our experiments, this result is not statistically significant at conventional levels after controlling for other confounders. Females may be more risk averse in rural Africa because they are responsible for fending for their families and, therefore, might be more reluctant than males to venture into risky activities. Further, the immediate need to provide food for their families might lead females to highly discount later returns, even if these returns are larger.

That risk aversion and impatience reduced with the level of education and assets among participants in our experiments (Figures 1-3) is indicative of the importance of education and wealth in determining risk and time preferences. Wealthy individuals, as well as the educated, might be better able to insulate themselves from risk. Liu (2013) found similar results among cotton farmers in China. For our sample, females had lower levels of education and assets than did their male counterparts. This could also partially explain their aversion to risk and their impatience.

6.2 Risk Aversion, Impatience, and CA Adoption: A Recapitulation

Our findings suggesting that both risk aversion and impatience were negatively correlated with CA adoption in the experiments and in real life (for risk aversion) are indicative of the importance of these behavioral traits in technology adoption. The unexpected positive impact of impatience on CSA adoption in real life could be related to the fact that we are using preference measures computed at $t+1$ to explain past adoption behavior. Preferences are inherently time invariant. Impatience had a larger negative effect compared to risk aversion on the probability of adopting CSA. Although economic returns such as profit (and yield) are important in technology adoption (Michler et al. 2018), the findings in this paper suggest that adoption decisions are also influenced by non-pecuniary factors such as risk and time preferences. As suggested in Holden and Quiggin (2017), we found that subjective risk perceptions also matter for technology adoption. In particular, farmers' subjective perceptions of the riskiness of CA were an important determinant of CA adoption both in our experiments and in real life (during the 2017/2018 season). Taken together, these results imply that the omission of risk and time preference considerations in the promotion of CSAs could partly explain low adoption and the omission of risk and time preference in many adoption studies could bias results.

Risk aversion and impatience are also important factors that interact with other levers to nudge adoption in very complex ways. For example, even after introducing CA with insurance and CA with a green subsidy as third choices in two separate follow-on games, the absolute adoption of CA only increased by 10 and 8 percentage points, respectively, from adoption levels in the base games. In terms of probable adoption, introducing insurance and subsidies increased the likelihood of adoption by 6 and 12 percentage points respectively. These findings are in spite of the fact that the CA with insurance and CA with subsidy options generally had higher payoffs than CA without subsidy and insurance, and conventional agriculture in the follow-on games. Subsidies, which presumably address both risk and time preference, had large effects on adoption when compared to insurance, which is only a risk mitigation strategy.

Risk aversion and impatience significantly increased and reduced, respectively, the likelihood of switching from CA to CA with insurance. This is in line with a priori expectations because insurance is mainly a risk mitigation strategy. Thus, while introducing insurance and subsidies may nudge the probability of adoption by some 6 – 12 percentage points (as in this paper), they are not a panacea. Larger gains in adoption could come from having access to extension specific to CA and perceiving CA as risk reducing, which in our paper increased the likelihood of adopting CA in real life by 38 and 14 percentage points, respectively. Brick and Visser (2015) come to a similar conclusion based on experiments where they found that some South Africa farmers still opted for traditional agriculture despite providing insurance and credit to facilitate investments in improved seed varieties.

A number of factors could explain these findings. First, risk and time preferences, and other factors such as access to extension and farmers' subjective perceptions of the riskiness of the CA, condition adoption in some complex ways. Second, even if uninsured risk is an important constraint to farmer investments (Karlan et al. 2014), rainfall insurance cover as presented in this paper (and in real life) is not 100% and in most cases does not cover residual production risk and basis risk (Brick and Visser 2015). Lastly, farmers may be reluctant to increase adoption despite insurance and subsidies because they do not trust that they will receive the payouts, have had bad experiences with subsidies (e.g., FISP) in the past, or because they do not understand the insurance and subsidy products presented to them. In fact, only 8% of those who enrolled in the e-FISP weather-indexed insurance in our sample said they received payouts following the 2017/2018 season. See Cole et al. (2013) for discussions on the importance of trust and understanding in insurance uptake.

The content of CA messages matter: bundling CA with green subsidies was an artifact of our experiments that is yet to be implemented in the study sites and therefore, unlikely to be part of the current CA extension messages. This could explain the findings that access to CA extension is positively associated with CA adoption in real life but negatively correlated to CA adoption in our experiments. Participants may not have related the information received about CA in real life to CA adoption choices in the experiments. The results might have been different if the experiments included learning effects. Our findings that risk aversion was negatively correlated with CA adoption in real life gives credence to the experimental results and to the experimental design used in this paper. We can also conjecture from this result that the participants in our experiments revealed their true behavior.

The external validity and generalizability of findings from experimental studies like ours is a major concern in economics—for this, we urge caution. Our experiments were conducted only in parts of seven villages from two districts where CA had been promoted. As such, these results neither represent the entire study districts nor Zambia at large. It is encouraging, however, that the main results on the role of risk and time preferences are qualitatively similar for adoption in our experiments and adoption in real life.

That not all farmers chose the dominant CA with insurance or CA with subsidy options in our games suggests that the choices participants made in the experiments mirrored those in real life. This is because farmers would have automatically chosen the options with higher returns had the pecuniary benefits been the only motivation and CA adoption in real life would have been very high. To some extent, these findings could partly explain why, despite several years of promoting CA and framing it as 'a silver bullet to low productivity', its uptake remains low. In fact, framing the adoption games to represent the start of a farming season when farmers had to choose farming options before they knew how seasonal rainfall would be in the upcoming season mirrors real life experiences. Because farmers only came to know whether the rainfall was good or bad after they had chosen the farming option served as much as a check on their behavior in subsequent experiments as in real life. Moreover, nearly all participants (99%) said that participating in the adoption experiments helped them think about how they make farming choices in real life.

As a further check on external validity, we computed the correlations between whether a participant used CA in the 2017/2018 season (in real life) and whether they chose CA in base, insurance or subsidy games. CA use in real life was only significantly correlated to the choice of CA in the subsidy games, suggesting that revealed behavior in our experiments mirrored real-life choices. This again validates our experimental designs.

7. CONCLUSION AND POLICY IMPLICATIONS

There is consensus on the urgent need to sustainably increase agricultural production to feed a rapidly growing world population, meet changing dietary preferences, and to reduce rural poverty. This is most profound in Sub-Saharan Africa where the population is projected to reach 2.2 billion by 2050. Climate-smart agriculture is considered part of the solution. However, the uptake of climate-smart agriculture practices such as conservation agriculture, although rising, remains (s)low and there are gaps in understanding why.

This paper assessed the role of risk and time preferences in the adoption of conservation agriculture among smallholder farmers in Zambia. Conservation agriculture is one of the most prevalent types of climate-smart agriculture practiced in Zambia. We conducted risk and time preferences games with 323 randomly selected farmers to elicit time and risk preference parameters and then used the elicited parameters to analyze their effects on adoption and adoption switching behavior in subsequent framed field experiment games. We introduced insurance and subsidies in the adoption games and tested whether these can significantly incentivize adoption. Participants in our adoption experiments chose between conventional and conservation agriculture at the start of a farming season. Returns to conventional and conservation agriculture were triggered by seasonal rainfall, which was only determined through a lottery (with a 25% chance of good rainfall) after participants had selected their preferred farming option. We incentivized all experiments with real monetary payoffs.

Overall, the majority of the participants in our experiments were risk averse and impatient. Risk aversion and impatience were negatively correlated with the likelihood of adopting conservation agriculture and preferences influenced adoption switching. In particular, risk aversion and impatience reduced the probability of adoption by 7 and 10 percentage points, respectively and increased and reduced the likelihood of switching from conservation agriculture in base games to conservation agriculture with insurance in follow-on games. Introducing insurance and green subsidies increased the level of adoption by 10 and 8 percentage points and the probability of adoption by approximately 6 – 12 percentage points.

We, thus, draw two main conclusions. While money matters in technology adoption as suggested in Michler et al. (2018), non-pecuniary factors such as risk and time preferences also matter and condition adoption in complex ways. These behavioral traits could partly explain the perceived low adoption of climate-smart agriculture practices such as conservation agriculture. We also conclude in line with Brick and Visser (2015) that while insurance and subsidies might have a role in addressing adoption problems, they are unlikely to be a panacea. Several factors including uninsured basis risk, trust and how well farmers understand insurance and subsidy incentives, negative past experiences with the products, knowledge of the technology, and subjective perceptions of its riskiness influence adoption choices. Access to extension and subjective risk perceptions were stronger determinants of adoption in real life.

Three implications for policy follow from our results. First, because subjective risk perceptions matter for adoption, there is need to retool both public and private extension services to better demonstrate and educate farmers on the risk-reducing effects of conservation agriculture. Second, if insurance and subsidies are to be used successfully to nudge adoption, efforts will be needed to better educate farmers on how the systems work and how they can benefit from them, and to overcome past implementation challenges and the potentially negative farmer perceptions. This is important to build trust in the incentive systems. Smallholder farmers in Zambia are increasingly aware of insurance since a weather-indexed insurance product is now mandatory in the electronic voucher-based Farmer Input Support Program (e-FISP), but unclear payout mechanisms might be engendering mistrust among farmers. The e-FISP has also encountered several implementation challenges that may also color farmer attitudes about it and their behavioral responses to green subsidies like those that are modeled here. Third, because subsidies, which presumably address both risk aversion and impatience, had larger effects on adoption than did insurance alone, innovative tools that address both factors— such as green subsidies and augmented agriculture/climate financing—are needed to increase uptake of climate-smart agricultural practices. Lastly, although e-FISP may be able to serve as a means to implement conservation agriculture with insurance and/or green subsidies at scale, there is a need to assess ex-ante, the effectiveness and efficiency of such interventions.

APPENDICES

Appendix Table A 1. Decision Sheet for Risk Game with a 25% Gamble

Participant ID______________ Experiment ______ Village ____________

	Option 1	✓		Option 2	✓
[1]	K1 for sure		OR	Choose a ball : K / K	
[2]	K2 for sure		OR	Choose a ball : K / K	
[3]	K3 for sure		OR	Choose a ball : K / K	
[4]	K4 for sure		OR	Choose a ball : K / K	
[5]	K5 for sure		OR	Choose a ball : K / K	
[6]	K6 for sure		OR	Choose a ball : K / K	
[7]	K7 for sure		OR	Choose a ball : K / K	
[8]	K8 for sure		OR	Choose a ball : K / K	
[9]	K9 for sure		OR	Choose a ball : K / K	
[10]	K10 for sure		OR	Choose a ball : K / K	
[11]	K11 for sure		OR	Choose a ball : K / K	
[12]	K12 for sure		OR	Choose a ball : K / K	
[13]	K13 for sure		OR	Choose a ball : K / K	
[14]	K14 for sure		OR	Choose a ball : K / K	
[15]	K15 for sure		OR	Choose a ball : K / K	
[16]	K16 for sure		OR	Choose a ball : K / K	
[17]	K17 for sure		OR	Choose a ball : K / K	
[18]	K18 for sure		OR	Choose a ball : K / K	
[19]	K19 for sure		OR	Choose a ball : K / K	
[20]	K20 for sure		OR	Choose a ball : K / K	

Appendix Table A 2. Decision Sheet for Time Preference Games

Participant ID______________ Experiment ______ Village ____________

	Option 1	✓		Option 2	✓
[1]	K10 today		OR	K10 in 2 weeks	
[2]	K10 today		OR	K11 in 2 weeks	
[3]	K10 today		OR	K12 in 2 weeks	
[4]	K10 today		OR	K13 in 2 weeks	
[5]	K10 today		OR	K14 in 2 weeks	
[6]	K10 today		OR	K15 in 2 weeks	
[7]	K10 today		OR	K16 in 2 weeks	
[8]	K10 today		OR	K17 in 2 weeks	
[9]	K10 today		OR	K18 in 2 weeks	
[10]	K10 today		OR	K19 in 2 weeks	
[11]	K10 today		OR	K20 in 2 weeks	
[12]	K10 today		OR	K21 in 2 weeks	
[13]	K10 today		OR	K22 in 2 weeks	
[14]	K10 today		OR	K23 in 2 weeks	
[15]	K10 today		OR	K24 in 2 weeks	
[16]	K10 today		OR	K25 in 2 weeks	
[17]	K10 today		OR	K26 in 2 weeks	
[18]	K10 today		OR	K27 in 2 weeks	
[19]	K10 today		OR	K28 in 2 weeks	
[20]	K10 today		OR	K29 in 2 weeks	

REFERENCES

Abdulai, A.N. 2016. Impact of Conservation Agriculture Technology on Household Welfare in Zambia. *Agricultural Economics* 47.6: 729-741.

Alem, Y., H. Eggert, and R. Ruhinduka. 2015. Improving Welfare through Climate-Friendly Agriculture: The Case of the System of Rice Intensification. *Environmental and Resource Economics* 62.2: 243-263.

Binswanger, H.P. 1980. Attitudes toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics* 62.3: 395-407.

Braimoh, A., A. Mwanakasale, A. Chapoto, R. Rubaiza, B. Chisanga, N. Mubanga, Samboko, P., Giertz, A., Obuya, G., 2018. Increasing Agricultural Resilience through Better Risk Management in Zambia. Washington, DC: World Bank. Available at http://documents.worldbank.org/curated/en/330211524725320524/Increasing-agricultural-resilience-through-better-risk-management-in-Zambia.

Brick, K. and M. Visser. 2015. Risk Preferences, Technology Adoption, and Insurance Uptake: A Framed Experiment. *Journal of Economic Behavior & Organization* 118: 383-396.

Brick, K., M. Visser, and J. Burns. 2012. Risk Aversion: Experimental Evidence from South African Fishing Communities. *American Journal of Agricultural Economics* 94.1: 133-152.

Canning, D., R. Sangeeta, and Y.S. Abdo. 2015. *Africa's Demographic Transition: Dividend or Disaster?* World Bank; and Agence Française de Développement. Washington, DC:World Bank.

CIAT, WorldBank. 2017. Climate-Smart Agriculture in Zambia. CSA Country Profiles for Africa Series. International Center for Tropical Agriculture (CIAT). Washington, DC: World Band, CIAT.

Cole, S., X. Giné, J. Tobacman, P. Topalova, R. Townsend, and J. Vickery. 2013. Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics* 5.1: 104-35.

Duflo, E., M. Kremer, and J. Robinson. 2008. How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya. *American Economic Review* 98.2: 482-88.

Duflo, E., M. Kremer, and J. Robinson. 2011. Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya. *American Economic Review* 101.6: 2350-90.

FAO. 2013. *Climate Smart Agriculture Source Book*. Rome: FAO.

Feder, G. 1980. Farm Size, Risk Aversion and the Adoption of New Technology under Uncertainty. *Oxford Economic Papers* 32.2: 263-283.

Giller, K.E., J.A. Andersson, M. Corbeels, J. Kirkegaard, D. Mortensen, O. Erenstein, and B. Vanlauwe. 2015. Beyond Conservation Agriculture. *Frontiers in Plant Science.* 6.37.

Grabowski, P., J.M. Kerr, S. Haggblade, and S. Kabwe. 2014. *Determinants of Adoption of Minimum Tillage by Cotton Farmers in Eastern Zambia*. IAPRI Working Paper No. 87. Lusaka, Zambia: Indaba Agricultural Policy Research Institute.

Holden, S.T. and J. Quiggin. 2017. Climate Risk and State-Contingent Technology Adoption: Shocks, Drought Tolerance, and Preferences. *European Review of Agricultural Economics*. 44.2: 285-308.

Holt, C.A. and S.K. Laury. 2002. Risk Aversion and Incentive Effects. *The American Economic Review*. 92.5: 1644-1655.

IPCC. 2014. Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In *Climate Change 2014*, ed. V.R. Barros, C.B. Field, D.J. Dokken, … and L.L. White. United Kingdom and New York: Cambridge University Press.

Jaleta, M., M. Kassie, K. Tesfaye, T. Teklewold, P.R. Jena, P. Marenya, and O. Erenstein. 2016. Resource Saving and Productivity Enhancing Impacts of Crop Management Innovation Packages in Ethiopia. *Agricultural Economics* 47.5: 513-522.

Jin, J., W. Wang, and X. Wang. 2016. Farmers' Risk Preferences and Agricultural Weather Index Insurance Uptake in Rural China. *International Journal of Disaster Risk Science* 7.4: 366-373.

Jones, X.H. and P. Franks. 2015. *Food vs Forests in Sub-Saharan Africa: A Challenge for the SDGs*. IIED Briefing Paper. London: IIED.

Just, R.E. and D. Zilberman. 1988. The Effects of Agricultural Development Policies on Income Distribution and Technological Change in Agriculture. *Journal of Development Economics*. 28.2: 193-216.

Kahneman, D. and A. Tversky. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica*. 47.2: 263-291.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. Agricultural Decisions after Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics* 129.2: 597-652.

Laurance, W.F., J. Sayer, and K.G. Cassman. 2014. Agricultural Expansion and Its Impacts on Tropical Nature. *Trends in Ecology and Evolution* 29.2: 107-116.

Laurance, W.F., S. Sloan, L. Weng. And J.A. Sayer. 2015. Estimating the Environmental Costs of Africa's Massive "Development Corridors". *Current Biology* 25: 1-7.

Lipper, L., P. Thornton, B.M. Campbell, T. Baedeker ... and E.R. Torquebiau. 2014. Climate-Smart Agriculture for Food Security. N*ature Climate Change* 4: 1068.

Liu, E.M. 2013. Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *The Review of Economics and Statistics* 95.4: 1386-1403.

Lobell, D.B., M.B. Burke, C. Tebaldi, M.D. Mastrandrea, W.P. Falcon, and R.L. Naylor. 2008. Prioritizing Climate Change Adaptation Needs for Food Security in 2030. *Science* 319.5863: 607-610.

Michler, J.D., E. Tjernström, S. Verkaart, and K. Mausch. 2018. Money Matters: The Role of Yields and Profits in Agricultural Technology Adoption. *American Journal of Agricultural Economics* (TSI). Pages 1-22.

Mupangwa, W., M. Mutenje, C. Thierfelder, M. Mwila, H. Malumo, A. Mujeyi, and P. Setimela. 2017. Productivity and Profitability of Manual and Mechanized Conservation Agriculture (CA) Systems in Eastern Zambia. *Renewable Agriculture and Food Systems* 1-15.

Ng'ombe, J.N., T.H. Kalinda, and G. Tembo. 2017. Does Adoption of Conservation Farming Practices Result in Increased Crop Revenue? Evidence from Zambia. *Agrekon 56*.2: 205-221.

Ngoma, H. 2018. Does Minimum Tillage Improve the Livelihood Outcomes of Smallholder Farmers in Zambia? *Food Security*. 10.2: 381-396.

Ngoma, H., A. Angelsen, T.S. Jayne, and A. Chapoto. Forthcoming. Conservation Agriculture: Is It Climate Smart? Can It Be? A Synthesis from Sub-Saharan Africa.

Ngoma, H., B.P. Mulenga, and T.S. Jayne. 2016. Minimum Tillage Uptake and Uptake Intensity by Smallholder Farmers in Zambia. *African Journal of Agricultural and Resource Economics* 11.4: 249-262.

Reardon, T. and S.A. Vosti. 1995. Links between Rural Poverty and the Environment in Developing Countries: Asset Categories and Investment Poverty. *World Development* 23.9: 1495-1506.

Sutter, M., M.G. Kocher, D. Glätzle-Rützler, and S.T. Trautmann. 2013. Impatience and Uncertainty: Experimental Decisions Predict Adolescents' Field Behavior. *American Economic Review*. 103.1: 510-31.

Tambo, J.A. and J. Mockshell. 2018. Differential Impacts of Conservation Agriculture Technology Options on Household Income in Sub-Saharan Africa. *Ecological Economics* 151: 95-105.

Tanaka, T., C.F. Camerer, and Q. Nguyen. 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review* 100.1: 557-71.

Thierfelder, C., P. Chivenge, W. Mupangwa, T.S. Rosenstock, C. Lamanna, and J.X. Eyre. 2017. How Climate-Smart Is Conservation Agriculture (CA)? – Its Potential to Deliver on Adaptation, Mitigation, and Productivity on Smallholder Farms in Southern Africa. *Food Security* 9.3: 537-560.

Thierfelder, C., R. Matemba-Mutasa, W.T. Bunderson, M. Mutenje, I. Nyagumbo, W. Mupangwa. 2016. Evaluating Manual Conservation Agriculture Systems in Southern Africa. *Agriculture, Ecosystems & Environment* 222: 112-124.

van Ittersum, M.K., L.G.J. van Bussel, J. Wolf, J., and …K.G. Cassman. 2016. Can Sub-Saharan Africa Feed Itself? *Proceedings of the National Academy of Sciences*. 113.52: 14964-14969.

Zulu-Mbata, O., A. Chapoto, and M. Hichaambwa. 2016. Determinants of Conservation Agriculture Adoption among Zambian Smallholder Farmers. IAPRI Working Paper No. 114. Lusaka, Zambia: IAPRI. Available at http://www.iapri.org.zm/images/WorkingPapers/Determinants_WP114.pdf.

Zulu-Mbata, O., A. Chapoto, M. Hichaambwa, and S. Kabwe. 2016. Comparison of Labour Costs between Conservation and Conventional Farming. Submitted to the European Union Delegation in Zambia. Lusaka, Zambia: IAPRI. Svailable at http://www.iapri.org.zm/images/Emerging_Issues/CA/Labour%20Cost%20Comparisons.pdf