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Risk aversion, impatience, and adoption of conservation agriculture practices among smallholders in Zambia

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ABSTRACT

Sustainable agricultural practices such as conservation agriculture have been promoted in southern Africa for nearly three decades, but their adoption remains low. It is of policy interest to unpack behavioural drivers of adoption to understand why adoption remains lower than anticipated. This paper assesses the effects of risk aversion and impatience on the extent and intensity of the adoption of conservation agriculture using panel data collected from 646 households in 2021 and 2022 in Zambia. We find that 12% and 18% of the smallholders were impatient and risk averse, respectively. There are two main empirical findings based on panel data Probit and Tobit models. First, on the extensive margin, being impatient is correlated with a decreased likelihood of adopting combined minimum-tillage (MT) and rotation by 2.9 percentage points and being risk averse is associated with a decreased propensity of adopting combined minimum tillage (MT) and mulching by 3.2 percentage points. Being risk averse is correlated with a decreased chance of adopting basins by 2.8 percentage points. Second, on the intensive margin, impatience and risk aversion are significantly correlated with reduced adoption intensity of basins, ripping, minimum tillage (MT), and combined MT and rotation by 0.02–0.22 ha. These findings imply a need to embed risk management (e.g., through crop yield insurance) in the scaling of sustainable agricultural practices to incentivise adoption. This can help to nudge initial adoption and to protect farmers from yield penalties that are common in experimentation stages.

1. Introduction

More than 60% of the population in Zambia lives in rural areas and relies on rain fed agriculture [1] with the majority cultivating less than 5 ha [2]. Smallholder farmers play a pivotal role in food production, yet their dependence on rainfed agriculture makes them susceptible to climate risks [1,3]. A key consideration for Zambia is to sustainably increase food production to feed a growing population while addressing the growing impact of climate change. Sustainable Intensification Practices (SIPs) are widely considered part of the solution [4,5]. According to Pretty, Toulmin [6], SIPs are defined as agricultural practices, policies, and measures that raise productivity without causing negative environmental externalities. Central to agricultural intensification is the idea that the level of

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yield can be increased by raising input use efficiencies. There are several examples of SIPs in different agricultural contexts. In crop-livestock and maize-based farming systems of southern Africa, options include Conservation Agriculture (CA), agroforestry, improved seeds, inorganic and organic fertilizers, various integrated soil fertility management systems, and other climate smart agriculture practices [5,7–9]. SIP adoption offers a range of benefits including enhanced soil fertility, increased crop productivity, and decreased greenhouse gas emissions (GHG). It equips farmers to meet rising food demands by boosting productivity and overall production, as shown by Droppelmann, Snapp [7], Lipper, Thornton [9] and Thierfelder, Chivenge [5].

Within the framework of the foregoing evidence, SIPs such as CA are part of national policies in southern Africa and are among the top priorities on the agendas of governments, non-governmental organisations, and development partners to sustainably grow agriculture productivity in the region [10,11]. Minimum tillage (MT) in the form of basins, ripping, or zero tillage; crop rotation; and residue retention [4] form the basis of CA. Minimum tillage reduces soil erosion since the soil is largely left undisturbed [12], while residue retention and planting basins facilitate moisture retention [13] and improve soil fertility. Crop rotation involves rotating cereals with nitrogen-fixing legumes on the same plots over successive years.

Despite several years of promoting SIPs in southern Africa, and some demonstrated biophysical and economic benefits, uptake remains low [14]. Various bottlenecks and trade-offs have been identified. For example, Arslan, Floress [15], Baudron, Delmotte [16] and Brown, Nuberg [17] identify the competition for the use of crop residues as mulch, biomass for cooking, and/or as animal feed during the dry season as a major trade-off that potentially hinders the uptake of mulch by smallholder farmers. Binding credit and labour constraints, the high cost of capital when available, and limited technical competence also negatively affect the uptake of SIPs [4,15,18]. Additionally, farmer behaviour is an important factor that influences adoption decisions for various farming activities.

In some cases, where key barriers to uptake of SIPs have been addressed, uptake still remains low, leading to arguments that factors, other than resource constraints limit the adoption of SIPs [19]. Except for Ngoma, Mason-Wardell [19] in Zambia, Ward, Bell [14], Bell, Parkhurst [20] in Malawi, and Tufa, Kanyamuka [21] in Zambia, Malawi, and Zimbabwe, there is a dearth of research on the role of risk and time preferences in the uptake of SIPs in southern Africa. This paper contributes towards filling this gap. We use two-wave panel data to assess the extent to which risk and time preferences influence the adoption of CA-based SIPs among smallholder farmers in Zambia. We hypothesize that risk aversion and impatience reduce the likelihood of adopting CA practices by smallholders.

Risk preferences refer to individual attitudes towards risky choices, whereas time preferences address the inclination to receiving something now versus later. In accordance with previous studies, e.g. Ref. [22], we employed self-reported measures of risk and time preferences captured using five-point Likert-Scale type questions. While experimental based measures of risk and time preferences are ideal, it was not feasible to use them at the time of the surveys. Instead, we used self-reported measures that have been found to be suitable predictors of individual preferences [22]. Farmers who responded, “not at all” and/or “somewhat willing” to take risks in the first question (responses 1 and 2) were considered risk averse whereas those who indicated “not at all” and/or “somewhat willing” to wait to get things for question 2 (responses 1 and 2) were considered impatient.

Adoption refers to farmer’s use of a given CA practice during the 2020/2021 and 2021/2022 cropping seasons and adoption intensity is measured by the size of land cultivated under a given CA practice. The risk perceptions of farmers are a key determinant of technology adoption [23,24]. However, this will differ in different contexts and for different technologies. Brick and Visser [25] suggest that risk-averse smallholders are more likely to opt for conventional agriculture compared to ‘risk lovers’, who are likely to adopt conservation agriculture. This is not unexpected because most smallholder farmers are risk averse. As such, they will try to avoid risky investments and may dis-adopt technologies whose perceived benefits are less than the associated costs [23,26]. In instances where farmers are aware of the risk reducing aspects of CA, one would expect risk-averse farmers to be more likely to adopt CA. It appears, however, smallholders perceive CA to be risky given the learning involved and the possibility of yield penalties in the initial years of adoption [19]. Overall, results are context specific.

2. Literature review

2.1. Drivers of CA adoption

The bulk of the evidence on the drivers of CA adoption in the region highlights socio-economic, demographic, and institutional factors in various contexts. A recent meta-analysis of 168 papers from 23 countries in sub-Saharan Africa found that access to information/extension on specific technologies, wealth, landholding, socio-demographics (income, age, education), social capital (kin ties), land tenure security, labour availability, and access to credit had a positive and significant influence on the adoption of improved technologies, including CA, in about 25% of instances. However, there are differences across countries [27]. Other important drivers of adoption include limited or lack of access to improved inputs such as seed and fertilisers, access to markets, off-farm income opportunities, lack of CA expertise among farmers, climate-related factors, and farm characteristics [4,5,13,21,28–33].

Tufa, Kanyamuka [21], identified limited technical competence as the main cause of non-adoption and dis-adoption of CA practices in Malawi, Zambia, and Zimbabwe, while unavailability of finance to buy CA inputs, poor extension services, unavailability of legume seeds to manage rotations, cost of fertilizer (perceived as key in CA), and high labour costs also emerged as contributing factors. Moreover, Nkonki-Mandleni, Manenzhe [34] found that farmer extension visits and access to credit had a positive impact on the adoption of CA in Kwazulu-Natal, South Africa. The importance of finance (credit) is echoed by Andersson and D’Souza [35] who note that financial challenges and over-reliance on family labour for farming activities makes it difficult for smallholder farmers in southern Africa to sustain the adoption of CA.

Learning is an important driver of technology adoption because educated or well-informed individuals tend to be more inclined towards embracing new technologies as they have the capacity to comprehend new and complex information. Additionally, educated individuals ordinarily have better access to resources and opportunities compared to those without formal education. Experience, observations, and access to information precede learning. To move from learning to adoption, farmers create beliefs about the expected returns from adopting a given technology and once these returns are deemed positive, then adoption is more likely [36]. This could explain why, in the study by Tufa, Kanyamuka [21], CA adopters in Malawi, Zambia, and Zimbabwe had a higher education level than non-CA adopters. The slow and low CA uptake could also be driven by beliefs by farmers that CA is not as beneficial, that its returns take time to accrue, and/or that CA is risky.

2.2. Risk preferences and adoption

Risk preference refers to attitudes towards risk and is a key factor in determining how people make decisions [37–39]. Risk-averse individuals tend to be more cautious, and prioritize stability and reliability over potential, but risky gains [40]. Conversely, individuals or groups tolerant to risk might exhibit a greater propensity to adopt new ideas, technologies, or practices despite the accompanying uncertainties.

Attempts to understand the effects of risk preference in the adoption of agriculture technology dates back to the 1900s. In his seminal work, Feder [23] found that adoption of modern crop varieties or improved technologies reduced with increasing risk aversion. When a farmer faces higher levels of uncertainty, it is anticipated that they will attempt to minimize risk by reducing their investment in modern technologies. This, in turn, leads to a decrease in the allocation of resources towards these technologies. Further, the risk perceptions of farmers play a role. For example, Feder, Just [41], found that the level of usage of modern inputs depends on whether these inputs are perceived to decrease or increase risk. Similarly, Binswanger [42] found that risk averse farmers are more likely to choose more conservative options and risk aversion increases with income. Interestingly, Ward and Singh [43] found that farmers exhibiting risk-seeking behaviour tended to have significantly lower wealth compared to moderately risk-averse farmers. This observation could potentially signify two factors: poor households might display a degree of desperation, leading them to take unnecessary risks; or this correlation might also indicate that the poor economic outcomes experienced by risk-seeking farmers stem from the unfavourable consequences of their risky decision-making.

More recent applications include Brick and Visser [25] who found that risk-averse individuals in South Africa were more inclined to favour traditional maize varieties, that offered lower returns but had lower risks, compared to improved maize varieties. Even after providing insurance, the outcomes did not change, leading authors to conclude that this could have been caused by residual production risk and basis risk which are not covered in standard crop insurance. In contrast, Freudenreich and Muβhoff [44] observed that offering full insurance increased the adoption of hybrid maize among farmers in Mexico. In a related study, Holden and Quiggin [45] found that risk-averse farmers were more likely to adopt drought-tolerant maize and local maize, but were less likely to adopt other improved maize varieties. In India, Ward and Singh [43] found that risk and loss averse farmers were more likely to adopt new seed varieties that were considered risk-reducing, while Liu [37] found that farmers who are more risk and loss averse tend to adopt Bt cotton later than other farmers.

2.3. Time preferences and adoption

Time preference, a fundamental concept in behavioural economics, refers to the inherent inclination of individuals to value immediate rewards more than delayed ones. This preference often leads to decisions that prioritize short-term gains over long-term benefits [46,47]. Behavioural economists posit that time preference is not uniform across individuals; rather, it varies based on psychological, social, economic, and environmental factors. Mao, Zhou [48] found that farmers with a strong inclination toward present-oriented thinking tend to be less inclined to adopt new technologies. Their immediate-focused mindset seems to hinder their willingness to embrace technological advancements, resulting in a reduced rate of technology adoption among them. It is important to grasp the relationship between time preferences and CA adoption. This understanding is vital because evidence suggests that the benefits of CA aren't immediate; it takes time for soil quality to improve and for farmers to gain sufficient experience in implementing CA before realizing improvements in yields [49].

2.4. Risk and time preferences and adoption of climate smart agriculture

The relationship between risk aversion, impatience, and the adoption of climate smart agriculture practices like CA is intricate and multifaceted. It is contingent on the objective and subjective perception of the farmers regarding the riskiness of the technology. Generally, risk aversion is expected to lead to uncertainty among smallholders, which in turn, affects their behaviour towards new technologies [23,32]. The process of embracing innovations involve a deliberate evaluation of potential risks against potential gains. Diverse risk preferences among entities or individuals often result in varying inclinations toward adopting different practices [23,32,40,50,51]. For instance, when farmers anticipate simultaneous increases in returns and risks, risk-averse households are less inclined to opt for farming strategies that escalate risk despite the higher returns. Furthermore, farmers' risk preferences strongly correlate with the livelihood strategies adopted [52]. Because risk-averse farmers are more likely to adopt conventional as opposed to conservation agriculture [25], it can be conjectured that risk averse farmers may not be so amenable to adopt CA practices – whether these are risk reducing or not – as long as farmers perceive such technologies to be risky [24]. Farmers may also be reluctant to try new farming practices that they perceive to be unfamiliar and whose results take time to be realized [53].

There are mixed findings on the links between risk and time preferences and technology adoption in agriculture in sub-Saharan Africa. In Malawi, Holden and Quiggin [45] used economic field experiments to assess adoption of drought tolerant maize varieties among smallholders and found that risk averse households were less likely to adopt drought tolerant maize varieties, but were more likely to adopt traditional varieties. Ward, Bell [14] found a positive association between an agglomeration bonus payment and the adoption of mulching in Malawi. An agglomeration payment is an incentive scheme that can be used to encourage uptake of pro-environmental practices or conservation by providing pay-outs if participants comply with a conservation activity and includes an additional payment if such compliance is contiguous among neighbours [20].

Ngoma, Mason-Wardell [19] used incentivised framed economic field experiments among farmers in Zambia and found that impatience and risk aversion were associated with decreased likelihood of farmers adopting climate smart agricultural practices by 9 and 7 percentage points, respectively. Brick and Visser [25] investigated how farmers make decisions about technological innovation and found that poor households opted for low-risk agriculture and low return technologies and were less likely to use modern farming methods. Using cross section data from Malawi, Zambia, and Zimbabwe, Tufa, Kanyamuka [21] found contrasting results. Risk aversion was associated with reduced chances of adopting minimum tillage in Zambia and Zimbabwe, mulching in Malawi and Zimbabwe, and rotation in Zambia. Yet, it increased the probability of adopting mulch in Zambia. Overall, Tufa et al. found that CA adopters were less risk averse and more patient.

Given this background, there is need for a nuanced understanding of how attitudes towards risk influence decisions by farmers to adopt CA. Farmers are frequently presented with a variety of technologies that can be used in combination, as complements, or as substitutes to mitigate and adapt to climate change. Except for studies that elicited risk and time preferences using experiments, others depended on cross section data. Thus, one of the current study's contributions is to identify and compare the effects of risk and time preferences on adoption of conservation agriculture practices using panel data that allows to control for both observed and unobserved heterogeneity that may confound outcomes. In addition, the study provides a definition of adoption which is based on use of CA elements on non-demonstration or supported plots.

3. Materials and methods

3.1. Conceptual framework

Researchers have been investigating the role of risk in agricultural technology adoption since the early 20th century; with initial work pioneered by Binswanger [24] and Feder [23]. At the core of these early studies was a need to understand decision making in a scenario where a farmer had a choice between a known, less risky, low-return technology and an unknown, high-risk, high-return alternative. The findings suggest that risk-averse farmers will often choose the former. Such suboptimal choices leave farmers trapped in what has been called a risk-induced poverty-trap, in which, because of risk-aversion, farmers opt for less risky strategies even when these offer low-returns, which worsens poverty [25,54].

Choices under uncertainty can be explained based on either the expected utility theory or the prospect theory. The expected utility theory suggests that when confronted with a choice between two competing options, a rational decision maker will go for the option with higher expected utility of returns. In applying this theory, Just and Zilberman [55] showed, with a monotonically increasing utility function, that the probability of adoption is inversely related to risk aversion. Whether a given technology is perceived as

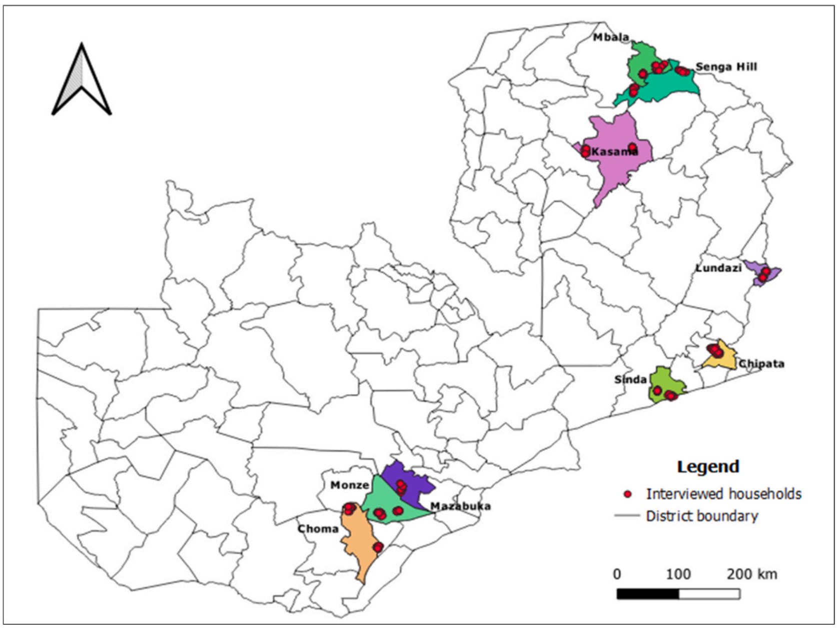

Fig. 1. Locations of households interviewed.

risk-increasing or risk-reducing, in addition to other enablers (e.g., access to credit and wealth), is significant for adoption [23].

Conversely, Prospect Theory, argues that human behaviour is not always rational, and therefore does not always align with rational economic thinking [56]. Prospect Theory holds that people tend to over weigh small probabilities and under weigh large probabilities. As such, people might be more averse to losses than gains. This behaviour departs from the standard expected utility theory and leads to risk aversion in choices involving gains, and risk seeking in choices involving losses. Prospect theory has been used to study choices under risk [e.g., 37,45,57].

Learning is an important element in the decision-making process of farmers. This ultimately determines whether a farmer adopts a technology or not. Learning is a function of experience and beliefs, and occurs when there is behavioural change that increases private benefits [58]. Positive or negative experiences influence belief formation and inform expectations around the benefits to be derived from adoption. Thus, farmer experiences and beliefs about the potential benefits of CA determine whether they adopt it or not. Belief formation, in some cases, can be informed by learning. According to Foster and Rosenzweig [58], farmers sometimes do not adopt given technologies when (i) they do not know the potential benefits of adoption, (ii) are risk averse or (iii) they fail to implement the new technology to maximize benefits. Consequently, farmer attitudes towards risk and time preferences influence behaviour.

For this study, the expected utility theory better explains farmer decision-making because CA offers higher average returns than conventional agriculture and, as such, risk aversion, rather than loss aversion, may better explain adoption decisions. In addition, the expected utility theory is better able to portray adoption decisions by farmers on CA, whose benefits are uncertain and take time to be realized. Given the unique characteristics of CA, we argue that the time and risk preferences of farmers can explain CA adoption decisions. This paper aims to bolster the evidence base for papers that measure time and risk preferences over time by using panel data methods.

3.2. Data sources and sampling strategy

Data were drawn from two household surveys conducted in nine districts of Zambia in the Eastern, Northern, and Southern provinces (Fig. 1). Fieldwork was done in selected communities where the International Maize and Wheat Improvement Centre (CIMMYT) is promoting various SIPs using the mother and baby trial approach under the Sustainable Intensification of Smallholder Farming Systems in Zambia (SIFAZ) project. Mother trials are managed by researchers and hosted by farmers. These are learning centres where farmers are exposed to several technologies. Baby trials are managed by farmers who implement selected technologies from mother trials.

The survey covered the semi-arid Southern Province districts of Choma, Mazabuka, and Monze with mean annual rainfall between 600 and 800 mm. The growing season is relatively short (80–120 days), often characterized by erratic rainfall distribution with frequent in-season dry spells, leading to a high risk of crop failure. In Eastern Province, the survey covered Chipata, Lundazi, and Sinda districts where annual rainfall averages 800–1100 mm. Rainfall distribution is not as erratic as in the Southern province, but dry spells are common, with growing seasons of 100–140 days. Surveys in the high-rainfall Northern Province were conducted in Kasama, Mbala, and Senga Hill districts which receive over 1000 mm of rainfall annually, with 120–160 day growing seasons. The Northern region is characterized by leached and acidic soils.

Fieldwork was conducted in June and July 2021 for the 2021 wave, and in May and June 2022 for the 2022 wave. A multistage sampling approach was used. For the first wave of the survey, we purposively selected all 18 camps which hosted the SIFAZ research trials in 2021. In each camp, we selected households from three categories: mother trial host farmers, baby trial host farmers, and other farmers. To do this, up-to-date lists of 35 or more other farmers who were not baby and mother trial hosts were collected from the Ministry of Agriculture camp extension officers. From each camp, we selected 50% from the host farmers (all mother trial host farmers and some randomly selected baby trial hosts) while the other 50% was from randomly sampled farmers who did not host any trials under the SIFAZ project. Adoption in this paper refers to use of CA practices on non-demonstration, non-trial plots which are not supported by any external project. The farmers who did not host any trials under the SIFAZ project were those in the villages around the SIFAZ mother trial hosts and within a radius of 10–20 km from mother trial hosts. The same households interviewed during the first wave in 2021 were engaged for the second wave of the survey in 2022. The distribution of the households was planned as follows: 228 households per province; 76 households per district; and 38 households per camp for a total sample of 684 in 2021. Six hundred and seventy-eight (678) were interviewed in 2021, of which 646 were re-interviewed in 2022 for a balanced panel sample of 1292 observations over the two waves. Ethical approval to conduct this study was obtained for both 2021 and 2022 surveys from ERES Converge limited, with approval reference Ref. No.2021-May-099.

3.3. Variables

3.3.1. Dependent variable

The CA practices considered as dependent variables in the analysis were, use of basins, ripping, minimum tillage, minimum tillage and mulch, and minimum tillage and crop rotation on non-demonstration or trial plots in the 2020/2021 and 2021/2022 cropping seasons. Minimum tillage encompasses the three practices of zero tillage, ripping, and basins. For each of these, we define the extent of adoption, i.e., whether a farmer adopted a given CA practice (yes = 1) and adoption intensity represented by hectares (ha) of cultivated land under a given CA practice. The extent of adoption is binary with a value of 1 if a household used basins, ripping, minimum tillage (MT), minimum tillage with mulching (MT-mulch), or minimum tillage with rotation (MT-rot) on non-demonstration plots in the season under consideration, and 0 if otherwise.

3.3.2. Independent variables

Several farm, household, and institutional factors thought to influence the adoption of CA were controlled for in the analysis based on literature on drivers of adoption [e.g., 19, 27, 59]. As stated, the main variables of interest were risk and time preference. To measure risk aversion, we asked the question, "How do you see yourself: are you generally a person who is willing to take risks, or do you try to avoid taking risks?" using a five-point Likert scale question coded as *(1) not at all willing to take risks, (2) somewhat not willing to take risks (3) neutral, (4) somewhat willing to take risks, (5) always willing to take risks*. Farmers that indicated options 1 and/or 2 were considered risk averse. To measure time preference, we asked farmers the following question: "How do you see yourself: are you generally a person who is impatient and wants to have 'things' now, or can you wait to get them later?" using a five-point Likert-scale question coded as *(1) not at all willing to wait to get things, (2) somewhat not willing to wait, (3) neutral, (4) somewhat willing to wait, (5) always willing to wait before I take my turn*. Farmers that answered options 1 and 2 were considered impatient. The other independent variables used in the empirical model are explained below.

3.3.3. Empirical strategy

A panel data Probit model was employed to assess factors influencing the extent of adoption of CA. The Probit model is appropriate because the outcome variable is binary. The other dependent variable is adoption intensity which is measured by area cultivated under a given practice. Measuring adoption intensity is important because some farmers only adopt particular components of CA as opposed to the full CA package. Land cultivated under CA is a continuous variable, but it is censored with large pileups at zero given low adoption. Thus, a censored regression framework such as the Tobit regression model is appropriate for analysis [59]. The Probit model can be specified as in equation (1):

$$Pr\ (Y_t = 1|X_t) = \Phi X_t^I \beta\ (Yt = 1|Xt)Xt^I, \tag{1}$$

where Pr is the probability, Φ is the Cumulative Distribution Function (CDF) of the standard normal Distribution, β are parameters to be estimated using maximum likelihood, $\boldsymbol{X}$ is a vector of regressors which influence adoption, Y is the response variable at time t, and t is the time period. We can motivate the Probit model as a latent variable model (Equation (2)):

$$Y_{it}^{*} = \boldsymbol{X}_{it}^{'}\beta + \varepsilon_{it}, \tag{2}$$

Where: $\varepsilon \sim$ N (0, 1), Y is an indicator for whether the latent variable is positive at time t, for household i. We can write an estimable econometric specification of equation (2) as shown in equation (3):

$$\begin{aligned} CA_{ijt} &= \beta_0 + \beta_1 age_{it} + \beta_2 education\_level_{it} + \beta_3 gender_{it} + \beta_4 hhsize_{it} + \beta_5 landsize_{it} + \beta_6 access\_information_{it} \\ &+ \beta_7 cooperative\_membership_{it} + \beta_8 extension_{it} + \beta_9 income_{it} + \beta_{10} risk\_aversion_{it} + \beta_{11} time\_preference_{it} + \varepsilon_i \end{aligned} \tag{3}$$

where CA_{ijt} is the dependent variable measuring adoption (yes = 1) for the Probit model and area cultivated (ha) under each SIP for the

Table 1
Summary statistics of key variables included in the models.

	2021		2022		Mean-diff	t
	n	Mean	n	Mean		
Adoption dependent variables						
Basins, %	678	2.950	646	2.632	0.318	0.351
Ripping, %	678	19.322	646	30.495	−11.174***	−4.744
MT, %	678	23.451	646	34.056	−10.604***	−4.293
MT-rot, %	677	4.136	646	12.384	−8.248***	−5.536
MT-mulch, %	677	11.965	646	20.124	−8.159***	−4.074
Adoption intensity dependent variables						
Cultivated land under basins, ha	678	0.016	646	0.023	−0.007	−0.889
Cultivated land under ripping, ha	678	0.511	646	0.817	−0.307***	−2.638
Cultivated land under Min till (MT), ha	678	0.534	646	0.847	−0.313***	−2.690
Cultivated land under MT-rotation, ha	678	0.040	646	0.145	−0.105***	−4.470
Cultivated land under MT-mulch, ha	678	0.295	646	0.372	−0.077	−0.993
Risk averse, %	678	19.764	646	16.563	3.201	1.509
Impatient, %	678	11.947	646	12.539	−0.592	−0.328
Age of household head, years	678	45.277	646	46.695	−1.418*	−1.948
Education of household head, years	678	7.145	646	7.176	−0.032	−0.183
Household size, number	678	6.963	646	7.099	−0.136	−0.811
Female household head, %	678	16.814	646	16.099	0.715	0.350
Access to extension services, %	677	58.493	646	72.291	−13.798***	−5.320
Member of cooperative, %	677	76.071	646	81.269	−5.198**	−2.308
Off farm income, %	677	33.530	646	37.307	−3.776	−1.436
Used weather information, %	567	85.714	521	84.645	1.069	0.496
Distance from main road, km	678	2.868	646	2.484	0.385	0.775

Source: SIFAZ 2021 and 2022 surveys.

Tobit model for household *i,* practice *j*, at time *t*. *Age* is the age of the household head; *education level* is number of years of formal education completed by the household head; *gender* is sex of the household head (=1 if household head is male); *hhsize* is the number of members of the household. Further, land size is the total landholding size in ha; *access_information* (=1 if household accessed weather related information in the cropping season under consideration (2020/2021 or 2021/2022)); and *extension* (=1 if household received any extension service in the 2020/2021 (2021/2022)). Finally, *off-farm income* is a dummy variable (=1 if anyone in the household earned off farm income in the past season); *cooperative membership* (=1 if anyone in a household is a member of a cooperative); *risk aversion* (=1 if the household is risk averse); and *time preference* (=1 if household is impatient). Equation (3) also controlled for year effects.

There are concerns that the standard Probit model can be biased in the presence of endogeneity caused by correlation between regressors and outcomes, which may lead to inconsistent estimates. In this case, the alternative is an instrumental variable probit (IVP) which explicitly controls for endogeneity using instrumental variables. The difficulty with this approach is finding instrumental variables. In our case, with a multiplicity of variables such as access to weather information, cooperative membership, and extension can be argued to be potentially endogenous, which can create complexities. We perform robustness checks and present the results in supplementary materials where we (i) estimated a bare-bone regression with only risk and time preferences as regressors, (ii) omitted the suspected endogenous variables, and (iii) omitted the suspected endogenous variables plus all demographic variables. The results from the robustness checks are qualitatively similar, as shown in the supplementary materials (Tables 5, 6, and 7).

4. Results

4.1. Descriptive results

The use of MT, ripping, MT-rotation, and MT-mulching on non-demonstration plots was significantly higher in the 2021/2022 season compared to 2020/2021 season (Table 1, Fig. 2). Adopters allocated more cultivated area to ripping, MT, and MT-rotation during the 2021/2022 season than in the 2020/2021 season. On average, MT and rotation occupied 0.15 ha, ripping occupied 0.82 ha and MT occupied 0.85 ha per household during the 2021/2022 season compared to 0.04 ha, 0.51 ha, and 0.53 ha during the 2020/2021 season (Table 1).

Household heads were on average 46 years old and had completed 7 years in school. The sample was dominated by male headed households with only 16% of the sample headed by females. The average household size comprised 7 members. About 65% of sampled households received extension services and 79% of the farmers were members of a farmer cooperative. A larger proportion of the interviewed households used weather-related information during the 2021/2022 season compared to the 2020/2021 season.

About 17–20% of the sample were risk averse over the two waves, whereas 11.95% of the farmers were impatient during the 2020/2021 season compared to 12.54% during the 2021/2022 season.

A closer look at adoption of CA practices by year, province, risk, time preferences, and gender of household head highlighted the following findings: First, the use of MT, ripping, MT-rotation, and MT-mulching was higher during the 2021/2022 season compared to the 2020/2021 season, while the use of planting basins was higher during the 2020/2021 season compared to the 2021/2022 season (Table 1, Fig. 2).

Second, the use of MT, planting basins, MT-rotation, and MT-mulching was higher in the Eastern Province, while the use of ripping was higher in the Southern province (Table 2). At provincial level, there was an increase in the use of MT, ripping, MT-rotation, and MT-mulching in the Eastern and Southern provinces during both the 2020/2021 and 2021/2022 seasons. As expected, the use of CA practices in the high-rainfall Northern province is very low compared to the other two provinces.

Third, a higher proportion of risk-loving farmers adopted MT, planting basins, ripping, MT-rotation, and MT-mulching compared to risk averse farmers (Fig. 3A), while a higher proportion of impatient farmers adopted planting basins and MT-mulching compared to those that are patient (Fig. 3B). Thus, albeit indirectly, risk and time preferences appear to play a role in the adoption of different CA practices in Zambia.

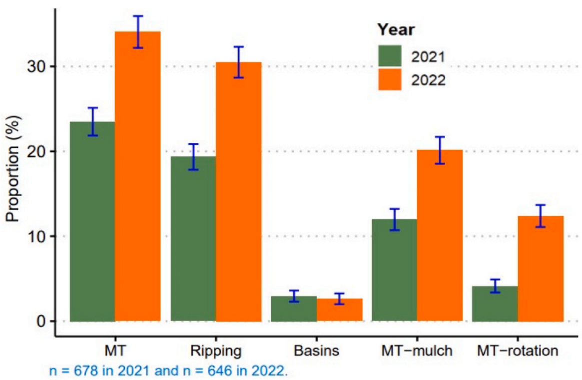

Fig. 2. Adoption of conservation agriculture practices during the 2020/2021 and 2021/2022 cropping seasons.

Table 2
Adoption of conservation agriculture practices (%) by provinces in 2021 and 2022.

	2021		2022		mean-diff	t
	n	Mean	n	Mean		
Eastern						
Basins	225	5.778	217	4.608	1.169	0.552
Ripping	225	28.000	217	41.475	-13.475***	-3.000
MT	225	32.889	217	45.161	-12.272***	-2.661
MT-rot	224	9.821	217	19.355	-9.533***	-2.861
MT-mulch	224	18.304	217	29.493	-11.190***	-2.776
Northern						
Basins	225	1.778	212	1.415	0.363	0.301
Ripping	225	3.111	212	4.245	-1.134	-0.630
MT	225	9.333	212	10.849	-1.516	-0.525
MT-rot	225	0.889	212	2.830	-1.941	-1.513
MT-mulch	225	2.222	212	3.774	-1.551	-0.953
Southern						
Basins	228	1.316	217	1.843	-0.528	-0.446
Ripping	228	26.754	217	45.161	-18.407***	-4.118
MT	228	28.070	217	45.622	-17.552***	-3.898
MT-rot	228	1.754	217	14.747	-12.992***	-5.161
MT-mulch	228	15.351	217	26.728	-11.377***	-2.973

Source: SIFAZ 2021 & 2022 surveys

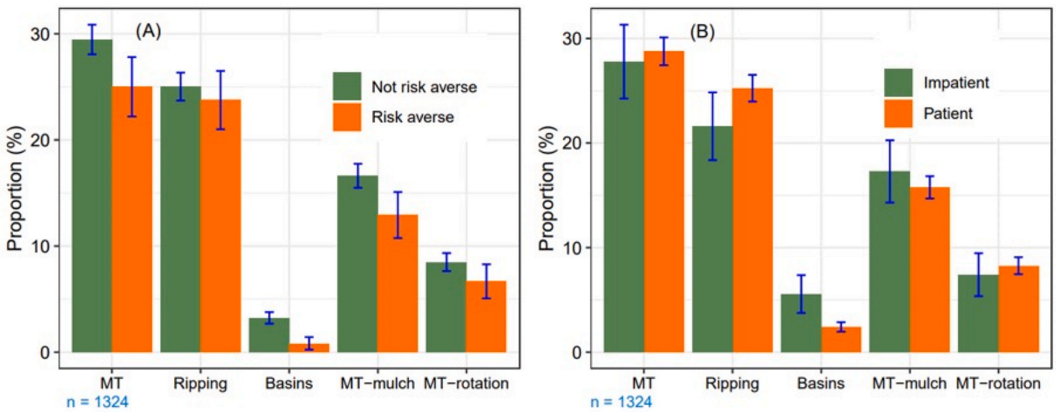

Fig. 3. Adoption of sustainable intensification practices (%) by risk preference (A) and time preference (B).

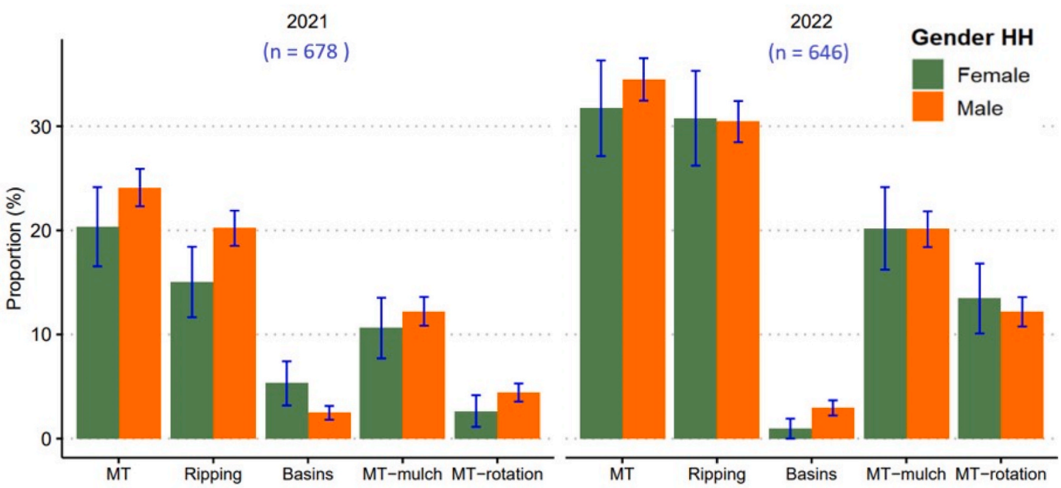

Fig. 4. Adoption of conservation agriculture practices (%) by gender of household head split by year.

Finally, a slightly lower proportion of female headed households adopted MT than did the male headed households during both the 2020/2021 and 2021/2022 seasons (Fig. 4). These results are expected because the majority (more than three quarters) of the sampled households are male headed.

4.2. Empirical results

4.2.1. Drivers of the extent of adoption among smallholder farmers

A panel data Probit model was used to analyse determinants of the extent of CA adoption among smallholder farmers. Results suggest that being impatient was correlated with a reduced likelihood of adopting ripping by 8.3 percentage points, MT by 5.1 percentage points, and combined MT and rotation by 2.9 percentage points. These results are statistically significant at 5%. As expected, being risk averse was associated with a lower propensity to adopt basins by 2.8 percentage points (significant at 1%) and combined MT and mulch by 3.2 percentage points at 10% significance level (Table 3). Access to extension services was correlated with an increased likelihood of adopting MT by 11.4 percentage points, ripping by 12.7 percentage points, combined MT and rotation by 4.3 percentage points, and combined MT and mulch by 11.2 percentage points (Table 3); these results are strongly significant at 5–10% levels. Results from the robustness checks are not reported here for brevity but indicate that, qualitatively, our findings on the negative association between risk and time preference and CA adoption are preserved under alternative specifications where we omit suspected endogenous and demographic variables.

The education of the household head was correlated with an increased likelihood of adopting ripping, MT, and combined MT and rotation. The other factors affecting adoption of individual CA practices included age of household head, gender of the household head, membership to a cooperative, and use of weather-related information received in the previous season.

4.2.2. Drivers of the intensity of CA adoption among smallholder farmers

Results from a panel data Tobit model on the determinants of the intensity of adoption (Table 4) were qualitatively similar to those of the Probit model (Table 3). Risk aversion was correlated with a decrease in adoption intensity of basins by 0.02 ha (significant at 1%) while being impatient was significantly correlated with reduced adoption intensity of ripping, MT, and MT and rotation by 0.22 ha, 0.17 ha and 0.04 ha, respectively. These results are significant at 5–10%. The education level of the household head was correlated significantly at 1% level with increased adoption intensity of ripping by 0.55 ha, minimum tillage by 0.50 ha, and combined MT and rotation by 0.09 ha. Farm size was correlated significantly with increased adoption intensity of MT by 1.18 ha, ripping by 1.06 ha, and MT and mulch by 0.54 ha (Table 4) and these results are significant at 5–10% level. Other factors that affected the intensity of adoption were age of the household head, household size, household use of weather-related information in the previous season, access to extension services, and cooperative membership.

Table 3
Covariates influencing the extent of adoption for different CA practices.

	(1)	(2)	(3)	(4)	(5)
	Basins	Ripping	MT	MT & rotation	MT & mulch
Risk averse (1 = yes)	−0.028***	0.002	−0.035	−0.006	−0.032*
	(-2.625)	(0.054)	(-0.997)	(-0.470)	(-1.645)
Impatient (1 = yes)	0.031	−0.083**	−0.051**	−0.029**	−0.014
	(1.233)	(-2.495)	(-2.135)	(-1.998)	(-0.804)
Access to extension services (1 = yes)	0.001	0.127***	0.114***	0.043**	0.112***
	(0.048)	(3.769)	(3.788)	(2.334)	(5.158)
Age of household head	0.013	0.131	0.134	0.097*	0.177**
	(0.214)	(1.248)	(1.585)	(1.736)	(2.420)
Education of household head	0.025	0.140***	0.125***	0.071***	0.022
	(1.639)	(4.457)	(3.772)	(2.832)	(0.971)
Female household head (1 = yes)	0.007	−0.043	−0.049*	−0.006	−0.010
	(0.411)	(-1.222)	(-1.905)	(-0.308)	(-0.522)
Household size	0.018	0.019	0.019	0.023	0.042
	(1.224)	(0.501)	(0.472)	(1.358)	(1.438)
Farm size	−1.035	1.365	1.219	0.003	0.833
	(-0.791)	(1.195)	(1.000)	(0.007)	(0.843)
Used weather information (1 = yes)	0.001	0.013	−0.006	0.044***	0.035*
	(0.128)	(0.499)	(-0.239)	(3.196)	(1.690)
Member of cooperative (1 = yes)	0.000	0.044	0.046*	0.024	−0.014
	(0.030)	(1.374)	(1.788)	(1.446)	(-0.591)
Observations	1324	1324	1324	1324	1324

Note: z-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors clustered at camp/ward level.

Table 4
Covariates influencing the adoption intensity of different CA practices.

	(1)	(2)	(3)	(4)	(5)
	Basins	Ripping	MT	MT & rotation	MT & mulch
Risk averse (1 = yes)	−0.018***	0.024	−0.057	−0.005	−0.077
	(-3.160)	(0.237)	(-0.592)	(-0.185)	(-1.161)
Impatient (1 = yes)	0.018	−0.221**	−0.170*	−0.038*	−0.052
	(1.255)	(-2.287)	(-1.703)	(-1.717)	(-0.690)
Access to extension services (1 = yes)	0.001	0.354***	0.333***	0.058***	0.297***
	(0.116)	(4.459)	(4.186)	(3.244)	(5.808)
Age of household head	0.008	0.474	0.481	0.138*	0.411*
	(0.263)	(1.314)	(1.366)	(1.860)	(1.807)
Education of household head	0.019	0.547***	0.498***	0.085***	0.113
	(1.483)	(3.637)	(3.364)	(2.609)	(1.189)
Female household head (1 = yes)	0.002	−0.117	−0.134	−0.020	−0.029
	(0.232)	(-0.996)	(-1.169)	(-0.857)	(-0.380)
Household size	0.011	0.549***	0.584***	0.030	0.389***
	(0.886)	(3.917)	(4.110)	(0.964)	(4.239)
Farm size	−0.051	1.062***	1.177***	0.041	0.544**
	(-0.568)	(2.876)	(3.087)	(0.504)	(2.283)
Used weather information (1 = yes)	0.001	0.029	−0.007	0.058***	0.079
	(0.106)	(0.328)	(-0.082)	(3.246)	(1.277)
Member of cooperative (1 = yes)	−0.002	0.143	0.141	0.036*	−0.019
	(-0.162)	(1.468)	(1.427)	(1.666)	(-0.246)
Observations	1324	1324	1324	1324	1324

Note: z-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors clustered at camp/ward level.

5. Discussion

5.1. Adoption of conservation agriculture practices and time and risk preferences

Our study revealed significantly higher adoption of minimum tillage, ripping, minimum tillage with mulching, and minimum tillage with rotation in the 2021/2022 season compared to the 2020/2021 season. Since adoption is defined as use of CA elements outside demonstration or supported plots, these findings are suggestive of diffusion where trial host and non-host farmers are increasingly applying CA principles on plots not supported by any project. We also found a marginally higher adoption rate of minimum tillage, ripping, minimum tillage with mulch, and minimum tillage with rotation among male-headed households compared to female-headed households within our overall sample. This finding aligns with prior research by Zulu-Mbata and Chapoto [60] and Mujeyi, Mudhara [61] underscoring the tendency for male household heads to engage more in conservation agriculture practices than their female counterparts. Understanding barriers to women using CA can be considered an important aspect for future research.

In terms of risk and time preferences, we found that approximately 18% of the sampled farmers exhibited risk-averse behaviour, a significantly lower proportion than previously reported in the literature. For example, Alem, Eggert [62] and Ngoma, Mason-Wardell [19] found that 65% of farmers interviewed in Tanzania and Zambia, were risk averse. While it is difficult to say why, such differences could be driven by elicitation methods used. On the qualitative front, compared to patient farmers, we observed a higher inclination among impatient farmers to adopt planting basins and minimum tillage combined with mulching. Additionally, a smaller subset of risk-averse farmers demonstrated a lower propensity to embrace various CA practices in contrast to risk-loving farmers. These findings resonate with prior studies. For example, Sulewski, Wąs [63] and Tong, Swallow [64] found that risk aversion prompts farmers to diversify into different agricultural and non-agricultural activities and can, on average, reduce adoption of specific activities. These findings are also in line with Ngoma, Angelsen [53] who suggest that risk averse farmers may be unwilling to take up unfamiliar agricultural practices whose risk reducing capabilities are poorly understood, and Tufa, Kanyamuka [21] who found that these preferences reduce the probability of adoption.

5.2. Drivers of the extent of adoption of conservation agriculture

Risk aversion was negatively correlated with the extent of the adoption of basins and minimum tillage with mulching while impatience was negatively correlated with adoption of minimum tillage, ripping with minimum tillage, and rotation (Table 3), which is consistent with *a priori* expectations and past studies. For instance, Ngoma, Mason-Wardell [19] and Tufa, Kanyamuka [21] found that both risk aversion and impatience reduced the probability of adopting conservation agriculture practices. The effects of impatience on adoption are also in line with Mao, Zhou [48] who postulated that time preferences affect the adoption of new technologies to the degree that patient or far-sighted farmers have a higher propensity to pursue long term benefits of new technologies and are willing to adopt new technologies whose benefits are realisable in the medium to long-term. This is unlike impatient farmers with a high discount rate whose main interest is to satisfy 'here and now' needs.

Our results are also consistent with Brick and Visser [25], indicating that the adoption decisions of farmers are influenced by their risk preferences. Additionally, Khanal, Mishra [39] also noted a negative correlation between risk preference and the adoption of good agricultural practices. Building on the suggestion by Mao, Zhou [48], it becomes evident that adverse effects stemming from risk and time preferences might significantly impede adoption. Farmers might choose a 'wait-and-see' approach, delaying their decisions on whether to embrace new technologies. This cautious stance could be influenced by observations of other farmers or early adopters but ultimately slows down the adoption process.

Several other factors that affect the adoption of CA practices in this paper are consistent with other studies in Southern Africa. First, the education level of the household head increased the likelihood of adopting CA practices, which shows the vital role played by education in the adoption of knowledge intensive technologies like CA practices. This is consistent with Abegunde, Sibanda [65], Mugandani and Mafongoya [66], Arslan, Floress [27] and Tufa, Kanyamuka [21] who observed that educational status had a positive influence on the adoption of CA practices among smallholders. The effect of education is correlated with risk preferences. Education affects the willingness of farmers to take on risks and the more educated a farmer is, the less risk averse they become [67]. Second, the positive effect of farm size on the intensity of adoption in this paper is similar to results found by Tufa, Kanyamuka [21], Abegunde, Sibanda [65] and Arslan, Floress [27]. These studies indicate that farmers with larger farmland are more likely to adopt CA practices than those with smaller farmland. Third, the positive effect of agricultural extension on the extent and intensity of adoption was as expected and corroborates findings in Tufa, Kanyamuka [21], Abegunde, Sibanda [65] and Arslan, Floress [27]. Finally, the socio-demographic characteristics of household heads are important since agricultural decisions are mainly made by the household head. These findings confirm those of Dohmen, Falk [22] and Mugandani and Mafongoya [66] who found that the gender and age of the household head have an economically significant impact on the willingness to take risks.

5.3. Drivers of the intensity of adoption of conservation agriculture

Results showing that risk aversion was significantly negatively correlated with increased adoption intensity of basins (Table 4) agree with the findings of Pedzisa, Rugube [68] who posit that risk aversion contributes to piecemeal adoption of conservation agriculture because farmers have little ability to absorb CA related risks. These results also corroborate those of Haggblade, Tembo [69] who found that a combination of tillage systems with partial adoption may well be the ideal option for smallholders who are highly risk averse. These findings on the intensive margin also support the findings of Spiegel, Britz [26] which suggested that risk aversion negatively affects the scale of adoption of agricultural technologies. The positive effect of farm size is expected as farmers with more land have the leeway to experiment with CA elements better than those farmers who are land constrained [53].

The findings in this paper, derived from panel survey data, underscore the influential role of risk and time preferences in shaping the uptake of conservation agriculture (CA) practices. The observed negative effects of risk and time preferences discounting on the adoption of such practices signals the need for strategies rooted in behavioural nudges to facilitate initial adoption. Additionally, safeguarding farmers from potential yield penalties during the experimental phase becomes paramount. Notably, the negative effects of risk and time preferences on adoption underscores the need to re-evaluate, not only the mix, but sequence of promoted CA practices. This prompts a critical re-evaluation of the mix of CA practices advocated for, aiming to align them more closely with the risk preferences of farmers for enhanced adoption rates and long-term sustainability.

Some limitations are worth mentioning. Measuring time and risk preferences is a complex task due to its multifaceted nature [24]. Our protocols, using self-reporting, proved effective and yielded sound results, albeit with the risk that it may not be objective. Thus, future research could explore more cost-effective and flexible protocols for measuring risk and time preferences and consider including a gender perspective. In addition, we were unable to control for how long farmers have used or have been exposed to the different CA practices. Despite these limitations, this study helps in understanding the association between risk and time preference and CA adoption.

6. Conclusion

Enhancing agricultural productivity is key to improving livelihoods and the well-being of rural households. This requires concerted efforts to improve availability and accessibility of technologies that improve yield while conserving natural resources. Despite the longstanding promotion of sustainable agricultural practices in southern Africa for nearly three decades, their uptake remains disproportionately low, and yet, these are part of national and regional policies. Thus, it is important to decipher the underlying reasons for low adoption, in particular the role of non-standard material determinants of adoption like risk and time preferences. This study assessed the effects of risk aversion and impatience on the extent and intensity of adopting conservation agriculture practices using a two-wave panel survey conducted during the 2021/2022 and 2020/2021 agricultural seasons in Zambia.

We found that about 18% of smallholders in the overall sample were risk averse. Empirical results suggest that risk aversion is significantly correlated with less chances of adopting basins and minimum tillage with mulching on the extensive margin. Risk aversion is also correlated with a decrease in adoption intensity. Impatience is negatively correlated with chances of adopting ripping and minimum tillage, on its own and in combination with rotation. Other significant factors affecting the extent and intensity of adoption are age, gender, education level of household head, farm size, access to extension services, off farm income, and the use of weather-related information by the household in the preceding season.

Since both risk aversion and impatience negatively affect the extent and intensity of adoption, a major implication of these findings is a need to manage risk when scaling sustainable intensification practices such as conservation agriculture. This includes both objective and subjective risk. There is need to promote and raise awareness on the importance of insurance that can help manage objective risk preferences. Examples include area yield insurance where payments are triggered should crop yield fall below a given threshold. Similarly, linking payments for ecosystem services (PES) to sustainable agricultural practices creates incentives by offsetting potential yield penalties during the initial adoption phase. This approach not only addresses initial adoption challenges, but also shields farmers from the common yield penalties experienced during experimental phases. Essentially, this strategy acts as a foundational step in managing risk, nudging adoption, and safeguarding farmers as they transition to sustainable agricultural practices.

Subjective risk can be managed by better framing of the riskiness of given sustainable intensification practices. If indeed, such practices are risk reducing, one strategy is to ensure that farmers are aware of this possibility. Another option that could help support adoption and to manage risks is livelihood diversification. Having alternative livelihood sources can help boost off-farm incomes which, in turn, can be invested on farm. Furthermore, timely provision of weather-related information can help farmers make informed decisions. Because the negative effects are more pronounced for specific practises such as basins in the case of risk aversion, this implies a need to re-examine the mix of technologies promoted. Future research could re-evaluate the correlation between risk and adoption by measuring risk preferences using economic field experiments involving lotteries and test the effectiveness of suggested adoption levers individually and in bundles. There is scope to systematically document the risk-reducing effects of sustainable intensification and to package this information for dissemination to farmers.

Data availability statement

The data can be made available upon request.

CRediT authorship contribution statement

Esau Simutowe: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hambulo Ngoma:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mark Manyanga:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **João Vasco Silva:** Writing – review & editing. **Frédéric Baudron:** Writing – review & editing. **Isaiah Nyagumbo:** Writing – review & editing. **Kelvin Kalala:** Writing – review & editing. **Mukwemba Habeenzu:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Christian Thierfelder:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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