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Do Adverse Events Influence Time Preferences? Evidence From Smallholder African Farmers

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ABSTRACT

Time preferences play a critical role in the agri-food value chains of low-income countries, impacting the choices of local operators, including innovation uptake. This paper assesses the association between smallholder farmers' individual characteristics, their exposure to diverse adverse events, and their intertemporal choices using in-the-field experiments conducted across five African countries. By jointly estimating time and risk preferences, we find that farmers who have experienced social setbacks during the previous year are more likely to be patient. This suggests that time preferences may vary over time, particularly when farmers are exposed to social distress (e.g., food shortage, health issues, violence, or crime). Moreover, we find gender to be a prominent factor associated with farmers' time preferences, with female farmers showing greater patience. These findings hold direct implications for both research and public policy initiatives aimed at influencing agricultural choices in the aftermath of social distress. By understanding the factors influencing time preferences, policy practitioners can develop more targeted and effective strategies to support smallholder farmers, thereby enhancing the resilience of agri-food value chains in low-income countries.

JEL Classification: D90, C93, O55, Q12

1 | Introduction

Farmers' livelihoods and farming activities are highly vulnerable to socio-economic challenges and climate change-related events. Factors such as rainfall variability and vulnerable health conditions lead to uncertainty and frequently to poor yields, which in turn cause a decline in farmers' revenues

(Crawford et al. 2003). African smallholder farmers are particularly exposed to these adverse conditions (Naazie et al. 2023), with potentially economic and social consequences. Indeed, Africa heavily depends on its approximately 33 million smallholder farmers, who produce 75%–90% of major food commodities in sub-Saharan Africa (Demmler 2020). Beyond food production, smallholder farms are vital for providing

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employment and sustaining livelihoods, especially for vulnerable groups such as rural women (Gollin 2014). For instance, in African low-income countries, smallholder farmers account for roughly 60% of the national workforce, underscoring their central role in economic and social stability (African Development Bank Group 2023).

Intergovernmental actions and frameworks such as the 2023 Comprehensive African Agriculture Development Program, the Alliance for a Green Revolution in Africa and, from a broader perspective, the Sustainable Development Goals (SDGs), have been deployed to mitigate the effects of climate change on farmers and improve rural livelihoods (Mohammed et al. 2023; Mapfumo et al. 2013). While these initiatives have the potential to enhance farmers' livelihoods in the long term (Antwi-Agyei and Nyantakyi-Frimpong 2021; McKenzie 2013; Padel 2001), their outcomes are affected by individual farmers' attitudes towards change, which often entail complex decision-making processes (Ayisi et al. 2022; Rogers 2010). Given the contribution of smallholder farmers to the African food system and their exposure to stressors, it thus becomes crucial to understand farmers' behaviours in times of distress. This paper takes a step in that direction.

Farmers' behaviour depends on a wide range of factors. First, demographic characteristics and farm-specific features are widely recognised as key determinants. Second, a growing body of research has investigated the role of behavioural factors such as risk propensity, beliefs, trust, and attitudes as additional elements impacting farmers' decisions (de Oca Munigua and Llewellyn 2020; Iyer et al. 2020; Rippo and Cerroni 2023). Finally, time preferences have been identified as a significant factor, and an increasing number of studies have explored their role in shaping farmers' behaviours.

Standard economic theory traditionally assumes that time preferences are stable and exogenous to context. This foundational assumption has been supported by some empirical studies that find little or no change in time preferences despite socio-economic shifts (e.g., Stigler and Becker 1977; Chuang and Schechter 2015; Hardardottir 2017; Drichoutis and Vassilopoulos 2021). Conversely, other studies have questioned their consistency over time, especially during periods of crisis and uncertainty (e.g., Kirby et al. 2002; Kirby 2009; Krupka and Stephens 2013; Cassar et al. 2017; Di Falco and Vièder 2022). Given these contrasting perspectives, additional cross-country evidence becomes essential to better understand the extent to which time preferences are context dependent.

In our work, we aim to assess whether time preferences remain stable over time among a large cross-country sample of African farmers who may have experienced various (perceived) adverse events. In so doing, we build on Cassar et al. (2017) and Di Falco and Vièder (2022) into the impact of shocks and adverse events on time preferences. We focus on the following research questions: (i) What types of adverse events affect smallholder farmers in the studied African contexts? (ii) To what extent do these different adverse events, as perceived by farmers, relate to time preferences? Both questions are particularly relevant for policymakers, agro-service providers, and research organisations

working in Africa, which are often tasked with designing organisational and technological innovations to enhance the resilience of local food-farming systems, and their ability to adapt to stressors. For these interventions to be effective in the long term, substantial changes in farmers' behaviours and in their responsiveness to critical events are often required (Mapfumo et al. 2013).

Our empirical analysis relies on standardised surveys and in-the-field experiments. We collected survey data in 12 and experimental data in five rural areas from five African countries (Kenya, Morocco, Tanzania, Tunisia, and Uganda). To study the association between farmers' time preferences and their adverse experiences, we implement a joint estimation with risk preferences using maximum likelihood estimators (MLE) à la Andersen et al. (2008), incorporating environmental, social, and economic setbacks experienced by individual smallholder farmers as main predictors. Our results point to a significant relationship between farmers' patience and their exposure to setbacks of social nature (e.g., food shortage, health issues, violence or crime). Smallholder farmers who have experienced adverse social events are more likely to exhibit higher levels of patience. Additionally, we identify a significant gender effect, with female farmers showing greater patience than their male counterparts.

The rest of the paper is structured as follows. An overview of the literature guiding the development of our research, as well as the contributions we make to the literature is presented in Section 2. Section 3 provides an overview of the study areas and describes the methodological procedures employed. In Section 4, we present the data used in the study along with the main descriptive statistics. Section 5 details the empirical strategy and reports the key findings. Section 6 concludes.

2 | Literature and Contribution

Intertemporal choices are decisions with consequences that materialize over time (Berns et al. 2007). Understanding the motivations behind such choices is crucial in economics to predict decisions such as spending and investments, purchasing habits, health and education choices, to only mention a few. Intertemporal choices play a critical role at many levels of the agri-food value chain. On the supply side, they influence farmers' access to credits and payments (e.g., farmers with limited access to savings may prefer delayed payments when they are given in regular installments; Casaburi and Macchiavello 2019; Kramer and Kunst 2020); farmers' willingness to adopt innovations, e.g., new crops (farmers with liquidity constraints might be reluctant to adopt innovations that generate a return only in the medium-long term; Bocquého and Jacquet 2010); or farmers' choices regarding the marketing channels for agricultural outputs (e.g., less risky, private output markets offering immediate payments can be more attractive for poorer farmers with impatient behaviors; Kamoyo and Makochekanwa 2018). On the demand side, time preferences can influence consumers' propensity to purchase food with varying taste and nutritional profiles (impulsivity vs. self-control over long-term health benefits; Barlow et al. 2016; Muñoz Torrecillas et al. 2018), as well as consumers' spending habits, which are related to budgetary constraints (Hall et al. 1980).

Standard economic theory assumes that time preferences are stable, context-independent, and exogenously given. This underpins classical models of intertemporal choice, and has long guided economic predictions of consumption, savings, and investment decisions. However, a growing body of research challenges the universality of this assumption, especially in environments marked by volatility, uncertainty, or external shocks. In the following paragraphs, we elaborate on this strand of the literature, which questions whether time preferences remain fixed or may instead evolve in response to individual experiences and contextual changes.

Literature has shown that individual patience is a key driver—along with risk, habits, uncertainty, and feelings of anticipation—in shaping time preferences of individuals (Casari and Dragone 2010). Impatience is the characteristic of individuals tending to forego larger rewards in the future and opt for smaller and sooner rewards. Previous research has documented heterogeneity in the degree of patience when measured across different types of individuals (Frederick et al. 2002). Comparing impatience levels (and related discount rates) can be of interest for market segmentation based on individuals' different geographical, cultural, and demographic characteristics (Rambaud and Torrecillas 2016). Impatience is also dependent on the context, and on the framing of the investment problem, as shown by experiments using different designs (e.g., small vs. larger payments, short vs. long delays, different resources or items assessed, and framing; Zauberman and Urminsky 2016).

Impatience is a critical variable in farming activities as it is associated with decisions in terms of innovation uptake, among others. Farmers' patience is influenced by several situational and individual factors ranging from socio-demographic variables to personal experiences, and risk attitudes. Le Cotty et al. (2014) showed that elicited individual time preferences of farmers in Burkina Faso correlate with fertiliser use, with more impatient farmers less likely to modify their agricultural inputs. Teklewold (2012) studied the association between farmers' impatience and their propensity to apply manure, finding significant linkages between time preferences and the use farmers make of manure (selling vs. internal use). In Uganda, Bartos et al. (2018) assessed the relationship between poverty and time preferences in a controlled longitudinal experiment, showing that concerns over poverty-related problems increase farmers' impatience. Di Falco et al. (2019) studied the effect of income on time preferences in an Ethiopian farming system, finding that farmers' income variations increase individual farmers' discount rates, and thus their impatience.

Finally, a series of studies have looked at the relationship between risk attitudes and time preferences (e.g., Clot et al. 2016; Ihli et al. 2022). According to these studies, and consistently with the broader literature on risk aversion, farmers who are more risk-tolerant tend to also be more patient. In particular, the works by Andersen et al. (2008) and Andreoni and Sprenger (2012) provide seminal insights into the relationship between risk and time preferences, challenging the assumption that time discounting can be straightforwardly interpreted without considering its interplay with risk preferences. The joint elicitation method developed by Andersen et al. (2008) has been widely used in studies examining time and risk preferences as

well as their heterogeneity with respect to socio-demographic characteristics in the farming sector of developing countries (Liebenehm and Waibel 2014; Fischer and Wollni 2018; Sawosri and Mußhoff 2020).

In addition to the abovementioned behavioural traits, shocks and adverse events such as floods, droughts, and pest invasion can modify farmers' time preferences, thus affecting their propensity to invest in farming activities (Cassar et al. 2017). For instance, literature has identified an overconfident approach to risk by farmers who have faced adverse events (Barsbai et al. 2022), but also more risk intolerance due to macro and micro-level shocks (Cameron and Shah 2015; Sakha 2019). Although the literature has studied farmers' risk aversion and its determinants, precise measurements of how farmers' past experiences of distress affect their patience levels are currently lacking. In general, previous studies focusing on social groups different from farmers show that impatient behaviour might be the result of past negative experiences and shocks (Cassar et al. 2017). Barnett and Breakwell (2001) found that individuals' negative experiences weaken their propensity to take risks but, on the other hand, individuals who repeatedly experience certain setbacks in the long term might become less sensitive to future adverse events and thus show more patience. Furthermore, the experience of adverse events has been found to interact with demographic factors in shaping individuals' patience and time preferences (Coletta et al. 2019). All in all, a review of the topic by Chuang and Schechter (2015) revealed that the literature lacks consensus regarding the impact of past economic or climatic shocks on time preferences. In this perspective, we believe that it is valuable to seek reconciliation by presenting additional and cross-country evidence on the association between farmers' individual characteristics and experienced setbacks, and their time preferences, drawing on a large sample of African farmers.

Through this study, we contribute to the experimental literature on agricultural time preferences in three ways. First, we deliver new field evidence on the relationship between farmers' experiences and worries, and their time preferences. This evidence is particularly valuable for designing effective policy interventions. A significant association between negative experiences and patience levels would suggest that time preferences vary over time, particularly when farmers face distress. Varying time preferences in the aftermath of adverse events implies that interventions deployed by researchers and policymakers (e.g., technological or organisational innovations) to respond to farmers' distresses (e.g., famines) might be more or less likely to be accepted by individual farmers depending on their exposure to the distress. This topic has received limited attention in the literature to date.

Second, our study provides experimental evidence on a wide cross-country sample from five rural settings from both northern (Morocco and Tunisia) and sub-Saharan Africa (Kenya, Tunisia, and Uganda), thus allowing comparability. Systematic and coherent protocols for eliciting farmers' time preferences in large cross-country studies have been identified as a promising area for future research in a recent review by Wuepper et al. (2023), which primarily focused on studies involving European and North American farmers. Additionally, our experiments involved in-person samples of smallholder farmers,

which are generally excluded from behavioral and experimental economic studies executed in laboratory or online settings (e.g., European Commission 2021; Tjernström et al. 2021).

Third, our study contributes to the growing strand of literature on incentivised experiments on time preferences. A key question in time preference elicitation studies is whether incentivisation can help mitigate the hypothetical bias. The main disadvantage of hypothetical choices, as noted in Frederick et al. (2002), is that they may predict inaccurately what participants would do if outcomes were real. Wuepper et al. (2023) found a limited effect of incentivisation on the discount rate, which tends to be higher in unincentivized games. Cardenas and Carpenter (2008) emphasise the importance of real incentives while acknowledging the broader challenges of implementing experiments in developing country contexts, such as situations where trust in the institutions delivering the experiment may be lacking. According to Chuang and Schechter (2015), while risk preference experiments are often difficult for participants to understand, time preference experiments are simpler and thus tend to perform better than survey-based measurements. While we do not claim to make a methodological contribution with this article, we aim to enrich the understanding of time preferences involving monetary rewards by providing additional evidence from a broad cross-country sample.

3 | Materials and Methods

In this section, we describe our geographical settings and subject pools (Section 3.1). We then detail the survey and experimental design and related procedures (Section 3.2).

3.1 | Study Areas and Subject Pool

The data used in this study derive from an international research and innovation project.¹ They were collected in 12 rural areas from five African countries (Kenya, Morocco, Tanzania, Tunisia, and Uganda) from April until December 2021.² The rural areas and their geographical boundaries were purposively selected by project partners based on the local agricultural productions, and their suitability for the demonstration of innovations being developed in the project. Within each region, the project established so-called 'food hubs', i.e., 'communities of local operators making joint research and development decisions and enabling the adoption of innovations' (Carloni et al. 2025). As a preliminary step, and before implementing any other project activities, we collected data on farm conditions and behaviors to establish a baseline for the successful dissemination of various innovations.

In each region, small crop farmers (or fish farmers, depending on the local focus) were recruited through stratified random sampling, with strata based on age, gender, and farm size. When one gender (usually females) represented less than one third of the reference population, the group was oversampled to shed light on dynamics and conditions that would otherwise be overlooked, in line with the requirements of the funder. Survey questionnaires were administered in all regions, for a total of 5456 responses. In one region from each country, behavioural experiments were also implemented, either jointly with the survey (four countries), or separately but in a coordinated manner

(Tunisia). Overall, 2393 of the above farmers took part in the behavioural experimental sessions.

The location of the 12 regions is shown in the map in Figure 1, while Table 1 provides an overview of their geographical, cultural, and socio-economic background characteristics, further detailed in the rest of this section. Given the focus of the project, our goal was not to gather a representative sample of each country's farming population but rather of producers in each food hub area. Therefore, our data cannot be used to make inferences on the composition or behavioral characteristics of the national farming population. Equally, the local samples are not fully comparable, and for this reason, in our cross-country models we control for country- and session-fixed effects. Nevertheless, the stylized facts detected may extend beyond the borders of the single areas or countries.

3.1.1 | Kenya

The three Kenyan food hubs are Mukurweini, Kitui, and Kisumu. The Mukurweini food hub is located in the central part of Kenya and administratively is a sub-county of Nyeri County. The Kitui food hub is located in the Eastern drylands of Kenya, in Kitui County. The Kisumu food hub is located in the western part of Kenya, in the Lake Victoria basin, and is a sub-county of Kisumu County, where farmers practice fish capture and fish farming. The main food crops grown and sold in the three food hubs include cereals such as maize, sorghum, and millets; pulses such as green grams, cowpeas, and pigeon peas; root crops such as cassava, sweet and Irish potatoes, and arrow roots; industrial crops such as coffee, cotton, sisal, and sunflower; horticultural crops represented mainly by fruits such as mangoes, pawpaw, and watermelons; and vegetables such as tomatoes, kales, onions and bullet chilies.

3.1.2 | Morocco

Two major agricultural regions in Morocco were selected for the project: the Meknès–Fès region and the Beni Mellal–Khénifra region. The Fès–Meknès region, located in the center-north of Morocco, and more specifically in the Meknès–El Hajeb food area, which dominates the Saïs plain, is characterised by market vegetable crops (potatoes and onions) that rely on drip irrigation, in addition to dry crops (cereals, olives, and fodder). The area has significant agricultural potential, but faces the problem of intensifying agricultural production through the extension and extensive use of irrigation, which poses problems in terms of sustainability of agricultural activities due to water scarcity, the effects of climate change (drought), and farmers' failure to control irrigation inputs (over-irrigation) (Benouniche et al. 2014; Molle and Tanouti 2017).

The Beni Mellal–Khénifra region, located in central Morocco, and more specifically in the Dir de Beni Mellal area, consists of a narrow strip of fertile land in a transitional position between the plain and the mountains, some 20 km wide to the south-west, and narrowing towards the north-east. The area is dominated by olive groves, the region's traditional crop. This is essentially subsistence farming, with low levels of farm income. Agriculture is the leading sector in the local economy, employing 42% of the working population. The food hub area covers 137,000 ha, 40% of which is used for farming.

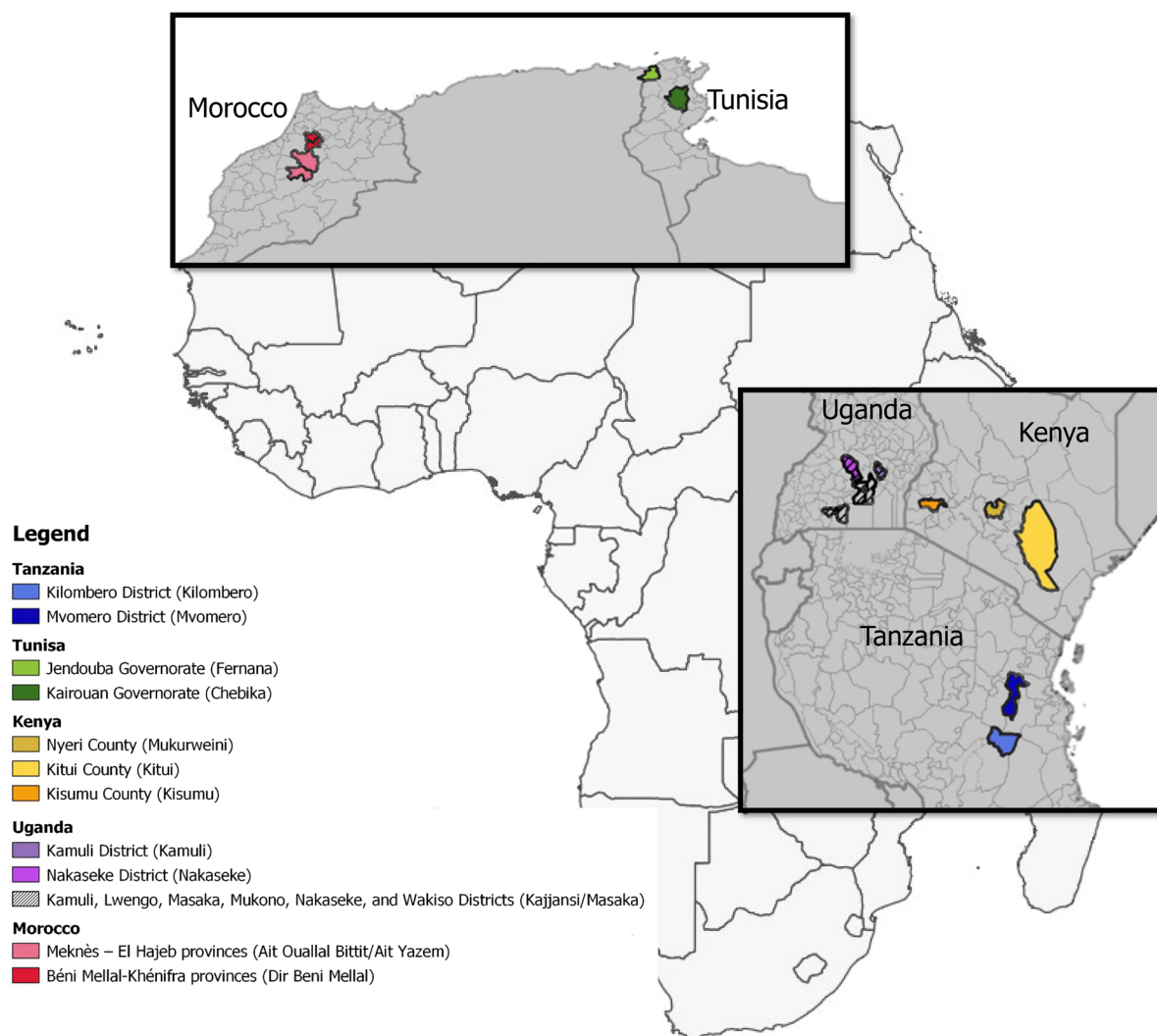


FIGURE 1 | Geographical location of the 12 food hubs (names in parentheses) and their respective macro administrative levels. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1111/1477-9552.70012)]

3.1.3 | Tanzania

In Tanzania, the study was conducted in the Kilombero and Mvomero food hubs, located respectively in the southern and northern parts of the Morogoro region, and spanning a total area of 7325 km². Most of the residents in the Kilombero district are sugarcane and rice producers. On a small scale, beans, pigeon peas, sweet potatoes, and cowpeas are also grown as sources of food and supplemental income. In Mvomero, the cultivation of sugarcane, rice, maize, beans, and sorghum is more predominant (Olmos 2001). Livestock keeping is done as well by pastoralist communities, especially the Maasai.

3.1.4 | Tunisia

In Tunisia, the study was conducted in the Chebika and Fernana food hubs. The delegation of Fernana (governorate of Jendouba) is predominantly rural with limited infrastructures and high unemployment and illiteracy rates. Agriculture is very varied, and mainly focused on cereals, livestock, fodder, and

market gardening. Agricultural land in the delegation is approximately 27,400 ha, with an average farm size of 6.9 ha. Small farms (under 10 ha) represent 50% of the surface area and 86% of the farms. This situation has a significant impact on yields and contributes to the high poverty rate of 37% as well as to the migration of young people to the main Tunisian cities (National Institute of Statistics-World Bank 2020).

The delegation of Chebika (governorate of Kairouan) is characterised by subsistence agriculture, dominance of the rural environment, weakness at the level of basic infrastructure, high unemployment rate, high illiteracy rate, very low levels of education, significant outmigration, and a high poverty rate of 35% (National Institute of Statistics-World Bank 2020). Agriculture is the primary economic sector for the local economy, employing 30% of the active population. The agricultural area covers 46,178 ha. The governorate of Kairouan is best known for its production of vegetables (peppers, tomatoes) and fruit (apricots, almonds, and olives). In fact, it is the country's leading producer of chilies, with almost 95,000 tons in 2020, and apricots, with over 15,000t.³

TABLE 1 | Socio-economic characteristics of the 12 food hubs.

Food hub	Country	Macro administrative level	Population (year)^a	Main agricultural productions	Average farm size (ha)	Farmers' type	Sample size (survey)	Sample size (experiments)
Mukurweini	Kenya	Nyeri County	759,164 (2019)	Cereals, pulses, root crops, arrow roots, industrial crops, horticultural crops	0.75	Crop	505	505
Kitui	Kenya	Kitui County	759,164 (2019)	Maize, sorghum, and millets, pulses (green grams, cowpeas and pigeon peas), root crops (cassava, sweet potatoes and arrow roots); industrial crops (cotton, sisal)	0.5	Crop	482	—
Kisumu	Kenya	Kisumu County	1,155,574 (2019)	Lake capture fishing, aquaculture farming, maize, sorghum, and millet, industrial crops (cotton, sisal)	0.5	Fish	403	—
Dir Beni Mellal	Morocco	Béni Mellal-Khénifra provinces	946,642 (2018)	Olives, cereals, pulses, fodder crops, horticultural crops	5.7	Crop	400	—
Ait Ouallal Bittit/Ait Yazem	Morocco	Meknès-El Hajeb provinces	865,419 (2018)	Vegetables (potatoes, onion), horticultural crops, olives, cereals, pulses	9.9	Crop	500	500
Mvomero	Tanzania	Mvomero District	421,741 (2022)	Sugarcane, rice, maize, beans and sorghum	3.1	Crop	504	482
Kilombero	Tanzania	Kilombero District	582,960 (2022)	Sugarcane, rice, aquaculture	4.3	Crop, fish	423	—
Chebika	Tunisia	Governorate of Kairouan	749,657 (2022)	Vegetables (peppers, tomatoes) and fruit (apricots, almonds and olives)	8.8	Crop	431	—
Fernana	Tunisia	Governorate of Jendouba	404,853 (2022)	Cereals, livestock, fodder, and market gardening	6.9	Crop	500	500
Kamuli	Uganda	Kamuli District	558,500 (2020)	Maize, sweet potatoes, beans, tomatoes, cassava, soybeans, bananas and groundnuts	1.0	Crop	400	—
Nakaseke	Uganda	Nakaseke District	234,600 (2020)	Beans, cassava, maize, coffee, bananas, fruits (mangoes, Pineapples, oranges) and vegetables (tomatoes and cabbages)	2.0	Crop	400	—

(Continues)

TABLE 1 | (Continued)

Food hub	Country	Macro administrative level	Population (year) ^a	Main agricultural productions	Average farm size (ha)	Farmers' type	Sample size (survey)	Sample size (experiments)
Kajjansi/Masaka	Uganda	Wakiso, Mukono, Lwengo, Masaka, Kamuli and Nagaseke Districts ^b	3,850,164 (2014) ^b	Smallholder fish farming (Nile Tilapia and African catfish), coffee, Matooke, sweet potatoes, pineapples, tomatoes	1.4 ^b	Fish	508	406

^aThe population figure is available only for the larger macro administrative level.

^bThe 'Kajjansi/Masaka' food hub, where the focus there was on fish farming, comprises a territory that spans six districts. The population data shown is the sum of the population data of all six districts in 2014. The average farm size is instead the average of the individual districts' sizes.

3.1.5 | Uganda

In Uganda, data were collected from three food hubs: Kamuli, Nakaseke, and Kajjansi–Masaka.

In the Kamuli district, agriculture is the main source of livelihood. About 93% of the households are engaged in agriculture and a great percentage (78%) largely depend on subsistence farming as their source of livelihood (Uganda Bureau of Statistics 2014). Maize, sweet potatoes, beans, tomatoes, cassava, soybeans, bananas, and groundnuts are the commonly grown crops for home consumption, whereas cash crops are dominated by sugarcane and robusta coffee. Farmers also make use of seasonal wetlands to grow rice and vegetables. Agriculture in the district is affected by declining soil fertility, crop and livestock pests and diseases, prolonged droughts, counterfeit inputs on the market, and poor post-harvest handling and storage. The district has high poverty and illiteracy rates that have limited investments in businesses.

The Nakaseke district has two agro-ecological zones: the northern pastoral zone dominated by cattle keepers (making up more than three-quarters of the land), and the southern crop-based one, where the project's activities were conducted. Other major economic activities in the district include charcoal burning, brick making, and sand mining. In recent years, the district has attracted investors in the established industrial park in Kapeeka town. The growing number of industries in the park has not only created jobs for the locals but also provided agri-processing services to farmers, especially fruit farmers who were previously experiencing high post-harvest losses.

Finally, the Kajjansi–Masaka food hub spans six districts, with Masaka being the main one. For the past 20 years, smallholder fish farming has been gaining popularity among households in Masaka and the other five districts as an alternative source of income. The most grown species are Nile tilapia and African catfish. However, fish predators such as snakes, high costs of feed, the lack of capital, and theft of fish represent major constraints to the enterprises (Atukunda et al. 2018; Hyuha et al. 2011).

3.2 | Survey and Experimental Design and Administration

In this study, we use data from both the standardised questionnaire and the in-the-field experiments. The questionnaire included 36 questions and was delivered in all 12 study areas to investigate smallholder farmers' habits and conditions, levels of trust, (stated) propensity to innovate, risk perception, experiences, and demographic as well as contextual factors (Piras et al. 2023).⁴ The questionnaire was drafted in English, translated into local languages, back translated for consistency checks, and pilot tested with students and then farmers.

The behavioural experiments, which were run in five of the 12 abovementioned study areas, consisted of three incentive-compatible games presented in fixed order (to reduce complexity for the enumerators): (i) a two-round public good game with country-specific treatments; (ii) a lottery game to elicit risk preferences (from Holt and Laury 2002); and finally, (iii) a task to

elicit time preferences (Kuhfuss et al. 2022). Only the latter two are used in this study.⁵

All the activities were conducted by the institutions coordinating fieldwork in the single countries, which were also project partners, without intermediation except for recruitment, where local cooperative and farmers' groups provided support if required. Local enumerators (often university students or researchers) were hired and trained for conducting the activities. Farmers were invited to the locality where the survey and the experimental sessions were organised. Each session was meant to include at least 20 participants to create two or more groups to perform the public good game—but the actual size varies depending on local recruiting conditions—and lasted for around 3 h, including filling in the questionnaire. Participants' responses to the questionnaire and their choices in the behavioural experiments were recorded using pen and paper, except in Morocco and Tanzania, where data collection was implemented using tablets. The enumerators provided one-to-one support to farmers to complete the required tasks. During the behavioural experiments, stakes were expressed in experimental tokens, and banknotes with the brand of the project reporting the values in tokens were used for the public good game. After the instructions of each game were read out loud by the lead enumerator, participants had the chance to ask questions to the enumerators.

Risk preferences were elicited through a multiple price elicitation task (Holt and Laury 2002). Each participant had to make 10 choices between pairs of lotteries with varying odds of winning the higher stake (Lottery B was riskier than Lottery A, i.e., the difference between the stakes was larger). In both lotteries, the odds of winning the higher stake increased for each choice (from 0.1 to 1.0).

Time preferences were elicited using a multiple price list (Andersen et al. 2008). Each participant had to make 10 choices between two options. Option A paid 100 tokens 2 weeks after the end of the experiment, while Option B paid a larger amount after 4 weeks.⁶ The amount paid in Option B increased by around 6% from one choice to the other, ranging from 105 to 166 tokens. After the end of the game, participants were asked to respond to two additional control questions (Kuhfuss et al. 2022).

During the experimental sessions, the payoffs were expressed in tokens. At the end of the experimental session, the participants received a show-up fee and a payoff that depended on the results of the games, converted into local currencies using a rate (communicated at the start of the session) that ensured the same average payoff at purchasing power parity across the five countries. More precisely, the average total payoff, inclusive of the show-up fee, was set as equal to 1.5 times the daily agricultural wage in the region.⁷ To avoid spillover effects, the draws to calculate the payoffs in the risk and time preference games were implemented at the end of the full session, and the farmers were paid privately in a separate room and asked to leave the venue immediately afterwards. The payoff of the time preference game was transferred by mobile phone—a common practice in African rural areas, including for the payment of agricultural products—after 2 or 4 weeks, depending on the respondent's selected option.⁸ In the few cases when this option was not feasible, the payment was delivered

in person by the experimental team by returning to the locality. The average payments received for the risk and time elicitation games by farmers in each country are presented in Appendix A, Table A1 and range, in total, between 226 tokens for Morocco and 260 tokens for Tunisia. Participant farmers were also paid travel costs and provided refreshments. The experimental and survey protocols, including procedures, instructions for researchers and enumerators, and logistic aspects were archived in Zenodo (Kuhfuss et al., 2022).

Prior to fieldwork, ethical clearance was obtained both from the Bioethics Committee of the institution leading the project, and from the ethics committees of the institutions coordinating fieldwork in single countries. A consent form (in the local language of each food hub) was used to gather the participants' consent to take part in experimental and survey activities. Local enumerators ensured that each participant understood the aforementioned information to make an informed decision. No sensitive personal data were collected.

In total, 2393 participants took part in the experimental sessions, of which 52 did not respond to the survey questionnaire. Therefore, the final sample considered for the analysis presented in Section 4.3, which combines both survey and experimental data, includes 2341 observations (Section 5).⁹

4 | Data and Descriptive Statistics

In this section, we describe our outcome of interest (Section 4.1), and the explanatory variables (Section 4.2). We then present a series of summary statistics, with a specific overview of the setbacks experienced by farmers within each of the studied African countries (Section 4.3).

4.1 | Outcome Variables

The main goal of this research is to assess the relationship between smallholder farmers' averse experiences and their time preferences. The primary outcome of interest is thus the farmers' patience levels, elicited through the time preferences task. One way to interpret these variables is in terms of a threshold, the switch point, i.e., the point at which a participant changes their preference between the smaller, sooner reward (Option A), and the larger, later rewards (Option B). A similar approach can be adopted for the risk preferences in the respective task. Evaluating switch point patterns across participants can provide useful information about their patience levels and overall decision-making behaviour (Bigoni et al. 2022). Yet scholars working on time preferences suggest more comprehensive analyses which can consider time preferences and risk preferences jointly (see, for instance, the seminal work by Andersen et al. 2008). Indeed, relying only on the switching behaviour in a single experiment does not allow to separate the influences of risk preferences (aversion to risk) and time preferences (impatience, or discounting the future) on the choices. In our study, we express the time preferences as discount rates, estimated jointly with risk preferences using maximum likelihood estimation (MLE) à la Andersen et al. (2008). We rely on the binary choices between sooner

and later payments in the time preference task, and on the choices between lotteries in the risk preference game to structurally and jointly estimate the discount rate δ and the risk preference r of the farmers in our sample. We then introduce a series of covariates to account for heterogeneity in risk and time preferences. This procedure enables us to retain in our analysis the participants with multiple switch points, which need not be excluded during the estimation.¹⁰ Inconsistent behaviours in time and especially risk elicitation games is common in economic experiment conducted in developing countries, and this behaviour in our sample was explored in Kahsay et al. (2024); omitting these observations as generally done in more standard modelling approaches would lead to a significant loss of information.

4.2 | Explanatory Variables

The main covariates of interest are 10 environmental, social, and economic setbacks that individual smallholder farmers experienced during the year prior to the sampling date. Farmers were asked to assess, on a 1–5 Likert scale, to what extent they had experienced the setbacks, which are presented in Table 2 (*Did you experience any of the following setbacks during the last year?*). Setbacks were retrieved from Kijima (2019), and adapted to the context-specific situation of the studied areas (i.e., crop versus fish farmers). We aggregated the setbacks into the three social, economic, and environmental macro-classes presented in Table 2 using the arithmetic mean and rounded to the nearest integer.¹¹ These 1–5 scales were used to generate dummies for each macro-class measuring whether a farmer

had experienced social, economic, or environmental setbacks to any extent, as opposed to not experiencing them, on average. Following the literature explored in Section 2, we expect that farmers who have experienced adverse social, environmental, and economic events are more likely to be impatient (Cassar et al. 2017), thus opting for smaller yet close-to-certain agricultural rewards rather than larger and uncertain rewards in the future.

Besides the three abovementioned variables related to setbacks, we include in our model a series of explanatory factors that are expected to be related to farmers' time preferences. These include:

1. *Farmer's worries about the future.* We include the measurements of a series of worries to experience the same setbacks in their near future (*Regarding your near future, are you worried about any of the reasons below?*). We expect farmers having greater economic, social, and/or environmental worries to be more likely to modify their agricultural practices potentially affected by future adverse experiences. Worries about the future were aggregated in three macro-classes (social, economic, and environmental) through their arithmetic mean, and then turned into binary variables in the same way as for the setbacks.
2. *Farmer's stated preferences towards innovation, risk, and trust.* We include in our estimation three measures of the farmers' own perception of risk, their trust in agricultural organisations, and their state openness to new ways of production, which we found to be significantly related to farmers intention to adopt innovations (omitted for peer review). These traits were measured on a five-point Likert scale ranging from complete disagreement (1) to complete agreement (5). The highest level corresponds to farmer profiles with the greater openness to new ways of production, risk aversion, and trust towards organisation promoting innovation in agriculture. From these variables, we generated dummies that indicate the farmer's overall agreement or disagreement concerning stated preferences on risk, trust, and innovation. We expect that higher levels of patience are associated with risk-tolerant profiles, greater openness to new ways of production, and more trust towards organisations promoting innovation.
3. *Socio-demographic and farm production variables.* We finally include a set of controls expected to have an impact on the individual farmer's patience levels: the farmer's age, level of education (illiterate, literate with no qualifications, and literate with qualifications), gender, share of household income spent on food purchases (above or below 50%), and land/pond total size.¹²

TABLE 2 | List of setbacks assessed by farmers, mean values, and SDs ($N = 2341$).

Setbacks	Category	Mean	SD
<i>Social setbacks (aggregate)</i>	—	2.40	1.07
Food shortage	Social	2.91	1.63
Health	Social	2.72	1.55
Social problems (violence or crime)	Social	1.63	1.27
<i>Environmental setbacks (aggregate)</i>	—	2.39	0.98
Drought	Environmental	2.68	1.63
Flood	Environmental	1.52	1.15
Pest infestation	Environmental	3.03	1.63
<i>Economic setbacks (aggregate)</i>		2.68	0.94
Dispossession	Economic	1.48	1.14
Cost increase (price of fertiliser and seed)	Economic	3.70	1.52
Job loss	Economic	2.00	1.51
Income reduction	Economic	3.48	1.52

4.3 | Descriptive Statistics

In Table 3, we report descriptive statistics for the outcome and explanatory variables. The patience level (measured as the time preference switch point) is highest in Kenya and Tanzania, and lowest in Morocco. Reported exposure to social, economic, and environmental setbacks and worries varies significantly across

TABLE 3 | Descriptive statistics by country—outcome and explanatory variables.

Variable	Mean (overall)	Mean (KE)	Mean (MA)	Mean (TN)	Mean (TZ)	Mean (UG)	ANOVA test (F value)
Patience level (switch point)	6.80	7.80 ^a	5.44	7.10	7.64 ^a	6.34	33.12***
Social setbacks	0.78	0.76	0.67	0.82 ^a	0.82 ^a	0.83 ^a	13.22***
Economic setbacks	0.93	0.91 ^{a,b}	0.92 ^b	0.99	0.88 ^a	0.93 ^b	11.19***
Environmental setbacks	0.83	0.89 ^a	0.74	0.87 ^a	0.95	0.66	46.65***
Social worries	0.83	0.82 ^b	0.77 ^a	0.89 ^c	0.81 ^{a,b}	0.88 ^c	8.71***
Economic worries	0.91	0.89	0.93 ^a	0.98	0.83	0.93 ^a	21.01***
Environmental worries	0.85	0.87 ^b	0.80 ^a	0.93	0.88 ^b	0.76 ^a	14.87***
Age (years)	46.40	52.27	48.22	45.51 ^a	41.14	43.83 ^a	41.80***
Education (illiterate = 1)	0.18	0.04 ^a	0.36	0.29	0.12	0.05 ^a	79.36***
Education (literate, no qualification = 1)	0.11	0.29	0.00	0.06 ^a	0.11	0.06 ^a	68.71***
Education (literate with qualification = 1)	0.71	0.68 ^a	0.63 ^a	0.65 ^a	0.77	0.89	23.88***
Gender (female = 1)	0.35	0.43 ^a	0.14	0.47 ^a	0.42 ^a	0.30	40.50***
Income spent on food	0.57	0.48	0.59 ^a	0.75	0.62 ^a	0.32	46.94***
Land/Pond size (Min-Max transformation)	0.008	0.00002 ^a	0.0002 ^a	0.0001 ^a	0.00004 ^a	0.050	127.40***
Farmer's risk aversion (low = 1)	0.38	0.19	0.48	0.71	0.11	0.38	149.06***
Farmer's risk aversion (neutral = 1)	0.09	0.09 ^a	0.13	0.08 ^a	0.08 ^a	0.07 ^a	3.00***
Farmer's risk aversion (high = 1)	0.53	0.72	0.39	0.21	0.81	0.56	148.12***
Farmer's trust (low = 1)	0.15	0.18 ^{c,d}	0.21 ^d	0.15 ^{b,c}	0.09 ^a	0.12 ^{a,b}	8.23***
Farmer's trust (neutral = 1)	0.11	0.10 ^a	0.11 ^{a,b}	0.14 ^b	0.10 ^a	0.09 ^a	1.87***
Farmer's trust (high = 1)	0.74	0.72 ^a	0.68 ^a	0.71 ^a	0.81 ^b	0.79 ^b	7.51***
Farmer's innovation (low = 1)	0.09	0.10 ^c	0.05 ^{a,b}	0.17	0.08 ^{b,c}	0.03 ^a	15.40***
Farmer's innovation (neutral = 1)	0.04	0.02 ^a	0.05 ^b	0.04 ^{a,b}	0.04 ^{a,b}	0.03 ^a	1.90*
Farmer's innovation (high = 1)	0.87	0.88 ^a	0.89 ^a	0.79	0.89	0.94 ^a	11.55***
Risk aversion level (switch point)	5.50	2.78	6.01 ^a	5.29	5.98 ^a	3.89	36.83***

Note: Superscript letters identify the groups that do not differ significantly between each other. A row contains more than one letter, it means that the group does not differ significantly from each of the groups identified by those letters. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Abbreviations: KE, Kenya; MA, Morocco; TN, Tunisia; TZ, Tanzania; Uda.

countries, with Morocco consistently showing lower exposure compared to other sites. Risk and trust preferences also show substantial variation: farmers in Tanzania report higher risk aversion and trust, while Moroccan farmers are more likely to be risk-neutral or risk-seeking. This shows the high degree of heterogeneity that exists across different countries when evaluating farmers' worries, distresses, and stated or revealed preferences. In our models, we control for this heterogeneity through country-fixed effects.

As a preliminary check, correlation tests between the explanatory variables and the farmers' patience levels measured through the switch point were run (Appendix B, Table B1). The highest significant correlations were found between impatience levels and social and environmental setbacks (8% and 7% respectively), being literate but with no qualification (9%) and being female (14%). Regarding farmers' preferences, we found a negative correlation between patience levels and neutral (stated) trust preferences (8%) as well as a negative correlation with farmers' revealed (experimental) risk preferences (12%). Although significant, all these correlation coefficients are very small.

Figure 2 shows how common the 10 specific setbacks are among smallholder crop and fish farmers in our five country samples. The three highest rated concerns based on past experiences are: (i) the shortage/quality/cost of available inputs—fingerlings (fish farmers), pesticides and seed feeds (crop farmers); (ii) loss of income; and (iii) pest infestation, with average values of 3.7, 3.5 and 3.0, respectively, on the original 1–5 scale. Due to the COVID-19 pandemic, and the ongoing disruption of supply chains, farmers in Africa, particularly those cultivating irrigated crops, experienced a sharp rise in the cost of imported inputs such as potassium fertilisers, seeds, plant protection products, and agricultural equipment. This increase in production costs intensified concerns among farmers regarding their incomes and profit margins (Nchanji et al. 2021).

When looking at individual countries, variations in the relevance of the experienced setbacks can be observed. While the increase in the price of farm inputs is a shared concern across countries, other country-based issues emerge as relevant. In Kenya and Tunisia, food shortage scores an average of 3.1 and 3.5 respectively. This is probably due to severe drought resulting from four consecutive failures of rainy seasons, leading to millions of people in these countries facing hunger and thirst. High inflation, climate-related disasters, conflicts, and displacement are additional local and global challenges impacting food shortages in rural Kenya.

In Morocco and Tunisia, the highest scores are observed for drought and increasing input costs. Starting from 2021, Morocco has been hit by the worst droughts in history, a consequence of climate change and inefficient water management. According to data from the Ministry of Equipment and Water (DGM 2023), drought is set to become progressively more severe in Morocco until 2050 because of scarce rainfall and rising temperatures. In particular, the 2021–2022 agricultural season was the driest in the last 40 years at least, having been marked by extreme drought, accompanied by exceptionally high temperatures, especially during the critical phases of

the cereal cycle. This is the most important factor explaining farmers' setbacks in relation to reduced rainfall and shortage of water for irrigated crops, in addition to the increased costs associated with irrigation.

In Tunisia, the effects of rising input and fuel prices, combined with stagnating farm-gate prices, are being strongly felt by local smallholder farmers. As a consequence, many farmers are reducing the area they sow. Rising prices for agricultural raw materials are also having a severe impact on livestock production, which is suffering from the combined effects of drought, forage shortages, and rising feed prices, leading to a decline in livestock numbers in recent years (Gana 2023).

In Tanzania, farmers are particularly worried about pest infestations. This is a common concern for Tanzanian farmers, already highlighted in the survey conducted by Pallangyo et al. (2019), who show that crop pests and diseases are major constraints to crop production in rural Tanzania.

Finally Ugandan farmers were mostly affected by an increase in input costs, a reduction in income, and health problems. The former two can be attributed to an increase in not only counterfeit seed and fertiliser but also their prices, and yet these are some of the most significant driving factors for optimum production. Increased input prices contribute to higher farm expenditures whilst reduced harvests owing to other factors such as weather and pest infestation result in fewer entries, consequently reducing farm income. The importance of health setbacks is probably linked to farm labour dynamics and produce marketing. Data collection was carried out amid the COVID-19 pandemic, during which farmers had experienced labour shortages. Therefore, some farmers either had not carried out some production activities or had done so with difficulty. Ugandan farmers had also faced post-harvest losses due to their inability to sell their products because of disruptions in the local food value chains.

5 | Empirical Analysis and Results

In this section, we first present the empirical model and estimation strategy used to evaluate the associations between smallholder farmers' individual characteristics, past experiences, and their time preferences, namely the MLE approach developed by Andersen et al. (2008) (Section 5.1). Then, we detail the results obtained by jointly estimating farmers' time and risk preferences, and incorporating our explanatory variables into the estimation of the discount rate (Section 5.2). Finally, we report the results of the robustness checks (Section 5.3).

5.1 | Estimation Strategy

Following Holt and Laury (2002) and Andersen et al. (2008), we assume that individual preferences over monetary outcomes in our experiment can be represented by a constant relative risk aversion (CRRA) utility function of the form:

$$U(M) = \frac{(\omega + M)^{(1-r)}}{1-r} \quad (1)$$



FIGURE 2 | Setbacks experienced by farmers during the previous year in each studied country. Self-evaluation reported on a 1–5 Likert scale. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

where M indicates the monetary reward offered in the experimental choice, ω stands for the individual's background consumption outside the experiment, and r is the relative risk aversion parameter, determining the curvature of the utility function. In particular, $r = 0$ denotes risk neutrality, $r > 0$ indicates risk aversion, and finally, $r < 0$ stands for risk-taking behaviour (with $r \neq 1$ and $\omega > 0$).

Given this functional form, the expected utility of each lottery in the risk preference task is calculated as:

$$EU = p \cdot U(\omega + M_1) + (1 - p) \cdot U(\omega + M_2) \quad (2)$$

where M_1 and M_2 represent the two outcomes of the lottery, and $U(\cdot)$ is the CRRA utility function as defined in Equation (1). To account for stochastic choice behaviour, the expected utility of each option is converted into choice probabilities via a structural noise parameter (μ), which controls for the sensitivity of choice probabilities to differences in expected utility.

Similarly, in the time preference task, we computed the present value (PV) of each delayed reward by summing period-by-period discounted utility flows, assuming that each payment was integrated with background consumption ω over periods. Considering the CRRA utility form given in Equation (1), the PVs are:

$$PV_A = \sum_{i=t}^{t+\lambda-1} \frac{1}{(1+\delta)^{i-t}} \cdot \left(\omega + \frac{M_A}{\lambda} \right)^{1-r} + \sum_{i=t+\tau}^{t+\tau+\lambda-1} \frac{1}{(1+\delta)^{i-t}} \cdot \omega^{1-r} \quad (3)$$

$$PV_B = \sum_{i=t}^{t+\lambda-1} \frac{1}{(1+\delta)^{i-t}} \cdot \omega^{1-r} + \sum_{i=t+\tau}^{t+\tau+\lambda-1} \frac{1}{(1+\delta)^{i-t}} \cdot \left(\omega + \frac{M_B}{\lambda} \right)^{1-r} \quad (4)$$

where λ is the number of periods over which the reward is consumed, τ is the time gap between Option A and Option B (in our case, 2 weeks), t the front-end delay (also 2 weeks), and $M_{A,B}$ the two outcomes of the time preference task.¹⁷ The exponent $1 - r$ reflects risk preferences, while the discount rate δ captures time preferences. A higher value of δ corresponds to greater impatience, as individuals assign less importance to delayed rewards compared to immediate ones. Similarly to the risk preferences, the PV of each option is converted into choice probabilities via a structural noise parameter (v).

The log-likelihood equation, maximised using standard numerical methods, was formulated as follows¹⁸:

$$\ln L(r, \delta, \mu, v; y, \omega, \lambda, X) = \sum_j ((\ln(\nabla EU)|y_j^{RP} = 1) + \ln(1 - \nabla EU)|y_j^{RP} = -1)) + \sum_j ((\ln(\nabla PV)|y_j^{TP} = 1) + \ln(1 - \nabla PV)|y_j^{TP} = -1)), \quad (5)$$

where $y_j^{RP} = 1$ (-1) corresponds to selecting Option B (A) in choice j of the risk preference task, while $y_j^{TP} = 1$ (-1) denotes the choice of Option B (A) in the time preference task j .¹³ Equation (5) indicates that the joint likelihood of risk and discount rate responses depends on the risk parameter r , the discount rate δ , and their respective noise parameters (μ and v). Equation (5) also assumes exogenous and time-invariant values of background consumption ω and of the periods λ over which the two delayed monetary amounts are integrated with ω . Finally, X represents a vector of farmers' individual characteristics, including farmers' self-evaluation of their exposure to social, economic, and environmental setbacks.¹⁴

To estimate our baseline specification, we assume that $\lambda = 1$, meaning that the delayed income obtained by each participant from the time preference tasks is integrated with daily background consumption and consumed over one week. The daily background consumption was set equal to 48 tokens using World Bank data on mean consumption.¹⁵ In addition to this baseline specification, we also consider variations of λ (biweekly and monthly integration in background consumption) to test the sensitivity of our estimates to different assumptions (Appendix D, Tables D1 and D2). We further conduct robustness checks by excluding the farmers who gave inconsistent responses in either the or time preference tasks (Appendix E, Table E1).

5.2 | Results

When the risk and time preference parameters are estimated without controlling for individual characteristics and experienced setbacks, we find that the farmers in our sample are, on average, moderately risk-averse, and exhibit a tendency towards impatience. As reported in Table 4, the discount rate parameter δ is estimated at 4.3% per week, implying a strong preference for immediate consumption. When annualised, this corresponds to an implied discount rate of around 90%, which is considerably higher than the rates typically reported in the literature on time preferences conducted in the lab with students in the Global North (around 10%–15% in Andersen et al. 2008; Ferecatu and Öncüler 2016, and Aungles 2021). Given the demographic characteristics of our sample, which comprises rural and often illiterate farmers, it is unsurprising that the discount rate we found is higher compared to studies involving university-educated participants. Other studies involving non-university participants report discount rates that are either aligned with or exceed our estimate (e.g., Frederick et al. 2002). The risk parameter r at 0.678, is aligned with the literature. The estimates of the two error terms provide evidence of statistically significant noise in the experiments and are aligned with Andersen et al. (2008), with larger estimates of noise for the risk task compared to the time preference one (as already discussed, risk preference games are cognitively harder than time preference tasks).

Table 5 presents the risk and time preference parameters estimated simultaneously with our covariates of interest. This

approach enables us to assess the relationship between various socio-demographic descriptors and the discount factor, which is jointly estimated alongside the risk profile of farmers.

We find a significant and negative association between farmers' time preferences and experienced social setbacks, but no link with adverse economic and environmental events. Specifically, farmers who have experienced adverse social setbacks exhibit a lower expected discount rate δ , suggesting greater patience (estimate in the model with demographic controls and session fixed effects: -0.015 ; $s.e. = 0.008$, $p = 0.06$). This effect persists across all MLE specifications reported in Table 5. This result provides new evidence on the complex relationship between adverse events and farmers' decision-making—a relationship not yet fully disentangled (Chuang and Schechter 2015) and still debated in the literature. It helps to identify the adjustment mechanisms implemented in response to experienced distress (Sullivan-Wiley and Short Gianotti 2017; Arias et al. 2019; Freudenreich and Kebede 2022), and confirms the heterogeneity in the effects that different shocks generate on farmers' time preferences (Umer and Kurosaki 2025).

Contrary to previous findings (e.g., Chesson and Viscusi 2000; Ferecatu and Öncüler 2016), we also identify a significant gender effect, with female farmers displaying significantly higher patience levels compared to their male counterparts (estimate: -0.019 ; $s.e. = 0.007$, $p = 0.01$). This finding is not universal. For instance, Aungles and Aidan (2021) and Falk and Hermle (2018) found that gender plays a role, though with different directionality, while Bauer and Chytilová (2013) confirm gender differences with women with children exhibiting a higher level of patience. Finally, the country fixed effects (not reported in the table) are significant, indicating that heterogeneity in time preferences is partly driven by geographical variations (Di Falco and Vieder 2022).

5.3 | Robustness Checks

In this section, we present a series of robustness checks to assess the consistency of our findings across alternative specifications and modeling choices.

First, we consider different values of λ to assess the sensitivity of our estimates to different background consumption models. We estimate risk and discount rates with $\lambda = 2$ (biweekly integration), and $\lambda = 4$ (monthly integration). These models correspond to scenarios where subjects do not consume the cash received all at once, presenting smoothing behaviour. The results of this check, based on the models without covariates, are presented in Figure 3. These are consistent with Andersen et al. (2008), showing only marginal changes in the risk parameter r , and more variation in the discount rate δ . The δ parameter increases from 4.3% to 4.8% when $\lambda = 2$ (11.6% increase from the value with $\lambda = 1$), and continues to rise up to 5.3% (23.3% increase) when considering monthly integration ($\lambda = 4$). This check suggests a certain sensitivity of the discount rate to increments of λ . In low-income settings like ours, some households may consume their monetary income immediately to meet urgent needs, while others may smooth consumption over time in response to,

TABLE 4 | MLE parameter estimates.

Parameter	Estimate	Robust SE	Lower 95% CI	Upper 95% CI
Risk parameter r	0.678***	0.054	0.573	0.783
Discount rate δ	0.043***	0.004	0.036	0.050
Noise parameter μ	0.145***	0.023	0.100	0.190
Noise parameter ν	0.033***	0.006	0.020	0.045

Note: Number of observations: 46,820; Number of clusters: 2341. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE 5 | MLE parameter estimates for the observed heterogeneity model, showing the impact of farmers' individual characteristics on time preferences (robust standard errors in parentheses).

Variable	Estimates on δ				
	(a)	(b)	(c)	(d)	(e)
Social setbacks	−0.023*** (0.008)	−0.018** (0.008)	−0.017** (0.008)	−0.016* (0.008)	−0.015* (0.008)
Economic setbacks	−0.014 (0.012)	−0.014 (0.012)	−0.017 (0.012)	−0.015 (0.012)	−0.017 (0.012)
Environmental setbacks	−0.010 (0.009)	0.005 (0.009)	0.003 (0.009)	0.006 (0.009)	0.003 (0.009)
Social worries	0.006 (0.010)	0.004 (0.010)	0.006 (0.009)	0.006 (0.010)	0.006 (0.009)
Economic worries	0.028** (0.013)	0.016 (0.013)	0.017 (0.012)	0.015 (0.013)	0.016 (0.012)
Environmental worries	−0.019** (0.010)	−0.014 (0.010)	−0.010 (0.009)	−0.015 (0.010)	−0.009 (0.009)
Age (years)				−0.000 (0.000)	−0.000 (0.000)
Education: literate, no qualification				−0.004 (0.013)	−0.010 (0.013)
Education: literate with qualification				0.003 (0.009)	−0.004 (0.008)
Gender (female = 1)				−0.019*** (0.007)	−0.019*** (0.007)
Income spent on food				−0.003 (0.006)	−0.008 (0.006)
Land/Pond size				0.049 (0.088)	0.072 (0.092)
Farmer's stated risk aversion (low)				0.000 (0.010)	0.000 (0.010)
Farmer's stated risk aversion (high)				0.007 (0.010)	0.010 (0.010)
Farmer's trust (low)				−0.008 (0.011)	0.006 (0.011)
Farmer's trust (high)				−0.004 (0.009)	0.002 (0.009)
Farmer's innovation (low)				0.010 (0.017)	0.006 (0.017)
Farmer's innovation (high)				−0.004 (0.014)	−0.010 (0.014)
Constant	0.067*** (0.014)	0.046*** (0.015)	0.056*** (0.019)	0.074*** (0.027)	0.076*** (0.029)
Country fixed effects	No	Yes	No	Yes	No
Session fixed effects	No	No	Yes	No	Yes

Note: Number of observations: 46,820; Number of clusters: 2341. Robust SEs in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

e.g., income uncertainty. By testing alternative values of λ , we capture both possibilities, allowing for a more flexible and realistic representation of consumption behaviour in this context.

When comparing models including individual characteristics, the results are consistent, confirming the stability of our main findings (Appendix D). Notably, the coefficient for social setbacks remains negative and statistically significant in all cases but becomes slightly larger in magnitude as λ increases. This suggests that when assuming longer consumption horizons, the association between social setbacks and impatience becomes more pronounced.

Second, we assess the robustness of our results by excluding the farmers who gave inconsistent responses in either the risk or time preference tasks (17% and 47.5% of the initial sample of 2341 individuals). Such inconsistencies may reflect limited understanding of the experimental procedures and could lead to biased parameter estimates, especially for the risk parameters

given their relevant incidence on the overall sample (see Kahsay et al. 2024 for a more detailed discussion). The discount rate δ increases from 4.3% to 7.5% when inconsistent responses are removed, suggesting that the full sample may underestimate impatience due to noise introduced by participants who struggled with the experimental tasks (Table 6). Still, both estimates reflect relatively impatient time preferences. A more striking change is seen in the risk parameter r , which drops sharply from 0.678 in the full sample to 0.175 in the subsample of consistent farmers. This suggests that risk aversion is likely overestimated in the full sample, possibly due to misinterpretation of the risk tasks, which are cognitively demanding especially for subjects in low-income countries (Bruns et al. 2022). In summary, the exclusion of inconsistent respondents yields higher estimated impatience and lower risk aversion, underscoring the importance of response quality in experimental elicitation of preferences.

When assessing the association between the discount rate and individual characteristics, results for the variables of interest

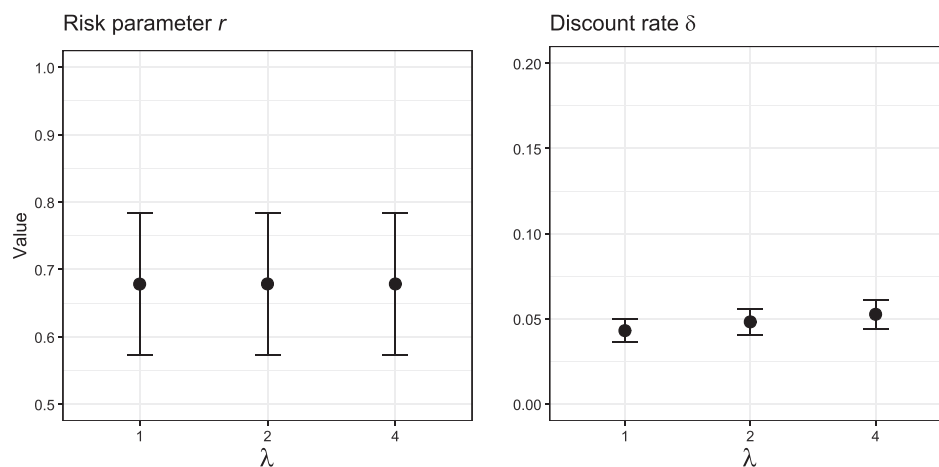


FIGURE 3 | Estimated risk and discount rates under different background consumption models ($\lambda = 1$: Weekly integration; $\lambda = 2$: Biweekly integration; $\lambda = 4$: Monthly integration).

remain robust to this exclusion, with no substantial changes in the estimated parameters (Appendix E). Farmers who have experienced adverse social setbacks continue to display significantly lower estimated discount rates δ , suggesting greater patience. One difference observed in this restricted sample is that the parameters related to concerns about future economic conditions (economic worries) are now estimated with higher precision. This pattern is consistent with the estimates obtained from a Quasi-MLE Poisson model using only consistent responses (Appendix C), suggesting that future financial insecurity may intensify present bias. If inconsistency is driven by the subjects' cognitive skills and their understanding of the experimental procedures (Bruns et al. 2022; Kahsay et al. 2024), those who understood the tasks better (i.e., those who provided consistent responses) appear to make intertemporal choices more systematically based on their expectations of future financial conditions. In contrast, social setbacks show robust effects across all samples, meaning that past social hardship is consistently associated with more patient, future-oriented choices, regardless of response consistency.

6 | Conclusions and Policy Implications

In this paper, we assessed how different adverse experiences faced by African smallholder farmers are related to their time preferences. We provide empirical evidence of this association through variables obtained from surveys combined with in-the-field experiments where we elicit farmers' time preferences by means of standard, incentive-compatible procedures. Our key finding is that there is a significant direct link between the experience of social setbacks and farmers' patience behaviour. Even though our measurement of farmers' setbacks lacks granular temporal detail and is self-reported, linking time preferences to social shocks helped shed light on decision-making behaviours African smallholder farmers might adopt in real-world situations. This represents a significant novelty in the debate on time preferences as the relation between farmers' experiences and their patience attitude has not been sufficiently explored to date.

TABLE 6 | MLE parameter estimates excluding inconsistent responses in the time and risk preference tasks.

Parameter	Estimate	Robust SE	Lower 95% CI	Upper 95% CI
Risk parameter r	0.175***	0.046	0.086	0.264
Discount rate δ	0.075***	0.004	0.066	0.083
Noise parameter μ	0.149***	0.010	0.130	0.169
Noise parameter ν	0.068***	0.006	0.057	0.079

Note: Number of observations: 23,620; Number of clusters: 1181. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Our findings suggest that farmers' time preferences are not stable over time but may shift in response to adverse social shocks leading to greater patience. This contrasts with evidence from earlier studies reporting that natural and economic setbacks are associated with greater impatience (Voors et al. 2012; Cassar et al. 2017; Bartos et al. 2018; Di Falco et al. 2019; Meles et al. 2025). At the same time, our results are consistent with Callen (2015), Chantarat et al. (2019), Begho and Anik (2022) and Umer and Kurosaki (2025), who find that farmers exposed to health-related or specific natural shocks exhibit more patient behaviours, hence anticipating future shocks. The novel contribution of this paper lies in highlighting the role of social setbacks (e.g., food shortages, health issues, violence or crime) in shaping farmers' decision-making: they appear to learn from such experiences, strengthening their ability to adjust decisions in a more forward-looking manner.

Furthermore, we find no significant effects of other potentially transitory setbacks (economic, environmental), which supports the idea that exposure to distress may induce desensitisation

under specific conditions—particularly when such events exert a direct and lasting impact on individual well-being (e.g., food insecurity, health-related challenges) or assume a collective dimension (e.g., community-wide social disruptions). This aligns with the findings of Arias et al. (2019), who explored the association between conflict dynamics and households' agricultural decisions, concluding that households may learn to adapt and operate amid social distresses such as violence or conflicts. This however contrasts with earlier studies that link impatience to past negative economic experiences, such as agricultural input price increases or income reductions (Bartos et al. 2018; Di Falco et al. 2019). One possible explanation is that economic shocks may not uniformly translate into changes in intertemporal decision-making in certain low-income rural settings where such shocks are often persistent and normalised. Farmers may adapt to chronic economic instability, rendering such setbacks less salient than social disruptions. Also, social setbacks tend to have a stronger emotional or psychological imprint (e.g., see the link between household shocks and individual mental health explored in Alem and Tato 2023). These setbacks can foster more future-oriented outlooks (e.g., higher patience) as a coping mechanism. Further research is needed to disentangle these mechanisms, especially in rural contexts in developing countries.

We also find gender to be a prominent factor associated with farmers' time preferences. This highlights the significant role that socio-demographic characteristics play in shaping the heterogeneity of time preferences, despite the lack of consensus in the extant literature (Schechter and Francis 2010). As expected, we find a significant association between revealed risk and time preferences (Appendix C). Farmers with a higher propensity to take risks are also more prone to bet on a long-term remunerating investment. This confirms the extant literature on risk and time preferences (e.g., Clot et al. 2016; Ihli et al. 2022), and the necessity of estimating both preferences jointly (Andersen et al. 2008). Scholars have also highlighted that the relationship between risks and time preferences depends on contextual factors (e.g., exogenous shocks, local history, demographic variables; Tanaka et al. 2010), thus confirming the importance of investigating the role of past experiences in influencing individuals' intertemporal and risk preferences.

Our results can help policymakers interpret how African smallholder farmers might make decisions over long-term spending and investments, purchasing habits, health and education choices in the aftermath of adverse social events. This contribution is particularly relevant for African fragile areas, where tensions and conflicts can result in quick deterioration in the living conditions and food security of farmers and communities living in rural contexts (Saulter 2014). Given the association between social distress and farmers' time preferences, policy interventions and research/sectorial strategies requiring farmers to modify their long-term spending and investments plans (e.g., for boosting agricultural productivity and innovation) should be carefully designed and properly targeted. We believe that interventions can be more effective when implemented swiftly after a localised social distress (e.g., famines, conflicts). Our work has thus direct implications for international agencies and national bodies aiming at transforming Africa's agriculture to improve its

competitiveness, speed up innovation adoptions, and fight food insecurity globally.

Author Contributions

V.M.G. formal analysis, methodology, software, writing – original draft, writing – review and editing, conceptualization, visualisation. E.C.: writing – original draft, investigation, resources. G.D.F. formal analysis, writing – Original Draft, writing – review and editing. F.K.: writing – original draft, investigation, resources. J.K.: writing – original draft, investigation, resources. N.M.: writing – original draft, investigation, resources. R.N.M.: writing – original draft, investigation, resources. E.L.N.: writing – original draft, investigation, resources. S.P.: methodology, writing – original draft, data curation, writing – review and editing, supervision. M.S.: writing – review and editing, supervision, funding acquisition.

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Ethics Statement

Approval for the activity 'FOOD and Local, Agricultural, and Nutritional Diversity (FOODLAND)-Studies of farmers' behaviours' was obtained from the Bioethics Committee of the Alma Mater Studiorum-University of Bologna (no. 190211 of 17/09/2020) and the overall project (grant no. 862802) was approved by the European Commission's ethics reviewers (panel meeting 9 September—31 October 2022). The activities presented in this article have also received approval from appropriate institutions in the countries where the fieldwork took place: (1) for Morocco, the Director of the National School of Agriculture of Meknes (approval no. 1452/D/ENA of 2 November 2020); (2) for Kenya, the Kenyatta National Hospital—University of Nairobi Ethics Research Committee (ERC) (approvals P623 and P662 of 25 November 2020), with compliance verified and confirmed ex-post by the Department of Food Science Nutrition and Technology of the University of Nairobi on 19 October 2023; (3) for Tanzania, the National Institute for Medical Research (approval no. NIMR/HQ/R.8a/Vol. IX/3605 of 9 February 2021, extended with approval no. NIMR/HQ/R.8c/Vol. I/2074 of 21 July 2022); (4) for Tunisia, the National Authority for the Protection of Personal Data (approval no. 20/01-1097 of 23 December 2020); (5) for Uganda, the Research Ethics Committee of the School of Social Sciences of Makerere University (approval no. MAKSS REC 08.20.432/AR of 11 September 2020) and the Uganda National Council for Science and Technology (approval no. A95ES of 30 November 2020).

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data associated with this manuscript are archived in Zenodo (<https://doi.org/10.5281/zenodo.14284426>). In line with the funder's requirements, it will be published with an embargo of five years from the end of the project.

Endnotes

- ¹ The FOODLAND (Food and Local, Agricultural, and Nutritional Diversity) Project is an EU Horizon 2020-funded initiative that has been running from September 2020 to February 2025. <https://cordis.europa.eu/project/id/862802>.
- ² At the time of the data collection, no COVID-19-related lockdown was in place in the studied countries. The sanitary requirements followed by the experimental teams during data collection did not impact farmers' responses according to the assessment of these teams.
- ³ Data obtained from the Kairouan regional commission for agricultural development.
- ⁴ Three of the 12 food hubs involved smallholder farmers producing fish (aquaculture). These are: Kilombero (Tanzania), where nevertheless fish farmers constitute a small subset of the sample, Kisumu (Kenya), and Kajjansi-Masaka (Uganda). Some of the survey questions were adapted to their different contexts.
- ⁵ This specific study, and the questionnaire and experimental protocols in general, were not pre-registered.
- ⁶ We used 2 and 4 weeks rather than zero and two because otherwise the choices could also be driven by transaction costs and trust towards the experimenters who should have provided the payments. With two and four, the choices should only be determined by the farmers' time preferences, since these two elements are constant across Options A and B.
- ⁷ Before fieldwork, we calculated the theoretical maximum and minimum earning in a session: between 5 and 190 tokens in the risk preferences game; between 100 and 166 in the time preferences game; between 0–30 and 300–460 tokens (different countries were assigned different treatments) in each round of the public good game; and 100 tokens as a show-up fee. The average between the minimum and maximum was set equal to 1.5 times the agricultural wage to obtain the conversion rate.
- ⁸ This procedure does not require a smartphone. According to our survey, 93.9% of the farmers who took part in the experimental sessions owned a mobile phone (99.8% in Tunisia, 98.6% in Morocco, 98.1% in Uganda, 92.7% in Kenya, and 81.1% in Tanzania). The local experimental team had access to the phone numbers of the farmers, which were used for recruitment and, where necessary, for further project activities. In Tanzania, where phone coverage is lower, most of the farmers came from a single village, which facilitated in person payments when required.
- ⁹ With such sample size, given a 0.50 baseline proportion, the minimum effect detectable in a one-proportion test with an acceptable power of 0.80, a significance level of 0.05, and a confidence interval of 0.95, is 0.029. Since some observations are lost for various reasons, the minimum detectable effect given these parameters can be slightly lower, as specified in the following.
- ¹⁰ Farmers making inconsistent choices in the time preference game (i.e., switching more than once between Options A and B) are 403. These account for 17% of the initial sample of 2341 individuals. Inconsistent responses to the risk preference game are instead 1112; 47.5% of the sample.
- ¹¹ Other dimensionality reduction techniques such as principal component analysis (PCA) and confirmatory factor analysis were trialled, but they proved ineffective in identifying a reduced number of factors that could explain a significant share of the variance.

- ¹² In the three food hubs where the sample is made of smallholder farmers producing fish (aquaculture), the farm size was not assessed in hectares, but as the total size (m²) of the farmer's ponds/tanks/cages. To facilitate uniform analysis across different measurement scales, we implemented Min-Max normalisation, creating a continuous variable that standardises the original distributions of land or production system sizes to a range between 0 and 1.
- ¹³ As in Andersen et al. (2008), we apply a clustering procedure to account for panel effects arising from unobserved individual heterogeneity. Indeed, the dataset used for the implementation of the MLE consists of a panel with 46,820 risk aversion and discount rate choices by 2341 participants.
- ¹⁴ Differently from Andersen et al. (2008), our analysis does not implement a simulated MLE, as the focus is on assessing MLE results in relation to individual characteristics and exposure to adverse events, rather than modelling unobserved heterogeneity.
- ¹⁵ For estimate the daily background consumption ω , we use the value of the World Bank's mean consumption per capita of the bottom 40% of the population (2017 PPP \$ per day), converted into 2021 local currency units and then into tokens using the conversion rate provided to the participants during the experiments. We use the value for the bottom 40% rather than for the whole population because our experiments are conducted in rural areas which are significantly poorer than the country overall. We also apply a flat rate 10% reduction to the value since the World Bank aggregate includes the consumption of durable goods. The resulting ω is the average of this value for the five countries studied. We allow for country heterogeneity through country dummies. The 'Survey mean consumption or income per capita, bottom 40% of population (2017 PPP \$ per day)' was retrieved from <https://data.worldbank.org/indicator/SI.SPR.PCAP>; the 'PPP conversion factor, GDP (LCU per international \$)' was retrieved from <https://data.worldbank.org/indicator/PA.NUS.PPP>; the 'Inflation, consumer prices (annual %)', used for the countries whose consumption level pre-dates 2021, was retrieved from <https://data.worldbank.org/indicator/FP.CPI.TOTL.ZG>.
- ¹⁶ The model goodness-of-fit was assessed using the deviance and Pearson chi-squared statistics. The deviance statistic for a Poisson regression was 2599.19, $p < 0.001$, and the Pearson chi-squared statistic was 1751.64, $p < 0.001$. This indicated evidence of poor fit leading to the selection of a Quasi-MLE Poisson model.
- ¹⁷ The structure of our experiment involved a short time horizon (i.e., two weeks) to allow for real-life payments given the timing and budgetary constraints of our project. This time horizon results in exceptionally low values for both τ and t (as per equations 7' and 8' in Andersen et al. (2008)), which, when estimating the MLE model, led to an inflation of the estimated discount rate δ . To address this issue, we estimated weekly discount rates, by adjusting the time-related exponents t and τ (Eqs. 3 and 4) to reflect the number of weeks. The structure of the utility function remains unchanged, and we maintain the assumption of daily background consumption (ω), consistently with Andersen et al. (2008), who assume that consumption utility is experienced daily even when discounting occurs over longer time horizons.
- ¹⁸ Differently from Andersen et al. (2008), our model does not assume responses that reflect indifference.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** jage70012-sup-0001-DataS1.zip.

Appendix A

TABLE A1 | Average payoff across countries and experiments.

Country	Average payoff (number of tokens)		
	Risk preferences	Time preferences	Total
Kenya	107.1	125.3	232.4
Morocco	104.3	121.7	226
Tanzania	113.5	125.8	239.3
Tunisia	132.0	128.0	260
Uganda	99.9	134.2	234.1
Average	111.8	126.7	238.5

Appendix B

TABLE B1 | Pearson's correlation tests between the time preference switch point and the explanatory variables.

Explanatory variable	Pearson's correlation coefficient	p
Social setbacks	0.08	<0.001
Economic setbacks	0.03	0.029
Environmental setbacks	0.07	<0.001
Social worries	0.04	<0.001
Economic worries	−0.03	<0.001
Environmental worries	0.05	<0.001
Age (years)	0.02	0.005
Education (illiterate = 1)	−0.04	<0.001
Education (literate, no qualification = 1)	0.09	<0.001
Education (literate with qualification = 1)	−0.03	<0.001
Gender (female = 1)	0.14	<0.001
Income spent on food	0.02	0.003
Land/Pond size	−0.04	0.000
Farmer's risk aversion (low = 1)	−0.03	<0.001
Farmer's risk aversion (neutral = 1)	−0.01	1.0
Farmer's risk aversion (high = 1)	0.03	<0.001
Farmer's trust (low = 1)	−0.03	<0.001
Farmer's trust (neutral = 1)	−0.08	1.0
Farmer's trust (high = 1)	0.03	<0.001
Farmer's innovation (low = 1)	0.00	1.0
Farmer's innovation (neutral = 1)	−0.01	1.0
Farmer's innovation (high = 1)	0.00	1.0
Risk aversion level	−0.12	<0.001

Appendix C

In this supplementary analysis, we estimate the association between smallholder farmers' attitudes and their patience level employing a Quasi-MLE Poisson model to accommodate the count data structure of our outcome variable, adjusting standard errors to account for overdispersion.¹⁶ We also account for the boundary at the upper limit of the time preference switch point (Figures C1 and C2). We treat this as an upper corner solution, given that the clustering of switch points at 10 represents a conscious, utility-maximising decision, where farmers consistently prefer the delayed but larger reward (Option B).

Our empirical equation reads as follows:

$$E[Y_{i(c,s)}] = \exp\left(\alpha + S'_{i(c,s)}\beta + W'_{i(c,s)}\gamma + X'_{i(c,s)}\delta + P'_{i(c,s)}\theta + \mu \text{risk}_{i(c,s)} + \rho_c + \partial_{s(c)}\right) + \epsilon_{i(c,s)}, \quad (\text{C1})$$

where $E[Y_{i(c,s)}]$ is the expected switch point of time preferences for the i th farmer's from country c and experimental session s , measured on a 0 to 10 patience level. The regressors of interest are farmers' experienced social, economic, and environmental setbacks ($S'_{i(c,s)}$). The model also considers social, economic, and environmental worries towards the future ($W'_{i(c,s)}$), a series of socio-demographic controls $X'_{i(c,s)}$ (farmer's age, education, gender, income spent on food purchases, and land/pond total size), farmer's stated preferences towards innovation, risk, and trust ($P'_{i(c,s)}$), as well as a measurement of the farmer's revealed risk preferences ($\text{risk}_{i(c,s)}$). We include this latter element to assess the association between temporal and risk preferences of the study participants. Finally, we include country fixed effects (ρ_c) and experimental session-fixed effects ($\partial_{s(c)}$) to control for time-invariant country- and session-specific heterogeneity. All models were tested for multicollinearity, with diagnostic results indicating no evidence of multicollinearity among the main independent variables.

Based on Equation C1, four complementary specifications for our Quasi-MLE Poisson model were estimated. The first two specifications include only social, economic, and environmental setbacks ($S'_{i(c,s)}$) and worries ($W'_{i(c,s)}$), with the second one including country fixed effects. The third specification adds the socio-demographic controls $X'_{i(c,s)}$, farmers' stated preferences towards innovation, risk, and trust ($P'_{i(c,s)}$), and the switching point in the risk preference experiment ($\text{risk}_{i(c,s)}$). The fourth one includes experimental session fixed effects ($\partial_{s(c)}$). Given that this analysis relies on consistent switching patterns, farmers exhibiting inconsistent responses in either the time or risk elicitation games were removed from the sample.

Results. Table C1 reports the estimated incident rate ratios (IRRs) from the Poisson regression models. In all specifications, the results show a positive and statistically significant effect of the experienced social setbacks on farmers' time preferences, suggesting that experiencing social setbacks is associated with higher patience. In the last two specifications, we also observe a significant and negative effect of economic worries on farmers' time preferences, suggesting that these worries lead to less patience.

Looking at the estimates from the most comprehensive specification (e), we observe that farmers who have experienced adverse social setbacks exhibit a 19% higher patience, *ceteris paribus*, while farmers who express greater concerns about future economic conditions exhibit a 17% lower patience, *ceteris paribus*. Finally, a unit increase in farmers' risk aversion, measured through the experimental lottery, is associated with a 2.7% decrease in patience. Farmers' gender, and perceived trust in the organisations promoting innovation are also significantly associated with farmers' time preferences. In particular, female farmers and farmers with higher self-reported trust in organisations are, on average, more patient, respectively by 15% and 13%.

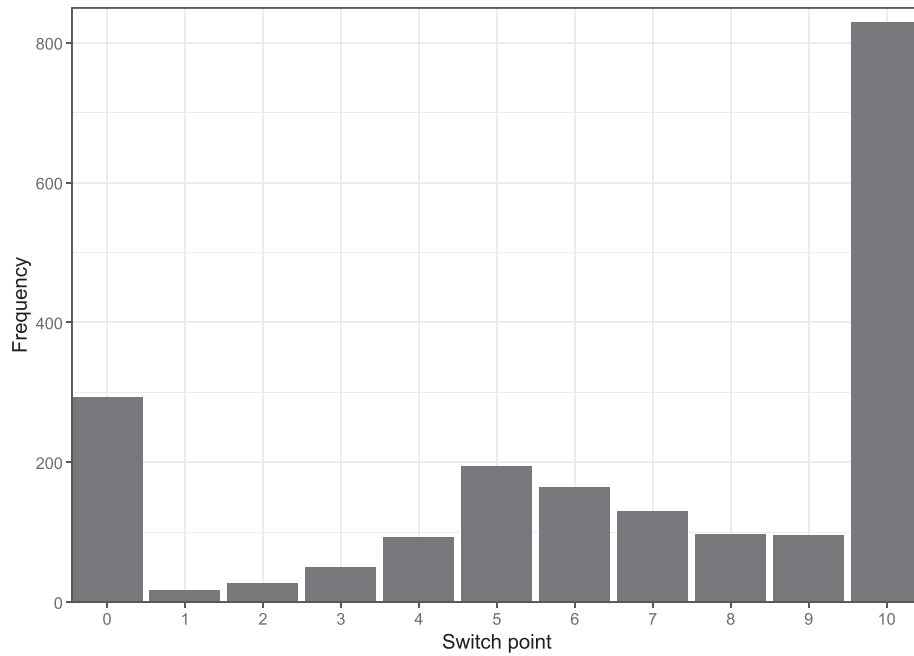


FIGURE C1 | Frequency distribution of farmers' patience (switch point); aggregate data ($N=1938$).

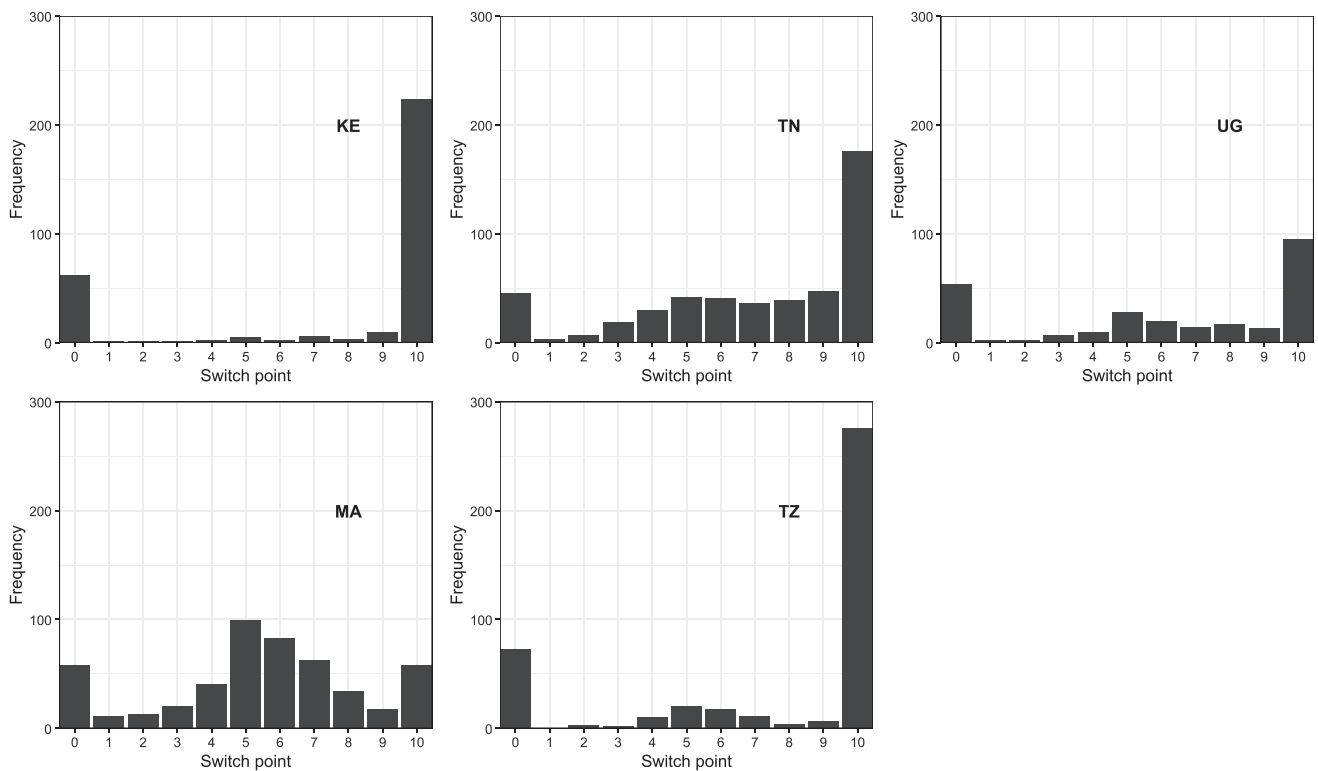


FIGURE C2 | Frequency distribution of farmers' patience (switch point) per country. KE, Kenya; MA, Morocco; TN, Tunisia; TZ, Tanzania; UG, Uganda.

TABLE C1 | Estimated effects on farmers' patience (Poisson model incident rates with robust standard errors in parentheses).

Variable	(a)	(b)	(c)	(d)	(e)
Social setbacks	1.141*** (0.049)	1.101** (0.048)	1.103** (0.049)	1.151*** (0.058)	1.190*** (0.063)
Economic setbacks	1.047 (0.069)	1.054 (0.071)	1.086 (0.073)	1.050 (0.085)	1.039 (0.082)
Environmental setbacks	1.076* (0.048)	0.973 (0.044)	0.987 (0.046)	0.940 (0.052)	0.955 (0.055)
Social worries	0.978 (0.048)	1.000 (0.050)	0.984 (0.050)	0.921 (0.053)	0.886** (0.053)
Economic worries	0.833*** (0.052)	0.900* (0.057)	0.903* (0.056)	0.824** (0.064)	0.837** (0.063)
Environmental worries	1.078 (0.055)	1.066 (0.054)	1.039 (0.053)	1.097 (0.066)	1.094 (0.070)
Age (years)				1.000 (0.001)	0.999 (0.001)
Education: literate, no qualification				1.135 (0.097)	1.159 (0.110)
Education: literate with qualification				0.989 (0.042)	1.017 (0.045)
Gender (female = 1)				1.153*** (0.048)	1.158*** (0.056)
Income spent on food				0.983 (0.038)	1.013 (0.045)
Land/Pond size				2.705* (1.529)	2.564 (1.547)
Farmer's stated risk aversion (low)				1.078 (0.071)	1.068 (0.070)
Farmer's stated risk aversion (high)				1.010 (0.067)	1.015 (0.068)
Farmer's trust (low)				1.071 (0.075)	1.001 (0.072)
Farmer's trust (high)				1.126** (0.066)	1.127** (0.067)
Farmer's innovation (low)				1.035 (0.100)	1.064 (0.105)
Farmer's innovation (high)				0.968 (0.078)	0.981 (0.079)
Risk aversion level				0.974*** (0.008)	0.980** (0.008)
Country FE	No	Yes	No	Yes	No
Session FE	No	No	Yes	No	Yes
Observations	1938	1938	1938	1181	1181

Note: Robust standard errors in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Appendix D

TABLE D1 | MLE parameter estimates for the observed heterogeneity model, with $\lambda = 2$, biweekly integration (robust SE in parentheses).

Variable	Estimates on δ				
	(a)	(b)	(c)	(d)	(e)
Social setbacks	−0.026*** (0.009)	−0.021** (0.009)	−0.019** (0.009)	−0.018* (0.009)	−0.018* (0.009)
Economic setbacks	−0.015 (0.014)	−0.016 (0.014)	−0.020 (0.013)	−0.017 (0.014)	−0.013 (0.014)
Environmental setbacks	−0.011 (0.010)	0.006 (0.010)	0.003 (0.010)	0.007 (0.010)	0.000 (0.010)
Social worries	0.007 (0.011)	0.005 (0.011)	0.007 (0.011)	0.007 (0.011)	0.004 (0.011)
Economic worries	0.032** (0.014)	0.019 (0.014)	0.019 (0.013)	0.017 (0.014)	0.012 (0.013)
Environmental worries	−0.022** (0.011)	−0.016 (0.011)	−0.011 (0.011)	−0.016 (0.011)	−0.006 (0.011)
Age (years)				−0.000 (0.000)	0.000* (0.000)
Education: literate, no qualification				−0.005 (0.015)	−0.023 (0.015)
Education: literate with qualification				0.003 (0.010)	0.002 (0.010)
Gender (female = 1)				−0.021*** (0.008)	−0.024*** (0.008)
Income spent on food				−0.004 (0.007)	−0.006 (0.007)
Land/Pond size				0.056 (0.100)	0.086 (0.104)
Farmer's stated risk aversion (low)				0.000 (0.012)	0.002 (0.011)
Farmer's stated risk aversion (high)				0.008 (0.012)	0.013 (0.011)
Farmer's trust (low)				−0.009 (0.013)	0.005 (0.013)
Farmer's trust (high)				−0.004 (0.011)	0.004 (0.010)
Farmer's innovation (low)				0.011 (0.020)	−0.006 (0.019)
Farmer's innovation (high)				−0.005 (0.016)	−0.012 (0.016)
Constant				0.083*** (0.031)	0.059* (0.033)
Country FE	No	Yes	No	Yes	No
Session FE	No	No	Yes	No	Yes

Note: Number of observations: 46,820; Number of clusters: 2341. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE D2 | MLE parameter estimates for the observed heterogeneity model, with $\lambda = 4$, monthly integration (robust SE in parentheses).

Variable	Estimates on δ				
	(a)	(b)	(c)	(d)	(e)
Social setbacks	−0.029*** (0.011)	−0.023** (0.011)	−0.021** (0.010)	−0.020* (0.011)	−0.021** (0.010)
Economic setbacks	−0.017 (0.016)	−0.018 (0.016)	−0.022 (0.015)	−0.019 (0.016)	0.002 (0.015)
Environmental setbacks	−0.012 (0.011)	0.007 (0.011)	0.004 (0.011)	0.007 (0.011)	0.013 (0.011)
Social worries	0.008 (0.012)	0.005 (0.012)	0.008 (0.012)	0.008 (0.012)	0.004 (0.012)
Economic worries	0.035** (0.016)	0.021 (0.016)	0.021 (0.015)	0.019 (0.016)	−0.005 (0.015)
Environmental worries	−0.025* (0.013)	−0.018 (0.012)	−0.013 (0.012)	−0.018 (0.012)	−0.009 (0.012)
Age (years)				−0.000 (0.000)	0.001*** (0.000)
Education: literate, no qualification				−0.006 (0.017)	−0.037** (0.017)
Education: literate with qualification				0.003 (0.011)	−0.007 (0.011)
Gender (female = 1)				−0.023*** (0.009)	−0.021** (0.009)
Income spent on food				−0.004 (0.008)	−0.010 (0.008)
Land/Pond size				0.062 (0.111)	0.133 (0.117)
Farmer's stated risk aversion (low)				0.001 (0.013)	−0.002 (0.013)
Farmer's stated risk aversion (high)				0.009 (0.013)	0.006 (0.013)
Farmer's trust (low)				−0.009 (0.015)	0.005 (0.015)
Farmer's trust (high)				−0.005 (0.012)	0.013 (0.012)
Farmer's innovation (low)				0.013 (0.022)	0.008 (0.022)
Farmer's innovation (high)				−0.005 (0.018)	−0.025 (0.017)
Constant	0.084*** (0.018)	0.058*** (0.020)	0.070*** (0.024)	0.092*** (0.034)	0.067* (0.038)
Country FE	NO	YES	NO	YES	NO
Session FE	NO	NO	YES	NO	YES

Note: Number of observations: 46,820; number of clusters: 2341. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Appendix E

TABLE E1 | MLE parameter estimates for the observed heterogeneity model, after removing the farmers who behaved inconsistently in either the risk or time preference experiment.

Variable	Estimates on δ				
	(a)	(b)	(c)	(d)	(e)
Social setbacks	−0.043*** (0.011)	−0.035*** (0.011)	−0.039*** (0.011)	−0.030*** (0.011)	−0.035*** (0.011)
Economic setbacks	−0.013 (0.018)	−0.008 (0.018)	−0.008 (0.017)	−0.008 (0.018)	−0.007 (0.017)
Environmental setbacks	−0.015 (0.012)	0.006 (0.012)	0.004 (0.012)	0.011 (0.012)	0.008 (0.012)
Social worries	0.014 (0.013)	0.014 (0.013)	0.022* (0.013)	0.018 (0.013)	0.024* (0.013)
Economic worries	0.069*** (0.020)	0.043** (0.019)	0.038** (0.017)	0.043** (0.019)	0.039** (0.018)
Environmental worries	−0.017 (0.014)	−0.010 (0.013)	−0.011 (0.013)	−0.017 (0.013)	−0.016 (0.013)
Age (years)				0.000 (0.000)	0.000 (0.000)
Education: literate, no qualification				−0.038 (0.024)	−0.042* (0.024)
Education: literate with qualification				−0.001 (0.010)	−0.006 (0.009)
Gender (female = 1)				−0.033*** (0.010)	−0.035*** (0.011)
Income spent on food				0.001 (0.009)	−0.005 (0.009)
Land/Pond size				−0.216 (0.160)	−0.173 (0.151)
Farmer's stated risk aversion (low)				−0.017 (0.014)	−0.013 (0.014)
Farmer's stated risk aversion (high)				−0.003 (0.014)	−0.005 (0.014)
Farmer's trust (low)				−0.014 (0.015)	−0.001 (0.015)
Farmer's trust (high)				−0.027** (0.013)	−0.027** (0.012)
Farmer's innovation (low)				−0.000 (0.022)	−0.008 (0.021)
Farmer's innovation (high)				0.014 (0.018)	0.008 (0.017)
Constant	0.071*** (0.021)	0.022 (0.037)	−0.703*** (0.046)	0.051 (0.045)	−0.762*** (0.052)
Country FE	No	Yes	No	Yes	No
Session FE	No	No	Yes	No	Yes

Note: Number of observations: 23,620; Number of clusters: 1181. Robust standard errors in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.