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ORIGINAL ARTICLE

Dealing with low-probability shocks: The role of selected heuristics in farmers' risk management decisions

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Abstract

Dealing with weather extremes is a major challenge for farmers and often comes at high costs for public budgets. Therefore, we investigate the influence of specific simplified decision rules, so-called heuristics, on farmers' willingness to pay (WTP) for protecting themselves against low-probability and high-consequence weather shocks. To this end, we conducted a framed field experiment with 237 farmers in Germany, using incentivized lottery-based multiple price lists. We explored the effects of different heuristics within the prospect theory framework. Our results indicate that, on average, farmers exhibit risk-loving behavior towards monetary losses, leading to a low WTP for risk mitigation. The results also suggest that the imitation heuristic, shock experience heuristics, and the threshold of concern heuristic influence farmers' WTP. Farmers specifically imitate successful farmers when these are risk-loving. The lack of personal experience with low-probability events induces farmers to assign less weight to low-probability shocks, which lowers their WTP. Farmers also systematically assign less weight to low-probability shocks that they consider "too rare to be concerned about." Accounting for the use of these heuristics can help design improved risk management instruments and policies.

KEYWORDS

behavioral economics, catastrophic risk, decision analysis, heuristics, prospect theory, risk management

JEL CLASSIFICATION

C93, D81, D91, Q12, Q54

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1 INTRODUCTION

Low-probability weather shocks, such as extreme events of hail, drought, heat, frost, or floods, are often associated with serious consequences.[1] Such events may result in yield losses, thereby threatening a farm's liquidity. Climate change increases the severity of such risks (IPCC, 2019). Farmers usually have the option of protecting themselves against these risks by paying for risk management measures such as insurance, hail nets, or irrigation. However, their willingness to pay (WTP) for protection is often low (Du et al., 2016; Glauber, 2004), and contrary to standard economic theory, it is lower than the average expected loss (Feng et al., 2020). Such deviations in risk management decisions are particularly observed for low-probability events (Kunreuther et al., 2013). Lack of self-protection can result in substantial public expenditures. For instance, the OECD countries paid over €3 billion for agricultural disaster relief in response to natural disasters in 2017–2019 (OECD, 2020, 2021). If the policy-makers want to improve the risk management policies and predict their impact, it is crucial for them to understand what motivates farmers to protect themselves against low-probability weather shocks. We explore the influence of the use of heuristics on farmers' WTP for protection against these shocks.

Heuristics, also known as "rules of thumb," are decision-making strategies that accelerate and simplify decisions by ignoring parts of the information available in the decision situation (Gigerenzer & Gaissmaier, 2011; Shah & Oppenheimer, 2008). Studies from economics and psychology have demonstrated people's conscious or subconscious application of heuristics during decision-making under risk (for an overview and discussion, see Gilovich & Griffin, 2002). People preferably imitate others instead of investing time and effort to thoroughly assess their own situation (Delfino et al., 2016). People also tend to rely on their personal shock experience, ignoring critical information that objectively reflects the probabilities (Kahneman, 2011). Furthermore, people generally neglect low probabilities that they think do not concern them (Robinson & Botzen, 2020). Simple reasoning strategies are discussed as a critical factor that explains decisions regarding low-probability shocks (Barberis, 2013; Camerer & Kunreuther, 1989; Kahneman, 2011). Numerous authors have highlighted the need for further research on heuristics in agricultural economics (Darnhofer, 2014; Just et al., 1990; Murray-Prior & Wright, 2001; Öhlmér, 1998).

Based on literature's focus on the relevance of the imitation heuristic, shock experience heuristics, and the threshold of concern heuristic for low-probability shocks, we selected these heuristics for our study (e.g., Camerer & Kunreuther, 1989; Hertwig et al., 2004; Meyer & Kunreuther, 2017). Previous research also indicates ways to influence their usage by policy-makers (e.g., Ingram et al., 2021; Meyer & Kunreuther, 2017; Robinson & Botzen, 2018). By limiting our study to the selected heuristics, we pragmatically try to strike a balance between illustrating different types of heuristics and the feasibility in our empirical study. The selection is not intended to provide a complete analysis of risk behavior.

Tversky and Kahneman's (1992) cumulative prospect theory provides a suitable framework for studying the impact of heuristics on people's decisions under risk (Pachur et al., 2017). However, when applying such a framework to analyze farmers' real-world risk behavior, it is challenging to control for all relevant confounding factors (Bozzola & Finger, 2020; Just & Pope, 2003). Therefore, agricultural economists use field experiments with farmers to analyze decisions under risk (Bocquého et al., 2014; Bougherara et al., 2017; Zhao & Yue, 2020). Studies examining the use of heuristics also use experiments to analyze the effects of imitation and experience by comparing multiple experimental treatments (Delfino et al., 2016; Hertwig et al., 2004), or to analyze the effects of threshold of concern by comparing experimental answers and specific survey questions (Robinson & Botzen, 2019a).

Field experiments of agricultural economics examine risk behavior and prospect theory parameters in "artefactual field experiments" using an abstract lottery game (e.g., Bocquého et al., 2014; Bougherara et al., 2017; Zhao & Yue, 2020). Conducting a "framed field experiment" could increase the external validity of decisions under risk by framing the experimental tasks as real farm business decisions (Cerroni, 2020; Iyer et al., 2020).[2] Also, the effect of heuristics depends on the framing of decisions (Kahneman, 2011). However, realistically framing an experiment can generate confounding factors. These may reduce the internal validity of the experiment and bias the results (Smith, 1976; Thoyer & Préget, 2019). The challenge is to balance the advantages and limits of a real and an abstract frame (Thoyer & Préget, 2019).

Existing agricultural economic studies have explored imitation (Conley & Udry, 2010; Maertens, 2017; Takahashi et al., 2019)[3] or the effect of shock experience (for an overview see Bozzola & Finger, 2020), using a prospect theory framework in lottery games (Freudenreich et al., 2017; Sagemüller & Mußhoff, 2020). However, we know of no study that has explored imitation, shock experience, or threshold of concern heuristics in agriculture using a

[1] In the remainder of the article, we refer to adverse low-probability and high-consequence shocks as "low-probability shocks."

[2] For details on the terminology of artefactual and framed field experiments see Harrison & List (2004).

[3] Since imitation is one form of social learning (for more details, see Nikolaeva, 2014), we included also studies on "social learning" in this literature review.

prospect theory framework in farm business decisions for low-probability shocks. In addition, agricultural economic studies rarely have examined the prospect theory parameters in the context of low-probability shocks. For instance, to our knowledge, only Bougherara et al. (2017) separately reported prospect theory parameters specifically for the risk of monetary losses. However, they used an abstract lottery game and only analyzed decisions for "low probabilities," using a 10% probability.[4] They refrained from collecting data on lower probabilities. The resulting monetary losses corresponded to less than 5% of the farm income (see European Commission, 2018), which is usually not an extreme loss (see Duden & Offermann, 2020).

Against this background, we aim to examine the extent to which the use of the imitation heuristic, shock experience heuristics, and the threshold of concern heuristic influence the WTP for risk management instruments against low-probability yield shocks from weather. We use the prospect theory framework to explore the effect of these heuristics in a framed field experiment with German farmers. In the experiment, we define low-probability risk as the 2.5%, 5%, and 10% probability of a 50% income drop. We quantify the effect of imitation and shock experience heuristics by comparing different treatments and the effect of the threshold of concern heuristic by means of additional survey questions. Our study makes a contribution to the limited amount of research on heuristic information processing in farmers' decision-making. Additionally, to the best of our knowledge, our article is the first to quantify the prospect theory parameters for low-probability weather shocks in agriculture and their dependence on imitation, shock experience, or threshold of concern heuristics in this context.

The remainder of this article is structured as follows: in Section 2, we refer to relevant literature to generate hypotheses on the impact of the selected heuristics on risk management decisions. Section 3 describes the experimental protocol and sample characteristics, followed by Section 4, which outlines the prospect theory framework and our econometric strategy. We present and discuss the results in Section 5 before concluding this article in Section 6.

2 | RELEVANT LITERATURE AND HYPOTHESES GENERATION

2.1 | Heuristics and prospect theory

When people make decisions under risk, integrating probabilities and outcomes is often too complex and time-intensive for many everyday decisions as it may overload people's cognitive capacities (see Pachur et al., 2017). Applying heuristics helps people find satisfactory solutions (Shah & Oppenheimer, 2008; Simon, 1979), yet in dealing with low-probability shocks, heuristics can result in strong biases (Kahneman, 2011; Kunreuther et al., 2013). These biases arise because the use of heuristics influences the subjective assessment of objective probabilities and risky monetary values (Kahneman, 2011; Kunreuther et al., 2013).

The prospect theory framework allows modeling of the subjective assessment of probabilities and monetary values, with two separate functions. The first function assigns weights to the probabilities. Neglecting low probabilities results in people assigning "less weight" to them. The second function models the assessment of risky monetary values, reflecting sensitivity to them. Thus, the prospect theory framework facilitates modeling the effects of simple decision strategies (Barberis, 2013; Kahneman, 2011; Pachur et al., 2017). Analyzing heuristics in the prospect theory framework helps understand decisions under risk because heuristics model the manner in which available information is processed (Pachur et al., 2017).[5]

2.2 | The effect of imitation

We propose that farmers tend to imitate other successful farmers in order to simplify their decision-making process. This means that they use the "imitate the successful" heuristic (Gigerenzer & Brighton, 2009; Mousavi & Gigerenzer, 2014).

Numerous studies have shown that people imitate the decisions of others (M. Andersson et al., 2014; Berg, 2014; Delfino et al., 2016). Imitating seemingly successful individuals is a frequently cited example of imitation behavior (Apesteguia et al., 2007; Nikolaeva, 2014; Offerman & Sonnemans, 1998). General economic literature emphasizes the relevance of imitation for disaster risk (Kunreuther, 2021). In agriculture, Maertens (2017) noted that a few "progressive farmers" are a major source of information on technological adoption. Moreover, previous research has indicated that extreme shocks trigger imitation behavior of farmers (Sutherland et al., 2012; Zilberman et al., 2012).[6] Against this background, we expect farmers to

[4] Other studies in a non-agricultural context often define "low" as ≤5% probability (Robinson & Botzen, 2019b).

[5] Originally, Kahneman and Tversky (1979) linked the prospect theory to a specific set of heuristics. However, in other studies, their concern was directed towards the simplifying principle of heuristics, which is not restricted to a certain set of specific heuristics (Kahneman, 2011; Tversky and Kahneman, 1992). Other authors link various heuristics to the prospect theory (e.g., minimax, maximax, priority, least-likely, and most-likely heuristics; Pachur et al., 2017).

[6] Apart from imitation heuristics, anchor heuristics can also play a role. Under anchoring, any given reference point ("anchor") can influence

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imitate risk management decisions of successful farmers (Hypothesis 1).

2.3 | The effect of shock experience

By "shock experience heuristics" we mean that farmers use their personal experience with shocks instead of an objective description of the risk for decision-making. More precisely, different types of specific, interrelated heuristics are potentially involved and described in the following.

Studies often explain the effect of shock experience on decisions with the availability heuristic (Kliger & Kudryavtsev, 2010; Nofsinger & Varma, 2013; Said et al., 2015). By applying the availability heuristic, decision-makers focus on readily available memories of events, which can be quickly recalled during risk management decisions. Furthermore, the existing literature discusses the fact that heuristics based on associativeness, that is, memories of similar already experienced shocks ("associativeness heuristic"; Mullainathan, 2002), or heuristics based on experience-related emotions ("affect heuristic"; Slovic et al., 2007), are applied to evaluate probabilities of weather-related shocks (Said et al., 2015). The existing literature also shows that people use the representative heuristic to evaluate shock experiences. In this case, people consider the information of a small subsample of observations as representative of the true risk (Tversky & Kahneman, 1971). As a result, after an extended period without shocks, people assign less weight to the shock probability than after an extended period with shocks (Fox & Hadar, 2006; Hertwig et al., 2004; Dumm et al., 2017; Dumm et al., 2020; Volkman-Wise, 2015).[7] The complete absence of shock experience plays a significant role in decision-making with respect to low-probability shocks, as these may not occur over an extended period (cf. "sampling error"; Fox & Hadar, 2006). Also farmers' future expectations depend on adverse events experienced in the past (Freudenreich & Kebede, 2022).

As a result, we hypothesize that the non-occurrence of low-probability past shocks decreases the weighting of low probabilities, in turn decreasing the WTP for risk management (Hypothesis 2).

decisions (Tversky & Kahneman, 1974). Nevertheless, since anchoring is usually an integral part of imitation, we refrain from further distinction.

[7] In contrast, the representative heuristic might induce the reaction that people, after a period with no shocks, overweight the probability of a shock because they think that a shock *has* to occur in the foreseeable future to meet the objective probability ("gamblers fallacy"; Tversky & Kahneman, 1971).

2.4 | The effect of a threshold of concern

Neglecting probabilities that are below a certain threshold is another heuristic relevant to low-probability shocks. If the perceived probability is below a subjective threshold level, known as the threshold of concern, people do not worry about possible losses (Kunreuther, 1996). Conceptual studies on decision-making for low-probability shocks emphasize the role of a threshold level (Camerer & Kunreuther, 1989; Kunreuther & Pauly, 2004; Slovic et al., 1977). In addition, existing empirical studies have found that homeowners apply the threshold of concern heuristic for assessing risk of floods (Botzen et al., 2015; Robinson & Botzen, 2018; Robinson & Botzen, 2019a). Applying a threshold level for low probabilities allows people to assign less weight to low probabilities, decreasing the WTP for risk management (Robinson & Botzen, 2020). Consequently, we expect farmers to use the threshold of concern heuristic, which decreases the weighting of low probabilities and thus decreases farmers' WTP for risk management (Hypothesis 3).

3 | EXPERIMENTAL PROTOCOL

We used a framed field experiment to elicit the WTP for risk management and its dependence on the use of certain heuristics. We manipulated the experiment for a subset of participants to analyze the imitation and shock experience heuristics. Section 3.1 describes the basic experimental design without manipulation, which is termed the "control treatment." Sections 3.2 and 3.3 illustrate manipulations of the control treatment to study the effect of imitation and shock experience heuristics. Section 3.4 describes the study's approach of exploring the threshold of concern heuristic. Finally, Section 3.5 presents further details on the implementation of the experiment.

To minimize potential biases during treatment comparison (Charness et al., 2012), the control, the imitation, and the shock experience treatment were separately implemented in three different groups of participants (see Figure 1). Participants were randomly assigned to Groups 1–3.

3.1 | Control

To elicit the WTP for risk management, we asked participants to choose between a risky option A (taking the risk of a yield loss) and a safe option B (paying a fixed amount to prevent weather-related yield losses). For this purpose, we used a multiple price list design and listed 20 binary

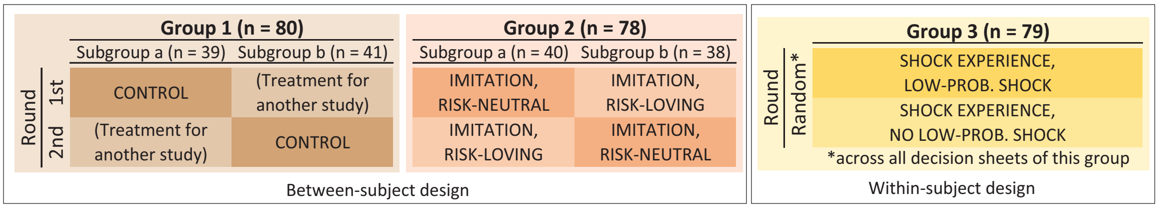

FIGURE 1 Overview of groups, treatments, and design used to compare the treatments (the treatments are highlighted in capitals).

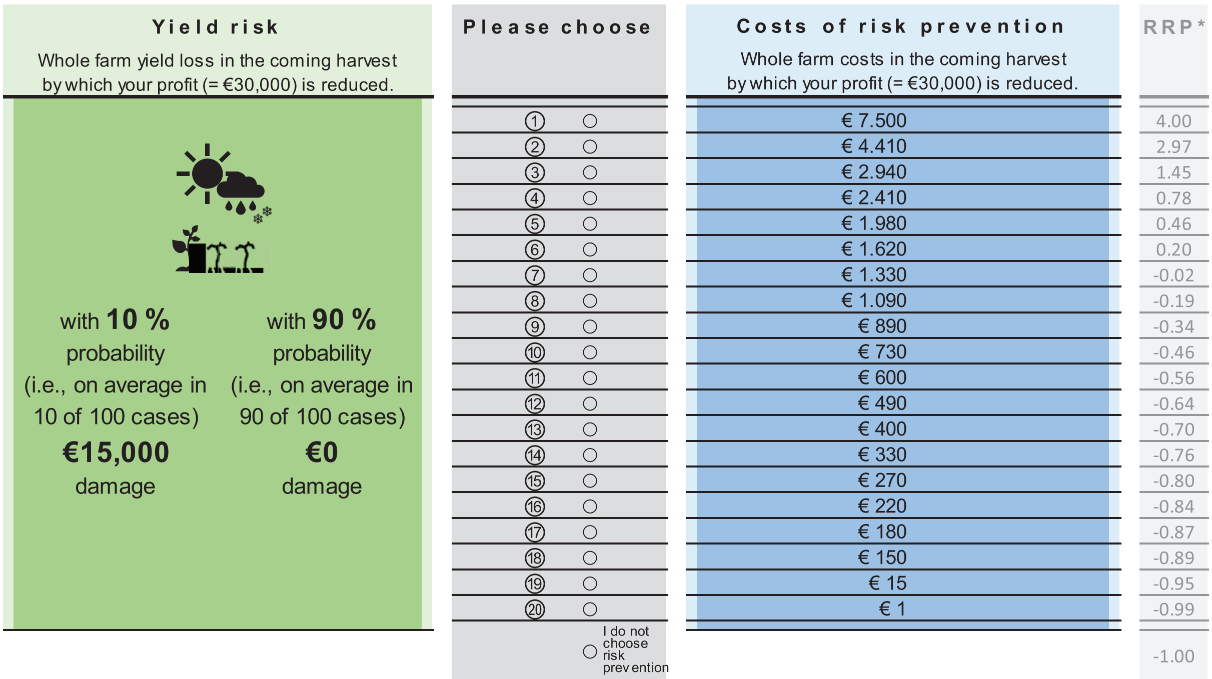

FIGURE 2 Screenshot of a decision sheet (for a farm with €30,000 profit and 10% probability of damage; translated from German).

Note: *RRP refers to the relative risk premium (see Section 5.1 for details). This column was not shown to participants.

choices in rows on a decision sheet (Figure 2). To enforce monotony of decisions, participants had to specify the maximum amount that they would pay for risk prevention. More precisely, on the decision sheet they had to specify the row at which they switched to use risk management, instead of taking the risk ("switching point"; cf. Tanaka et al., 2010). We stressed that, for costs listed in rows above the chosen switching point, they would prefer to face the presented yield risk, and that for the costs listed in rows equal to or below the chosen switching point, they would prefer the risk prevention.

The participants had to fill out several decision sheets. We included four decision sheets in the control, with different probabilities of damage ranging from 2.5%, 5%, 10%, to 30%. Although 30% is not a low probability, we included it in our study to obtain more stable estimation results and enable comparison with other studies. The decision sheets were presented in random order.

We selected the monetary values of the two options in a manner that enabled us to elicit a broad spectrum of different risk preferences for high-consequence losses. The potential loss of the risky option was 50% of the farm's profit. According to expert interviews and pre-tests, 50% is a high but realistic loss in German agriculture. The highest payment for the safe option was 25% of the profit, which corresponds to the outermost risk preference parameters of Tanaka et al. (2010) (i.e., $\sigma = 1.5, \gamma = .05$; cf. Section 4.1). The lowest offered payment for the safe option was €1 (see Bruhin et al., 2010; Robinson & Botzen, 2019a). Between the highest and the lowest values of the safe option, the payment decreased logarithmically to provide multiple risk-averse and risk-loving payment alternatives (see Tanaka et al., 2010; Tversky & Kahneman, 1992).

Our multiple price list design is a modified version of the frequently applied design introduced by Tanaka et al.

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(2010; see, e.g., Hou et al., 2020; Magnan et al., 2020; Villacis et al., 2021; Zhao & Yue, 2020). Our modification includes three changes. First, in addition to the probabilities of 10% and 30%, we also considered the probabilities of 2.5% and 5%. Second, we asked the participants to make a choice between a safe and a risky option, instead of two risky options. This simplified the experiment, a technique that is often employed in the literature (Bruhin et al., 2010; Freudenreich & Mußhoff, 2018; Robinson & Botzen, 2020; Zeisberger et al., 2012). Third, we framed the experiment in a farm business context instead of in a lottery game context (see Robinson & Botzen, 2019a; Rommel et al., 2019).

We used several measures to stress the farm business context. Following Rommel et al. (2019), we used "weather risk" as the reason for damage. In the introduction to the experiment, "weather risk" is explained as the damage from hail, heavy rain, storms, frost, drought, heat, or flooding. "Risk prevention" is further clarified as the usage of typical risk management tools, such as the adaptation of production technology, cultivation methods, or insurance.[8] Moreover, we strengthened the farm context by making the financial loss and the fixed payment dependent on the individual farm profit level (see Menapace et al., 2016). For this purpose, we asked for the individual profit level before the experiment started. In addition, we introduced the experiment to the participants with "cheap talk" (see Penn & Hu, 2018) and role-playing story (see Thomas et al., 2019; Thoyer & Préget, 2019) to minimize the potential hypothetical bias. To this end, we asked participants to "imagine" that they face the yield risk on their own real farm and "decide as if the experiment were about your own farm's money." Putting participants in a role-playing situation, that is, in a hypothetical but realistic situation that corresponds to a certain degree to real decision-making situations (Thoyer et al., 2017; Thoyer & Préget, 2019), has been increasingly used in the recent economic literature (Alekseev et al., 2017; Buchholz & Musshoff, 2021; Thomas et al., 2019; Thoyer & Préget, 2019; Viceisza, 2016). Furthermore, to avoid charity hazard behavior (see Miglietta et al., 2021), we informed the participants in our introduction that the government does not pay for disaster relief. We also explained that there is no basis risk; that is, the risk prevention in our experiment completely compensates for the illustrated yield loss. Finally, the adequacy of our contextualization was critically verified in our pre-test.

We followed literature and reduced a potential hypothetical bias by making choices "incentive compatible" (Harrison, 2007). This means that 10% of the participants were selected to receive between €50 and €100, depending on the decisions made in our experiment (see Bauermeister et al., 2018; Vollmer et al., 2019). For this, we endowed the participants with a starting capital of €100. We reduced the starting capital proportionally based on the losses incurred in the game. To determine the size of the loss, we selected one row from the entire multiple price list after completion of the experiment (see Harrison & Rutström, 2008). A random number generator specified whether a loss event had occurred. The participants could not lose their real money. To transfer the money to the winners, the participants chose between three different online shop vouchers. As an additional non-financial incentive, the participants could opt to receive an individual analysis of their own experimental choices as well as a report of the overall experimental results (see Menapace et al., 2016; Reynaud & Couture, 2012).

In addition to the control treatment, participants in Group 1 also had to complete, in reverse order, four additional decision sheets (see Figure 1). These include further variations in the damage levels and probabilities. Thus, in total, each participant in Group 1 had to complete eight decision sheets. However, except to check for order effects, the four additional decision sheets were not used in this study. The complete introduction to the experiment and screenshots of the control treatment and its manipulations are included in the supplementary material (Appendix A).

3.2 | Imitation treatment

To analyze the imitation heuristic (Group 2 in Figure 1), we manipulated the control treatment by adding an additional note on each decision sheet (see M. Andersson et al., 2014; Delfino et al., 2016). This additional note included a reference to the decision of a successful farmer. By measuring the difference between the answers of this manipulated treatment and the answers of the control treatment, we determined whether participants of this manipulation used the imitation heuristic. That is, we followed a between-subject design.

The additional note (for 10% damage probability and a farm with a profit of €30,000) was phrased as: "The manager of a successful farm of comparable structure and size in your region would spend a maximum of €1,330 on risk prevention in this situation." We performed this manipulation twice for each probability of damage. One manipulation (*IMITATION, RISK-NEUTRAL*) referred to a farmer whose maximum expenditure was equal to the expected value of damage. That is, the reference was risk-neutral, and probabilities have been neither overweighted

[8] The terms "weather risk" and "risk prevention" correspond to a level of abstraction regularly used, for instance, by widely read farm magazines in Germany (see; Brückner et al., 2018; Doms et al., 2017; Top Agrar, 2018; Top Agrar, 2020).

nor underweighted. The second manipulation (*IMITATION, RISK-LOVING*) used a reference that corresponds to a risk-loving person who both overweights low probabilities and is strongly insensitive to risky monetary values.[9] By changing the order of *IMITATION, RISK-NEUTRAL* and *IMITATION, RISK-LOVING* for half of the participants, we controlled for order effects (Charness et al., 2012; Rommel et al., 2019). In total, each participant in Group 2 had to complete eight decision sheets.

We referred to the two risk attitudes of "risk-neutral" and "risk-loving" in the imitation treatment, since according to existing literature (Bougherara et al., 2017), farmers' average risk attitude lies between these two references. By doing so, we ensure that farmers' average risk attitude and the successful farmers' risk attitude differ, which allows us to measure the use of the imitation heuristic.

To implement the additional note in our experimental setting, we extended the element of "role-playing" in the control treatment. We asked farmers not only to imagine facing the presented yield risk, but also to imagine the successful farmers' WTP in the note presented.[10] Receiving information about neighboring farmers' management decisions and preferences reflects a realistic scenario. Studies show that there are regional spillover effects of farmers management decisions (Tirkaso & Hailu, 2022), farmers exchange information of technologies in social networks (Albizua et al., 2021; Genius et al., 2014) and farmers communicate their preferences to other farmers (Läpple & Kelley, 2015).

3.3 | Shock experience treatment

Shock experience heuristics were explored in Group 3 in a within-subject design by comparing the WTP for risk prevention between two sub-treatments: (1) with the occurrence of low-probability shocks and (2) the absence of low-probability shocks (see Group 3 in Figure 1).

To introduce the treatment to the participants of Group 3, we expanded the role-playing situation of the control treatment. To this end, participants of Group 3 not only had to imagine facing the presented yield risk of future harvest, but had to also imagine experiencing a certain sequence of past shocks.[11] For this purpose, we implemented a "3-step simulation procedure" for each decision sheet.

The three-step simulation procedure began by describing the yield risk for the upcoming harvest (Figure 3, Step 1). In the second step, participants were then shown an animated representation of the historical shocks. To this end, we presented hypothetical historic shocks from 2001 to 2020, which appeared successively year by year, on a full-screen bar chart (Figure 3, Step 2). By representing a sequence of events to explore the effect of experience, we followed the literature (Bradbury et al., 2015; Eisele et al., 2021; Hertwig et al., 2004; Kaufmann et al., 2013). In the third step, participants had to make a decision using the same decision sheet that was shown to participants in the control.

This three-step simulation resembles, to some extent, a realistic situation of agricultural decision-making. In the first step, we emulate farmers being frequently confronted with expected frequencies of extreme weather events in news, agricultural magazines, or education. In the second step, we chose a 20-year history, since farmers have an average of 20 years of experience in a 40-years farming career. Our representation of the shock history also resembles, to some extent, the visualizations provided by accounting and farm management software.

Each participant completed the three-step simulation procedure ten times. Six times, the low-probability shocks occurred either in the first or second decade (*SHOCK EXPERIENCE, LOW PROBABILITY SHOCK*). In addition, there were three instances of complete absence of shock (*SHOCK EXPERIENCE, NO LOW PROBABILITY SHOCK*). To ensure completeness, we ran the simulation also once for 30% shock probability. To enable participant comparison, the years in which damages occurred were identical for all participants. For more details on the sequence of experienced shocks, see Appendix A.

3.4 | Indicator for the individual threshold of concern

After the experiment, we collected information on the threshold of concern heuristic for all participants of Groups 1–3. Participants were asked to comment on the statement with a 50% profit drop due to a weather-related yield loss: "At 2.5% [5%, 10%, 30%] probability, the damage would be too rare to be concerned about" (see Robinson & Botzen, 2019a; Robinson & Botzen, 2020). The participants responded on a 5-point Likert scale from "totally

[9] More exactly, the prospect theory parameters of this person are $\gamma = 0.4$, $\sigma = 0.4$ (cf. Section 4.1) and the relative risk premium is −0.42, −0.66, −0.73, and −0.80 for 2.5%, 5%, 10%, and 30% probability, respectively (cf. Section 5.1).

[10] To prevent deception, we informed the participants in the introduction that the situation was fictional and not real ("Of course, we do not really know what the farm in your region would pay, but only imagine this for the experiment.").

[11] Equivalent to the imitation treatment, we prevented deception (see Footnote 10).

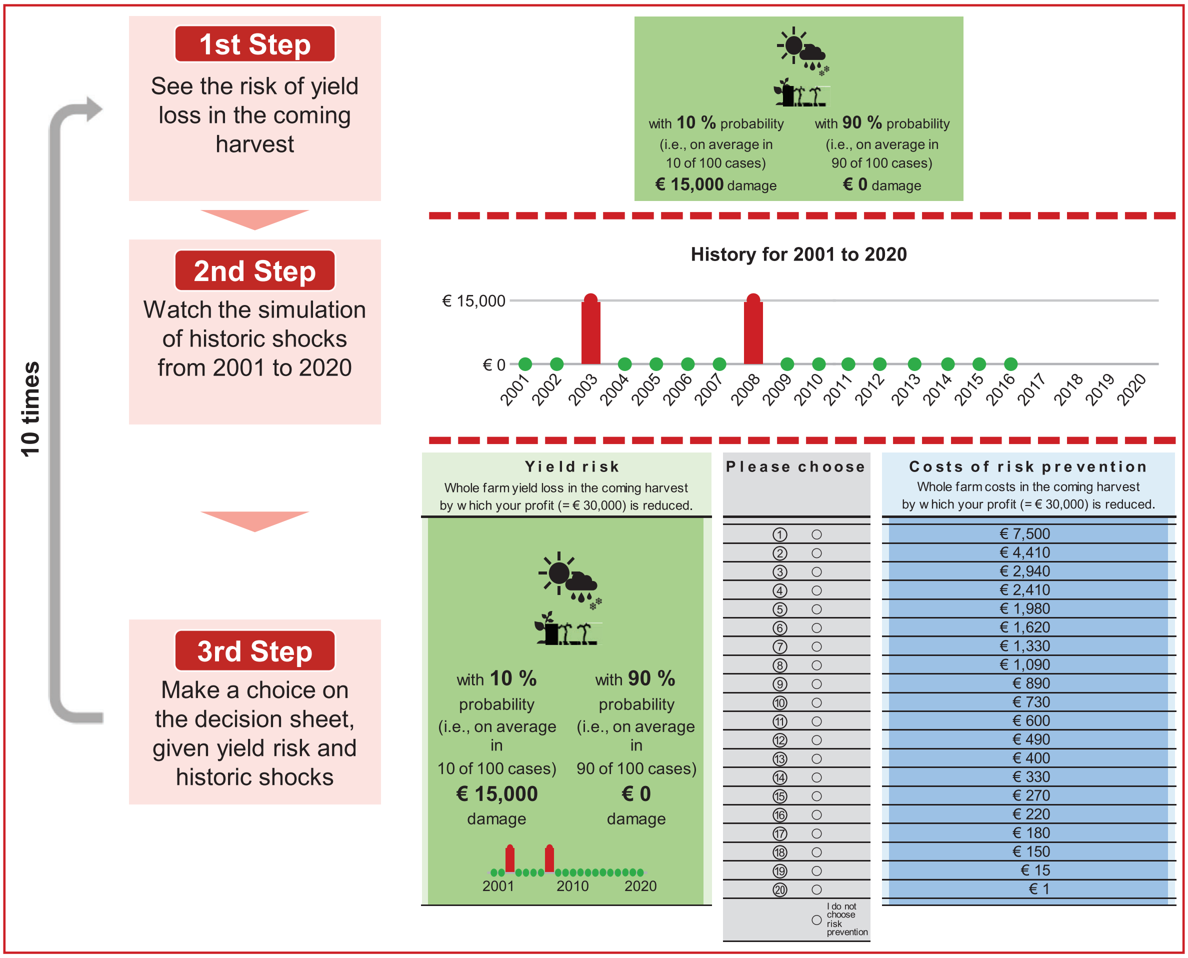

FIGURE 3 Description of the three-step simulation procedure in the shock experience treatment.

disagree” to “totally agree.” Based on their responses, we developed an indicator to measure the threshold of concern for low probabilities. The indicator is calculated as the mean response for low probabilities, that is, the mean response for 2.5%, 5%, and 10% probability. The higher the indicator, the higher the threshold of concern, and the more a participant agrees with ignoring 2.5%, 5%, and 10% probability. We accounted for the subjective definition of low probabilities by including multiple probabilities to measure the threshold of concern.

3.5 | Experiment implementation

The experiment was part of an online survey conducted between January and March 2021 in Germany. We recruited participants using mailing lists of farm consultants, agricultural magazines, and social media. Before the experiment started, information was collected on sociodemographics and farm types, followed by an introduction to the experiment and the presentation of two examples of our decision sheets. Subsequently, participants had to answer control questions to ensure their understanding of the tasks prior to the actual experiment. Finally, participants were asked to answer questions on additional farm and farmer characteristics.

A total of 237 farmers participated in the experiment. The median time required to complete the questionnaire was 30 min. Table 1 provides an overview of farm and farmer characteristics in comparison to the German farm population. Our sample overrepresents younger farmers and larger farms, presumably due to their comparatively increased interest in online experiments on management topics. Appendix B contains additional characteristics of sampled farms and farmers.

4 | PROCEDURE OF PARAMETRIC ANALYSIS

4.1 | Prospect theory framework

We explore the effect of heuristics based on the prospect theory framework. According to this framework, the

TABLE 1 Farmer and farm characteristics of our sample

Share	Participants of CONTROL	IMITATION	SHOCK EXPERIENCE	Total sample	Farm population[c]
Age < 35[a b]	.35	.26	.29	.30	.07
Age 35–55[a b]	.34	.41	.48	.41	.57
Age > 55[a b]	.31	.33	.23	.29	.36
Male[a]	.93	.92	.87	.91	.90
University degree[a]	.44	.42	.56	.47	.12
Arable land < 50 ha[a b]	.18	.12	.13	.14	.66
Arable land 50–200 ha[a b]	.46	.60	.49	.52	.29
Arable land > 200 ha[a b]	.36	.28	.38	.34	.05
Absolute number of farmers (N)	80	78	79	237	275,392

[a]No statistically significant difference between groups (Kruskal–Wallis test, p-value > .1).
[b]In accordance with the data protection rules and official statistics, age and arable land have been surveyed in classes, therefore we did not calculate the mean for these variables.
[c]German farm population(Federal Ministry of Food and Agriculture, 2019).

utility U for an option with two possible outcomes ($y_1; y_2$) and their associated probabilities ($p; 1-p$), is calculated as:

$$U = v(y_1) \cdot w(p) + v(y_2) \cdot (1 - w(p)), \quad (1)$$

where w is a function that reflects the weighting of probability p , and v is a function that determines people's valuation of monetary outcomes y . The form of the probability weighting function is discussed in the literature (see Fehr-Duda & Epper, 2012). We chose Tversky and Kahneman's (1992) one-parameter weighting function, commonly used in the relevant literature (Babcock, 2015; Bougherara et al., 2017; Zhao & Yue, 2020). The weighting function is given by:

$$w(p) = \frac{p^{\gamma}}{\left(p^{\gamma} + (1-p)^{\gamma}\right)^{1/\gamma}} \quad (2)$$

Parameter γ determines the curvature of the probability weighting function. If $\gamma < 1$, the function has an inverse-S-shaped curvature. In this case, low probabilities are overweighted ($w(p) > p$), and high probabilities are underweighted ($w(p) < p$). If $\gamma = 1$, the relationship is linear ($w(p) = p$). If $\gamma > 1$, the function has an S-shaped curvature, which includes underweighting of low probabilities and overweighting of high probabilities.

Following Tversky and Kahneman (1992), we use a power function to describe the valuation v of monetary losses y as $v(y) = -(-y)^{\sigma}$. The parameter σ determines the shape of the value function, and thus indexes the sensitivity for monetary values. The parameter σ is often between 0 and 1, which corresponds to a convex value function in the loss domain (Tversky & Kahneman, 1992). A smaller σ indicates an increasing convexity, implying a decreased sensitivity for changes in monetary values. In contrast to several applications of the prospect theory, our value function does not include a second parameter for "loss aversion" because we only consider monetary losses (Bruhin et al., 2010).

We define loss as any reduction in the farmer's wealth due to their experimental decisions (cf. "reference point"; Bocquého et al., 2014; Kahneman & Tversky, 1979). Thus, we assume that participants perceive both yield damage and insurance costs as losses.

4.2 | Parameter estimation

We applied the maximum likelihood approach in accordance with Harrison and Rutström (2008) and Bocquého et al. (2014) to estimate the prospect theory parameters, γ and σ, and their correlation with individual characteristics. Assuming that farmers are maximizing their utility, their choice is determined by the difference in utility between options A and B, which can be modeled with the latent decision index $\Delta U_i = (U_i^A - U_i^B)/\mu$. The parameter μ is a structural noise parameter, which was introduced by Fechner and popularized by Hey and Orme (1994).

We estimated the influence of individual characteristics X_i on each of the prospect theory parameters, γ and σ. We assume a linear relationship between X and the parameters γ and σ, respectively. For the instance of γ, $\gamma = \beta_{\gamma} X$. Vector β includes the coefficients to be estimated. For σ, we proceeded similarly. Since noise can bias risk preferences (O. Andersson et al., 2016), we also consider μ to be dependent on X_i (see Harrison & Rutström, 2008; Robinson & Botzen, 2020). As a result, we can describe decision

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c between options A and B depending on X_i with the following latent regression model:

$$c_i^* = \Delta U_i\ (X_i) + \varepsilon_i \text{ and } c_i = \begin{cases} A \ \ if\ c_i^* > 0 \\ B\ \ otherwise \end{cases} \qquad (3)$$

The error term ε is normally distributed with mean 0 and standard deviation μ. Consequently, from Equation (3), we can derive that the probability of choosing option A corresponds to the standard normally distributed cumulative distribution function $\Phi(\Delta U_i(X_i))$. This "probit" function converts ΔU_i into a number between zero and one. We used the probit function derived from Equation (3) to establish the following conditional likelihood function, which estimates the prospect theory parameters γ and σ:

$$\begin{aligned} &\ln\left(L\left(\gamma,\sigma;c_k,\ X_k\right)\right) \\ &= \sum\nolimits_{k\,=\,1}^{K} \left[\ln\left(\Phi\left(\Delta \mathrm{U}_k\right)\right)\cdot I\left(\,c_k\,=\,A\right) + \ln\left(1-\Phi\left(\Delta \mathrm{U}_k\right)\right)\cdot I\left(\,c_k\,=\,B\right)\right], \end{aligned} \qquad (4)$$

where I is an indicator function, which equals 1 [0], if participants chose option B [A]. Variable k is an index of all observations, including all individuals, decision sheets, and rows of the decision sheets. We implemented the estimation in STATA with clustered standard errors by individuals (Harrison, 2008).

To test Hypotheses 1–3, the matrix for individual characteristics X_i includes the threshold of concern index and a set of dummy variables to measure the effects of our treatments. A treatment dummy is set to one if a choice is a part of the respective treatment. Appendix D presents the estimation results including socio-demographics and additional farmer and farm characteristics in X_i, to control for potentially confounding factors.

5 | RESULTS AND DISCUSSION

5.1 | Descriptive results

This subsection describes the farmers' WTP and its dependence on the use of heuristics with non-parametric measures. We calculated the median relative risk premium (RRP) to make the WTP comparable for different probabilities of damages. It is defined as $RRP\ =\ (EV - CE)/|EV|$, where EV is the expected value of the risky option, and CE is its certainty equivalent (see Bruhin et al., 2010; Robinson & Botzen, 2020). In our case, CE equals participants' WTP for risk prevention.[12] A negative RRP indicates risk-loving

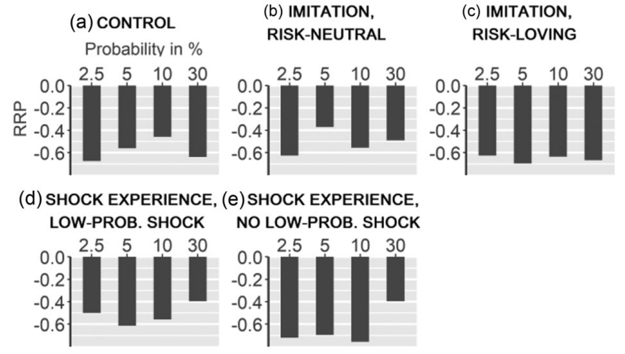

FIGURE 4 Relative risk premium (RRP) depending on probability and treatment (N= 80, 78, 78, 79, and 79 for panel a, b, c, d, and e, respectively).

behavior and a positive risk-averse behavior. In our experiment, the median RRP for the control treatment is −.57. In addition, differentiated for all treatments and probabilities, the median RRP is always negative (Figure 4). That is, participants of our experiment are risk-loving when dealing with monetary losses caused by low-probability shocks.

How does the observation about participants' risk-loving behavior with respect to low-probability shocks correspond to the numerous studies that observe risk-averse behavior? Most studies examining risk attitudes focus on monetary gains (see Iyer et al., 2020). However, the risk attitudes in the gain and loss domains usually differ (N. C. Barberis, 2013; Tversky & Kahneman, 1992). In the loss domain, empirical studies on farmers find risk-loving behavior in a stylized lottery context (Bougherara et al., 2017), as well as in the context of weather-related yield losses (Feng et al., 2020), confirming the results of our study. This risk-loving behavior implies that participants only pay for risk prevention if its costs are lower than the expected losses. However, unsubsidized insurance premiums are usually higher than expected losses. Hence, our results confirm that farmers only buy insurance against weather-related yield losses if crop insurances are highly subsidized (see Du et al., 2016; Feng et al., 2020).

The RRP measured for the control treatment is relatively low at a probability of loss of 30% and increases at a probability of 10% (Figure 4a). Such a dependence of the RRP on the likelihood of loss suggests overweighting of low probabilities and a departure from the expected utility theory often used to model decisions under risk.[13]

Due to overweighting of low probabilities, some studies find higher, even positive, risk premiums in the loss domain (Bruhin et al., 2010; Tversky & Kahneman, 1992). The consistent occurrence of negative risk premiums in our study is due to farmers' low sensitivity to monetary val-

[12] More precisely, the WTP is the midpoint of the lowest risk prevention cost at which a participant is willing to take the yield risk and the highest risk prevention cost at which a participant is willing to pay for risk prevention.

[13] We thank an anonymous reviewer for discussing the expected utility theory in this context.

ues, predominating the overweighting of low probabilities (see Section 5.2).[14]

In contrast to prospect theory predictions, we find RRPs decreasing for very low probabilities (2.5% and 5%). One reason for the low WTP for 2.5% and 5% probability might be that people are not concerned about very low probabilities—that is, they use the threshold of concern heuristic.

Comparing the control with the treatment *IMITATION, RISK-NEUTRAL* (Figure 4a,b), we expect, in accordance with Hypothesis 1, that the participants behave more risk-neutrally by referring to a risk-neutral farmer. However, we find no strong evidence for a change of the RRP (the median RRP increases for 2.5%, 5%, and 30% probability, but decreases for 10% probability; differences are not supported by a Wilcoxon rank-sum test). Comparing the control with the treatment *IMITATION, RISK-LOVING*, we expect farmers to change their behavior towards the aforementioned risk-loving farmer. The decreasing average WTP in our results confirms our expectations (Figure 4a,c; also supported by an additional Wilcoxon rank-sum test). Thus, our results indicate that participants imitate the behavior of a highly risk-loving, successful farmer.

To determine whether the absence of shock experience affects the WTP (Hypothesis 2), we compare the shock experience treatments *LOW-PROBABILITY SHOCK* and *NO LOW-PROBABILITY SHOCK*. We find that missing shock experience substantially decreases the RRP for low probabilities (Figure 4d,e; difference also supported by an additional Wilcoxon signed-rank test). We conclude that the non-occurrence of low-probability shocks decreases the WTP for risk management, due to shock experience heuristics.[15]

The responses to our additional question on the threshold of concern show that for most participants, a 2.5% probability of loss is below their threshold of concern

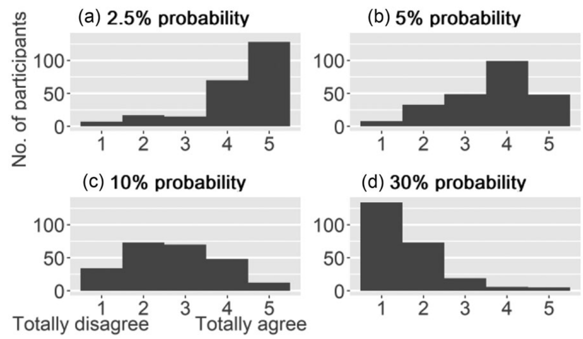

FIGURE 5 Distribution of participants' responses that the respective probability is too low to be concerned about (N=237).

TABLE 2 Average prospect theory parameters of the control treatment

	Coeff (SE)	p-value for H_0: Coeff = 1
γ	.54 (.03)	.00
σ	.45 (.02)	.00
μ	.68 (.06)	.00

Note: Nb. of obs./clusters = 6,400/80, log Lik = −2,546.03.

(Figure 5a). As expected, when the probability of damage increases, the number of farmers who express concern about potential loss grows as well (Figures 5b–d). Based on these responses, our indicator for the threshold of concern heuristic (i.e., mean response for 2.5%, 5%, and 10% probability) is on average 3.52 with a standard deviation of .94. We find that the threshold of concern indicator correlates negatively with the RRP for low probabilities (correlation coefficient = −.37). A hypothesis test confirmed a negative correlation. Thus, farmers used a threshold of concern which decreased the WTP for risk management instruments against low-probability events (Hypothesis 3).

5.2 | Parametric analysis within the prospect theory framework

We estimated the prospect theory parameters and their dependence on heuristics using Equation (4). The estimation results for the control in Table 2 show that participants are, on average, overweighting low probabilities because γ is smaller than 1. In addition, our estimation results confirm the average risk-loving behavior as σ is less than 1.[16] The estimated parameters are consistent with

[14] In the literature, the extent of positive RRP's for low probabilities in the loss domain is heterogenous. For instance, in the loss domain, studies (and prospect theory parameters elicited in these studies) indicate positive risk premiums for ≤ 50% probability (Bruhin et. al, 2010), for ≤ 34% probability (Tversky and Kahneman, 1992), for ≤ 0.01 % probability (Robinson and Botzen, 2020), or negative risk premiums for all probabilities (Bougherara et al., 2017).

[15] Furthermore, by comparing the control with *NO LOW-PROBABILITY SHOCK*, we see that adding a "3-step-simulation procedure" to the control increases the RRP for 2.5% and 30% probability (supported by a Wilcoxon rank-sum test) and decreases the RRP for 5% and 10% probability (not supported by a Wilcoxon rank-sum test). However, we do not use the comparison between the control and our shock experience treatments for further conclusions on shock experience heuristics, as these may be confounded by significant differences in the experimental setup. These differences are, for instance, using random order instead of a "block design" (see Figure 1) and conducting three steps per decision sheet instead of one.

[16] In this context, the absolute value of the noise parameter μ has no intuitive meaning. However, an increased (decreased) noise term indicates increased (decreased) random choices of participants (for further discussion see Appendix I).

TABLE 3 Influence of treatments and the threshold of concern index on probability weighting (γ), value function curvature (σ), and noise (μ)

	γ	σ	μ
IMITATION, RISK-NEUTRAL[a]	−.06	−.01	−.11
	(.04)	(.03)	(.08)
IMITATION, RISK-LOVING[a]	−.09**	−.06**	−.22**
	(.04)	(.03)	(.08)
SHOCK EXPERIENCE[a]	.03	.03	.00
	(.05)	(.03)	(.09)
SHOCK EXPERIENCE, NO LOW-PROBABILITY SHOCK[a]	.15***	.04**	.17**
	(.04)	(.01)	(.06)
Index for the threshold of concern	.06**	-.03*	.02
	(.02)	(.02)	(.03)
Constant	.36***	.58***	.61***
	(.08)	(.07)	(.13)
Nb. of obs./clusters		36,260/237	
Log likelihood		−13,251.64	

Note: Standard errors in parentheses; *$p < .1$, **$p < .05$, ***$p < .001$.
[a] = 1 if yes.

the prospect theory. Existing studies performed with similar methods also find prospect theory parameters smaller than 1, although they are slightly higher than ours. Bougherara et al. (2017), the only known study conducted with loss-risk and European farmers, but with a different multiple price list design, found $\gamma = .84$ and $\sigma = .64$. Tversky and Kahneman (1992), the only known study for loss risk with the same prospect theory specification and a similar multiple price list design, but with a sample of university students, found $\gamma = .69$ and $\sigma = .88$. One possible reason for the higher prospect theory parameters in both these studies might be that they were conducted (1) in a lottery context rather than in a yield risk context and (2) with losses less than or equal to €1000, that is, substantially smaller than the losses in our study.

In Table 3, we present the influence of heuristics on prospect theory parameters. First, we compare the parameters of the control with the imitation treatment (Hypothesis 1). Confirming our descriptive results in Section 5.1, we find no strong evidence for changes in the average prospect theory parameters γ and σ when referring to a risk-neutral farmer (Table 3). For the *IMITATION, RISK-LOVING* treatment, we find evidence for decreasing γ, that is, increasing weights for low probabilities, and evidence for decreasing σ, that is, less sensitivity to monetary values. Hence, participants adjusted their decision-making behavior in the *IMITATION, RISK-LOVING* treatment, and their choices were closer to the predetermined answers of the risk-loving, successful farmer. Moreover, for the *IMITATION, RISK-LOVING* treatment, the variation of participants' answers becomes smaller as μ decreases. Thus, we also conclude that the heterogeneity of risk management decisions decreases due to imitation. The question remains as to why farmers imitate risk-loving behavior but not risk-neutral behavior. Consistent with straightforward use of the imitation heuristic, we would have expected participants to apply the imitation heuristic regardless of whether the farmer referred to was risk-loving or risk-neutral. According to the literature, one explanation for our surprising observation is that people are more willing to interact with people who are similar in terms of beliefs or preferences (Rogers, 2003). Thus, imitating people who have a similar risk attitude, might be a variant of homophily. The effect of imitation can also be affected by confirmation bias. In such biases, humans tend to prefer perceiving, processing, and using information that confirms one's own beliefs (Kahneman, 2011).

Second, we examine the effect of shock experience on prospect theory parameters (Hypothesis 2). For this purpose, we controlled for the general effects of the *SHOCK EXPERIENCE* treatment with the dummy shock experience. We further distinguish the *NO LOW-PROBABILITY SHOCK* treatment from the *LOW-PROBABILITY SHOCK* treatment by adding a separate dummy for *NO LOW-PROBABILITY SHOCK*. We find that the absence of low-probability shocks in the *NO LOW-PROBABILITY SHOCK* treatment substantially increases γ (on average, by .15), which implies that farmers give less weight to low probabilities in these cases. Thus, we conclude that farmers use shock experience heuristics. Conducting an additional analysis and estimating average γ for the treatment *NO LOW-PROBABILITY SHOCK* reveals that γ becomes closer to 1 ($\gamma = 0.79$) but still is smaller than 1 (p-value $\leq .01$; see Appendix F). That is, participants are still overweighting low probabilities. Moreover, we expected no effect of the *NO LOW-PROBABILITY SHOCK* treatment on the sensitivity to monetary values. However, our results show that the absence of shocks increases sensitivity to monetary values, implying an increasing WTP for risk management. Nevertheless, the change in γ exceeds the change in σ, and we observe an overall increase in the WTP (cf. Section 5.1). In addition, the *NO LOW-PROBABILITY SHOCK* treatment increases the heterogeneity of responses ($\mu = .17$), which indicates that participants interpret the absence of shocks differently.

Our finding that, in the absence of low-probability shocks, people put less weight on low probabilities and thus have a lower WTP compared to situations in which shocks occur is in line with other studies (Fox & Hadar, 2006; Freudenreich et al., 2017; Hertwig et al., 2004; Li et al., 2011; Volkman-Wise, 2015). In contrast to our results, some of these studies additionally found that in the absence of recent shocks, not only the probability weight decreases but also that people underweight probabilities.

We explain this deviation from our results by the fact that these studies did not show the objective probability to participants, which can be expected to increase the effect of heuristics (Kahneman, 2011). Sagemüller and Mußhoff (2020) found no strong evidence that the absence of shocks affects probability weighting. Freudenreich et al. (2017) reported, similar to our results, that the absence of extreme shocks decreases probability weighting although farmers still overweight low probabilities.

Third, we explore the effect of neglecting low probabilities on the weighting of low probabilities (Hypothesis 3). If the threshold of concern index increases by one unit, γ increases by .06. Thus, we conclude that the threshold of concern heuristic contributes to explaining probability weighting. This finding echoes Robinson and Botzen (2020), who also found an effect of the threshold of concern heuristic for flooding risk. An additional analysis shows (see Appendix G) that for all participants who belong to the fourth quantile of the threshold of concern index (index ≥ 4), γ is still ≤ 1 (p-value $\leq .01$; $\gamma = .71$). This means that participants are overweighting low probabilities even though they state that they are not concerned about low-probability shocks. In addition, the results of Robinson and Botzen (2020) indicate a similar pattern of probability weighting for very low probabilities (<2% probability). This finding underscores the fact that overweighting of low probabilities often occurs unconsciously (Kahneman, 2011), and even if people state that they assign a low weight to certain probabilities, the weight can be relatively large compared to objective probability. Next, we find that the use of threshold of concern heuristic not only decreases the weighting of probabilities but also the sensitivity to monetary values, as the effect of the threshold of concern on σ is negative ($-.03$). This effect on sensitivity towards monetary values additionally decreases the WTP for risk management. Our results on imitation, shock experience, and threshold of concern heuristics, remain robust to various robustness checks.[17]

The following are methodological aspects for the interpretation of our results. First, the historical shocks and the behavior of the successful farmer are fictional, which could raise concerns regarding the degree of reflection of realistic farm decisions in the experiment. An alternative to using simulated fictional historic shocks could be to analyze the effect of actually experienced shocks on farmer's own farm. However, using actual shocks can bias the results, due to uncontrollable individual risk exposures (Bozzola & Finger, 2020; Freudenreich et al., 2017). Furthermore, shock simulations in the experiment ensure that the participants do not mentally compartmentalize experimental decisions and shock experiences (see Thaler, 1999). Similarly, we argue that our hypothetical design also helps measure imitation behavior, which is also difficult to quantify (see Manski, 1993). Using hypothetical experimental frames and role-playing is seen as an appropriate measure for coping with data scarcity in economic experiments (see Buchholz & Musshoff, 2021; Nielsen et al., 2013; Ortega & Ward, 2016; Thomas et al., 2019; Thoyer & Préget, 2019; Wachenheim et al., 2019). By implementing various contextualization measures and incentives (see Section 3.1), we minimized a potential hypothetical bias. Furthermore, to our knowledge, no reasons exist that other frequently mentioned causes for hypothetical biases (e.g., ethically motivated social desirability, or the persecution of particular political goals; see Penn & Hu, 2018) affect our results on the use of heuristics.

Second, the introduction of a farm business context raises doubts about the degree of contextualization. Our experiment still includes abstractions because we do not specify the type of weather risk (e.g., drought or hail) and the type of risk prevention (e.g., insurance or irrigation). This specific abstraction is intentional to improve the transferability of this study's results, as a farm typically faces a wide range of weather risks (Webber et al., 2020) that are mitigated by the individually preferred variety of risk management tools (Meraner & Finger, 2019). In addition, our slight abstraction reduces the danger of participants responding automatically without paying attention to the experimental instructions, which could undermine the internal validity of the experiment (Alekseev et al., 2017; Viceisza, 2016).

6 | CONCLUSION

This study used a framed field experiment with 237 German farmers to investigate WTP for managing risks against low-probability weather shocks and its dependency on heuristics. Our results reveal that when low-probability weather shocks require decisions involving monetary losses, average farmers exhibit risk-loving behavior. This means that the WTP is lower than the average expected yield loss. This risk-loving behavior also explains the low weather insurance take-up without subsidies (see Feng et al., 2020). Our results also highlight the influence of heuristics on risk management decisions against low-probability shocks. Farmers use the imitation heuristic to imitate other successful farmers when such farmers exhibit risk-loving behavior and not risk-neutral behavior. Farmers use shock experience heuristics; in particular, the

[17] Our results do not change qualitatively if we additionally consider confounding factors for the experimental design, farm and farmer characteristics, the individual risk exposure, and unobserved heterogeneity (see Appendix C, D, E and H). Also, the results remain robust to alternative calculations of the threshold of concern index (see Appendix J).

non-occurrence of low-probability shocks leads farmers to assign less weight to low probabilities. Furthermore, farmers apply the threshold of concern heuristic and generally neglect low probabilities, decreasing their WTP for risk management. Finally, heuristics also affect the heterogeneity of the farmers' risk management decisions.

The prospect theory allows the implementation and parameterization of heuristics in an economic framework. This study elucidates the influence of heuristics on the sensitivity to probabilities and monetary values. The observed influence indicates that the farmers did not exclusively use the given objective probabilities and multiply them with potential losses to arrive at decisions. They also relied on heuristics, which changed their WTP for risk management against low-probability events.

Many governments are interested in supporting risk management for low-probability shocks (OECD, 2021). Against this background, our study points to different policy implications. Our analysis highlights the complexities of the imitation heuristic. Only referencing "best practice farms" that exhibit a high WTP for risk management will not increase protection against low-probability risks. Our findings on the use of shock experience heuristics imply that risks should be communicated in terms of longer time periods to avoid biases due to sampling errors for low-probability events. For instance, a 5% probability of a shock occurring in the next year can be reframed as a 40% probability that the event occurs at least once in a 10-year period. Such reframing of probabilities would also reduce the danger of communicated probabilities dropping below farmers' threshold of concern (Keller et al., 2006). Risks of extreme weather due to climate changes do aggravate the bias arising from past events. Focusing on objective probabilities is important to eliminate this bias. Implementing multi-year contracts for insurance and other risk management instruments is another potential policy instrument to stabilize risk management decisions, making them independent of single past observations (Kunreuther & Michel-Kerjan, 2015).

Individual risk attitudes and the use of heuristics are firmly rooted in subconscious human decision-making (see Kahneman, 2003). Since farmers use heuristics, changing farmers' behavior with risk education might take a long time (if at all possible). In contrast, mandatory risk management (e.g., mandatory insurance) or subsidizing risk protection (e.g., for insurance) will have a much more immediate effect. However, this advantage has to be weighed against drawbacks of market distortions (OECD, 2009, 2021), especially since our results show the need for substantial subsidies to achieve high market penetration of risk management instruments against low-probability weather shocks.

Our study has some limitations. Although the degree of contextualization is higher than in agricultural economics literature with multiple price lists (Rommel et al., 2019; Villacis et al., 2021), there is room for improvement, for instance, by asking specifically for the WTP for drought insurance. We expect that the effect of heuristics will be amplified through a higher degree of contextualization, which will lead to further intuitive actions. The use of heuristics depends on the context, thus opening avenues of further research on heuristics with other types and degrees of contextualization.

Another limitation is the lack of varying levels of loss in the experiment due to experimental time constraints. Such variation in future studies will aid in an in-depth exploration of its influence on the WTP for risk management. It would also be of interest to future researchers to examine alternative farmers' reference point in the prospect theory framework (see Feng et al., 2020). Finally, future research should investigate the effect of heuristics in situations where the probability of damage is unknown and must be estimated by farmers. Since probability estimation is assumed to involve a similar process as probability weighting (Kahneman, 2011), we expect that the effect of heuristics will increase under ambiguity.

DATA APPENDIX AVAILABLE ONLINE

A data appendix to replicate the main results is available in the online version of this article. Please note: Wiley-Blackwell is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the corresponding author for the article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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