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Research

From risk behavior to perceived farm resilience: a Dutch case study

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ABSTRACT. In an era where farmers face considerable levels of intertwined risks and uncertainties, farm resilience is developing into a focal point for agricultural policies. Using survey data from 916 Dutch farmers, we explore how risk behavior relates to perceived resilience. We capture the dynamics of resilience thinking by investigating past risk-management portfolios, current risk preferences, future risk perceptions, and perceived resilience. Partial least squares structural equation models (PLS-SEM) indicate that higher perceived robustness, adaptability, and transformability relate to these farmers with a more resilient future. Additionally, results show the importance of risk management in assessing perceived resilience. More specifically, we find that more diverse risk-management portfolios are associated with (i) higher perceived adaptability and (ii) in specific cases, higher perceived transformability.

Key Words: *Adaptability; Partial Least Squares Structural Equation Model (PLS-SEM); resilience; risk management; risk perception; risk preference; robustness; transformability*

INTRODUCTION

In an unpredictable world with changing economic, environmental, social, and institutional conditions, dealing with risk and uncertainty has always been a ubiquitous feature of agricultural production (Chavas 2011). To cope with these interrelated risks and uncertainties, farm adaptation and transformation are becoming increasingly relevant (Ghahramani and Bowran 2018). Moreover, stimulating farm adaptation and transformation requires a shift from dealing with the expected to the unknown future. Depending on farmers' ability to overcome the consequences of risks and uncertainties, farm resilience is potentially threatened (Darnhofer 2014). As farmers' risk-management strategies, risk perceptions, and risk preferences determine how farmers cope with risks (van Winsen et al. 2016, Meraner and Finger 2019), risk behavior is inherently related to resilience. To this end, this paper explores the role of farmers' risk behavior in assessing perceived farm resilience.

Resilience thinking acknowledges the role of complexity and the unknown in a dynamic farm operating environment (Cabell and Oelofse 2012, Darnhofer 2014). Our understanding of farm resilience is adapted from Meuwissen et al. (2019), who defined resilience as the ability to ensure the provision of functions while facing increasingly complex and accumulating economic, environmental, social, and institutional shocks and stresses through the resilience capacities of robustness, adaptability, and transformability. Robustness relates to the capacity to withstand expected and unexpected shocks and stresses (Walker et al. 2009). Adaptability is the capacity to adjust to shocks and stresses by changing the composition of inputs, production, marketing, and risk management (Meuwissen et al. 2019). Transformability is the capacity to radically change the internal farm structure to cope with severe shocks and enduring stresses, which might also imply the delivery of alternative and/or additional farm functions (Meuwissen et al. 2019). Although this social–ecological understanding of resilience underlines the importance of adaptation and transformation, empirical assessments of these capacities remain challenging due to the abstract nature of resilience (Cumming et al. 2005).

As resilience is a latent concept (Clare et al. 2017), indirect assessment methods are required. These assessments can be classified into two approaches. The first approach captures the multidimensionality of resilience by defining several indicators (e.g., Resilience Alliance 2010, Cabell and Oelofse 2012, Choptiany et al. 2017, Jones and Tanner 2017, Diserens et al. 2018, Stone and Rahimifard 2018, Jones and d'Errico 2019). Despite their implicit objective orientation, operationalization and quantification of the resilience indicators remain complex as these resilience assessments are context specific, resulting in incomparable assessments across different regions (Pelling 2011, Jones et al. 2018). The second approach assesses perceived farm resilience (e.g., Marshall et al. 2011, Béné et al. 2012, Marshall and Smajgl 2013, Marshall et al. 2014, Peerlings et al. 2014, Jones et al. 2018, Jones and d'Errico 2019). This approach recognizes farmers' ability to judge their own resilience capacities (Jones et al. 2018) and explains behavior and decision making under risk and uncertainty (Jones and d'Errico 2019). Additionally, perceived resilience assessments allow for comparison across regions, as the questions are applicable in other contexts (Clare et al. 2017). Our perception-based approach uses self-assessment questions to measure farmers' robustness, adaptability, and transformability.

Although perceived resilience and risk behavior are evidently related (Ansah et al. 2019), no empirical applications exist that simultaneously investigated how risk management, preferences, and perceptions are associated with perceived farm resilience. Previous studies succeeded in partially capturing these relationships, including how single risk-management strategies might enhance specified farm resilience—the resilience to deal with one specific risk (Carpenter et al. 2001, Folke 2016). For instance, there is mixed evidence on how diversification might enhance perceived resilience to cope with agricultural policy changes. Peerlings et al. (2014) found that specialized farmers perceived themselves as more resilient, whereas Sutherland et al. (2017) showed that Scottish crofters applied diversification into agritourism and forestry as an adaptation strategy to agricultural policy changes. However, these studies did not account for the

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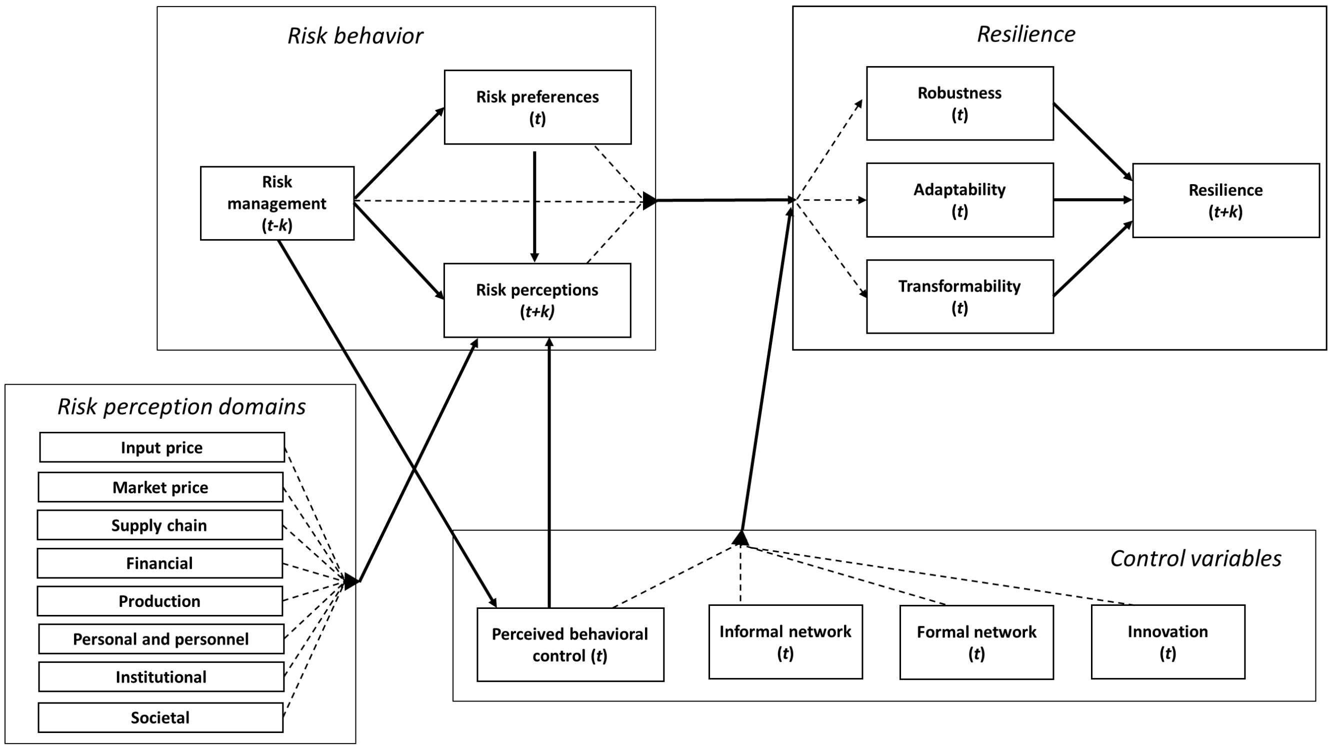
Fig. 1. Conceptual framework to assess perceived farm resilience. Past (t-k), current (t), and future (t+k) variables are included. The arrows from the control variables and risk behavior boxes to resilience indicate that all variables within the corresponding box relate to perceived robustness, adaptability, and transformability.



unknown as they target one specific risk. We investigate general resilience, which is more complex than specified resilience as it embodies dealing with risk in general (Folke 2016) and the unknown (Carpenter et al. 2012). A broad view on risk management, which embraces a portfolio of strategies, is likely to be required to prepare farmers for an unknown future. Although several empirical investigations explain why farmers adopt certain risk-management portfolios (Coffey and Schroeder 2019, Meraner and Finger 2019, Vigani and Kathage 2019), none of these studies connected farmers' risk-management portfolios to general resilience. To fill this research gap, this study investigates how farmers' risk behavior is associated with general resilience.

A decent farm income helps ensure farm continuity (Saint-Cyr et al. 2019) and foster resilience (Cabell and Oelofse 2012). In resilience thinking, farm income is considered as one of the functions provided by farmers (Meuwissen et al. 2019). Other examples of farm functions are maintaining natural resources in good condition, managing animal welfare, or providing employment and good working conditions. Farmers often pursue a combination of economic and noneconomic functions (Anderson and McLachlan 2012); however, a decent farm income is required to facilitate other functions (ten Napel et al. 2006). Therefore, it is worth investigating how farm income shapes perceived resilience.

Against this background, we aim to explore the relationship between farmers' risk behavior and perceived resilience. This paper expands the current literature in two ways: (1) we examine how farmers' risk-management portfolios, perceptions, and preferences are related to perceived general resilience in terms of robustness, adaptability, and transformability, and (2) we explore how farm income explains differences in perceived resilience. Our empirical application focuses on Dutch farmers, who have recently faced a complex mix of risks. Therefore, Dutch farmers are a relevant population for resilience research.

CONCEPTUAL FRAMEWORK

We build upon agricultural risk behavior (Hardaker et al. 2015) and resilience theory (Holling 1973, Darnhofer 2014, Folke 2016) to explore how risk management, perceptions, and preferences relate to perceived resilience (Fig. 1). Our conceptual framework describes (1) the relationship between risk-management portfolios, perceptions, and preferences, (2) how perceived robustness, adaptability, and transformability relate to perceived resilience, (3) the relationship between risk behavior and perceived resilience, and (4) how several control variables relate to risk behavior and perceived resilience. Capturing backward- and forward-looking system dynamics is required to assess resilience (Folke 2016). Therefore, we investigate farmers' past perceptions (*t-k*), current perceptions (*t*), and perceptions of future events (*t+ k*), where *t-k* refers to the past 5 years, *t* refers to the current year, and *t+k* refers either to the next 5 or 20 years. The next subsections will discuss the various building blocks of the conceptual framework.

Risk behavior

Risk-behavior theory uses static approaches to investigate the complex interactions between farmers' current risk-management decisions, risk perceptions, and risk preferences (Meuwissen et al. 2001, Meraner and Finger 2019). This simplified representation of risk behavior does not account for the influence of past behavior on current or future decision making under risk (van Winsen et al. 2016). To this end, we use a dynamic approach that accounts for farmers' risk-management portfolio in the last 5 years, current risk preferences, and future risk perceptions over the next 20 years. As past risk-management decisions cannot be explained by current or future perceptions, we investigate the role of past risk-management strategies in shaping current risk preferences and future risk perceptions.

Traditional understandings of risk management primarily underlined the economic dimension of risk coping. For instance, Schmit and Roth (1990) defined risk management as the strategies to minimize the costs of risks regarding potential losses, while considering the costs of risk reduction. In the context of resilience, we understand risk management as the portfolio of strategies that farmers adopt to minimize the impact and potential costs of risk on economic, environmental, and social farm functions. Risk perceptions are farmers' subjective interpretations of domain-specific risks (Meraner and Finger 2019). To account for domain specificity, we selected eight predefined risk-perception domains (Fig. 1). Risk preferences are a farmer's orientation toward taking or avoiding risk (Gardebroek 2006, van Winsen et al. 2016). Farmers can range from risk averse to risk neutral to risk taking, and most empirical findings suggest that farmers are to some degree risk averse (Iyer et al. 2019). Therefore, more risk-averse farmers will be referred to as farmers with low risk preferences, and less risk-averse farmers are those farmers with high risk preferences. Heterogeneity in risk preferences is shaped by differences in wealth or farm income (Dohmen et al. 2011, van Winsen et al. 2016), and can be further explained by several other farm and farmer characteristics, including age (Dohmen et al. 2017), gender (Dohmen et al. 2011), and farm size (van Winsen et al. 2016).

We expect that farmers who have adopted a more diverse risk-management portfolio in the last 5 years have taken more actions to reduce the presence of risk (van Winsen et al. 2016). Therefore, they will be better equipped to cope with future risks. Hence, hypothesis 1a (H1a) states that farmers with a more diverse risk-management portfolio in the last 5 years will perceive lower future risk (Table 1). Furthermore, a more diverse risk-management portfolio over the last 5 years allows farmers to take more risks as it widens response options to risks. We hypothesize that farmers with more diverse risk-management portfolios over the last 5 years are less risk averse (H1b). Several lines of evidence suggest that less risk aversion results in lower perceived risk (Keil et al. 2000, Cho and Lee 2006, van Winsen et al. 2016). Therefore, we argue that less risk-averse farmers are expected to have lower future risk perceptions, as they perceive future risky situations as less severe (H1c).

Table 1. Overview of the hypothesized relationships and their expected signs. + positive relationship, - negative relationship, -/+ the relationship will be determined by the study

Relationship	Expected sign
H1a Risk management (t-k) → risk perceptions (t+k)	-
H1b Risk management (t-k) → risk preferences[†] (t)	+
H1c Risk preferences (t) → risk perceptions (t+k)	-
H2a Robustness (t) → resilience (t+k)	+
H2b Adaptability (t) → resilience (t+k)	+
H2c Transformability (t) → resilience (t+k)	+
H3a Risk management (t-k) → robustness (t)	+
H3b Risk management (t-k) → adaptability (t)	+
H3c Risk management (t-k) → transformability (t)	+
H4a Risk perceptions (t+k) → robustness (t)	-
H4b Risk perceptions (t+k) → adaptability (t)	-
H4c Risk perceptions (t+k) → transformability (t)	-
H5a Risk preferences (t) → robustness (t)	-
H5b Risk preferences (t) → adaptability (t)	-/+
H5c Risk preferences (t) → transformability (t)	+

[†] In this study, risk preferences are understood as a scale ranging from risk averse to risk taking. Therefore, the positive sign indicates that farmers with more (less) diverse risk-management portfolios are expected to be less (more) risk-averse farmers. This applies to all hypotheses.

Resilience

Resilience theory describes how robustness, adaptability, and transformability are exploited to manage a dynamic and uncertain world (Folke 2016). The importance of the three complementary resilience capacities depends on the context in which farms operate, the timescale, and the depth of change (Cabell and Oelofse 2012, Termeer et al. 2019). In a predictable era of slow and marginal changes, the farm focus will be more on robustness and adaptability, whereas farmers need to emphasize the ability to transform in a period of radical change (Darnhofer 2014, Béné and Doyen 2018). Our conceptual framework describes how these resilience capacities jointly shape farmers' perception of future resilience. To this end, we expect that an improved ability to absorb, adapt, or radically change ensures the provision of farm functions (Meuwissen et al. 2019). Therefore, we hypothesize that higher perceived robustness, adaptability, or transformability are related to higher future farm resilience (H2a–2c).

Besides describing how farmers exploit their resilience capacities, resilience theory emphasizes the importance of delivering essential farm functions (i.e., the delivery of public and private goods) (Walker et al. 2004, Meuwissen et al. 2019). We account for farm functions by considering how farm income might explain differences in perceived resilience. Several studies have begun to examine how farmers with different financial goals and functions differ in terms of risk behavior (Greiner et al. 2009, Greiner and Gregg 2011, Bopp et al. 2019). We will expand this conceptual lens by comparing the perceived resilience of two groups: a group of farmers who perceived obtaining farm income as more important and a group who perceived obtaining farm income as less important.

From risk behavior to perceived resilience

Understanding the relationship between risk behavior and perceived resilience requires thorough insights into the interactions among risk management, perceptions, preferences, and perceived resilience capacities. Both risk and resilience literature describe how risk-related variables help to explain resilience (e.g., Scholz et al. 2012, Park et al. 2013, Aven 2017, 2019). Therefore, we describe how risk management, preferences, and perceptions are related to perceived resilience (Marshall and Marshall 2007, Grothmann and Patt 2005, Marshall and Stokes 2014, Marshall et al. 2014).

Farmers with more diverse risk-management portfolios enhance their response diversity, which helps them to deal with unknown future risks (Resilience Alliance 2010). An increased response diversity to risks will help farmers improve their capacity to absorb negative consequences, adjust responses, or radically change their farm. Therefore, farmers with a more diverse portfolio of risk-management strategies over the last 5 years are expected to perceive themselves as more robust, adaptable, and transformable (H3a –3c).

Ansah et al. (2019) described that risk perceptions negatively shape all perceived resilience capacities because farmers with higher risk perceptions struggle more to overcome the consequences of risks. The separate relationship between risk perceptions and perceived robustness (Marshall and Marshall 2007), adaptability (Marshall and Stokes 2014), or transformability (Marshall et al. 2014) has been examined. For instance, Marshall et al. (2014) found that higher risk perceptions restricted farmers' ability to identify new transition opportunities, constraining perceived transformability. Extrapolating the findings of Marshall et al. (2014) to all perceived resilience capacities, we expect farmers' future risk perceptions to be negatively related to perceived robustness, adaptability, and transformability (H4a–4c).

More risk-averse farmers are less likely to make big and risky investments and are more likely to maintain the status quo (Ansah et al. 2019), whereas less risk-averse farmers are expected to more easily introduce radical changes and are better able to transform. Although some transformations might result in less risky production systems, the radical change toward a new production system is risky and requires willingness to take risk. We expect less risk-averse farmers to perceive themselves as less robust (H5a). The relationship between risk preferences and perceived adaptability could be either positive or negative (H5b), whereas less risk-averse farmers are expected to perceive higher transformability (H5c).

Control variables

We control for farmers' perceived behavioral control, openness to innovation, and formal and informal networks in relation to perceived resilience. First, perceived behavioral control reflects the perceived ability to overcome obstacles in reaching one's goals (Ajzen 2002). In this study, perceived behavioral control is framed as a farmer's perceived ability to deal with risk. Therefore, perceived behavioral control is expected to be positively related to perceived resilience (Ansah et al. 2019) and negatively associated with risk perceptions (van der Linden 2015). Second, more innovative farmers are more likely to try out new farm practices or technologies, which makes them better equipped to change (Glover 2012). We expect a positive relationship between openness to innovation and all perceived resilience capacities. Finally, having a larger informal or formal network improves farmers' social capital (Hunecke et al. 2017) and is therefore expected to enhance resilience (Cabell and Oelofse 2012).

EMPIRICAL MODEL

To explain the relationship between risk behavior and resilience theory (Fig. 1), a partial least squares structural equation model (PLS-SEM) was estimated using Smart PLS 3 (Ringle et al. 2015). Most of the elicited constructs are latent, indicating that they cannot be directly observed and measured. PLS-SEM is a nonparametric multivariate technique that investigates latent constructs by combining the structural model, which specifies the relationships between latent constructs, and the measurement model (Hair et al. 2016). Measurement models specify how each latent construct was formatively or reflectively measured. Formative measurement models present a relationship from indicators to latent constructs, where changing indicators cause the construct to change (Diamantopoulos and Winklhofer 2001, Sarstedt et al. 2017). Reflective measurement models explain the relationship from the latent construct to the indicators, where a change in the latent construct reflects on the indicators (Bollen and Lennox 1991, Diamantopoulos and Siguaw 2006). As our study is exploratory and combines formative and reflective measurement models into a complex model, PLS-SEM is the most suitable estimation approach (Hair et al. 2017). We followed the measurement invariance of the composite models (MICOM) procedure (Henseler et al. 2016) to account for observed heterogeneity based on the perceived importance of farm income. This procedure determines if the data set is suitable for multigroup analysis (MGA).

DATA

A survey among Dutch farmers was conducted to assess how risk behavior is associated with perceived resilience. Two experts of the Dutch Farmers Union and an interdisciplinary group of researchers provided feedback on the survey. Subsequently, four Dutch farmers pretested the survey, after which some statements were reformulated or omitted. The finalized survey was sent out by e-mail in November 2018 to about 9000 randomly selected Dutch farmers, using a database of an agricultural publisher. To the best of our knowledge, the readership of this publisher can be considered to cover the diversity of the Dutch farming sector and comprehensively reflects the sector as a whole. Additionally, we placed advertisements on the website of this publisher and sent a reminder in December 2018 to increase response rates. This resulted in 1537 responses (17% response rate) of which 926 (60.25%) completed surveys without any missing data. The high dropout rate (39.75%) can be explained by the relatively long duration of the survey. We randomly raffled one tablet and 24 vouchers of €25 among the respondents. Ten respondents indicated to be agricultural contract workers and were left out for further analysis, resulting in a final sample of 916 farmers. This sample meets the sample size requirements of Barclay et al. (1995) who recommend a sample size of ten times the largest number of formative indicators in a construct or ten times the largest number of paths going from a construct into the structural model.

The survey was designed to measure six constructs: (1) perceived resilience, (2) risk-management portfolios, (3) risk perceptions, (4) risk preferences, (5) farm functions, and (6) other farmer characteristics. Unless stated otherwise, all items were measured on a seven-point Likert scale. The scores of the negatively worded items were reversed during the analysis. Table 2 presents the item wordings and summary statistics.

First, farmers selected their adopted risk-management strategies over the past 5 years (*RM*) from a list of 22 risk-management strategies (Meuwissen et al. 2001, Flaten et al. 2005, van Winsen et al. 2016, Meraner and Finger 2019). These risk-management strategies were classified into seven categories: flexibility, cooperation with others, financial risk management, measures to control environmental risks, specialization, diversification, and learning (see Table A1.1 for more details). An index of farmers' risk-management portfolios was created by counting in how many categories at least one strategy was selected.

Second, we used a subjective approach to elicit farmers' future risk perceptions (*RISK PERC*) with respect to 17 risk sources. The selected risk sources were based on a literature review (Meuwissen et al. 2001, van Winsen et al. 2016, Meraner and Finger 2019). Farmers were asked to indicate their expectations about how challenging certain risks would become in the next 20 years in the following domains: input price, market price, financial, supply chain, production, personal and personnel, institutional, and societal (Table 2). We controlled for farmers' domain-specific risk perceptions as first-order constructs and combined them into a second-order construct that represents general risk perception.

Third, we elicited farmers' risk preferences (*RISK PREF*) using a combination of self-assessment and business statements (Iyer et al. 2019). Farmers were asked to provide a general self-assessment of their risk preferences using one reflective item on an 11-point Likert scale (Dohmen et al. 2011). Additionally, we elicited domain-specific risk preferences using five formative business statements (e.g., Meuwissen et al. 2001, Meraner and Finger 2019). These statements elicited farmers' relative risk preferences—risk preferences relative to other farmers—regarding the following subjects: (1) production, (2) marketing and prices, (3) financial risks, (4) innovation, and (5) farming in general. The fifth statement was excluded from further analysis because it does not represent a specific domain. Therefore, this statement is not suitable to fit into a formative construct that comprises farmers' general risk preferences based on different domains.

Fourth, perceived farm resilience was measured using an indirect and direct method. Building upon several resilience frameworks (e.g., Marshall and Marshall 2007, Clare et al. 2017, Jones and d'Errico 2019), the indirect approach measured farmers' perceived robustness (*ROB*), adaptability (*ADAP*), and transformability (*TRANS*) using four statements per category. All resilience capacities were introduced with a nonagricultural example to ensure that farmers understood the statements. Additionally, we used two items to directly elicit farmers' future resilience (*RES*) for the next 5 and 20 years.

Fifth, farmers were asked to distribute 100 points over nine farm functions (*FUNC*). We grouped farmers based on the perceived importance of income as a farm function. The group *Low* consists of farmers who perceived income as relatively unimportant compared with other farm functions; these farmers distributed less than the median (less than 30 points) to farm income. The group *High* represents farmers who perceived income as one of the main farm functions (30 or more points).

Finally, we included several statements about farmers' openness to innovation (*INNO*), informal networks (*NET INF*), formal networks (*NET FOR*), and perceived behavioral control (*PBC*). Openness to innovation was measured using two items (Aubert et al. 2012). Two sets of three statements were used to measure farmers' formal and informal networks (Hunecke et al. 2017). Based on Armitage and Conner (1999) and Ajzen (2002), perceived behavioral control was measured as a four-item construct.

RESULTS

The PLS-SEM evaluation consists of the measurement and structural model assessment. The measurement model assessment examines the reflective and formative indicators that are used to operationalize the latent constructs. If sufficient measurement quality is confirmed, the structural model evaluation tests the hypothesized associations between the latent constructs (Hair et al. 2016). Finally, the results of the MGA will be presented.

Measurement model assessment

Evaluating the reflective measurement model includes an assessment of internal consistency reliability, convergent validity, and discriminant validity (Hair et al. 2016). Following the recommendations of Hair et al. (2018) for PLS-SEM with a second-order formative-formative construct, we used the repeated indicators approach with a factor weighting scheme, a maximum of 300 iterations, and a stop criterion of 10^{-7} as algorithm settings. The evaluation of the full model showed a lack of internal consistency reliability as *PBC* and *ROB* obtained Cronbach's alpha values smaller than 0.7 (Table A1.2). Furthermore, the outer loadings of *adap_4* (0.566), *pbc_2* (0.695), *pbc_4* (0.510), *rob_2* (0.180), and *trans_2* (0.227) are lower than 0.7, potentially causing low convergent validity. After removing *adap_4, pbc_4, rob_2,* and *trans_2*, the internal consistency reliability and convergent validity improved. All Cronbach's alpha values were larger than 0.7, and all composite reliability values ranged between 0.8 and 0.95 (Table 3). Additionally, all average variance explained (AVE) values exceed 0.5, confirming convergent validity. Discriminant validity is obtained as none of the 95% bias-corrected and accelerated (BCa) confidence intervals of the heterotrait–monotrait (HTMT) ratio (Henseler et al. 2016) include 1 (Table A1.3).

The formative measurement model assessment evaluates convergent validity, collinearity, and the significance of outer weights (Hair et al. 2016). First, a redundancy analysis was conducted to assess convergent validity between the formative and reflective *RISK PREF* measures. This resulted in a path coefficient with a magnitude of 0.805—exceeding the critical threshold of 0.70 (Sarstedt et al. 2017)—convergent validity was obtained. No redundancy analysis was conducted for *RISK PERC* and *RES* because these constructs were respectively a second-order construct or directly elicited. Second, all formative items obtained variance inflation factors (VIF) below 5 (Table A1.4), indicating that collinearity is not present at critical levels. Finally, we assessed the significance of outer weights and the relevance of outer loadings using a bootstrapping procedure (4000 samples, no sign changes option, BCa, two-tailed testing at α=0.05). Aside from farmers' financial risk preferences (*riskpref_3*), all formative items obtained significant outer weights (Table A1.4). The factor loading of *riskpref_3* exceeds the critical value of 0.50, indicating an absolute contribution to *RISK PREF*

Table 2. Item wordings and summary statistics (n = 916)

Item†		Mean	St dev
Risk behavior			
Risk management (RM) - single item. Eight-point scale, ranging from 0 (no risk management) to 7 (all seven categories in risk management portfolio)			
rm	The number of different risk management categories adopted by farmers. The following categories are distinguished: flexibility of farm activities, cooperation with others, diversification, specialization, learning, financial risk management, and measures to control environmental risks	3.98	1.35
Risk perception (RISK PERC) - second-order formative			
Input price risk perception (RISK PERC_1) - first-order formative			
riskperc_1	Persistently high input prices	4.44	1.53
riskperc_2	Input price fluctuations	4.16	1.47
Market price risk perception (RISK PERC_2) - first-order formative			
riskperc_3	Persistently low market prices	4.91	1.62
riskperc_4	Market price fluctuations	4.78	1.45
Supply chain risk perception (RISK PERC_3) - first-order formative			
riskperc_5	Low bargaining power toward processors and retailers	4.93	1.70
riskperc_6	Low bargaining power toward input suppliers	4.02	1.54
Financial risk perception (RISK PERC_4) - first-order formative			
riskperc_7	Limited access to loans from banks	4.17	1.74
riskperc_8	Late payments from buyers	3.42	1.75
Production risk perception (RISK PERC_5) - first-order formative			
riskperc_9	Persistent extreme weather events	4.50	1.61
riskperc_10	Pest, weed, or disease outbreaks	4.38	1.56
Personal and personnel risk perception (RISK PERC_6) - first-order formative			
riskperc_11	Limited availability of skilled farm workers	3.71	1.95
riskperc_12	Limited ability to work on the farm due to illness, divorce, or other personal circumstances	3.20	1.67
riskperc_13	Uncertainty about succession	3.68	1.99
Institutional risk perception (RISK PERC_7) - first-order formative			
riskperc_14	Strict regulations	5.51	1.50
riskperc_15	Reduction in direct payments of the Common Agricultural Policy (CAP)	4.36	1.92
Societal risk perception (RISK PERC_8) - first-order formative			
riskperc_16	Public distrust in agriculture	4.87	1.62
riskperc_17	Low societal acceptance of agriculture	4.84	1.69
Risk preferences (RISK PREF) - formative			
	I am willing to take more risks than other farmers in terms of...		
riskpref_1	Production	4.08	1.49
riskpref_2	Marketing and prices	4.39	1.50
riskpref_3	Financial risks	4.15	1.40
riskpref_4	Innovation	4.35	1.35
Risk preferences (RISK PREF) - reflective. Eleven-point Likert scale ranging from 0–10			
riskpref_5	How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?	5.99	2.03
Resilience			
Robustness (ROB) - reflective			
rob_1	After something challenging has happened, it is easy for my farm to bounce back to its current profitability	4.21	1.43
rob_2	As a farmer, it is hard to manage my farm in such a way that it recovers quickly from shocks	3.90	1.54
rob_3	Personally, I find it easy to get back to normal after a setback	4.44	1.47
rob_4	A big shock will <u>not</u> heavily affect me, as I have enough options to deal with this shock on my farm	4.02	1.53
Adaptability (ADAP) - reflective			
adap_1	If needed, my farm can adopt new activities, varieties, or technologies in response to challenging situations	3.97	1.71
adap_2	As a farmer, I can easily adapt myself to challenging situations	4.58	1.42
adap_3	In times of change, I am good at adapting myself and facing up to agricultural challenges	4.65	1.37
adap_4	My farm is <u>not</u> flexible and cannot easily be adjusted to deal with a changing environment	4.57	1.59
Transformability (TRANS) - reflective			
trans_1	For me, it is easy to make decisions that result in a transformation	3.84	1.58
trans_2	I am in trouble if external circumstances were to drastically change, as it is hard to reorganize my farm	4.08	1.56
trans_3	After facing a challenging period on my farm, I still have the ability to radically reorganize my farm	3.98	1.46
trans_4	If needed, I can easily make major changes that would transform my farm	3.72	1.57
Resilience (RES) - formative			
res_1	For the next 5 years, I expect my farm to be resilient to agricultural challenges	4.87	1.47
res_2	For the next 20 years, I expect my farm to be resilient to agricultural challenges	4.37	1.59
Farm functions (FUNC) - formative. 100 points			
	Number of points distributed to farm income		
func_1	Ensure a sufficient farm income	36.64	20.25
Control variables			
Innovation (INNO) - reflective			
inno_1	Compared with other farmers, I am among the first to try out a new practice on my farm	4.15	1.58
inno_2	I like to try out all kinds of new technologies or varieties	4.12	1.58
Informal network (NET INF) - reflective			
net_1	I know a lot of other farmers in my region	5.62	1.31
net_2	Concerning farming, I often interact with neighboring farmers	4.98	1.47
net_3	Farmers in my region tend to support each other when there is a problem	4.28	1.52
Formal network (NET FOR) - reflective			
net_4	I know a lot of agricultural professionals, experts, or value chain actors	5.09	1.35
net_5	When I attend agricultural events and meetings, I interact a lot with professionals, experts, or value chain actors	4.56	1.49
net_6	I feel I can receive support from agricultural professionals, experts, or value chain actors in my network	4.66	1.50
Perceived behavioral control (PBC) - reflective			
pbc_1	If I wanted to, it would be easy for me to deal with agricultural challenges on my farm	4.64	1.30
pbc_2	It is mostly up to me whether or not I can deal with the challenges on my farm	4.78	1.43
pbc_3	I have a lot of control about agricultural challenges affecting my farm	3.96	1.45
pbc_4	For me, it is difficult to deal with the challenges that affect my farm	4.43	1.46

†Unless otherwise stated, all items are measured on a seven-point Likert scale. Reversed scores of the negatively worded items are presented.

(Hair et al. 2016). Furthermore, previous research confirmed the theoretical importance of financial risk preferences (Reynaud and Couture 2012, Iyer et al. 2019). Therefore, we decided to keep *riskpref_3* in the measurement model. We continued with the structural model assessment because the reflective and formative measurement model assessments suggest satisfactory levels of reliability and validity.

Table 3. Internal consistency reliability and convergent validity of the reduced model

	Cronbach's alpha			Composite reliability			AVE†		
	All	Low	High	All	Low	High	All	Low	High
ADAP	0.795	0.811	0.785	0.879	0.887	0.874	0.710	0.725	0.701
INNO	0.856	0.851	0.858	0.933	0.930	0.933	0.874	0.869	0.875
NET FOR	0.813	0.768	0.831	0.888	0.866	0.897	0.726	0.684	0.744
NET INF	0.774	0.792	0.765	0.869	0.877	0.861	0.689	0.707	0.675
PBC	0.713	0.743	0.693	0.837	0.852	0.826	0.632	0.657	0.615
ROB	0.726	0.713	0.730	0.846	0.838	0.847	0.646	0.634	0.649
TRANS	0.846	0.860	0.835	0.907	0.915	0.901	0.765	0.782	0.752

† AVE = average variance explained.

Structural model assessment

The structural model assessment evaluates the potential presence of collinearity and the predictive capacity of the PLS-SEM. As the highest VIF value of all predictor constructs is 1.76, we found no indication of the presence of collinearity at critical levels. The second and sixth columns of Table 4 present, respectively, the direct and the total effects, which is the sum of the direct and indirect path coefficients.

Our results indicate that a more diverse risk-management portfolio over the last 5 years is associated with higher future risk perceptions, leading to the rejection of H1a. This suggests that farmers who have adopted risk-management strategies did so to cover the major perceived risks. However, although a more diverse risk-management portfolio might be beneficial to cope with present risks, future risk perceptions remain high as farmers could still be unaware of the consequences. We found support for H1b, indicating that farmers with a more diverse risk-management portfolio in the past are less risk averse. This suggests that a more diverse risk-management portfolio helps farmers to reduce the exposure to risk, which makes farmers less risk averse. As less risk-averse farmers experienced higher future risk perceptions, we rejected H1c. It could be that the current degree of risk aversion reflects on current risks, whereas the consequences of these risks arise in the future. Ultimately, this might increase farmers' future risk perceptions. Our findings contradict van Winsen et al. (2016), who found domain-specific relationships between risk preferences and perceptions.

The results support H2a–H2c as they suggest that farmers use their capacities to absorb, adapt, or transform in response to future risks, resulting in higher perceived future resilience. Our findings are in line with Darnhofer (2014), Folke (2016), and Meuwissen et al. (2019), who described that higher levels of robustness, adaptability, or transformability are needed to improve resilience.

The nonsignificant relationship between farmers' past risk-management portfolio and perceived robustness led to the rejection of H3a. The high costs involved in obtaining a diverse risk-management portfolio could restrain farmers from absorbing shocks (Vigani and Kathage 2019). This might indicate that individual financial risk-management strategies are more efficient tools to boost robustness.

More diverse risk-management portfolios are positively related to perceived adaptability (confirming H3b), suggesting that wider response options to future risks increase the maneuvering space of farmers. We reject H3c, as more diverse risk-management portfolios were not related to perceived transformability. A diverse risk-management portfolio alone might not be sufficient to enhance transformability because farmers need to be both able and willing to transform (Tong et al. 2016).

We found support for H4a, as future risk perceptions are negatively related to perceived robustness. Surprisingly, we found that future risk perceptions are unrelated to perceived adaptability and transformability, leading to the rejection of H4b and H4c. These findings contradict previous studies that described how higher risk perceptions partly explain farm adaptation (Grothmann and Patt 2005, Marshall and Stokes 2014) or transformation (Marshall et al. 2014). A potential explanation for this could be that robustness describes the capacity to recover from shocks, which could be perceived as dealing with risks (Bené et al. 2016). Perceived adaptability and transformability are related, respectively, to adjustments or radical changes, which are not reflected by risk perceptions.

Risk preferences are positively associated with perceived robustness, adaptability, and transformability, indicating that less risk-averse farmers perceive higher resilience capacities. Hence, we rejected H5a and found support for H5c. This suggests that less risk-averse farmers have an improved confidence to overcome the negative consequences of risks, which could enable them to better exploit their resilience capacities.

The largest path coefficients were found from perceived behavioral control to perceived robustness (0.351), adaptability (0.371), and transformability (0.385). This suggests that farmers with higher perceived behavioral control were more certain about their ability to tackle risks using their resilience capacities (Clare et al. 2017). Farmers' formal networks were positively related to robustness and adaptability, whereas informal networks were related to none of the resilience capacities. These findings suggest that farmers could use their formal networks to implement robustness and adaptation strategies, while informal networks are not exploited. Finally, a positive association between innovation and adaptability was found, suggesting that more innovative farmers are better able to adapt. This is line with Anderson and McLachlan (2012), who found that innovative Canadian farmers were able to improve adaptability to overcome mad cow disease.

R^2 values of 0.186, 0.282, 0.334 were obtained, respectively, for perceived robustness, adaptability, and transformability (Table A1.5). The exploratory aim of this study in combination with the complexity of resilience explains the relatively low R^2 values. Consequently, the f^2 effect sizes are relatively low as well (Table A1.6). The out-of-sample predictive relevance is confirmed as all Q^2 values are above zero (Table A1.5).

Table 4. Path coefficients of the PLS-SEM. Direct and total effects are reported

	Direct effects All (*n* = 916)	Low (*n* = 329)	High (*n* = 587)	Difference (Low–High)	Total effects All (*n* = 916)	Low (*n* = 329)	High (*n* = 587)	Difference (Low–High)
Risk behavior								
RM → RISK PREF	0.237***	0.225***	0.253***	-0.027	0.237***	0.225***	0.253***	-0.027
	(0.033)	(0.055)	(0.042)		(0.033)	(0.055)	(0.042)	
RM → PBC	0.109***	0.174***	0.076*	0.098	0.109***	0.174***	0.076*	0.098
	(0.034)	(0.055)	(0.043)		(0.034)	(0.055)	(0.043)	
PBC → RISK PERC[†]	-0.141***	-0.132	-0.143***	0.011	-0.141***	-0.132	-0.143***	0.011
	(0.044)	(0.088)	(0.051)		(0.044)	(0.088)	(0.051)	
RISK PREF → RISK PERC	0.082*	0.209***	-0.007	0.217**	0.082*	0.209***	-0.007	0.217**
	(0.047)	(0.076)	(0.054)		(0.047)	(0.076)	(0.054)	
RM → RISK PERC	0.162***	0.145**	0.149***	-0.004	0.162***	0.145**	0.149***	-0.004
	(0.036)	(0.060)	(0.045)		(0.036)	(0.060)	(0.045)	
Robustness								
RISK PERC → ROB	-0.098**	-0.002	-0.139***	0.138*	-0.098**	-0.002	-0.139***	0.138*
	(0.039)	(0.074)	(0.045)		(0.038)	(0.074)	(0.045)	
RISK PREF → ROB	0.096**	0.205***	0.026	0.180**	0.088**	0.205***	0.027	0.178**
	(0.042)	(0.073)	(0.052)		(0.041)	(0.071)	(0.051)	
RM → ROB	-0.018	-0.045	0.005	-0.049	0.027	0.063	0.017	0.046
	(0.032)	(0.055)	(0.039)		(0.037)	(0.063)	(0.046)	
INNO → ROB	-0.044	-0.085	-0.036	-0.049	-0.044	-0.085	-0.036	-0.049
	(0.040)	(0.069)	(0.048)		(0.040)	(0.069)	(0.048)	
NET FOR → ROB	0.093**	-0.017	0.149***	-0.166*	0.093**	-0.017	0.149***	-0.166*
	(0.044)	(0.073)	(0.054)		(0.044)	(0.073)	(0.054)	
NET INF → ROB	-0.013	0.067	-0.049	0.116	-0.013	0.067	-0.049	0.116
	(0.038)	(0.061)	(0.051)		(0.038)	(0.061)	(0.051)	
PBC → ROB	0.351***	0.356***	0.350***	0.005	0.365***	0.356***	0.370***	-0.014
	(0.041)	(0.073)	(0.049)		(0.040)	(0.072)	(0.048)	
Adaptability								
RISK PERC → ADAP	-0.028	0.017	-0.059	0.076	-0.028	0.017	-0.059	0.076
	(0.033)	(0.057)	(0.041)		(0.033)	(0.057)	(0.041)	
RISK PREF → ADAP	0.156***	0.141**	0.164***	-0.022	0.153***	0.145**	0.164***	-0.019
	(0.039)	(0.063)	(0.049)		(0.039)	(0.062)	(0.049)	
RM → ADAP	0.057**	0.049	0.056	-0.008	0.130***	0.150***	0.116***	0.034
	(0.029)	(0.048)	(0.036)		(0.034)	(0.055)	(0.043)	
INNO → ADAP	0.106***	0.058	0.132***	-0.074	0.106***	0.058	0.132***	-0.074
	(0.038)	(0.066)	(0.047)		(0.038)	(0.066)	(0.047)	
NET FOR → ADAP	0.073*	0.136**	0.041	0.095	0.073*	0.136**	0.041	0.095
	(0.041)	(0.064)	(0.051)		(0.041)	(0.064)	(0.051)	
NET INF → ADAP	0.031	0.062	0.019	0.043	0.031	0.062	0.019	0.043
	(0.037)	(0.056)	(0.048)		(0.037)	(0.056)	(0.048)	
PBC → ADAP	0.371***	0.386***	0.358***	0.027	0.375***	0.383***	0.367***	0.017
	(0.037)	(0.060)	(0.047)		(0.037)	(0.059)	(0.046)	
Transformability								
RISK PERC → TRANS	-0.047	-0.054	-0.035	-0.018	-0.047	-0.054	-0.035	-0.018
	(0.036)	(0.057)	(0.046)		(0.036)	(0.057)	(0.046)	
RISK PREF → TRANS	0.212***	0.202***	0.212***	-0.010	0.209***	0.191***	0.212***	-0.022
	(0.044)	(0.068)	(0.055)		(0.044)	(0.067)	(0.055)	
RM → TRANS	-0.027	0.000	-0.045	0.046	0.057	0.112*	0.031	0.081
	(0.030)	(0.051)	(0.038)		(0.038)	(0.061)	(0.048)	
INNO → TRANS	0.012	-0.051	0.045	-0.096	0.012	-0.051	0.045	-0.096
	(0.047)	(0.072)	(0.058)		(0.047)	(0.072)	(0.058)	
NET FOR → TRANS	0.062	0.055	0.071	-0.016	0.062	0.055	0.071	-0.016
	(0.041)	(0.067)	(0.053)		(0.041)	(0.067)	(0.053)	
NET INF → TRANS	-0.020	0.050	-0.065	0.115	-0.020	0.050	-0.065	0.115
	(0.037)	(0.057)	(0.050)		(0.037)	(0.057)	(0.050)	
PBC → TRANS	0.385***	0.422***	0.367***	0.055	0.392***	0.429***	0.372***	0.057
	(0.038)	(0.065)	(0.048)		(0.038)	(0.063)	(0.049)	
Resilience								
ROB → RES	0.267***	0.245***	0.289***	-0.043	0.267***	0.245***	0.289***	-0.043
	(0.041)	(0.066)	(0.050)		(0.041)	(0.066)	(0.050)	
ADAP → RES	0.230***	0.284***	0.200***	0.085	0.230***	0.284***	0.200***	0.085
	(0.046)	(0.070)	(0.057)		(0.046)	(0.070)	(0.057)	
TRANS → RES	0.114**	0.113	0.108*	0.005	0.114**	0.113	0.108*	0.005
	(0.047)	(0.071)	(0.060)		(0.047)	(0.071)	(0.060)	
RISK PERC → RES					-0.038**	-0.001	-0.056**	0.054
					(0.018)	(0.035)	(0.022)	
RISK PREF → RES					0.083***	0.113***	0.063**	0.050
					(0.021)	(0.035)	(0.027)	
RM → RES					0.043**	0.071**	0.031	0.039
					(0.019)	(0.034)	(0.024)	
INNO → RES					0.014	-0.010	0.021	-0.031
					(0.019)	(0.035)	(0.022)	
NET FOR → RES					0.049**	0.041	0.059**	-0.018
					(0.022)	(0.037)	(0.027)	
NET INF → RES					0.001	0.040	-0.017	0.057
					(0.018)	(0.029)	(0.024)	
PBC → RES					0.229***	0.245***	0.220***	0.025
					(0.024)	(0.047)	(0.026)	

[†] The domain-specific (first-order) effects of RISK PERC and most indirect effects are omitted for the sake of brevity. These results can be consulted in Table A 1.10 of Appendix 1.
* $p \leq 0.10$ ** $p \leq 0.05$; *** $p \leq 0.01$. Asterisks in the fifth and ninth column (Difference (Low–High)) refer to p values of the permutation test.

Multigroup analysis

The MICOM-procedure confirmed partial measurement invariance (Table A1.8 and A1.9), indicating that the subsets *Low* and *High* are suitable for MGA to investigate the importance of farm income in predicting differences in perceived resilience (Henseler et al. 2016).

Table 3 shows that the Cronbach's alpha value of perceived behavioral control for the group *High* (0.693) is slightly below the threshold of 0.7. No adjustments to the measurement model were made, as it is important to compare exactly the same models while conducting a MGA PLS-SEM. Therefore, we conclude that satisfactory reliability and validity levels of the reflective and formative measurement model were obtained.

Some path coefficients are significant for either *Low* or *High*, indicating that both groups have different constructs associated with the perceived resilience capacities (Table 4). The results of the permutation test with 3000 permutations (Chin and Dibbern 2010) indicate significant differences between *Low* and *High* for the path coefficients *RISK PREF* → *RISK PERC*, *RISK PERC* → *ROB, RISK PREF* → *ROB,* and *NET FOR* → *ROB*. Noteworthy are the path coefficients *RM* → *TRANS* and *RM* → *RES*, which are only significant for the group *Low*. To ensure robust estimation results, a sensitivity analysis with different threshold values for *High* (i.e., 35, 40, and 45 points) was conducted. No threshold values lower than 30 were selected as this would have resulted in extremely unequal sample sizes of both groups. Almost all path coefficients maintained the same direction and level of significance, indicating fairly robust estimation results. We will further detail the relationship between risk management and perceived transformability.

A more diverse risk-management portfolio is positively related to perceived transformability only for farmers who perceived obtaining farm income as less important. Note that only the total effects are significant, indicating that the sum of the direct and indirect effects together shape perceived transformability. A possible explanation for this could be that farmers who prioritized income less, found a mix of other functions, including the provision of public goods, more important. This could imply that these farmers use risk-management strategies to become better aware of potential opportunities for radical change. Additionally, farmers who prioritized income less, perceived themselves as better able to transform and obtained higher perceived behavioral control than those farmers who perceived income as more important (Table A1.11). These differences in intrinsic motivations shape farmers' decision making (Greiner and Gregg 2011) and might be associated with differences in perceived transformability.

DISCUSSION AND CONCLUSIONS

This article explores how risk behavior is related to perceived farm resilience. First, we have examined how farmers' perceived resilience capacities are associated with future resilience and how risk management, perceptions, and preferences are related to perceived resilience. All perceived resilience capacities are positively associated with perceived future resilience, indicating that the most resilient future farms obtain high levels of perceived robustness, adaptability, and transformability. Additionally, more diverse risk-management portfolios are associated with farmers with higher perceived adaptability and future resilience. Second, we have investigated differences in terms of perceived resilience between farmers who perceive farm income as being less important and those who prioritize farm income. Higher perceived transformability is obtained for farmers who perceive farm income as being less important. A more diverse risk-management portfolio is positively associated with perceived transformability only for these farmers.

To ensure the validity of our findings, a successful translation of the complex and latent nature of perceived resilience into a comprehensible and measurable construct is needed. In other words, it requires translation validity, i.e., the degree to which the operationalized construct is translated into measurable items (Onwuegbuzie et al. 2016). Three actions were taken to ensure translation validity. First, we based our perceived resilience statements on previous frameworks (e.g., Marshall and Marshall 2007, Clare et al. 2017, Jones and d'Errico 2019). Second, all resilience capacities were introduced with a short nonagricultural example to ensure that all statements were commonly interpreted. Third, we received feedback from an interdisciplinary group of researchers and specifically asked farmers to review all resilience statements when we pretested the survey. Several statements were rephrased based on the received feedback. Jointly, these three actions ensure translation validity (Netemeyer et al. 2003).

A limitation of this study is that it did not consider the potential trade-offs between perceived robustness, adaptability, and transformability. For instance, improving perceived robustness by creating financial buffers, might result in farmers who perceive themselves as being less able to adapt or transform. These additional insights are valuable to understand the potential costs of improving one resilience capacity. This motivates future research, which could investigate the potential trade-offs between robustness, adaptability, and transformability using panel data approaches.

Our findings have implications for agricultural policy makers and farmers. First, our results indicate that more diverse risk-management portfolios, consisting of a combination of economic, environmental, and social strategies, are associated with higher perceived adaptability and transformability. Most current European agricultural policies primarily consider robustness and emphasize how to tackle short-term risks (Candel et al. 2018). However, to ensure a resilient future for farmers, policies should also stimulate farm adaptation and transformation (Ohlund et al. 2015). To this end, policy makers could consider shifting from a narrow-minded view on risk management, where one specific tool is emphasized aiming to enhance robustness, to a holistic approach that highlights the importance of diverse risk-management portfolios (Coffey and Schroeder 2019, Meraner and Finger 2019, Vigani and Kathage 2019). In this way, risk management has the potential to enhance adaptability and transformability. Second, this study has implications for farmers because our findings show that resilient farmers combine robustness, adaptability, and transformability to overcome unknown future risks using a diversity of risk-management strategies.

Responses to this article can be read online at:
http://www.ecologyandsociety.org/issues/responses.php/11893

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Data Availability:

The data that support the findings of this study are openly available in DANS-EASY at https://doi.org/10.17026/dans-zb3-pp6f; reference number: 132914. The data will be publicly accessible from June 2021 onward.

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Appendix

Table A1.1 Overview of risk management strategies included in the survey

Flexibility of farm activities	**Cooperation with others**	**Financial risk management**	**Measures to control environmental risks**	**Specialization**	**Diversification**	**Learning**
Improved cost flexibility	Had access to a variety of input suppliers	Bought any type of agricultural insurance	Invested in technologies	Specialization	Diversified in production	Opened up my farm to the public
Improved flexibility in the timing of my production	Member of an (inter)branch organization	Used production or marketing contracts to sell (part of) my production	Implemented measures to prevent pests or diseases		Diversified in other activities on my farm	Used market information to plan my farm activities for the next season
Worked harder to secure production in hard times	Member of a producer organization, cooperative or credit union	Hedged (part of) my production with futures contracts			Had an off-farm job	Learned about challenges in agriculture
	Cooperated with other farmers to secure inputs or production	Maintained financial savings for hard times				Experimenting with precision agriculture, smart farming or drones.
		Had low debts or no debts at all to prevent financial risks				

Table A1.2 Item reliability, internal validity reliability, convergent validity and VIFs of the reflective indicators (full model)

	Outer loadings			Cronbach's alpha			Composite reliability			AVE			VIF		
	All	Low	High	All	Low	High	All	Low	High	All	Low	High	All	Low	High
ADAP				0.760	0.782	0.746	0.848	0.859	0.840	0.589	0.610	0.575	1.758	2.010	1.640
adap_1	0.715	0.711	0.718												
adap_2	0.875	0.881	0.874												
adap_3	0.870	0.894	0.856												
adap_4	0.566	0.600	0.538												
INNO				0.856	0.851	0.858	0.932	0.930	0.933	0.873	0.869	0.875	1.620	1.652	1.586
inno_1	0.944	0.948	0.941												
inno_2	0.925	0.916	0.930												
NET INF				0.774	0.792	0.765	0.869	0.877	0.862	0.689	0.706	0.675	1.527	1.391	1.636
net_1	0.808	0.846	0.788												
net_2	0.891	0.933	0.858												
net_3	0.786	0.731	0.818												
NET FOR				0.813	0.768	0.831	0.888	0.866	0.897	0.726	0.684	0.744	1.777	1.646	1.879
net_4	0.838	0.853	0.833												
net_5	0.864	0.852	0.870												
net_6	0.854	0.774	0.884												
PBC				0.646	0.648	0.643	0.792	0.794	0.789	0.495	0.506	0.488	1.406	1.415	1.404
pbc_1	0.827	0.837	0.829												
pbc_2	0.695	0.746	0.658												
pbc_3	0.743	0.780	0.722												
pbc_4	0.510	0.398	0.557												
ROB				0.576	0.520	0.599	0.762	0.717	0.775	0.484	0.476	0.487	1.323	1.340	1.309
rob_1	0.792	0.796	0.779												
rob_2	0.180	-0.083	0.294												
rob_3	0.771	0.797	0.752												
rob_4	0.827	0.792	0.831												
TRANS				0.715	0.725	0.703	0.828	0.830	0.823	0.582	0.593	0.572	1.705	2.071	1.554
trans_1	0.840	0.881	0.811												
trans_2	0.227	0.173	0.240												
trans_3	0.880	0.867	0.886												
trans_4	0.894	0.903	0.886												

Table A1.3. HTMT confidence intervals (reduced model)

		ADAP	INNO	NET FOR	NET INF	PBC	RM	ROB
INNO	All	[0.387; 0.535]						
	Low	[0.300; 0.536]						
	High	[0.383; 0.568]						
NET FOR	All	[0.303; 0.479]	[0.358; 0.505]					
	Low	[0.326; 0.595]	[0.241; 0.503]					
	High	[0.241; 0.462]	[0.366; 0.539]					
NET INF	All	[0.185; 0.366]	[0.154; 0.328]	[0.663; 0.786]				
	Low	[0.174; 0.421]	[0.062; 0.312]	[0.549; 0.767]				
	High	[0.151; 0.368]	[0.179; 0.379]	[0.691; 0.837]				
PBC	All	[0.572; 0.717]	[0.405; 0.577]	[0.355; 0.527]	[0.260; 0.447]			
	Low	[0.514; 0.764]	[0.330; 0.604]	[0.343; 0.605]	[0.168; 0.470]			
	High	[0.545; 0.735]	[0.387; 0.605]	[0.310; 0.534]	[0.254; 0.489]			
RM	All	[0.127; 0.274]	[0.197; 0.326]	[0.239; 0.371]	[0.114; 0.259]	[0.061; 0.194]		
	Low	[0.112; 0.349]	[0.168; 0.382]	[0.241; 0.461]	[0.084; 0.300]	[0.074; 0.314]		
	High	[0.092; 0.280]	[0.172; 0.333]	[0.206; 0.368]	[0.102; 0.278]	[0.038; 0.152]		
ROB	All	[0.490; 0.642]	[0.132; 0.306]	[0.190; 0.373]	[0.091; 0.256]	[0.455; 0.629]	[0.011; 0.095]	
	Low	[0.438; 0.713]	[0.096; 0.342]	[0.098; 0.367]	[0.088; 0.337]	[0.377; 0.684]	[0.008; 0.096]	
	High	[0.458; 0.649]	[0.103; 0.322]	[0.176; 0.408]	[0.076; 0.247]	[0.443; 0.657]	[0.006; 0.090]	
TRANS	All	[0.693; 0.807]	[0.268; 0.429]	[0.215; 0.383]	[0.093; 0.266]	[0.522; 0.676]	[0.021; 0.154]	[0.453; 0.609]
	Low	[0.766; 0.893]	[0.153; 0.427]	[0.194; 0.472]	[0.113; 0.368]	[0.497; 0.746]	[0.037; 0.242]	[0.468; 0.712]
	High	[0.617; 0.786]	[0.273; 0.461]	[0.167; 0.381]	[0.056; 0.239]	[0.469; 0.673]	[0.011; 0.135]	[0.382; 0.588]

Notes: The numbers in squared brackets present the 95% bias-corrected and accelerated confidence interval of the HTMT statistics. 4,000 bootstrapping samples were used with the no sign changes option.

Table A1.4 Formative item validity assessment (reduced model)

	Outer weight	St dev	Outer weight	St dev	Outer weight	St dev	Outer loadings			VIF		
	All	All	Low	Low	High	High	All	Low	High	All	Low	High
RM										1.140	1.160	1.142
RISK PREF										1.545	1.619	1.514
riskpref_1	-0.021	0.086	-0.035	0.161	-0.024	0.118	0.581	0.609	0.552	1.638	1.742	1.588
riskpref_2	0.561***	0.076	0.537***	0.115	0.609***	0.094	0.845	0.824	0.867	1.349	1.331	1.356
riskpref_3	0.462***	0.090	0.474***	0.152	0.470***	0.116	0.814	0.826	0.799	1.872	1.937	1.832
riskpref_4	0.220**	0.097	0.251*	0.147	0.157	0.116	0.737	0.750	0.701	1.731	1.772	1.715
RISK PERC										1.100	1.121	1.117
RISK PERC_1										1.637	1.449	1.637
riskperc_1	0.460***	0.069	0.422***	0.152	0.462***	0.079	0.865	0.850	0.865	1.650	1.664	1.643
riskperc_2	0.645***	0.063	0.679***	0.136	0.644***	0.072	0.934	0.945	0.933	1.650	1.664	1.643
RISK PERC_2										1.581	1.837	1.581
riskperc_3	0.574***	0.057	0.546***	0.104	0.570***	0.074	0.856	0.856	0.847	1.631	1.769	1.608
riskperc_4	0.589***	0.056	0.603***	0.101	0.599***	0.071	0.864	0.884	0.863	1.683	1.779	1.729
RISK PERC_3										1.743	1.735	1.743
riskperc_5	0.632***	0.045	0.710***	0.079	0.611***	0.057	0.894	0.938	0.877	1.665	1.946	1.719
riskperc_6	0.519***	0.049	0.415***	0.093	0.549***	0.059	0.838	0.806	0.846	1.775	1.838	1.654
RISK PERC_4										1.388	1.367	1.388
riskperc_7	0.708***	0.056	0.787***	0.093	0.690***	0.073	0.900	0.928	0.899	1.411	1.385	1.462
riskperc_8	0.477***	0.066	0.398***	0.125	0.486***	0.085	0.761	0.678	0.782	1.566	1.321	1.419
RISK PERC_5										1.236	1.330	1.236
riskperc_9	0.483***	0.083	0.480***	0.156	0.496***	0.131	0.824	0.810	0.837	1.510	1.539	1.531
riskperc_10	0.661***	0.075	0.673***	0.139	0.645***	0.119	0.910	0.908	0.907	1.566	1.562	1.674
RISK PERC_6										1.256		
riskperc_11	0.710***	0.122					0.873			1.305		
riskperc_12	0.515***	0.135					0.739			1.425		
RISK PERC_7										1.466	1.579	1.466
riskperc_14	0.721***	0.053	0.745***	0.083	0.677***	0.069	0.897	0.919	0.861	1.460	1.710	1.376

riskperc_15	0.476***	0.064	0.430***	0.105	0.540***	0.076	0.742	0.732	0.772	1.456	1.684	1.430
RISK PERC_8										1.402	1.348	1.402
riskperc_16	0.622***	0.126	0.597***	0.212	0.626***	0.175	0.979	0.969	0.983	4.308	3.630	4.941
riskperc_17	0.411***	0.129	0.446**	0.219	0.402**	0.179	0.952	0.944	0.958	4.265	3.560	4.885
RES												
res_1	0.591***	0.079	0.442***	0.149	0.670***	0.096	0.935	0.898	0.953	1.938	2.080	1.873
res_2	0.495***	0.080	0.634***	0.137	0.415***	0.105	0.906	0.952	0.872	1.938	2.080	1.873

Notes: outer weights and outer loadings of the risk perceptions items loading on the second order construct *RISK PERC* have been omitted for brevity. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$

Table A1.1. R^2 and Q^2 values of the structural model

	R^2			Q^2		
	All	Low	High	All	Low	High
ADAP	0.334	0.365	0.327	0.219	0.230	0.210
PBC	0.012	0.030	0.006	0.006	0.016	0.002
RES	0.250	0.288	0.233	0.198	0.226	0.178
RISK PERC	1.000	1.000	1.000	0.292	0.330	0.312
RISK PREF	0.056	0.051	0.064	0.026	0.024	0.027
ROB	0.186	0.193	0.194	0.110	0.098	0.113
TRANS	0.282	0.300	0.271	0.202	0.197	0.188

Table A1.6. f^2 statistics of the structural model

		ADAP	*PBC*	*RES*	*RISK PREF*	*ROB*	*TRANS*
ADAP	All			0.041			
ADAP	Low			0.056			
ADAP	High			0.032			
INNO	All	0.010				0.001	0.000
INNO	Low	0.003				0.005	0.002
INNO	High	0.016				0.001	0.002
NET FOR	All	0.004				0.006	0.003
NET FOR	Low	0.018				0.000	0.003
NET FOR	High	0.001				0.015	0.004
NET INF	All	0.001				0.000	0.000
NET INF	Low	0.004				0.004	0.003
NET INF	High	0.000				0.002	0.004
PBC	All	0.152				0.112	0.152
PBC	Low	0.169				0.113	0.183
PBC	High	0.140				0.112	0.136
RISK PERC	All	0.001				0.011	0.003
RISK PERC	Low	0.000				0.000	0.004
RISK PERC	High	0.005				0.022	0.002
RISK PREF	All	0.024				0.007	0.041
RISK PREF	Low	0.019				0.032	0.036
RISK PREF	High	0.026				0.001	0.041
RM	All	0.004	0.012		0.060	0.000	0.001
RM	Low	0.003	0.031		0.053	0.002	0.000
RM	High	0.004	0.006		0.068	0.000	0.002
ROB	All			0.073			
ROB	Low			0.063			
ROB	High			0.085			
TRANS	All			0.010			
TRANS	Low			0.009			
TRANS	High			0.010			

Table A1.7. q^2 statistics of the structural model

		ADAP	***RES***	***ROB***	***TRANS***
ADAP	All		0.030		
ADAP	Low		0.005		
ADAP	High		0.005		
INNO	All	0.005		0.000	-0.001
INNO	Low	-0.015		0.015	-0.007
INNO	High	0.020		-0.005	0.017
NET FOR	All	0.001		0.002	0.002
NET FOR	Low	-0.010		0.012	0.006
NET FOR	High	0.012		0.003	0.019
NET INF	All	0.000		-0.001	0.000
NET INF	Low	-0.013		0.013	0.005
NET INF	High	0.012		-0.004	0.018
PBC	All	0.085		0.062	0.099
PBC	Low	0.086		0.079	0.130
PBC	High	0.092		0.058	0.106
RISK PERC	All	0.000		0.006	0.002
RISK PERC	Low	-0.022		0.004	0.003
RISK PERC	High	0.014		0.008	0.019
RISK PREF	All	0.013		0.003	0.026
RISK PREF	Low	-0.007		0.029	0.022
RISK PREF	High	0.025		-0.006	0.043
RM	All	0.003		0.000	0.000
RM	Low	-0.015		0.011	0.001
RM	High	0.014		-0.005	0.017
ROB	All		0.052		
ROB	Low		0.008		
ROB	High		0.081		
TRANS	All		0.007		
TRANS	Low		-0.032		
TRANS	High		0.033		

Table A1.8. Compositional invariance assessment

	Original Correlation	5.0%	Permutation p-Values
ADAP	0.999	0.998	0.309
INNO	1.000	0.998	0.487
NET FOR	0.997	0.994	0.182
NET INF	0.986	0.968	0.209
PBC	1.000	0.996	0.787
RES	0.985	0.967	0.180
RISK PERC	0.990	0.990	0.067
RISK PERC_1	0.999	0.973	0.710
RISK PERC_2	1.000	0.973	0.966
RISK PERC_3	0.985	0.984	0.062
RISK PERC_4	0.994	0.963	0.437
RISK PERC_5	1.000	0.951	0.886
RISK PERC_6	0.801	0.820	0.040**
RISK PERC_7	0.987	0.963	0.241
RISK PERC_8	1.000	0.964	0.847
RISK PREF	0.994	0.917	0.910
RM	1.000	1.000	0.405
ROB	0.998	0.994	0.314
TRANS	0.999	0.999	0.060

Notes:* p≤0.10; ** p≤0.05; *** p≤0.01.

Table A1.9. Equal means and variance assessments

	Mean - Original Difference	Mean - Permutation Mean Difference	Permutation p-Values	Variance - Original Difference	Variance - Permutation Mean Difference	Permutation p-Values
ADAP	0.079	0.000	0.257	0.076	-0.001	0.413
INNO	0.189	0.002	0.004***	-0.008	-0.001	0.925
NET FOR	0.146	0.000	0.032**	-0.277	-0.003	0.003***
NET INF	0.021	0.000	0.757	0.089	-0.005	0.382
PBC	0.169	0.001	0.011**	0.052	-0.002	0.590
RES	0.092	0.000	0.179	-0.004	-0.001	0.968
RISK PERC	-0.166	0.001	0.017**	0.010	-0.001	0.938
RISK PERC_1	-0.029	0.001	0.665	-0.099	-0.001	0.297
RISK PERC_2	-0.134	0.000	0.051*	0.015	-0.002	0.872
RISK PERC_3	-0.130	0.001	0.059*	0.012	-0.003	0.902
RISK PERC_4	-0.076	0.001	0.260	-0.129	-0.001	0.108
RISK PERC_5	-0.019	0.003	0.787	-0.049	-0.001	0.589
RISK PERC_7	-0.236	-0.001	0.001***	0.130	-0.003	0.207
RISK PERC_8	-0.121	0.000	0.084	-0.088	-0.002	0.314
RISK PREF	0.225	0.002	0.001***	-0.110	-0.004	0.266
RM	-0.056	0.000	0.416	0.017	-0.002	0.834
ROB	0.185	0.001	0.009***	-0.204	-0.006	0.039**
TRANS	0.260	0.002	0.001***	0.088	-0.004	0.293

Notes:* p≤0.10; ** p≤0.05; *** p≤0.01.

Table A1.10. Path coefficients including domain-specific risk perceptions of the PLS-SEM. RP FIN = risk perception in the financial domain, RP INST = risk perception in the institutional domain, RP PERS = risk perception in the personal and personnel domain, RP INPUT = risk perception in the input price domain, RP MARKET = risk perception in the market price domain, RP PROD = risk perception in the production domian RP SC = risk perception in the supply chain domain, RP SOC = risk perception in the social domain.

	Direct effects				Total effects			
	All (N = 916)	Low (N = 329)	High (N = 587)	Difference (Low-High)	All (N = 916)	Low (N = 329)	High (N = 587)	Difference (Low-High)
Risk behavior								
RM → RISK PREF	0.237***	0.225***	0.253***	-0.027	0.237***	0.225***	0.253***	-0.027
	(0.033)	(0.055)	(0.042)		(0.033)	(0.055)	(0.042)	
RM → PBC	0.109***	0.174***	0.076*	0.098	0.109***	0.174***	0.076*	0.098
	(0.034)	(0.055)	(0.043)		(0.034)	(0.055)	(0.043)	
PBC → RISK PERC	-0.141***	-0.132	-0.143***	0.011	-0.141***	-0.132	-0.143***	0.011
	(0.044)	(0.088)	(0.051)		(0.044)	(0.088)	(0.051)	
PBC → RP FIN	-0.085**	-0.189***	-0.029	-0.106**	-0.085**	-0.189***	-0.029	-0.160**
	(0.039)	(0.072)	(0.046)		(0.039)	(0.072)	(0.046)	
PBC → RP INST	-0.167***	-0.102	-0.205***	0.102	-0.167***	-0.102	-0.205***	0.102
	(0.040)	(0.074)	(0.045)		(0.040)	(0.074)	(0.045)	
PBC → RP PERS	-0.060				-0.060			
	(0.047)				(0.047)			
PBC → RP INPUT	-0.027	0.020	-0.049	0.069	-0.027	0.020	-0.049	0.069
	(0.040)	(0.074)	(0.050)		(0.040)	(0.074)	(0.050)	
PBC → RP MARKET	-0.044	-0.062	-0.031	-0.031	-0.044	-0.062	-0.031	-0.031

	(0.044)	(0.087)	(0.051)		(0.044)	(0.087)	(0.051)	
PBC → RP PROD	-0.042	0.003	-0.067	0.070	-0.042	0.003	-0.067	0.070
	(0.041)	(0.076)	(0.051)		(0.041)	(0.076)	(0.051)	
PBC → RP SC	-0.149***	-0.186**	-0.125***	-0.060	-0.149***	-0.186**	-0.125***	-0.060
	(0.041)	(0.075)	(0.048)		(0.041)	(0.075)	(0.048)	
PBC → RP SOC	-0.139***	-0.115	-0.158***	0.042	-0.139***	-0.115	-0.158***	0.042
	(0.039)	(0.078)	(0.045)		(0.039)	(0.078)	(0.045)	
RISK PREF → RISK PERC	0.082*	0.209***	-0.007	0.217**	0.082*	0.209***	-0.007	0.217**
	(0.047)	(0.076)	(0.054)		(0.047)	(0.076)	(0.054)	
RISK PREF → RP FIN	0.114***	0.274***	0.040	0.234***	0.114***	0.274***	0.040	0.234***
	(0.041)	(0.076)	(0.049)		(0.041)	(0.076)	(0.049)	
RISK PREF → RP INST	-0.028	0.024	-0.044	0.068	-0.028	0.024	-0.044	0.068
	(0.042)	(0.076)	(0.052)		(0.042)	(0.076)	(0.052)	
RISK PREF → RP PERS	0.154***				0.154***			
	(0.048)				(0.048)			
RISK PREF → RP INPUT	0.072*	0.125*	0.041	0.084	0.072*	0.125*	0.041	0.084
	(0.041)	(0.070)	(0.051)		(0.041)	(0.070)	(0.051)	
RISK PREF → RP MARKET	0.008	0.163**	-0.068	0.231**	0.008	0.163**	-0.068	0.231**
	(0.044)	(0.072)	(0.053)		(0.044)	(0.072)	(0.053)	
RISK PREF → RP PROD	0.027	0.068	0.001	0.067	0.027	0.068	0.001	0.067

	(0.041)	(0.070)	(0.055)		(0.041)	(0.070)	(0.055)	
RISK PREF → RP SC	0.104**	0.227***	0.046	0.182**	0.104**	0.227***	0.046	0.182**
	(0.043)	(0.065)	(0.054)		(0.043)	(0.065)	(0.054)	
RISK PREF → RP SOC	-0.005	0.121	-0.059	0.180**	-0.005	0.121	-0.059	0.180**
	(0.043)	(0.076)	(0.052)		(0.043)	(0.076)	(0.052)	
RM → RISK PERC	0.162***	0.145**	0.149***	-0.004	0.162***	0.145**	0.149***	-0.004
	(0.036)	(0.060)	(0.045)		(0.036)	(0.060)	(0.045)	
RM → RP FIN	0.049	-0.047	0.104**	-0.151**	0.067*	-0.019	0.112**	-0.131*
	(0.034)	(0.053)	(0.045)		(0.034)	(0.055)	(0.045)	
RM → RP INST	0.117***	0.144**	0.088**	0.056	0.093***	0.131**	0.062	0.070
	(0.034)	(0.059)	(0.040)		(0.035)	(0.058)	(0.042)	
RM → RP PERS	0.120***				0.150***			
	(0.038)				(0.042)			
RM → RP INPUT	0.065*	0.019	0.088**	-0.069	0.079**	0.051	0.095**	-0.044
	(0.034)	(0.059)	(0.042)		(0.034)	(0.059)	(0.042)	
RM → RP MARKET	0.129***	0.093	0.147***	-0.054	0.126***	0.119**	0.128***	-0.009
	(0.034)	(0.057)	(0.041)		(0.034)	(0.059)	(0.042)	
RM → RP PROD	0.151***	0.164***	0.142***	0.021	0.153***	0.179***	0.138***	0.042
	(0.034)	(0.057)	(0.043)		(0.034)	(0.056)	(0.043)	
RM → RP SC	0.129***	0.090	0.149***	-0.059	0.138***	0.109**	0.151***	-0.042

	(0.034)	(0.055)	(0.044)		(0.034)	(0.055)	(0.044)	
RM → RP SOC	0.061*	0.094*	0.038	0.056	0.044	0.101*	0.011	0.090
	(0.034)	(0.055)	(0.044)		(0.035)	(0.054)	(0.046)	
RP FIN → RISK PERC	0.195***	0.175***	0.211***	-0.036*	0.195***	0.175***	0.211***	-0.036*
	(0.009)	(0.018)	(0.012)		(0.009)	(0.018)	(0.012)	
RP INST → RISK PERC	0.206***	0.224***	0.221***	0.003	0.206***	0.224***	0.221***	0.003
	(0.011)	(0.020)	(0.014)		(0.011)	(0.020)	(0.014)	
RP PERS → RISK PERC	0.144***				0.144***			
	(0.013)				(0.013)			
RP INPUT → RISK PERC	0.203***	0.213***	0.221***	-0.008	0.203***	0.213***	0.221***	-0.008
	(0.009)	(0.016)	(0.012)		(0.009)	(0.016)	(0.012)	
RP MARKET → RISK PERC	0.218***	0.247***	0.228***	0.019	0.218***	0.247***	0.228***	0.019
	(0.008)	(0.013)	(0.012)		(0.008)	(0.013)	(0.012)	
RP PROD → RISK PERC	0.160***	0.189***	0.150***	0.039	0.160***	0.189***	0.150***	0.039
	(0.010)	(0.020)	(0.016)		(0.010)	(0.020)	(0.016)	
RP SC → RISK PERC	0.232***	0.236***	0.258***	-0.022	0.232***	0.236***	0.258***	-0.022
	(0.008)	(0.012)	(0.011)		(0.008)	(0.012)	(0.011)	
RP SOC → RISK PERC	0.183***	0.188***	0.201***	-0.013	0.183***	0.188***	0.201***	-0.013
	(0.010)	(0.015)	(0.014)		(0.010)	(0.015)	(0.014)	

Robustness								
RISK PERC → ROB	-0.098**	-0.002	-0.139***	0.138*	-0.098**	-0.002	-0.139***	0.138*
	(0.039)	(0.074)	(0.045)		(0.039)	(0.074)	(0.045)	
RP FIN → ROB					-0.019**	0.000	-0.029***	0.029*
					(0.008)	(0.013)	(0.010)	
RP INST → ROB					-0.020**	0.000	-0.031***	0.030
					(0.008)	(0.017)	(0.010)	
RP PERS → ROB					-0.014**			
					(0.006)			
RP INPUT → ROB					-0.020**	0.000	-0.031***	0.030*
					(0.008)	(0.016)	(0.010)	
RP MARKET → ROB					-0.021**	0.000	-0.032***	0.031*
					(0.008)	(0.018)	(0.010)	
RP PROD → ROB					-0.016***	0.000	-0.021***	0.021*
					(0.006)	(0.014)	(0.007)	
RP SC → ROB					-0.023**	0.000	-0.036***	0.036*
					(0.009)	(0.017)	(0.012)	
RP SOC → ROB					-0.018**	0.000	-0.028***	0.028*
					(0.007)	(0.014)	(0.009)	
RISK PREF → ROB	0.096**	0.205***	0.026	0.180**	0.088**	0.205***	0.027	0.178**

	(0.042)	(0.073)	(0.052)		(0.041)	(0.071)	(0.051)	
RM → ROB	-0.018	-0.045	0.005	-0.049	0.027	0.063	0.017	0.046
	(0.032)	(0.055)	(0.039)		(0.037)	(0.063)	(0.046)	
INNO → ROB	-0.044	-0.085	-0.036	-0.049	-0.044	-0.085	-0.036	-0.049
	(0.040)	(0.069)	(0.048)		(0.040)	(0.069)	(0.048)	
NET FOR → ROB	0.093**	-0.017	0.149***	-0.166*	0.093**	-0.017	0.149***	-0.166*
	(0.044)	(0.073)	(0.054)		(0.044)	(0.073)	(0.054)	
NET INF → ROB	-0.013	0.067	-0.049	0.116	-0.013	0.067	-0.049	0.116
	(0.038)	(0.061)	(0.051)		(0.038)	(0.061)	(0.051)	
PBC → ROB	0.351***	0.356***	0.350***	0.005	0.365***	0.356***	0.370***	-0.014
	(0.041)	(0.073)	(0.049)		(0.040)	(0.072)	(0.048)	
Adaptability								
RISK PERC → ADAP	-0.028	0.017	-0.059	0.076	-0.028	0.017	-0.059	0.076
	(0.033)	(0.057)	(0.041)		(0.033)	(0.057)	(0.041)	
RP FIN → ADAP					-0.006	0.003	-0.012	0.015
					(0.006)	(0.010)	(0.009)	
RP INST → ADAP					-0.006	0.004	-0.013	0.017
					(0.007)	(0.013)	(0.009)	
RP PERS → ADAP					-0.004			

					(0.005)			
RP INPUT → ADAP					-0.006	0.004	-0.013	0.017
					(0.007)	(0.012)	(0.009)	
RP MARKET → ADAP					-0.006	0.004	-0.013	0.018
					(0.007)	(0.014)	(0.009)	
RP PROD → ADAP					-0.005	0.003	-0.009	0.012
					(0.005)	(0.011)	(0.006)	
RP SC → ADAP					-0.007	0.004	-0.015	0.019
					(0.008)	(0.014)	(0.011)	
RP SOC → ADAP					-0.005	0.003	-0.012	0.015
					(0.006)	(0.011)	(0.008)	
RISK PREF → ADAP	0.156***	0.141**	0.164***	-0.022	0.153***	0.145**	0.164***	-0.019
	(0.039)	(0.063)	(0.049)		(0.039)	(0.062)	(0.049)	
RM → ADAP	0.057**	0.049	0.056	-0.008	0.130***	0.150***	0.116***	0.034
	(0.029)	(0.048)	(0.036)		(0.034)	(0.055)	(0.043)	
INNO → ADAP	0.106***	0.058	0.132***	-0.074	0.106***	0.058	0.132***	-0.074
	(0.038)	(0.066)	(0.047)		(0.038)	(0.066)	(0.047)	
NET FOR → ADAP	0.073*	0.136**	0.041	0.095	0.073*	0.136**	0.041	0.095
	(0.041)	(0.064)	(0.051)		(0.041)	(0.064)	(0.051)	
NET INF → ADAP	0.031	0.062	0.019	0.043	0.031	0.062	0.019	0.043

	(0.037)	(0.056)	(0.048)		(0.037)	(0.056)	(0.048)	
PBC → ADAP	0.371***	0.386***	0.358***	0.027	0.375***	0.383***	0.367***	0.017
	(0.037)	(0.060)	(0.047)		(0.037)	(0.059)	(0.046)	
Transformability								
RISK PERC → TRANS	-0.047	-0.054	-0.035	-0.018	-0.047	-0.054	-0.035	-0.018
	(0.036)	(0.057)	(0.046)		(0.036)	(0.057)	(0.046)	
RP FIN → TRANS					-0.009	-0.009	-0.007	-0.002
					(0.007)	(0.011)	(0.010)	
RP INST → TRANS					-0.010	-0.012	-0.008	-0.004
					(0.008)	(0.013)	(0.010)	
RP PERS → TRANS					-0.007			
					(0.005)			
RP INPUT → TRANS					-0.010	-0.011	-0.008	-0.004
					(0.007)	(0.012)	(0.010)	
RP MARKET → TRANS					-0.010	-0.013	-0.008	-0.005
					(0.008)	(0.014)	(0.010)	
RP PROD → TRANS					-0.008	-0.010	-0.005	-0.005
					(0.006)	(0.010)	(0.007)	
RP SC → TRANS					-0.011	-0.013	-0.009	-0.004

					(0.008)	(0.013)	(0.012)	
RP SOC → TRANS					-0.009	-0.010	-0.007	-0.003
					(0.007)	(0.011)	(0.009)	
RISK PREF → TRANS	0.212***	0.202***	0.212***	-0.010	0.209***	0.191***	0.212***	-0.022
	(0.044)	(0.068)	(0.055)		(0.044)	(0.067)	(0.055)	
RM → TRANS	-0.027	0.000	-0.045	0.046	0.057	0.112*	0.031	0.081
	(0.030)	(0.051)	(0.038)		(0.038)	(0.061)	(0.048)	
INNO → TRANS	0.012	-0.051	0.045	-0.096	0.012	-0.051	0.045	-0.096
	(0.047)	(0.072)	(0.058)		(0.047)	(0.072)	(0.058)	
NET FOR → TRANS	0.062	0.055	0.071	-0.016	0.062	0.055	0.071	-0.016
	(0.041)	(0.067)	(0.053)		(0.041)	(0.067)	(0.053)	
NET INF → TRANS	-0.020	0.050	-0.065	0.115	-0.020	0.050	-0.065	0.115
	(0.037)	(0.057)	(0.050)		(0.037)	(0.057)	(0.050)	
PBC → TRANS	0.385***	0.422***	0.367***	0.055	0.392***	0.429***	0.372***	0.057
	(0.038)	(0.065)	(0.048)		(0.038)	(0.063)	(0.049)	
Resilience								
ADAP → RES	0.230***	0.284***	0.200***	0.085	0.230***	0.284***	0.200***	0.085
	(0.046)	(0.070)	(0.057)		(0.046)	(0.070)	(0.057)	
ROB → RES	0.267***	0.245***	0.289***	-0.043	0.267***	0.245***	0.289***	-0.043

	(0.041)	(0.066)	(0.050)		(0.041)	(0.066)	(0.050)	
TRANS → RES	0.114**	0.113	0.108*	0.005	0.114**	0.113	0.108*	0.005
	(0.047)	(0.071)	(0.060)		(0.047)	(0.071)	(0.060)	
RISK PERC → RES					-0.038**	-0.001	-0.056**	0.054
					(0.018)	(0.035)	(0.022)	
RP FIN → RES					-0.007**	0.000	-0.012**	0.012
					(0.004)	(0.006)	(0.005)	
RP INST → RES					-0.008**	0.000	-0.012**	0.012
					(0.004)	(0.008)	(0.005)	
RP PERS → RES					-0.005**			
					(0.003)			
RP INPUT → RES					-0.008**	0.000	-0.012***	0.012
					(0.004)	(0.007)	(0.005)	
RP MARKET → RES					-0.008**	0.000	-0.013**	0.012
					(0.004)	(0.009)	(0.005)	
RP PROD → RES					-0.006**	0.000	-0.008**	0.008
					(0.003)	(0.007)	(0.003)	
RP SC → RES					-0.009**	0.000	-0.014**	0.014
					(0.004)	(0.008)	(0.006)	
RP SOC → RES					-0.007**	0.000	-0.011**	0.011

	(0.003)	(0.007)	(0.004)	
RISK PREF → RES	0.083***	0.113***	0.063**	0.050
	(0.021)	(0.035)	(0.027)	
RM → RES	0.043**	0.071**	0.031	0.039
	(0.019)	(0.034)	(0.024)	
INNO → RES	0.014	-0.010	0.021	-0.031
	(0.019)	(0.035)	(0.022)	
NET FOR → RES	0.049**	0.041	0.059**	-0.018
	(0.022)	(0.037)	(0.027)	
NET INF → RES	0.001	0.040	-0.017	0.057
	(0.018)	(0.029)	(0.024)	
PBC → RES	0.229***	0.245***	0.220***	0.025
	(0.024)	(0.047)	(0.026)	

Table A1.11. Summary statistics all farmers, *Low*, and *High*.

	All (N = 916)		Low (N = 329)		High (N = 587)	
	Mean	St dev	Mean	St dev	Mean	St dev
Risk behavior						
RM	3.98	1.35	3.94	1.36	4.01	1.35
RISK PERC						
RISK PERC_1						
riskperc_1	4.44	1.53	4.41	1.47	4.46	1.56
riskperc_2	4.16	1.47	4.14	1.43	4.17	1.49
RISK PERC_2						
riskperc_3	4.91	1.62	4.69	1.61	5.04***	1.62
riskperc_4	4.78	1.45	4.77	1.44	4.78	1.46
RISK PERC_3						
riskperc_5	4.93	1.70	4.70	1.73	5.06***	1.67
riskperc_6	4.02	1.54	4.03	1.46	4.02	1.59
RISK PERC_4						
riskperc_7	4.17	1.74	4.02	1.73	4.26**	1.75
riskperc_8	3.42	1.75	3.49	1.63	3.39	1.81
RISK PERC_5						
riskperc_9	4.50	1.61	4.52	1.61	4.49	1.61
riskperc_10	4.38	1.56	4.33	1.53	4.41	1.57
RISK PERC_6						
riskperc_11	3.71	1.95	3.77	1.99	3.67	1.92
riskperc_12	3.20	1.67	3.17	1.62	3.22	1.70
riskperc_13	3.68	1.99	3.62	1.97	3.72	2.00
RISK PERC_7						
riskperc_14	5.51	1.50	5.27	1.57	5.65***	1.45
riskperc_15	4.36	1.92	4.21	1.91	4.44*	1.93
RISK PERC_8						
riskperc_16	4.87	1.62	4.76	1.59	4.94	1.64
riskperc_17	4.84	1.69	4.71	1.66	4.92*	1.71
RISK PREF						
riskpref_1	4.08	1.49	4.18	1.43	4.03	1.53
riskpref_2	4.39	1.50	4.64	1.42	4.26***	1.52
riskpref_3	4.15	1.40	4.27	1.36	4.08**	1.42
riskpref_4	4.35	1.35	4.42	1.34	4.32	1.36
Resilience						
ROB						
rob_1	4.21	1.43	4.36	1.32	4.13**	1.48
rob_2	3.90	1.54	3.90	1.48	3.90	1.57
rob_3	4.44	1.47	4.55	1.42	4.38*	1.50
rob_4	4.02	1.53	4.18	1.43	3.94**	1.58
ADAP						
adap_1	3.97	1.71	4.05	1.78	3.93	1.66
adap_2	4.58	1.42	4.64	1.40	4.54	1.42
adap_3	4.65	1.37	4.71	1.40	4.61	1.36

adap_4	4.57	1.59	4.76	1.54	4.45***	1.61
TRANS						
trans_1	3.84	1.58	4.00	1.57	3.75**	1.57
trans_2	4.08	1.56	4.23	1.50	4.00**	1.58
trans_3	3.98	1.46	4.23	1.48	3.84***	1.44
trans_4	3.72	1.57	3.98	1.60	3.58***	1.53
RES						
res_1	4.87	1.47	4.98	1.43	4.81*	1.49
res_2	4.38	1.59	4.43	1.62	4.35	1.58
Control variables						
INNO						
inno_1	4.15	1.58	4.37	1.59	4.02***	1.56
inno_2	4.12	1.58	4.25	1.56	4.04*	1.59
NET INF						
net_1	5.62	1.31	5.60	1.33	5.63	1.30
net_2	4.98	1.47	4.93	1.48	5.01	1.46
net_3	4.28	1.52	4.39	1.57	4.21*	1.49
NET FOR						
net_4	5.09	1.35	5.14	1.26	5.07	1.39
net_5	4.56	1.49	4.69	1.40	4.48**	1.53
net_6	4.66	1.50	4.82	1.42	4.57**	1.54
PBC						
pbc_1	4.64	1.30	4.79	1.28	4.56**	1.30
pbc_2	4.78	1.43	4.87	1.39	4.73	1.45
pbc_3	3.96	1.45	4.07	1.49	3.90*	1.43
pbc_4	4.43	1.46	4.51	1.50	4.38	1.43

Notes: All items are measured on a 7-point Likert scale, except the diversity of risk management strategies (RM). This item is the count of different types of risk management strategies, ranging from 0 to 7. Significant differences between *Low* and *High* were tested using a t-test. * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$.