The adoption of price risk management tools among farmers in four European Union countries

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Abstract

Agricultural businesses face risks and uncertainty, including human resources or price risk. There are multiple tools and strategies available to mitigate risk. Yet, farm-level adoption of risk management tools remains low. There has been an increase in research on farm managerial adoption behaviour towards different risk management strategies and instruments. This thesis aims to extend the literature on how farm and farmer characteristics, risk perception and risk attitude influence the adoption of price risk management tools to maintain a financially stable agricultural business. The study applies a Linear Probability Model (LPM) estimated via Ordinary Least Squares (OLS) to analyse survey data collected from agricultural enterprises across four European Union countries. The final sample consists of 529 agricultural businesses and provides information regarding farm and farmer characteristics, risk attitude, price risk perception and the use of financial risk management tools. The results indicate that highly educated farm managers and those without any household off-farm income were the most likely to adopt price risk management tools. High perceived output price risk was positively associated with adoption, while input price risk perception and risk aversion exhibited negative relationships. However, these findings were only marginally statistically significant and should be interpreted with caution. This thesis emphasises the possibility that there are more factors beyond farm and farmer characteristics, price risk perception and risk attitude that are vital for the strategic adoption of price risk management tools.

Keywords: risk perception, risk attitude, behavioural preferences, characteristics, agriculture, expected utility theory, prospect theory, farm, farmer, farm business

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1. Introduction

1.1 Problem background

Agricultural businesses have long been subject to multiple kinds of risks (Akhtar et al. 2021). Risks originate from different sources and vary across various geographical and political scales. The five most common categories are market risk, financial risk, production risk, institutional risk and human resource risk (OECD 2009; Duong et al. 2019; Akhtar et al. 2021; Finger et al. 2022).

Market risk concerns price volatility and changes in consumer demand. Financial risk refers to loans, credits and the ability to pay bills when due. Production risk includes weather-related hazards, pests and diseases, resulting in an uncertain quantity and quality of production. Institutional risk consists of changes in political and regulatory context, while human resource risk relates to the physical and mental health of the family and employees (Finger et al. 2022). These risks and the consequences of them may result in income losses for farm businesses, jeopardising agricultural enterprises and forcing farmers to adjust their production and management strategies to address the various risks (Duong et al. 2019). Farmers can manage the risks by using a variety of tools and strategies, as they aim to maintain financial stability in the business by smoothing out income swings (García-Machado et al. 2024). That way, utilisation of risk management tools can help farmers to better cover and run their farms, as well as achieve success in their business (ibid.).

Farmers' management response to risks is shown to be influenced by their subjective perceptions of the risk in the current context (García-Machado et al. 2024). They implement strategies including informal mechanisms at the farm level to formal mechanisms like insurance and contracting, based on how they perceive risks. These perceptions are based on diverse socio-economic backgrounds, resulting in various decision-making and strategic behaviour in the farming business (Ennew et al. 1992; Davis et al. 2005; Duong et al. 2019; Akhtar et al. 2021; Adnan et al. 2024; García-Machado et al. 2024). Local knowledge, experience, size of the business and the farmers' education level are also significant factors affecting agricultural decision making (Davis et al. 2005; Coffey & Schroeder 2019; Carrer et al. 2020; Fronda 2023).

1.2 Agricultural risk management strategies and tools

Risk management in agricultural enterprises involves a range of managerial instruments and practical tools aimed at reducing uncertainty and improving financial stability and business resilience. These approaches involve on-farm and financial strategies such as crop and animal diversification, the monitoring and prevention of pests and diseases, off-farm work, farm insurance, off-farm investment, debt reduction, low-cost production, as well as cooperation with other farmers (Duong et al. 2019). These practices include human, market, input, financial, policy and technological risk sources. In addition, knowledge support strategies include extension services, staying updated on government regulations, as well as training and education. The last component concerns productivity solutions, comprising crop and animal diversification and new technology adoption (Duong et al. 2019).

This thesis concerns price risk management tools such as futures, forward contracts, price insurance, swaps and options. These are the most common for hedging price risk with derivatives, aimed at reducing risk and maintaining financial stability (Fields & Gillespie 2008; Leppälä et al. 2015; García-Machado et al. 2024).

1.3 Problem

Despite the prominent risks and multiple tools and strategies available to manage them and secure financial stability in the farming enterprise, adoption rates remain low(Ennew et al. 1992; Finger et al. 2022; Spada et al. 2026). This has motivated research regarding the effect of individual farm and farmer characteristics on adoption of different financial strategies (Davis et al. 2005;Dang et al. 2025); Fronda 2023; Garcia-Machado et al. 2024), but also extensions incorporating farmers' risk attitudes and perceptions (Coffey & Schroeder 2019; Khanal et al. 2022; Spada et al. 2026).

Farmers' risk attitudes tend to show an association with managerial adoption decisions worldwide. Literature has examined multiple types of agricultural businesses, including Indian maize farmers, Brazilian soybean and corn farmers, midwestern grain farmers and cattle producers in the United States of America (USA). Risk management instruments analyzed in these contexts include improved practices and financial tools like insurance, contract farming and forward pricing techniques (Fields & Gillespie 2008; Coffey & Schroeder 2019; Carrer et al. 2020; Akhtar et al. 2021; Peng & Xu 2023; Patil & Veettil 2024). In addition, the diverse potential consequences of climate change often constitute a high risk perception (Ahmad et al. 2019; Dadzie 2023; Fronda 2023), which encourage farmers to adopt hedging instruments, as well as good agricultural practices (Akhtar et al. 2021; Hanger-Kopp & Palka 2022; Khanal et al. 2022; Dang et al. 2025). These risk attributes experienced in agricultural business appear to be vital factors that influence and shape farm operators' strategic decision-making regarding production, investment and management under uncertainty (Duden et al. 2023; Ennew et al. 1992).

Farm-level decisions to adopt management strategies and successfully manage risks are limited by several factors, emphasising the need to understand farmers' risk perception and the socio-economic factors that influence the perceptions, response to risks and barriers to implementing management strategies (Duong et al. 2019). Despite the growing interest in behavioural factors, empirical evidence combining behavioural preferences with actual adoption of risk management instruments remains limited (Khanal et al. 2022; Finger et al. 2023; García-Machado et al. 2024; Spada et al. 2026). Risk perception and risk attitude are often independently described and restricted across certain countries worldwide, while research concerning potential interaction between the behavioural factors are limited

(Khanal et al. 2019; 2022; Spada et al. 2026). Likewise, Knapp et al. (2021) emphasise the lack of analysis for whether risk preferences, personality and aspirations are substitutes or complements in explaining organisational decision-making.

1.4 Aim and research questions

This thesis contributes to the existing literature by assessing how managerial behavioural preferences influence the adoption of price risk management tools. The paper analyses how diverse market conditions impact producers' adoption of risk-mitigating tools to maintain financially stable agricultural business and production. Within the business and management framework, the concept "farm" refers to the agricultural enterprise (agribusiness), while the "farmer" is viewed as the central decision-maker and strategic manager of that enterprise.

The study establishes a baseline by assessing how primary farm and farmer characteristics influence adoption, treating these factors as essential determinants and control variables upon which the behavioural analysis is built. Advancing from this starting point, the analysis then isolates the specific impact of the behavioural factors by a stepwise approach and concludes by exploring their joint influence through interaction effects.

RQ1. How does the adoption of price risk management tools vary across different farm and farmer characteristics?

RQ2. How do farmers' price risk perception and general risk attitude affect the adoption of price risk management tools?

RQ3. How do farmers' price risk perception and general risk attitude jointly influence the adoption of price risk management tools?

1.5 Delimitations

This thesis relies on secondary data and is therefore delimited to four European countries: Germany, Italy, the Netherlands and Poland. While the dataset includes several dimensions of risk perception and risk attitude, this study focuses exclusively on price-related risk perception and general risk attitude in line with the research objective.

1.6 Outline

Following the introduction, the thesis presents the literature review and conceptual framework where relevant prior empirical research and concepts are presented. This is followed by the methodology chapter where the sample is introduced and the independent and dependent variables are accounted for. Finally, the results will be presented and discussed, followed by a conclusion which summarizes the core findings of the study.

2. Literature review and conceptual framework

This chapter begins by presenting the theoretical foundations of decision-making under risk, primarily through Expected Utility Theory (EUT) and Prospect Theory, which provide the conceptual basis for understanding how farmers evaluate and respond to uncertainty. Furthermore, the review will assess how behavioural factors, particularly risk attitude and risk perception, have been shown to impact farmers' decision-making under risk and their adoption of several risk management strategies. It further considers how socio-economic and socio-demographic characteristics may shape these behavioural processes and thus indirectly affect adoption decisions.

In this thesis, adoption of price risk management tools is interpreted as the observable outcome of underlying decision-making processes under risk, where farmers' perceptions, preferences and individual characteristics interact in shaping responses to uncertainty. Figure 1 exemplifies the conceptual relationships guiding the analysis.

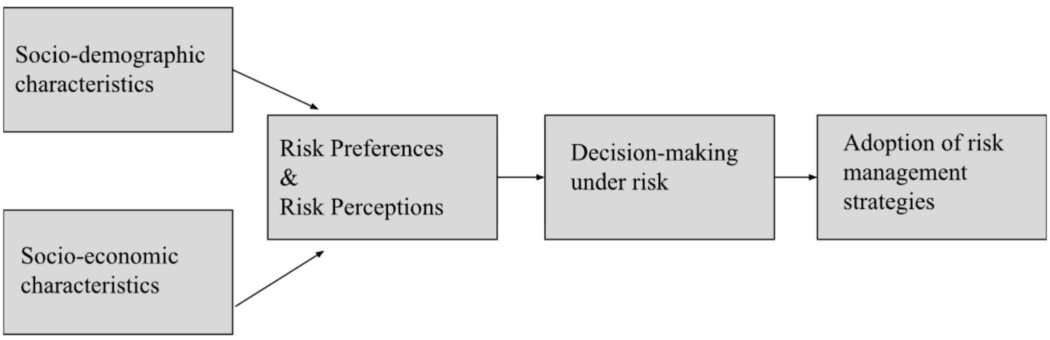

Figure 1. Conceptual framework of the farm-level decision-making process under risk. Source: author's own processing.

2.1 Theoretical framework

EUT, originally formalized by von Neumann & Morgenstern (1945) provides the standard framework for analysing decision-making under risk. It emphasises that individuals evaluate risky alternatives by maximising expected utility based on outcomes and their perceived probabilities, while in settings such as agricultural decision-making, this process is influenced by the decision environment, including restrictions, information and institutional conditions (Kulawik 2023). At its core, EUT supposes that individuals do not examine the potential profit in monetary terms, but rather at the subjective value (utility) the money provides, given their specific conditions and risk tolerance.

EUT is well suited to this study, as a farm operator's adoption of price risk management tools involves trade-offs between uncertain outcomes. EUT presents the rational financial aim for an agricultural business, that is, to maximise the farm's expected value and minimise financial risk. Thus, the adoption is conceptualised as a strategic investment that will enhance the business's assets. The framework suggests that decisions under uncertainty are influenced by underlying risk preferences as well as by how risks are perceived. In particular, the interaction between risk preferences and risk perception is expected to be important, as the effect of one may depend on the level of the other. Additional control variables can be interpreted as factors influencing either risk exposure or the capacity to manage risk.

Empirical evidence in agricultural economics commonly relies on EUT in order to examine adoption behaviour, with a specific focus on farmers' risk attitude (Hansson & Lagerkvist 2012; Khanal et al. 2022; Spada et al. 2026). Literature further indicates that decision-making is shaped not only by expected outcomes but also by subjective risk perceptions (Akhtar et al. 2021; Davis et al. 2005; Fronda 2023).

While EUT provides a consistent benchmark for assessing decisions under uncertainty, it has been criticised for its limited descriptive precision. Empirical applications suggest that farmers' behaviour may deviate from expected utility maximisation due to behavioural factors and subjective risk perceptions (Dessart et al. 2019; Duden et al. 2023; Khanal et al. 2019; Kulawik 2023). In addition, later refinements have introduced more nuanced concepts to better capture real-world complexities. Particularly, the inclusion of background risk and Decreasing Absolute Risk Aversion (DARA) allows for a more dynamic analysis of how a farmer's financial scale and external market pressures interact to shape adoption behaviour.

2.1.1 The role of background risk

Background risk refers to an inevitable and often uninsurable risk that is independent of the specific risk being analysed (such as labour income risk or health shocks) (Guiso & Paiella 2008). Risk aversion is positively affected by background risk, as literature shows that increasing background risk lowers absolute risk tolerance, but justifies that the variable itself explains only a small amount of the variability in attitudes towards risk (Guiso & Paiella 2008). Yet, an increased risk vulnerability might lead to a reduction in the adoption of formal risk management tools as farmers prioritize liquidity and financial flexibility to manage the key unhedged risk (Kulawik 2023; von Neumann & Morgenstern 1945).

2.1.2 Wealth effects and risk aversion

DARA is an economic preference model which proposes that an individual's absolute risk aversion declines as their wealth or income increases, making them more risk-willing (Pratt 1964). DARA is a common assumption in economic models, explaining increasing wealth inequality. In an agricultural context, this suggests that farmers with greater economic capacity, such as higher farm income or larger farm size, are more inclined to accept risks or bear the costs associated with risk management instruments, as potential losses have a diminishing effect on their total utility (Kulawik 2023).

2.1.3 Behavioural finance and Prospect Theory

While background risk and wealth effects provide a rational basis for varying levels of risk aversion within the EUT framework, they do not fully account for systematic deviations where farmers renounce hedging despite apparent financial benefits. To comprehend these behavioural patterns, it is necessary to move beyond utility maximisation and consider the psychological foundations of decision-making under uncertainty, as described by Prospect Theory.

Prospect Theory describes how individuals make decisions under risk, and shows that people evaluate potential gains and losses relative to a reference point, rather than absolute wealth (Kahneman & Tversky 1979). A key post of this theory is loss aversion, which implies that the psychological pain of a loss is significantly greater than the pleasure of a comparable gain. In the context of agricultural price risk management, loss aversion can explain why many farmers avoid adopting hedging instruments despite their potential to stabilise income. For a farmer, the cost of a hedging tool may be perceived as a certain loss if market prices later increase. The fear of missing a potential price peak, hence "losing" the additional profit often outweighs the perceived benefit of being protected against a price drop (Kahneman & Tversky 1979).

Furthermore, if a farmer's reference point is a historically high price or a specific production cost, any realised price below this point is deemed a loss. This framing can lead to a risk-seeking behaviour in the loss domain, where farmers avoid hedging tools in the hope that prices will recover so they can avoid a sure loss today, even if this exposes their business to even greater market risk. This behavioural bias offers a useful extension to the EUT framework by explaining why adoption rates stay low even when economic models suggest that hedging would be favourable.

Prospect Theory further suggests that individuals do not evaluate odds objectively, introducing the concept of probability weighting. As Kahneman and Tversky (1979) emphasise, this mechanism reflects individuals' perceived difficulties to comprehend and assess the extreme probabilities. People tend to overweight unlikely but emotionally prominent outcomes while underweighting more probable outcomes. In agricultural business, this may imply that farmers overestimate the likelihood of extreme price volatility or severe financial losses when evaluating formal hedging instruments.

2.2 Behavioural foundations of decision-making under risk

Risk attitude and risk perception constitute crucial factors for adoption decisions in agriculture (Spada et al. 2026). While risk-averse farmers tend to prioritate risk-reducing strategies, such as insurance and contract farming (Fields & Gillespie 2008; Akhtar et al. 2021; Khanal et al. 2022; Peng & Xu 2023), recent research questions the assumption of stable preferences. Risk attitudes seem to vary depending on context and time (Dessart et al. 2019; Finger et al. 2024), potentially making high risk aversion a barrier, reducing adoption when risk management tools are perceived as complex or uncertain (Biondo et al. 2025).

Risk perception is vital for decision-making, defined as “the awareness of the factors in the social and economic environment that create risk and the degree to which one factor is more critical than the other” (Wilson et al. 1988, p.545). This perception is formed by personal experience of past events and tools (Davis et al. 2005; Fronda 2023). Lack of experience may lead to an underestimate of low-probability risks, which reduces the incentives to purchase protection such as insurance (Duden et al. 2023). In contrast, prior experience with certain risk management tools can also reduce the tendency to adopt additional tools (Dang et al. 2025), while negative attitudes toward market tools often correlate with lacking experience with them (Ennew et al. 1992).

These subjective perceptions are deeply context dependent (Finger et al. 2023; Rigdon et al. 2023). For instance, perceived catastrophic risk is correlated to risk aversion in Bangladesh (Adnan et al. 2023), while risk-seeking farmers in Ghana show high tendency for adaptive behaviour when there is a drought (Dadzie 2023). This emphasises that decisions are not made in a vacuum, but shaped by balancing expected utility and perceived threat (Hansson & Lagerkvist 2012; Adnan et al. 2024). Consequently, decision-making often deviates from classical rationality; instead of objectively weighing probabilities, farmers frequently rely on heuristic and subjective judgements (Duden et al. 2023). These behavioural factors, including social norms, explain why adoption choices often diverges from what economic models anticipate (Khanal et al. 2019; Dessart et al. 2019).

2.3 Socio-demographic foundations of decision-making under risk

Beyond behavioural factors, empirical evidence shows that farmers’ decision-making under risk also deviates from socio-demographic and socio-economic characteristics, which influence both risk preferences and the feasibility of adopting specific risk management strategies. Akhtar et al. (2021) and Coffey and Schroeder (2019) indicate that young farmers are often receptive for innovation, less bounded to traditional strategies and more willing to handle complex information. This is consistent with Dang et al. (2025) and Fields and Gillespie (2008) who argue that older producers are less likely to purchase insurance products, particularly if they have alternative risk management strategies available.

Education is also a crucial factor for adoption decisions, as higher levels of formal education are associated with increased use of risk management tools, likely due to improved understanding of market mechanisms and financial instruments (Coffey & Schroeder 2019; Akhtar et al. 2021). This is confirmed by Fields and Gillespie (2008) who found that lack of understanding and expertise, often correlated with lower educational attainment, is a significant barrier to insurance purchase. In contrast, higher education can also be associated with lower participation in the income stabilisation tool (IST) (Dang et al. 2025), possibly due to preferences of an alternative risk management strategy or perception of the tool being less beneficial.

Gender has been identified as an influential factor in farmers' decision-making process, as female farmers generally seem to be less likely to adopt multiple formal risk management tools compared to male farmers (Dang et al. 2025; Akhtar et al. 2021). This can be interrelated to the suggestion that female farmers often perceive higher risk and may be more risk-averse, limiting their engagement with tools that require investment or expose them to financial uncertainty (Diyyala et al. 2025; Adnan et al. 2023).

There is a distinct heterogeneity within countries, as diverse farming practices (Finger et al. 2023; Rigdon et al. 2023), resource availability and local conditions (Fronda 2023) shift significantly affecting market access and how risk is perceived and decisions are made (OECD 2023; Duden et al. 2023). This suggests that farmers' risk profiles may vary substantially depending on the geographical setting in which they operate, and the subsequent circumstances of their farming enterprise.

In conclusion, the geographical origin of the agriculture constitutes a crucial prerequisite for varying risk preferences and decision-making processes (Duden et al. 2023; Finger et al. 2023; Fronda 2023). Farming systems and market availability are heavily dependent on the country in which the farmer operates, strongly influencing how risk is handled (Rigdon et al. 2023).

2.4 Socio-economic foundations of decision-making under risk

Farm size is widely investigated in studies regarding adoption of risk management tools, usually included as a standard control variable. Findings are dispersed, showing that farm size may influence the dependent variable differently in specific contexts. Carrer et al. (2020) suggest that farm size positively and significantly affects the probability of adopting agricultural rural insurance. Likewise, Coffey and Schroeder (2019) argue that farm size is one of the most important factors in predicting use of risk management tools by grain farmers, suggesting that large farms are more likely to use forward pricing tools. This approach can be emphasised by the findings of Diyyala et al. (2025), demonstrating that larger farms may have more capacity and resources to access various risk management tools. Evidence from South Africa shows a similar trend, with Kisaka-Lwayo and Obi (2012) reporting that relatively larger smallholder farms are more able to adopt protective measures, while smaller farms face financial and labour constraints that limit adoption and make them highly vulnerable to short-term shocks. In contrast, farm size also exhibits positive magnitude, but lack a statistically significant impact on the adoption of price risk management tools (Akhtar et al. 2021; Fields & Gillespie 2008).

From an expected utility perspective, the effect of income on the adoption of risk management tools is ambiguous. On the one hand, higher income may reduce the need for risk management due to greater ability to absorb losses. On the other hand, it may facilitate adoption by easing financial constraints and enabling access to risk management strategies. This two-edged role of income is supported by research emphasising that liquidity constraints can act as a background risk, influencing risk-taking behaviour (Adnan et al. 2024;2023; Guiso & Paiella 2008).

An associated aspect is the structure of income, specifically the role of off-farm income. Although off-farm income is often included among socio-economic characteristics, its direct effect on adoption decisions is rarely estimated (Diyyala et al. 2025; Khanal et al. 2022). However, its inclusion alongside variables related to risk attitude and perception suggests that income diversification may influence how farmers perceive and respond to risk. Having household off-farm income contributes to income stability, reducing the need to adopt risk management practices, while greater exposure to risk likely increases the incentive to implement such strategies (Fields & Gillespie 2008; Diyyala et al. 2025).

2.5 Hypotheses

The hypotheses are based on the theoretical framework, previous empirical findings and the research questions regarding risk perception and risk attitude. As the first research question is exploratory, no explicit hypothesis is formulated for it.

H1. Farmers with higher perceived price risks are more likely to adopt price risk management tools than farmers with lower perceived price risks.

H2. Farmers with more risk-averse attitudes are more likely to adopt price risk management tools than farmers with risk-willing attitudes.

H3. A positive interaction between farmers' price risk perception and risk attitude increases the likelihood of adopting price risk management tools.

3. Method

This chapter outlines the research design, sample and data collection methods used in the study. Furthermore, the analytical approach is presented, followed by a discussion of the study's limitations and potential sources of error.

3.1 Research design

This thesis is a secondary analysis and adopts a quantitative and deductive approach, applying and testing established theories within the risk management context in agriculture. Quantitative research is characterised by positivism and objectivism, arising from the belief that an objective reality exists independently of the researcher (Bryman & Bell 2017). By studying this reality, researchers aim to produce objective and generalisable knowledge (Bryman & Bell 2017).

The thesis uses a cross-sectional research design, which is highly appropriate as it allows for the collection and analysis of data on several variables from a large sample of agricultural enterprises at a single point in time (Bryman & Bell 2017). As the study relies on secondary survey data from the European Union (EU) project "AnalysinG of fossil-Energy dependence in agriculture to increase Resilience against input price fluctuations" (AgEnRes) (Mattsson et al. 2025), this design offer the necessary framework to examine wide-scale patterns, associations and behavioural differences across structurally diverse farming systems and geographical regions.

The thesis uses descriptive statistics and regression analyses to assess the relationship between several independent variables and the dependent variable. Hypotheses are developed based on existing theory and prior literature, with the intention of either confirming or prolonging current theoretical frameworks. The cross-sectional design of the study, together with the regression analyses identifies statistical association rather than definitive proof of cause and effect. Rigid causality cannot be established as potential issues such as reverse causality and omitted variable bias make it difficult to determine exact direction of the effects. However, the directionality of the models is grounded in existing literature, suggesting that X exerts an influence on Y.

3.2 Reliability and validity

For the purpose of being able to generalise and duplicate the results, research has to be reliable and valid (Bryman & Bell 2017). The reliability criteria require that measurements and calculations are accurate and consistent while information is correctly processed (Bryman & Bell 2017). Reliability is ensured by the use of secondary data that was gathered through a structured questionnaire with standardised Likert-type scales, making the measurement procedures consistent and replicable while minimising researcher bias during data collection.

The meaning of validity is the fact that the study measures what is supposed to be measured, but also to what extent there is a proper match between the researchers' observations and the theoretical concepts being examined (Bryman & Bell 2017). A difference is often made between internal validity and external validity, which concerns whether relationships are correctly identified. In this case, internal validity is assured by using EUT and Prospect Theory as the foundation to the econometric models, ensuring that the independent variables logically capture the intended behavioural and socio-demographic concepts. External validity refers to the extent to which findings can be generalised to other contexts, which may be limited in this case due to the contextual nature of the data. While the sample provides valuable insights into the agricultural businesses of the four surveyed EU nations, external validity may be limited due to the context-specific nature of the data. Caution should be exercised when applying the results to non-European agricultural frameworks.

Validity is enhanced through clear operationalisation of theoretical concepts into measurable variables, such as risk-related measures and farm and farmer characteristics. Thus, each concept is defined and converted into empirical indicators based on prior literature, improving the alignment between theory and measurement.

To ensure reliability and validity in this thesis, the author reviewed how similar studies have operationalised variables and designed their methodologies, particularly regarding measurement choices, calculations and theoretical framework. The dataset was thoroughly examined to identify errors or inconsistencies, which were controlled for prior to the analysis. Original data were not altered, instead, inaccurate observations were flagged and treated by creation of additional variables. All regressions and data filtering procedures were conducted using a copy of the original dataset, with all modifications documented. Finally, calculations and methodological choices were reviewed by an advisor and findings were critically reflected on throughout the research process.

3.3 Data collection

This thesis is based on a secondary analysis of a dataset provided in the EU-project AgEnRes by Mattsson et al. (2025). The data were collected across four EU countries, and with the aim for consistency, using a structured questionnaire with Likert-type scales. Since different recruitment strategies were used across the countries, the dataset relies on non-probability sampling, which is important to acknowledge when interpreting the generalisability of the findings. The primary authors utilised market research companies, farmers' associations, e-mail lists, agricultural apprenticeships websites and farms registered in the Farm Accountancy Data Network (FADN) system with a significant share of crop production (Mattsson et al. 2025).

The objective of the primary data collection was "to introduce tri-reference point theory to the agricultural economics literature and to examine its relevance for farmers' decisions under risk, especially for choices involving fossil-energyintensive inputs such as mineral fertilizer" (Mattsson et al. 2025, p.8). The resulting dataset allows for meaningful analysis of farmers' risk perceptions, risk attitudes, socio-economics and socio-demographics, which enables the analysis of decision-making processes and makes it suitable as a solid foundation for analysing individual decision-making processes in this thesis.

Employing a secondary analysis offers the benefits of exploring a large-scale dataset that would be impractical to replicate through primary data collection. In addition, this approach is time-efficient while permitting access to high-quality data.

3.4 Data cleaning and revising

Data cleaning was conducted to improve the integrity of the analysis. This included the manual removal of two implausible observations: one respondent providing their birth year instead of age, and one extreme outlier in farm size. Special cases such as observations reporting zero income were retained as they represent valid cases of farms with no gross income during the reference period. Respondents who selected only the "Other" option (n= 36) for the question regarding their use of price risk management tools were treated as missing values, as responses mainly aimed at strategies to deal with risk, and not a risk tool per se. Respondents reporting either "whole farm is organic" or "parts of farm are organic" were grouped into a single binary variable indicating organic production. Categorical variables were converted to factors while continuous variables were kept numeric. The initial dataset consisted of 729 observations. After the manual editing and the application of listwise deletion, the final regression models were estimated using a sample size of 529 observations. The reduction was mainly driven by missing data in the dependent variable and the income-related measures. All data cleaning, variable transformation and estimations were conducted using the statistical software R, and the Integrated Development Environment (IDE) RStudio to run R.

3.5 Sample

Respondents were distributed across the Netherlands (n = 194), Italy (n = 142), Poland (n =130) and Germany (n = 63) (see Table 1). The choice of the countries was partially a pragmatic choice driven by expertise among the partners in the project, but also with the purpose to cover Central/Western, Eastern and Southern Europe (Mattsson et al. 2025), which is considered to provide a good representation of different farming systems in Europe (Davidova & Thomson 2013; European Parliament Research Service 2014; OECD 2023).

The sample is somewhat skewed, with a larger share of conventional than organic farm businesses (approximately 88% and 12% respectively). This skewness, however, is reasonable and representative, as OECD (2023) shows that agricultural area under organic certification corresponds to 9.1% of the total utilised agricultural area in the EU during 2020. While the distribution is mathematically skewed, it accurately mirrors the reality of the sector. Likewise, a similar proportioned skewness is observed within the gender distribution. Female farmers are underrepresented (see Table 1), however, accurately reflecting the reality of the agricultural sector (OECD 2023). Gender was included due to the extensive behavioural literature suggesting substantial differences in risk aversion and decision-making between genders, as well as to reduce the risk for omitted variable bias.

A total of 267 farmers reported cropping as their primary farm enterprise, while 102 were engaged in livestock production. Finally, mixed or other production constitutes the main activity for 160 of the respondents. In conclusion, a total of 323 (61.05%) farmers used no financial tool to manage price risk, while 206 (38.94%) farmers reported use of at least one price risk management tool, as detailed in Table 1.

Table 1. Descriptive statistics of the sample (n=529)

	n	%
Country		
NL	194	36.67
DE	63	11.90
IT	142	36.84
PL	130	24.57
Production system		
Farm is organic	62	11.72
Farm is not organic	467	88.27
Gender		
Female	59	11.15
Male	470	88.84
Farm type		
Crop	267	50.47
Livestock	102	19.28
Mixed/other	160	30.24
Gender		
Price risk management tools		
Adopt at least one	206	38.94
None	323	61.05

Note: Descriptive statistics are presented for a subset of variables included in the analysis. A complete overview of all variables is provided in Table A1.1 in Appendix 1.

3.6 Data analysis

The primary analysis is conducted using a Linear Probability Model (LPM) estimated via Ordinary Least Squares (OLS), an approach that has become increasingly common in empirical analyses of binary outcomes (Möhring & Finger 2022; Bucheli et al. 2023; Wang et al. 2023; Zachmann et al. 2024). The OLS regression line is a straight line constructed using the OLS estimators β_0 and β_1 for predicting the value of Y (Stock & Watson 2007). The OLS estimates a line of "best fit" by minimising the distances between the line and the actual data points, representing the average trend of the observations.

$$Y = \beta_0 + \beta_1 X + \beta_2 \mathrm{Z} + u \tag{1}$$

Equation (1) is the linear regression model, in which Y is the dependent variable, X is the independent variable, Z represents a vector of socio-economic and demographic control variables and the term u is the error term (Stock & Watson 2007). The intercept β_0 and the slopes β_1 and β_2 are the coefficients, also referred to as estimates in this thesis, of the regression line. The slope β_1 reflects the change in Y associated with a change in X, holding all variables in Z constant. The intercept β_0 specifies the value of the regression line when $X = 0$ and $Z = 0$, that is, the point at which the regression line intersects the Y axis. The error term u captures unobserved factors affecting the dependent variable that are not included in the model. A major advantage of OLS is that it provides a highly intuitive and accessible interpretation, as the coefficients directly represents the marginal change in the probability of the outcome occurring for a one-unit change in the independent variable (Stock & Watson 2007; Wooldridge 2013). The straightforward interpretability is notably beneficial when evaluating interaction effects.

LPMs estimated by OLS and non-linear models such as logistic regressions frequently yield similar results when predicted probabilities are not concentrated near the extremes of zero and one (Angrist & Pischke 2009; Khanal et al. 2022). As shown in Table 5, 39% of the farmers reported adoption, indicating that predicted probabilities are not concentrated near the boundaries, justifying the use of OLS. Moreover, while the LPM offers interaction coefficients that can be interpreted directly and intuitively as a constant change in probability, the non-linear probability models such as Logit or Probit provide estimates that are highly complex and do not represent the true marginal interaction effect (Ai & Norton 2003). However, to ensure the findings were not sensitive to the choice of functional form, logistic regression models were performed as a robustness check, following the empirical approach applied by Dang et al. (2025).

The LPM is likely to suffer from heteroskedasticity, as the variance of the error term depends on the conditional mean of the binary dependent variable. To account for this, heteroskedasticity-robust standard errors were used in all OLS specifications, which is the most usual way to account for this problem and makes the findings more statistically reliable (Stock & Watson 2007).

3.7 Control variables

The regression models include several control variables based on prior literature, as detailed in Table 2. These variables capture appropriate farm and farmer characteristics and are included to enhance model specification and reduce the risk of omitted variable bias in the estimation of the main relationships.

Table 2. Overview of included control variables and their expected effects on the adoption of price risk management tools

Variable	Expected effect
Age	-
Education	+/-
Gender (female)	-
Farm size	+
No household off-farm income	+

Total farm income	-

3.8 Variable construction and transformation

Categorical variables were recoded into binary dummy variables, where the omitted category provides as the reference group. The most frequent category was used as the reference group to ensure stable estimates and to facilitate interpretation relative to the most representative group in the sample.

Treating age, experience, farm size and farm income as continuous preserves the high level of detail, facilitating a more precise estimate of each additional value. As shown in Table 3, all variables exhibit a substantial range and significant variation, indicated by their standard deviations. In addition, the use of continuous variables ensures efficiency by reducing the number of estimated parameters compared to a dummy-coded categorical approach.

However, as age may exhibit non-linear effects, the variable was also specified as a categorical variable, and used in a re-estimation as a robustness check. The variable was then categorised into three groups: 22-45 (young), 46-57 (middle) and 58-84 (old).

While age and experience exhibit approximately symmetric distributions with skewness values near zero, farm size and farm income exhibit extreme right-skewness, as detailed in Table 3. These values far exceed the common threshold of one for highly skewed data, justifying a logarithmic transformation to stabilise variance and ensuring more reliable regression estimates.

Table 3. Descriptive statistics of the continuous original control variables

	Min	Std.Dev	Mean	Max	Skewness
Age	22.00	11.80	50.08	84.00	-0.10
Experience	2.00	13.43	28.77	70.00	0.08
Farm size	0.50	215.88	98.84	3000.00	7.95
Total farm income	0.00	357,937.69	136,840.18	5,000,000.00	8.89

Note: The table is intended to illustrate the degree of skewness of the variables. See Table 6 and 7 for descriptive statistics of the independent variables risk perception and risk attitude.

Table 4 presents descriptive statistics for the log-transformed variables. Farm income was transformed as ln(farm_income + 1) to account for zero values (n= 2), while farm size was strictly positive and therefore transformed using the natural logarithm, ln(farm_size). The log-transformation efficiently adjusted the distribution of farm size, reducing its skewness to almost 0. For farm income, the transformation substantially reduced the extreme right-skewness, making the data more suitable for linear regression, whereas a slight left-skewness remains due to the presence of low-income observations.

The mean log-income was approximately 10.75 with a standard deviation of 1.73, indicating considerable variation in income levels across the 529 farms. The log-income values range from 0 to 15.42, corresponding to actual income ranging from

0 to approximately 5,000,000 Euro (EUR). For farm size, the log-values range from about -0.7 to 8.00, corresponding to actual sizes of 0.5 to 3,000 hectares.

The log-transformations help to mitigate the influence of extreme values and improve the stability of the regression estimates. Furthermore, this specification allows for the interpretation of estimated coefficients as percentage changes. This approach is consistent with established literature for skewed distributions in agricultural data (Coffey & Schroeder 2019; Carrer et al. 2020; Akhtar et al. 2021; Adnan et al. 2023; 2024).

Table 4. Descriptive statistics of the log-transformed variables for farm size and farm income

	Min	Std.Dev	Mean	Max	Skewness
Log farm size	-0.69	1.23	3.79	8.01	0.03
Log farm income	0.00	1.73	10.75	15.42	-1.69

3.9 Dependent variable

The adoption variable was constructed to identify farmers using at least one formal price risk management tool, capturing any engagement. It takes the value 1 if the respondent reported using at least one of the listed financial tools, and 0 if the respondent indicated that no tool was used. The distribution of the variable is presented in Table 5 below.

Table 5. Descriptive statistics of the adoption variable

	Min	Std.Dev	Mean	Max
Adoption	0.00	0.49	0.39	1.00

As this thesis comprises the adoption of price risk management tools such as futures, forward contracts, options and swaps, it emphasises that the adoption expenditures concern both explicit and implicit factors. These expenditures involve transactional and cognitive costs related to market monitoring, and require a standardised definition of their associated costs and resource commitments. These are direct premium payments, liquidity constraints from margin requirements and structural opportunity costs.

3.10 Independent variables

3.10.1 Price risk perception

The dependent variable concerns the adoption of formal price risk management tools, which are specifically designed to mitigate market-related financial uncertainty. This motivates the choice of input price variability and output price variability as theoretically relevant forms of perceived risk. The distinction between these dimensions allows for a nuanced analysis of how different sources of economic uncertainty may influence the farm manager's incentives and decision-making as well as the business's capacity to adopt formal price risk management tools. These forms of market risk directly influence the profitability of the farm enterprise, production costs, revenue stability and long-term financial planning, making them key sources of business risk within farming operations (OECD 2009; Akhtar et al. 2021; Finger et al. 2022). From a business and management perspective, such risks are therefore highly relevant for understanding the organisational incentives to adopt price risk management tools.

Risk perception is measured using self-reported survey responses across the domains; input price variability and output price variability. Respondents rated their perceived level of risk on a four-point Likert scale ranging from 1 ("Not at all") to 4 ("To a great extent"). The option "Don't know" (representing less than 1% of the sample) was treated as missing data and excluded from the analysis. Although the variable is ordinal, it is treated as continuous in the analyses, consistent with common practice for Likert-type measures (Finger et al. 2023).

Both variables exhibit negative skewness due to the relatively high mean values, meaning that respondents perceived agricultural price risks as high (see Table 6 below). Although there is a sufficient dispersion for the variables to be analytically meaningful, it may somewhat limit variation. The pattern suggests that respondents perceive a high level of agricultural price risk, which is consistent with current market volatility and uncertainty within agricultural markets (Finger et al. 2023; OECD 2023). Given that the risk variables are bounded (scale 1-4), and their left-skewed distributions, log-transformation was not considered appropriate.

Table 6. Descriptive statistics of output and input price risk perception

	Min	Std.Dev	Mean	Max	Skewness
Output price risk perception	1.00	0.59	3.67	4.00	-1.79
Input price risk perception	1.0	0.71	3.34	4.00	-0.71

3.10.2 Risk attitude

Following Dohmen et al. (2011) and consistent with recent applications in Agricultural Economics (Finger et al. 2023; Michels et al. 2023), farmers' risk attitude was measured using a self-assessed numerical rating scale from 0 to 10, where higher values indicate greater willingness to take risks. The variable was treated as continuous, consistent with common practice in previous literature (Finger et al. 2023; Michels et al. 2023).

For the regression analyses, the variable was reverse-coded to reflect risk aversion. The transformation ensures that higher values correspond to greater risk aversion, resulting in a scale from 1 (very willing to take risks) to 11 (not willing at all). It provides interpretation, as greater values directly correspond to greater risk aversion, which is anticipated to be positively associated with the adoption of price risk management tools. The re-scaling preserves the underlying variance and distribution, ensuring that the estimated slope coefficients and the corresponding standard errors remain mathematically unaffected (Wooldridge 2013). The risk attitude variable displays reasonable variation across the scale and only minor skewness (see Table 7), supporting its treatment as a continuous variable.

Table 7. Descriptive statistics of risk attitude

	Min	Std.Dev	Mean	Max	Skewness
Risk attitude	1.00	2.04	5.31	11.00	0.26

3.11 Main regression models

To test the proposed hypotheses, a series of regression models was estimated. A stepwise approach was applied, where the independent variables - risk perception, risk attitude and their interaction – were introduced sequentially to the baseline model controlling for the control variables farm and farmer characteristics, as detailed in Table 8. Regression 2 introduces risk perception to test H1. Regression 3 replaces this with risk attitude to test H2 and finally, Regression 4 and 5 include both variables and their interaction term, aiming to examine H3.

Table 8. Main regression models specification

	Control variables	Independent variables		
	Farm and farmer characteristics	Risk perception	Risk attitude	Interaction
Regression 1	✓			
Regression 2	✓	✓		
Regression 3	✓		✓	
Regression 4	✓	✓	✓	✓
Regression 5	✓	✓	✓	✓

Note: In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception.

Following standard recommendations (Aiken et al. 1991; Iacobucci et al. 2016), variables included in the interaction terms were mean-centered primarily for interpretive clarity, serving as a methodological refinement in line with best practice for interaction analyses. Mean centering is highly relevant for continuous Likert-data, and encourages the elucidation of the main effect terms (Iacobucci et al. 2016). This method implies that the estimated coefficients of the variables included in the interaction term can be interpreted as effects at the average level of the interacting variable rather than at zero, which is less meaningful for the analysis of the interaction term (Aiken et al. 1991; Iacobucci et al. 2016). This approach is crucial for the assessment of the interplay between risk attitude and risk perception, as the coefficients are typically interpreted with all other factors held constant. While mean-centering does not reduce multicollinearity or affect model estimates (Echambadi & Hess 2007), multicollinearity was instead examined separately using correlation matrices and Variance Inflation Factors (VIF).

3.12 Robustness check

Robustness checks were conducted for the main regression models (2 to 5) to challenge the results for the independent variables. These tests naturally tested the robustness of the included control variables as well.

Additional variables were included to assess whether the main results were sensitive to the inclusion of further controls. Robustness variables were selected based on the premise that they are related to the dependent variable, may affect the results, but are not central or necessary to identify the main association of the model (Lu & White 2014). The regression models were re-estimated separately, controlling for each country and allowing for the opportunity to capture heterogeneity across national settings and reflect variation in estimations for the independent variables and control variables. This approach naturally resulted in smaller sub-samples for each individual regression, as the analyses were restricted to observations within each specific national context.

Further robustness variables concerned multiple farm types and organic vs non-organic farms to account for the structural discrepancies between production systems and agricultural practices that may influence the adoption of price risk management tools. Different production types represent distinct business models with varying cash flow and asset structures. Experience was included as an indirect proxy for exposure to risky events and prior use of risk management tools. Although imperfect, a longer work-related history may increase the probability that farm operators have faced adverse shocks and gained experience with risk management instruments, which may in turn shape risk perception and adoption decisions.

Moreover, models excluding control variables were conducted in order to assess whether the magnitude of estimates, significance and degree of explanation varies substantially.

To account for potential non-linear relationships between risk attitude, risk perception and adoption, quadratic terms of the respective variables were included. This approach eases the assumption of linearity and allows for effects to vary across different levels of the variables. The inclusion of squared terms is a standard approach in econometric modeling to capture non-linear relationships and avoid functional form misspecification (Wooldridge 2013). Interaction effects are included in linear form without imposing additional non-linear structure on the interaction term.

3.13 Statistical tests

Potential issues of multicollinearity and endogeneity could influence the interpretation of the regression coefficients. Multicollinearity occurs when independent variables and control variables are highly correlated, which could inflate standard errors and reduce the precision of estimated coefficients. To ensure the validity of the regression models, multicollinearity was examined using a Pearson correlation matrix, see Table A5.1 in Appendix 5. As a rule of thumb, correlation coefficients above 0.70 are considered an indication of strong linear relationships that may affect coefficient precision. As noted by Wooldridge (2013), bivariate correlations cannot identify multidimensional collinearity. Thus, VIF values were computed as the main diagnostic tool to examine the total inflation of standard errors, and calculated for both the main models and the robustness specifications (see Table A5.2 and A5.3). In this manner, potential multicollinearity introduced by the additional robustness variables was controlled for.

Following Wooldridge (2013), a common VIF threshold of 10 was established as the upper limit for acceptable collinearity. Considering the inclusion of interaction terms, Generalized Variance Inflation Factors (GVIF) were computed and transformed using GVIF^(1/(2*Df)) to ensure comparability with standard VIF measures. This approach is vital, as interaction terms may automatically increase correlations among explanatory variables (Wooldridge 2013).

3.14 Limitations

Several methodological limitations should be acknowledged. Although statistical tests did not indicate that multicollinearity was a concern, some degree of multicollinearity between the explanatory variables may still be present.

The negatively skewed distribution of the risk perception variables, where a majority of farmers reported higher levels of perceived risk (scores 3 and 4) indicates a concentration at the upper end of the scale. While the sample size is large enough to maintain statistical power, the limited variation implies that the models primarily reflect differences between moderate and high levels of risk perception. Consequently, the results should be interpreted with some caution when generalised to farmers with very low risk perception (score 1), as this group is underrepresented in the sample.

Although the smaller share of female farmers reflects the actual structural reality of the sector, it must be acknowledged as a methodological limitation. The major imbalance implies that the statistical power to detect stable coefficients for female operators is reduced. The results for the gender coefficients should therefore be interpreted with some caution.

Despite multiple included control variables, the possibility that relevant explanatory factors have been omitted cannot be excluded which can give rise to omitted variable bias. Moreover, arising from the non-probability sampling method, the findings are unlikely to be fully generalisable to the broader population (European farmers).

4. Results

This chapter will summarise the findings testing the hypotheses of the thesis starting with the baseline model including farm and farmer characteristics. By a stepwise approach, risk perception, risk attitude and their interaction will be included. The results from the robustness checks will conclude this section.

4.1 Statistical tests

The variables age and experience, as well as farm income and farm size exhibit high correlation coefficients (0.8 and 0.6 respectively), as detailed in the correlation matrix in Table A5.1 in Appendix 5. This is reasonable given that experience typically increases with age, and that larger farm businesses are typically associated with higher income levels due to greater production capacity and economies of scale. However, these values do not appear to pose a threat to the regression models as the VIF values reported in Table A5.2 remain below commonly accepted thresholds of ten, indicating that multicollinearity is not a critical concern.

4.2 Main regression results

4.2.1 Farm and farmer characteristics

The result of the baseline model presents only a limited number of variables showing a statistically significant association with adoption, as detailed in Table A1.2 in Appendix 1. In particular, high education is positively associated with adoption, suggesting that farm operators possessing vocational/professional training or a university degree are more likely to adopt price risk management tools. Moreover, farm size and farm income are somewhat positively related to adoption and exhibit a marginal positive association ($p < 0.10$), suggesting a tendency where larger agribusinesses and those with higher operational revenues are more likely to adopt, although these effects are only weakly significant. Since these variables were log-transformed, their coefficients reflect a percentage-to-percentage-point relationship with the probability of adoption. More specifically, a doubling in farm size and farm income increases the probability of adoption by 3.6 percentage points and 2.5 percentage points respectively. Farmers without any household off-farm income were 10.8 percentage points more likely to adopt than those who hold income sources outside of the core agribusiness, which may reflect a higher reliance on farm revenues and thus a greater need for risk management. Other farm managerial characteristics, such as age and gender do not exhibit statistically significant effects.

4.2.2 Risk attitudes and perceptions

Regarding risk perception (see Regression 2 in Table 9 below), results show that input price risk perception was negative and marginally significant ($p<0.10$), while output price risk perception exhibited a positive and statistically significant effect ($p<0.05$). This suggests a weak negative trend for input price risk perception, whereas a one-unit increase in output price risk perception is associated with an increase in the probability of adoption by around 8 percentage points. The findings are consistent across all model specifications 2 to 5, providing partial support for H1, as only output price risk perception suggesting a positive and significant association with adoption.

In Regression 3, risk attitude indicated a negative association with adoption, consistent with the other two models, with the exception of marginal significance in Regression 4. The uniformity of the coefficients' signs suggests a robust directional trend, but the overall lack of conventional statistical significance indicates no clear evidence of an association with adoption. Therefore, it is not possible to conclude that more risk-averse farmers are more likely to adopt price risk management tools, indicating that H2 is not supported.

When the interaction terms were introduced in Regression 4 and 5, the main effects for risk perception and risk attitude remained stable in magnitude and significance at average levels of the interacting variable. The interactions, however, showed both positive and negative estimates, but no significant support for a moderation effect. The insignificant terms in both Regression 4 and 5 indicate that the influence of risk perception does not consistently vary with risk attitude. The evidence does not provide empirical support for H3, and it is insufficient to reject the null hypothesis.

Concerning the control variables, the effect of farm income gained statistical significance as the behavioural variables were included. Its significance level improved from the 10% level in the baseline to the 5% level in most of the following specifications. Farm size, however, lost significance once controls were added.

Table 9. Results from the OLS regressions assessing how the adoption of risk management tools vary, including risk perception, risk attitude and their interaction

Variable	Regression 2	Regression 3	Regression 4	Regression 5
Risk attitude		-0.017	-0.017 *	-0.017
		(0.010)	(0.010)	(0.010)
Risk perception				
Input price risk perception	-0.053*		-0.053*	-0.053*
	(0.031)		(0.031)	(0.031)
Output price risk perception	0.082 *		0.084*	0.085 *
	(0.037)		(0.037)	(0.037)
Interaction term risk perception × risk attitude			0.003	-0.006
			(0.015)	(0.014)
Age	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Gender (ref: male)				
Female	0.001	0.012	0.017	0.014
	(0.066)	(0.067)	(0.067)	(0.067)
Education (ref: low level)				
High level	0.116 ***	0.114 ***	0.115 ***	0.115 ***
	(0.044)	(0.044)	(0.044)	(0.044)
Farm income (EUR)	0.028 **	0.024*	0.027 **	0.028 **
	(0.013)	(0.013)	(0.013)	(0.013)

Household off-farm income (ref: yes)				
No off-farm income	0.112 **	0.109 **	0.112 **	0.111 **
	(0.045)	(0.045)	(0.045)	(0.045)
Farm size (hectares)	0.029	0.031	0.024	0.023
	(0.020)	(0.020)	(0.020)	(0.020)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception.*

4.3 Robustness checks

4.3.1 Check for heteroskedasticity

The baseline results remain largely unchanged in terms of statistical significance and magnitude when using robust standard errors (see Table A2.1 in Appendix 2), emphasising that heteroskedasticity does not affect the main conclusions.

4.3.2 Logit regressions

Logistic regressions were conducted parallel to the OLS models to account for the binary nature of the dependent variable, and the complete logistic regression results for Regression 1 to 5 are presented in Table A2.2. In order to enable a direct comparison between OLS and logit estimates, marginal effects were computed for the logit models. The comparison is detailed in Table A2.3.

The results show that the marginal effects from the logit models are overall similar in direction and significance to the OLS estimates, indicating that the patterns of significance and direction are robust across model specifications.

4.3.3 Additional robustness variables/omitted variable robustness

The effects of the main explanatory variables consistently show a lack of substantial statistically significant effects across most countries and model specifications, presented in Tables A2.4 to A2.7. Risk attitude is generally not statistically significant, with the exception of a negative effect observed in Poland in some specifications. There is some evidence ($p<0.1$) of a relationship between input price risk perception and adoption of price risk management tools, mainly in the Netherlands, but also in some case, Poland.

Output price risk perception shows some positive and statistically significant ($p< 0.05$) estimates in Germany, but these are not consistent across specifications, suggesting limited robustness. The lack of consistent effects across countries indicates that these relationships can be context specific rather than generalisable. However, when analysing the countries individually, it is vital to note the deviation in sample sizes. To illustrate, while the model for NL includes 194 observations, the DE model is based on 63 scenarios, which limits its statistical power.

While the primary focus is on the stability of the risk-related variables, the control variables are included in all specifications, allowing for an indirect assessment of their robustness. Overall, their coefficients remain rather stable, with only minor variation across countries and model specifications. Gender (female) exhibits a positive and statistically significant effect in Italy, while no consistent effects are observed in other countries (see Table A2.4–A2.7). High level of education is positively associated with adoption of price risk management tools in the original models and in the Netherlands, but remains insignificant elsewhere. Likewise, farmers with no household off-farm income are positively related to adoption in Poland, indicating some heterogeneity across countries. Farm size indicates a positive and significant effect in the Netherlands, with weaker evidence in Italy and Poland. In the German sample, age displays a consistent weakly significant association ($p<0.1$), while farm income shows marginal significance in several estimated models.

Overall, the control variables do not considerably alter the main results and exhibit limited and country-specific effects, further supporting the robustness of the findings related to risk attitude and risk perception.

When including additional control variables (farm type, production system and experience) to the main regression models, the results remain largely consistent, confirming the stability of the main findings (see Table A2.8). Risk attitude sustains its estimates and gain weak significance in Regression 3, while input price risk perception maintains its magnitude and marginal significance ($p<0.1$) across all specifications. Output price risk perception stays positive, whereas its significance level slightly drops from the 5% level to the 10% level when controlling for production systems. The interaction terms between risk perception and risk attitude exhibit the same magnitude and stay statistically insignificant in all models, implying no interaction effects. Note that the inclusion of the "Organic" variable shows a strong significant effect ($p<0.01$), despite the small sub-sample of organic farms (approximately 12%). Yet, it does not considerably alter the direction or magnitude of the primary risk-related variables, further supporting the robustness of the original models. High level education and the absence of off-farm income remain strongly significant across all specifications. In contrast, farm income shows only weak and inconsistent significance. In comparison with the main regression models (see Table 9 above), these results suggest that only education and off-farm income are the most robust predictors, and not farm income.

In conclusion, the results are broadly consistent across model specifications and not sensitive to the inclusion of additional control variables. The independent variables exhibit limited and mostly weak significance, while their estimated effects remain relatively stable.

4.3.4 Functional form robustness

To examine the robustness of the results to alternative functional forms of age, the OLS models were re-estimated using categorical age groups (young, middle and old). While the categorical specification suggests slightly higher adoption levels for the middle-aged and older groups compared to the younger reference category, these differences are not statistically significant, as detailed in Table A3.1 in Appendix 3. The main results were largely robust to alternative specifications of age, although risk attitude gained marginal significance at the 10% level in Regression 3 when controlling for age groups.

When excluding all control variables, the coefficients for risk perception were largely unchanged, indicating limited omitted variable bias (see Table A3.2). The statistical significance increased for risk attitude, suggesting enhanced estimation precision once the control variables were not taken into account. However, the inclusion of control variables substantially increases the explanatory power of the model, as reflected by higher R-squared values. This suggests that farm and farmer characteristics account for an important share of the variation in adoption decisions, although they do not considerably alter the estimated effects of the key variables of interest.

To further test the sensitivity to the main results to functional form assumptions, the model was re-estimated including non-linear specifications of risk attitude and risk perception. Data in Table A4.1 in Appendix 4 reflect that the linear terms for risk perception and risk attitude were positive while the squared terms were negative, suggesting inverted U-shaped relationships between input price risk perception and adoption, and risk attitude and adoption. This suggests that moderate levels of input price risk perception and risk attitude increase adoption, while very high levels reduce it. The 10% statistically significant squared term for input price risk perception, and 5% significant squared term for risk attitude resulted in distinct inverted U-shapes, as illustrated in Figure A1 and A3 in Appendix 4. The squared term for output price risk perception shows a negative sign, but no statistical significance, resulting in a less pronounced visual pattern, as shown in Figure A2. As the effects for input price risk perception is weakly significant, the inverted U-shape cannot be considered empirically supported. Bar plots indicating the adoption probabilities for different levels of risk perception and risk attitude are reflected in Figures A4 to A6.

5. Discussion

This segment assesses the results in relation to previous research and discusses them in the light of EUT and Prospect Theory.

5.1 The role of farm and farmer characteristics

The positive estimates for both farm income and farm size indicate a tentative correlation between a business's financial capacity and the adoption of price risk management tools. Within the framework of EUT, the variables function as proxies for the farmers' wealth, and under the assumption of DARA, EUT implies that firms with stronger financial positions exhibit greater capacity to bear risk. Larger agricultural enterprises often hold a sufficient operational and financial scale to absorb upfront costs, reducing the relative cost of the tool. This is consistent with Coffey and Schroeder (2019) and Diyyala et al. (2025), confirming that larger farms tend to have better access to vital managerial resources. Vice versa, smaller farms are more resource constrained and therefore more vulnerable to shocks (Kisaka-Lwayo & Obi 2012). This scale and liquidity effect, however, is not universally robust (Akhtar et al. 2021) and may depend on the specific proxies used, such as herd size versus hectare (Fields & Gillespie 2008).

The impact of income on adoption can also be interpreted through EUT by examining the role of background risk. While the size of the farm business enhances the capacity to bear the loss, income levels directly determine immediate liquidity. In the light of EUT, liquidity barriers act as unavoidable background risks, where a farmer facing high background risk consequently has a lower tolerance for subsequent risks. In contrast, high-income levels may mitigate this monetary background risk, thus easing financial constraints and improving the adoption of price risk management tools (Guiso & Paiella 2008; Adnan et al. 2023). This is a possible explanation for the contrary theoretical view of income as it does not only change the farm business equity baseline, but actively reduces the compounding pressure of background risks on the farmer's decision-making behaviour.

The findings can be interpreted through Prospect Theory, mainly regarding reference points and loss aversion. For low-income or small-scale farmers, the immediate cost of a price risk management tool displays a certain and instant loss. As a result of loss aversion, this cost is weighted more heavily than the uncertain future benefit of price stability. If these farmers manage their agricultural enterprise close to its survival reference point, the guaranteed premium cost might push them into a perceived loss domain, discouraging adoption. Probability weighting also suggests that farmers running smaller farm businesses may overestimate the low probability of extreme market upswings, making them waive hedging in hopes of capturing high prices, despite their vulnerability to shocks. While larger or high-income farming enterprises operate considerably above their critical reference points, they may evaluate the costs of risk tools rationally rather than as a threatening loss.

The findings demonstrate that farmers without household off-farm income exhibit a higher probability of adopting price risk management tools. This is highly consistent with background risk, as farmers in households entirely dependent on the agricultural business income lack a “natural hedge”. This intensifies their exposure to market volatility and increases the financial value of formal risk mitigation tools (Fields & Gillespie 2008; Diyyala et al. 2025). This dynamic also emphasises the crucial role of the farmer’s reference point. The behaviour of farmers without off-farm income suggests that the threat of catastrophic market shocks overrides the loss aversion to upfront tool expenditure. For the farmers in households not possessing income outside of the farm business, a severe price drop risks pushing the entire household below its survival reference point. The loss aversion to a disastrous income loss outweighs the aversion to the guaranteed cost of hedging, causing a higher reliance on formal price risk management tools to secure their financial reference point.

Similar to how off-farm income functions as a diversification strategy, the negative and significant coefficient for organic farming within the robustness checks suggests that this production system may act as an internal natural hedge. Achieving statistical significance despite the small size of the organic sub-sample highlights a remarkably strong effect. From an EUT perspective, this lower adoption rate may imply that organic agricultural enterprises use structural forms of risk mitigation that lower the overall background risk. Specifically, organic production faces less exposure to taxes and rising commodity prices of fossil-based inputs, grants access to extended subsidies while allowing farmers to sell their products at a higher retail price premium. This integrated stabilisation reduces the financial value of adopting price risk management tools. When evaluating the results through Prospect Theory and its emphasis on reference-dependent preferences, an organic farm business fundamentally involves higher baseline operational costs, shifting the farm operators financial reference point upward. The immediate cost of a price risk management contract may therefore be perceived as a loss that threatens to push them below their critical reference point. The aversion to this loss outweighs the uncertain future benefit of price smoothing, discouraging organic farmers from adoption.

The considerable effect of education on adoption highlights the importance of managerial capability in risk decision-making as the evaluation of expected utility requires the decision-maker to process complex market data and probability distributions. Higher education may enhance farmers’ ability to evaluate price uncertainty and understand the operational functioning of price risk management tools. As emphasised by EUT, the decision-maker tends to optimise corporate returns based on available data, and without the analytical capacity to interpret data, the calculation will be difficult to implement. This restraint stresses the transition from perfect rationality to bounded rationality, where lack of information acts as an informational barrier to adoption (Fields & Gillespie 2008; Akhtar et al. 2021). On the other hand, the role of education can be recognized through Prospect Theory, specifically regarding probability weighting. Higher education may lead to a more objective framing of potential market outcomes, allowing farmers to better assess opportunity costs and mitigate systematic psychological biases. It makes educated decision-makers less prone to the non-linear probability weighting that typically characterises choice under uncertainty. That is, the tendency to overweight low-probability catastrophic events and underweight realistic market volatility. Reduced sensitivity to behavioural biases may enable farmers to objectively assess, and opt out of mediocre price risk management tools (Dang et al. 2025) and select instruments based on financial considerations rather than emotional responses.

In contrast to previous research (Akhtar et al. 2021; Dang et al. 2025), this thesis found no significant association between adoption and the demographical variables of age and gender. This may indicate that the analytical processes and the profit-optimisation described by EUT in this case are more homogeneous across demographical groups than anticipated. From a Prospect Theory perspective, this may imply that risk perception, reference points and probability weighting do not systematically differ between male and female farmers, thus challenging the conventional assumptions regarding demographic variations in managerial risk aversion (Diyyala et al. 2025). However, the substantial overrepresentation of male farmers within the sample may have constrained the statistical power necessary to detect demographic variations, calling for caution when these findings are interpreted. It is highly probable that institutional factors outside the theoretical framework of EUT and Prospect Theory such as specific networks or availability of resources play a crucial role in the decision-making process. For instance, the significance of farm income in Germany may reflect structural differences in the agricultural sector, where capital requirements or market conditions differ from those in other surveyed regions.

5.2 Effects of risk perception and risk attitude

5.2.1 Input price risk perception

The observed findings regarding input price risk perception which are however only weakly significant, align with the definition of perception as a subjective awareness of environmental factors (Wilson et al. 1988), revealing a nuanced and unconventional relationship with tool adoption. Within the framework of EUT, the negative sign suggests that severe input price risk perception functions as a background risk that tightens liquidity constraints. Accordingly, farm managers optimise corporate returns by maintaining cash reserves to manage immediate operational costs rather than allocating capital to tools that leave their primary source of risk unmitigated. This offers support for the concept that financial decision-making is intensely shaped by immediate contextual pressures (Finger et al. 2023; Rigdon et al. 2023). The findings appear consistent with the nature of the available risk management instruments.

This behaviour can further be clarified through the concept of reference-dependent preferences within Prospect Theory. Rising input prices may push the farm business into a perceived loss domain relative to its reference point, resulting in decision-making that deviates from classical rationality (Duden et al. 2023). Instead of objectively weighing probabilities, there is a shift in farmers’ risk tolerance. This reflects behavioural evidence observed globally. Similar to the findings in Bangladesh (Adnan et al. 2023), a high perceived catastrophic risk regarding production costs may contribute to a defensive and risk-seeking mindset in the loss-domain where formal hedging tools are neglected in favour of instant liquidity. Farmers tend to retain instant liquidity instead, choosing to gamble on potentially high future market prices to offset their inflated production costs. These findings support the notion that decisions are ultimately shaped by balancing financial stability with perceived contextual threats (Hansson & Lagerkvist 2012; Adnan et al. 2024). Deviations from the classical economic models could be explained by the fact that farmers frequently rely on heuristic and subjective judgements under uncertainty instead of objectively weighing probabilities (Dessart et al. 2019; Khanal et al. 2019).

5.2.2 Output price risk perception

The observed positive estimates for output price risk perception align with the fundamental projections of EUT. As a farm operator perceives higher volatility in output prices, the fluctuations of the future income streams of the agricultural business increase, incentivizsing the adoption of price risk management tools as a certainty equivalent to secure income and stabilise the firm's profitability. This is also demonstrated by previous research that emphasises that individual decision-making is continuously shaped by a complex balancing between calculating financial returns and evaluating perceived environmental threats (Hansson & Lagerkvist 2012; Adnan et al. 2024). For a risk-averse farm operator, a wider distribution of potential price outcomes severely diminishes the financial viability of leaving market exposure unhedged.

This linear and positive relationship also clarifies how psychological frames function regarding output market volatility. Within Prospect Theory, loss aversion can theoretically introduce ambiguity, as farmers might interpret the upfront potential premium of a contract as an immediate loss, the results suggest that the fear of market-driven deficits outweighs the aversion to the costs of the tools. The individual risk perception and subsequent decision-making is deeply context-dependent (Finger et al. 2023; Rigdon et al. 2023) as it reflects how severe perceived risk directly correlates with shifts in risk tolerance in Bangladesh (Adnan et al. 2023) and drives flexible behaviours during external shocks in Ghana (Dadzie 2023). Escalating output price volatility threatens to put the farm business below its financial reference point, and since the psychological pain of a severe loss on product sales is heavily weighted, the farm manager is more prone to pay the upfront cost of hedging to protect the business from catastrophic downside shifts. The findings emphasise that instead of evaluating market information through a rational corporate decision-making framework, farm operators often rely on heuristic and subjective judgements under uncertainty (Duden et al. 2023), which explains why empirical adoption choices often deviate from classical economic models (Dessart et al. 2019; Khanal et al. 2019).

5.2.3 Risk attitude

The coefficient for risk attitude maintains a stable negative sign, although it was only marginally significant in one specification, suggesting that higher levels of risk aversion may be associated with a lower probability of tool adoption. This result contrasts with the core principles of EUT, which argue that risk-averse individuals experience greater incentives to adopt risk-mitigating instruments to stabilise corporate cash flows and mitigate financial risk. A great share of empirical literature supports this traditional view, confirming that risk-averse farmers frequently prioritise risk-mitigating strategies such as insurance and contract farming (Fields & Gillespie 2008; Akhtar et al. 2021; Peng & Xu 2023). The findings challenge this economic baseline and provide tentative support for the arguments presented by Dessart et al. (2019) and Finger et al. (2024) that risk preferences are dynamic, context-dependent and reliant to time variation rather than static. This deviation from EUT can be explained within the Prospect Theory framework by assessing how psychological preferences operate when facing complicated financial decisions. The certain upfront cost of adopting a price risk management tool along with the uncertainty regarding whether it will yield a net positive return may trigger severe loss aversion. This is supported by Biondo et al. (2025), which emphasises that high risk aversion unexpectedly becomes a barrier if the risk management tool itself is perceived as a risky factor. In addition, lack of familiarity with price risk management tools may lead to risk- averse farmers rather trusting heuristic and subjective prejudices than objective risk assessment (Khanal et al. 2019; Duden et al. 2023). This behaviour aligns with the perspective of background risk, where farmers facing high fundamental or institutional uncertainty become more cautious overall and avoid unfamiliar operational innovations (Fronda 2023). Under the light of DARA, highly risk-averse farmers may also have limited financial resources, restricting their ability to adopt such instruments. Tight resource constraints may confine the structural capacity to bear hedging costs, thus discourage implementation of formal instruments despite their exposure to market volatility.

The consistent direction of the risk coefficients suggests that the underlying psychological mechanisms regarding risk operate similarly across different contexts. However, the lacking or and varying statistical significance may be attributed to variations in sample size or specific local market conditions, such as price stabilization policies, which could weaken the observable impact of risk perception and attitude.

5.3 Interaction between risk perception and risk attitude

The interaction terms between risk perception and risk attitude provide both positive and negative estimates for the adoption of price risk management tools. Output price risk perception and risk attitude jointly influence adoption in a consistently positive manner, which is conceptually intuitive as EUT suggests that higher levels of risk aversion may act as a psychological driver that increases the subjective effect of market volatility. Similarly, for a highly risk-averse farm operator, an increase in perceived output price risk enhances the financial value of risk mitigation, thereby encouraging the farmer to adopt formal hedging instruments to stabilise future revenues for the agricultural enterprise.

The negative interaction coefficient for input price risk perception and risk attitude deviates from traditional EUT predictions, but can be explained from a Prospect Theory perspective in the concept of loss aversion. Farmers fundamentally evaluate market conditions relative to a perceived loss domain rather than a gain domain when production costs rise. Thus, high risk aversion does not intensify adoption, but rather triggers a defensive cognitive heuristic. The upfront costs associated with implementing a financial contract are deemed certain, immediate losses and the managerial risk aversion functions as a behavioural barrier, muting the expected protective value of the tools and discouraging adoption.

These patterns should be interpreted with caution and examined mainly as indicative rather than conclusive evidence, since none of the interaction effects are statistically significant in any specification. The insignificant interaction effects suggest that risk perception and risk attitude mainly function as independent influences in the decision-making process, implying that farmers evaluate their personal risk tolerance and external market volatility individually instead of as a combined decision-making framework.

5.4 Methodological reflections and future research

The cross-sectional design of the study makes it possible to clarify correlations, but it cannot prove and establish causality with absolute certainty. Therefore, caution should be exercised in drawing definite conclusions about causality. Although the results indicate that specific farm and farmer characteristics promote adoption, unobserved confounding factors cannot be left out from affecting the variables. Non-response bias is also a concern as those who chose not to participate in the study, or answer specific questions, may differ significantly from those actually participating, which can result in skewed and misleading results. Moreover, the sample of participants may be skewed from the beginning, due to the non-probability sampling method, which reduces the generalisability of the study.

The data on price risk perception exhibit a skewed distribution as the mean value for both variables is very high, meaning that the majority of the respondents reported high or extreme awareness of these market risks. This limits the variance in the lower range of the scales, constraining the statistical power of the regression models and concealing the effect of lower perceptions in adoption behaviour.

Future research would benefit from conducting a longitudinal design in order to assess fluctuations in decision-making processes over time. This design however, would call for the use of a panel regression model such as fixed-effects or random-effects specification, which would allow to control for time-invariant unobserved heterogeneity. This approach makes it possible to follow how individuals change as variables are measured over time, rather than getting a snapshot, making it easier to establish and understand causation. Collecting data across multiple points in time could provide greater variation and a more precise evaluation of whether the use of price risk management tools is driven by long-term corporate policy or short-term, shock-influenced behavioural factors, thereby capturing a wider range of subjective risk behaviour. This approach also provides the possibility to detect complex patterns and trends that are not visible in cross-sectional studies. Combined with qualitative interviews, this would provide a deeper understanding of the psychological barriers behind farm operators' decisions. Additionally, a greater and more heterogeneous sample concerning farmers from additional countries collected by probability sampling would reduce the risk for sampling bias and better represent the total population, also making it easier to generalise findings. A larger overall sample could enable a more even balance in sub-samples, enhancing the statistical power and making it easier to detect true behavioural differences between groups of respondents. This could also be done by employing a stratified sampling strategy and by intentionally oversampling underrepresented categories such as organic farm enterprises or female operators. It would provide the empirical models with the necessary statistical prerequisites to assess how distinct production systems and institutional frameworks influence the adoption of price risk management tools.

With a bigger sample size and higher rate of adoption of risk management tools, *Seemingly Unrelated Regressions* (SUR) would be an appropriate extension (Zellner & Huang 1962). SUR is a method for simultaneously estimating several regression equations where the error terms are allowed to be correlated across the equations, as farmers often assess risk management tools as part of a broader portfolio rather than in isolation. It does not require the dependent and independent variables to be identical, as the model is particularly useful when decision-making are related but not the same. SUR would improve the efficiency of the estimates compared to independent models and furnish a more nuanced insight of the interdependencies in farmers' decision-making processes (Zellner & Huang 1962).

6. Conclusion

By using data collected in the EU-project AgEnRes, this thesis has analysed the adoption of price risk management tools among farmers across four EU countries. To answer the research questions, this thesis identifies highly educated farmers, farm size, farm income and household off-farm income as the main predictors of adoption of price risk management tools. When controlling for additional robustness variables, the results suggest that highly educated farm operators and those without income outside of the farm business are the most probable to adopt price risk management tools. In contrast, the findings suggest that organic farm businesses are significantly less prone to adopt than non-organic farms. Similar to how off-farm income may function as a diversification strategy, organic production may act as an internal natural hedge for the farm business.

Input price risk perception among farmers suggested a negative relationship with adoption, where an increase reflected a decrease in the use of price risk management tools. Despite the lack of conventional levels of statistical significance, the consistently negative coefficient may reflect liquidity constraints or the fact that output-focused insurance does not mitigate input-side pressures. This potential inverse relationship justifies further investigation into how specific risk dimensions interact with adoption choices. On the other hand, farmers perceiving higher output price risk were significantly associated with adoption. This positive relationship agrees with the theoretical framework and verifies that farmers are highly responsive to risk management instruments when the tool's hedging capabilities directly match the specific market volatility – here, output price – that they find threatening.

Risk attitude consistently showed a negative and partly weak significant coefficient, suggesting that highly risk averse farmers in the sample are associated with a lower likelihood of adopting price risk management tools. The negative coefficient can be explained by the concept of loss aversion, unfamiliarity with the tool or limited resources to implement new instruments.

The interaction between risk attitude and input price risk perception suggest a negative relationship to adoption, emphasising the impression of input price related risks as an operational barrier discouraging adoption among risk averse farmers. In contrast, the interaction between output price risk perception and risk attitude exhibits a positive coefficient, suggesting that more risk-averse farm operators who perceive greater output price risk may be more willing to adopt price risk management tools. However, none of the interaction terms indicate statistical significance, implying that the influence of risk perception does not consistently vary with risk attitude.

This thesis suggests that the findings should be interpreted with caution and examined primarily as indicative rather than conclusive evidence, due to their marginal significance. It emphasises the possibility that there are more factors beyond the examined farm and farmer characteristics, risk perception and risk attitude that are substantial for farm operators' adoption of price risk management tools.

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Popular science summary

Imagine you are a farmer planning your next production season. Prices for both inputs and outputs are uncertain and every decision you make brings financial risk to the business. Meanwhile, as the human population grows and intensified global environmental changes are to be expected, it is vital that agricultural businesses are resilient and able to maintain production. There are multiple financial tools that can protect you from future price volatility, but the tools come at a cost, and so does the uncertainty they aim to mitigate. This uncertainty has a big impact on agricultural decision-making and risk management. As follows, this thesis assesses how farm and farmer characteristics, risk attitude and risk perception influence farmers' adoption of price risk managament tools. If we understand how managerial behaviour and risk assessment influence farmers' decision-making, we can also understand how markets and policies need to evolve to motivate the adoption of price risk management tools within the farm business.

The study is based on a survey concerning 529 farmers from four European Union countries. Results indicate that highly educated farm operators and those without income outside of the farm business are the most prone to adopt price risk management tools. In contrast, farm operators with organic agricultural businesses are significantly less prone to adopt these tools than their non-organic counterparts. Operating an organic agricultural enterprise and having off-farm income can be interpreted as structural forms of risk mitigation that lower the incentive to implement formal risk management tools.

Farm managers with a high input price risk perception are associated with lower likelihood to adopt price risk management tools, while farmers perceiving high output price risk are related to higher probability to adopt and implement tools. While severe input price risk may tighten the farm business's liquidity constraints and hinder adoption, the fluctuations in future income streams may incentivise the implementation of price risk management tools in order to stabilise its profitability. Risk aversion suggests a negative relationship with adoption, potentially working as a barrier if the price risk management tool is unknown and perceived as risky by the operator. While the study identified these interesting patterns, the findings should be interpreted with caution, as the evidence is not strong enough to confirm these relationships with certainty. It is important to acknowledge that adoption behaviour may also be affected by additional unobserved factors not captured in the present thesis.

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Appendix 1: Number and percentage of the used data and baseline regression model results

Table A1.1. Description of the composition of the sample (n= 529)

	n	%
Country		
NL	194	36.67
DE	63	11.90
IT	142	26.84
PL	130	24.57
Gender		
Female	59	11.15
Male	470	88.84
Age		
19-45 (young)	188	35.53
46-57 (middle)	176	27.59
58-84 (old)	165	31.19
Farm type		
Crop	267	50.47
Livestock	102	19.28
Mixed/other	160	30.24
Area arable land (hectares)		
<5 (small)	18	3.40
6-50 (medium)	272	51.41
>50 (large)	239	45.17
Educational level		
Primary school	9	1.70
Secondary school	130	24.57
Vocational or professional	159	30.05
University	231	43.66
Farm income EUR		
0-50,000	261	49.33
50,001-5,000,000	268	50.66
Household off-farm income		
Yes	356	67.29
No	173	32.70
Production system		
Farm is organic	62	11.72
Farm is not organic	467	88.27
Experience (years)		
1-22	180	34.02
23-35	184	34.78
36-70	165	31.19
Price risk management tools		
Adopt at least one	206	38.94
None	323	61.05

Note: Poland uses Zloty and reported values in Zloty. In the data, these values have been converted to Euro using the same exchange rate used at the time for designing the experiment (18 Feb 2025, 1 EUR = 4.15 PLN). The data for age, hectares, farm income and experience has been categorised into groups to provide a comprehensive overview in this table.

Table A1.2. Results from the OLS regression assessing how the adoption of risk management tools vary with respect to farm and farmer characteristics

	Coefficient
Regression 1	
Age	0.000
	(0.001)
Gender (ref: male)	
Female	-0.000
	(0.066)
Education (ref: low level)	
High level	0.115 ***
	(0.044)
Farm income (EUR)	0.025*
	(0.013)
Household off-farm income (ref: yes)	
No off-farm income	0.108 **
	(0.045)
Farm size (hectares)	0.036*
	(0.020)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. Low level education refers to primary and secondary school, while high level education refers to vocational or professional training and university.*

Appendix 2: Robustness checks

Table A2.1. Comparison of OLS estimates using conventional and heteroskedasticity-robust standard errors across model specifications

Variables	Regression 1	Regression 1 (Robust standard errors)	Regression 2	Regression 2 (robust standard errors)	Regression 3	Regression 3 (robust standard errors)	Regression 4	Regression 4 (robust standard errors)	Regression 5	Regression 5 (robust standard errors)
Risk attitude					-0.017 (0.010)	-0.017* (0.010)	-0.017* (0.010)	-0.017* (0.010)	-0.017 (0.010)	-0.017* (0.010)
Risk perception										
Input price risk perception			-0.053* (0.031)	-0.053* (0.030)			-0.053* (0.031)	-0.053* (0.030)	-0.053* (0.031)	-0.053* (0.031)
Output price risk perception			0.082 ** (0.037)	0.082 ** (0.035)			0.084 ** (0.037)	0.084 ** (0.036)	0.085 ** (0.037)	0.085 ** (0.035)
Interaction term risk perception × risk attitude							0.003 (0.015)	0.003 (0.012)	-0.006 (0.014)	-0.006 (0.013)
Age	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Gender (ref: male)										
Female	-0.000 (0.066)	-0.000 (0.063)	0.001 (0.066)	0.001 (0.062)	0.012 (0.067)	0.012 (0.063)	0.017 (0.067)	0.017 (0.064)	0.014 (0.067)	0.014 (0.063)
Education (ref: low level)										

High level	0.115 *** (0.044)	0.115 ** (0.044)	0.116 *** (0.044)	0.116 *** (0.044)	0.114 *** (0.044)	0.114 ** (0.044)	0.115 *** (0.044)	0.115 *** (0.044)	0.115 *** (0.044)	0.115 *** (0.044)
Farm income (EUR)	0.025* (0.013)	0.025 ** (0.011)	0.028 ** (0.013)	0.028 ** (0.011)	0.024* (0.013)	0.024 ** (0.011)	0.027 ** (0.013)	0.027 ** (0.011)	0.028 ** (0.013)	0.028 ** (0.011)
Household off-farm income (ref: yes)										
No off-farm income	0.108 ** (0.045)	0.108 ** (0.045)	0.112 ** (0.045)	0.112 ** (0.045)	0.109 ** (0.045)	0.109 ** (0.045)	0.112 ** (0.045)	0.112 ** (0.045)	0.111 ** (0.045)	0.111 ** (0.045)
Farm size (hectares)	0.036* (0.020)	0.036 ** (0.018)	0.029 (0.020)	0.029 (0.018)	0.031 (0.020)	0.031* (0.018)	0.024 (0.020)	0.024 (0.019)	0.023 (0.020)	0.023 (0.019)

*Notes: Standard errors and robust standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception.*

Table A2.2. Full logistic regression results for regression 1 - 5

Variables	Logit regression 1	Logit regression 2	Logit regression 3	Logit regression 4	Logit regression 5
Risk attitude			-0.078* (0.047)	-0.084* (0.048)	-0.080* (0.047)
Risk perception					
Input price risk perception		-0.234* (0.139)		-0.238* (0.139)	-0.241* (0.140)
Output price risk perception		0.380 ** (0.178)		0.407 ** (0.182)	0.398 ** (0.179)
Interaction term risk perception × risk attitude				0.045 (0.083)	-0.032 (0.064)
Age	0.003 (0.007)	0.003 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)
Gender (ref: male)					
Female	-0.024 (0.303)	-0.017 (0.306)	0.038 (0.306)	0.052 (0.309)	0.037 (0.308)
Education (ref: low level)					
High level	0.505 *** (0.196)	0.513 *** (0.197)	0.506 * (0.196)	0.513 *** (0.197)	0.514 *** (0.197)
Farm income (EUR)	0.120* (0.066)	0.136 ** (0.068)	0.120* (0.066)	0.135 ** (0.068)	0.137 ** (0.067)
Household off-farm income (ref: yes)					
No off-farm income	0.475 ** (0.198)	0.492 ** (0.200)	0.479 ** (0.199)	0.499 ** (0.200)	0.495 ** (0.200)
Farm size (hectares)	0.161* (0.092)	0.127 (0.094)	0.139 (0.092)	0.104 (0.094)	0.103 (0.094)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception. Each logit regression reflects each OLS regression (1-5).*

Table A2.3. Comparison of OLS estimates and logit marginal effects (ME) across model specifications

Variables	OLS Regression 1	Logit ME	OLS Regression 2	Logit ME	OLS Regression 3	Logit ME	OLS Regression 4	Logit ME	OLS Regression 5	Logit ME
Risk attitude					-0.017 (0.010)	-0.017 (0.010)	-0.017* (0.010)	-0.018* (0.010)	-0.017 (0.010)	-0.017* (0.010)
Risk perception										
Input price risk perception			-0.053* (0.031)	-0.052 (0.030)			-0.053* (0.031)	-0.052* (0.030)	-0.053* (0.031)	-0.052* (0.030)
Output price risk perception			0.082 ** (0.037)	0.084 ** (0.038)			0.084 ** (0.037)	0.088 ** (0.039)	0.085 ** (0.037)	0.087 ** (0.038)
Interaction term risk perception × risk attitude							0.003 (0.015)		-0.006 (0.014)	
Age	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Gender (ref: male)										
Female	-0.000 (0.066)	-0.005 (0.067)	0.001 (0.066)	-0.003 (0.067)	0.012 (0.067)	0.008 (0.068)	0.017 (0.067)	0.011 (0.068)	0.014 (0.067)	0.008 (0.068)
Education (ref: low level)										
High level	0.115 *** (0.044)	0.115 *** (0.044)	0.116 *** (0.044)	0.115 *** (0.044)	0.114 *** (0.044)	0.114 *** (0.044)	0.115 *** (0.044)	0.115 *** (0.044)	0.115 *** (0.044)	0.115 *** (0.044)
Farm income (EUR)	0.025* (0.013)	0.027 (0.014)	0.028 ** (0.013)	0.030 ** (0.015)	0.024* (0.013)	0.026 (0.014)	0.027 ** (0.013)	0.029 ** (0.014)	0.028 ** (0.013)	0.030 ** (0.014)
Household off-farm income (ref: yes)										
No off-farm income	0.108 ** (0.045)	0.108 ** (0.045)	0.112 ** (0.045)	0.111 ** (0.045)	0.109 ** (0.045)	0.109 ** (0.045)	0.112 ** (0.045)	0.112 ** (0.045)	0.111 ** (0.045)	0.111 ** (0.045)

Farm size (hectares)	0.036* (0.020)	0.036 (0.020)	0.029 (0.020)	0.028 (0.020)	0.031 (0.020)	0.031 (0.020)	0.024 (0.020)	0.023 (0.020)	0.023 (0.020)	0.022 (0.020)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. Marginal effects from logit models are reported alongside OLS coefficients for comparability. Statistical significance for marginal effects is reported using the same threshold as for the regression coefficients.*

Table A2.4. Regression 2 re-estimated for each country

Variables	Original model	NL	DE	IT	PL
Risk attitude					
Risk perception					
Input price risk perception	-0.053* (0.031)	-0.095* (0.051)	-0.047 (0.121)	-0.014 (0.048)	0.114* (0.067)
Output price risk perception	0.082 ** (0.037)	0.075 (0.058)	0.233* (0.124)	0.036 (0.055)	-0.020 (0.106)
Age	0.000 (0.001)	0.002 (0.003)	-0.011* (0.006)	-0.000 (0.002)	0.002 (0.003)
Gender (ref: male)					
Female	0.001 (0.066)	-0.121 (0.176)	0.110 (0.222)	0.234 *** (0.083)	0.003 (0.114)
Education (ref: low level)					
High level	0.116 *** (0.044)	0.142* (0.076)	0.100 (0.151)	0.035 (0.068)	0.008 (0.097)
Farm income (EUR)	0.028 ** (0.013)	-0.028 (0.039)	0.075* (0.040)	-0.000 (0.014)	0.071 (0.057)
Household off-farm income (ref: yes)					
No off-farm income	0.112 ** (0.045)	0.126 (0.079)	-0.090 (0.149)	0.099 (0.066)	0.202 ** (0.098)
Farm size (hectares)	0.029 (0.020)	0.105 ** (0.046)	-0.032 (0.065)	0.045 (0.027)	0.071 (0.055)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. Each column represents a separate regression model for the respective country. Sample sizes vary between countries due to differences in initial response rates and listwise deletion of missing values. Total n = 529 (NL = 194, DE = 63, IT = 142, PL = 130).*

Table A2.5. Regression 3 re-estimated for each country

Variables	Original model	NL	DE	IT	PL
Risk attitude	-0.017 (0.010)	-0.004 (0.022)	-0.013 (0.038)	-0.001 (0.012)	-0.074 *** (0.020)
Age	0.000 (0.001)	0.003 (0.003)	-0.010* (0.006)	-0.000 (0.002)	0.006* (0.003)
Gender (ref: male)					
Female	0.012 (0.067)	-0.090 (0.180)	0.151 (0.224)	0.232 *** (0.083)	0.028 (0.109)
Education (ref: low level)					
High level	0.114 *** (0.044)	0.163 ** (0.077)	0.078 (0.154)	0.031 (0.066)	-0.012 (0.093)
Farm income (EUR)	0.024* (0.013)	-0.030 (0.039)	0.070* (0.041)	-0.001 (0.014)	0.046 (0.055)
Household off-farm income (ref: yes)					
No off-farm income	0.109 ** (0.045)	0.106 (0.079)	-0.057 (0.148)	0.097 (0.065)	0.212 ** (0.093)
Farm size (hectares)	0.031 (0.020)	0.115 ** (0.046)	0.004 (0.064)	0.051* (0.026)	0.058 (0.052)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. Each column represents a separate regression model for the respective country. Sample sizes vary between countries due to differences in initial response rates and listwise deletion of missing values. Total n = 529 (NL = 194, DE = 63, IT = 142, PL = 130).*

Table A2.6. Regression 4 re-estimated for each country

Variables	Original model	NL	DE	IT	PL
Risk attitude	-0.017* (0.010)	0.001 (0.022)	-0.039 (0.042)	0.004 (0.012)	-0.081 *** (0.027)
Risk perception					
Input price risk perception	-0.053* (0.031)	-0.099* (0.051)	-0.055 (0.123)	-0.012 (0.048)	0.091 (0.064)
Output price risk perception	0.084 ** (0.037)	0.088 (0.059)	0.323 ** (0.147)	0.031 (0.055)	-0.137 (0.166)
Interaction term risk perception × risk attitude	0.003 (0.015)	0.038 (0.032)	0.099 (0.094)	0.019 (0.016)	0.043 (0.065)
Age	0.000 (0.001)	0.003 (0.003)	-0.010* (0.006)	0.000 (0.002)	0.005 (0.003)
Gender (ref: male)					
Female	0.017 (0.067)	-0.148 (0.181)	0.094 (0.228)	0.261 *** (0.087)	0.031 (0.111)
Education (ref: low level)					
High level	0.115 *** (0.044)	0.145* (0.077)	0.118 (0.153)	0.036 (0.068)	-0.004 (0.093)
Farm income (EUR)	0.027 ** (0.013)	-0.026 (0.039)	0.070 (0.042)	-0.000 (0.014)	0.038 (0.055)
Household off-farm income (ref: yes)					
No off-farm income	0.112 ** (0.045)	0.127 (0.079)	-0.075 (0.150)	0.100 (0.066)	0.220 ** (0.094)
Farm size (hectares)	0.024 (0.020)	0.108 ** (0.047)	-0.053 (0.068)	0.045 (0.028)	0.072 (0.053)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. Output price variability represents risk perception in the interaction term. Each column represents a separate regression model for the respective country. Sample sizes vary between countries due to differences in initial response rates and listwise deletion of missing values. Total n = 529 (NL = 194, DE = 63, IT = 142, PL = 130).*

Table A2.7. Regression 5 re-estimated for each country

Variables	Original model	NL	DE	IT	PL
Risk attitude	-0.017 (0.010)	-0.003 (0.022)	-0.021 (0.040)	-0.001 (0.012)	-0.068 *** (0.022)
Risk perception					
Input price risk perception	-0.053* (0.031)	-0.098* (0.055)	-0.054 (0.124)	-0.015 (0.049)	0.100 (0.073)
Output price risk perception	0.085 ** (0.037)	0.075 (0.058)	0.242* (0.128)	0.036 (0.056)	-0.047 (0.104)
Interaction term risk perception × risk attitude	-0.006 (0.014)	-0.003 (0.032)	-0.005 (0.077)	-0.001 (0.017)	-0.007 (0.029)
Age	0.001 (0.001)	0.002 (0.003)	-0.010* (0.006)	-0.000 (0.002)	0.005 (0.003)
Gender (ref: male)					
Female	0.014 (0.067)	-0.115 (0.180)	0.131 (0.229)	0.232 *** (0.085)	0.018 (0.110)
Education (ref: low level)					
High level	0.115 *** (0.044)	0.142* (0.078)	0.108 (0.157)	0.036 (0.069)	-0.002 (0.094)
Farm income (EUR)	0.028 ** (0.013)	-0.028 (0.039)	0.081* (0.044)	-0.000 (0.014)	0.039 (0.055)
Household off-farm income (ref: yes)					
No off-farm income	0.111 ** (0.045)	0.126 (0.079)	-0.087 (0.151)	0.100 (0.066)	0.216 ** (0.095)
Farm size (hectares)	0.023 (0.020)	0.105 ** (0.047)	-0.041 (0.068)	0.046 (0.028)	0.065* (0.053)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. Input price variability represents risk perception in the interaction term. Each column represents a separate regression model for the respective country. Sample sizes vary between countries due to differences in initial response rates and listwise deletion of missing values. Total n = 529 (NL = 194, DE = 63, IT = 142, PL = 130).*

Table A2.8. Main regression models 2-5 including robustness variables

Variables	Regression 2	Regression 3	Regression 4	Regression 5
Risk attitude		-0.017* (0.010)	-0.017* (0.010)	-0.016 (0.010)
Risk perception				
Input price risk perception	-0.056* (0.030)		-0.056* (0.030)	-0.057* (0.030)
Output price risk perception	0.064* (0.037)		0.065* (0.037)	0.066* (0.037)
Interaction term risk perception × risk attitude			0.007 (0.015)	-0.009 (0.013)
Age	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Gender (ref: male)				
Female	0.059 (0.069)	0.068 (0.069)	0.076 (0.070)	0.069 (0.069)
Education (ref: low level)				
High level	0.147 *** (0.044)	0.148 *** (0.044)	0.147 *** (0.044)	0.147 *** (0.044)
Farm income (EUR)	0.023* (0.014)	0.021 (0.013)	0.023 (0.014)	0.023* (0.014)
Household off-farm income (ref: yes)				
No off-farm income	0.124 *** (0.044)	0.122 *** (0.044)	0.125 *** (0.044)	0.124 *** (0.044)
Farm size (hectares)	0.030 (0.020)	0.031 (0.020)	0.025 (0.020)	0.025 (0.020)
Farm type (ref: Crop)				
Livestock	0.009 (0.057)	0.006 (0.057)	0.005 (0.057)	0.007 (0.057)
Mixed/other	-0.006 (0.047)	-0.002 (0.048)	0.001 (0.048)	0.001 (0.048)

Production system (ref:non-organic)				
Organic	-0.269 *** (0.066)	-0.280 *** (0.066)	-0.274 *** (0.066)	-0.277 *** (0.066)
Experience	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception.*

Appendix 3: Functional form robustness results

Table A3.1. Comparison of OLS main estimates (risk attitude, input price risk perception and output price risk perception) with age as a continuous variable (original) and age as a categorical variable and dummy coded by young, middle and old with young as the reference category.

Variables	Regression 2 originial	Alternative age specification	Regression 3 original	Alternative age specification	Regression 4 original	Alternative age specification	Regression 5 original	Alternative age specification
Risk attitude			-0.017 (0.010)	-0.017* (0.010)	-0.017* (0.010)	-0.017* (0.010)	-0.017 (0.010)	-0.017 (0.010)
Risk perception								
Input price risk perception	-0.053* (0.031)	-0.052* (0.031)			-0.053* (0.031)	-0.052* (0.031)	-0.053* (0.031)	-0.053* (0.031)
Output price risk perception	0.082 ** (0.037)	0.082 ** (0.037)			0.082 ** (0.037)	0.083 ** (0.037)	0.085 ** (0.037)	0.084 ** (0.037)
Interaction risk perception × risk attitude					0.003 (0.015)	0.004 (0.015)	-0.006 (0.014)	-0.006 (0.014)
Age (continuous)	0.000 (0.001)		0.000 (0.001)		0.000 (0.001)		0.001 (0.001)	
Young		Ref.		Ref.		Ref.		Ref.
Middle		0.024 (0.050)		0.033 (0.050)		0.032 (0.050)		0.033 (0.050)
Old		0.007 (0.051)		0.011 (0.051)		0.013 (0.051)		0.014 (0.051)

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception. Control variables included but not reported; results are consistent with main specification. Age group "Young" was used as the reference category.*

Table A3.2. Comparison of OLS main estimates with control variables included and excluded

Variables	Control variables included	Control variables excluded
Risk attitude	-0.017* (0.010)	-0.025 ** (0.010)
Adjusted R-squared	0.049	0.009
Risk perception		
Input price risk perception	-0.053* (0.031)	-0.061* (0.031)
Output price risk perception	0.082 ** (0.037)	0.089 ** (0.038)
Adjusted R-squared	0.053	0.009

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01.*

Estimates are largely unchanged when control variables are excluded, suggesting limited omitted variable bias. Statistical significance increases in one variable in the specification excuding control variables, indicating enhanced estimation precision without additional factors. However, the control variables taken into account increases the explanatory power of the model and suggests that farm and farmer characteristics capture an important share of the variation in adoption decisions.

Appendix 4: Evidence for non-linear effects

Table A4.1. Linear and non-linear (squared terms) specifications of risk perception and risk attitude.

	Regression 2		Regression 3	
Variable	Linear term	Squared term	Linear term	Squared term
Risk attitude			0.067 (0.040)	-0.007 ** (0.003)
Risk perception				
Input price risk perception	0.353 (0.231)	-0.065 * (0.037)		
Output price risk perception	0.214 (0.298)	-0.020 (0.047)		

*Notes: Standard errors in parentheses. Coefficients are annotated with * if p<0.1, ** if p<0.05, *** if p<0.01. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception. Control variables included but not reported; results are consistent with main specification.*

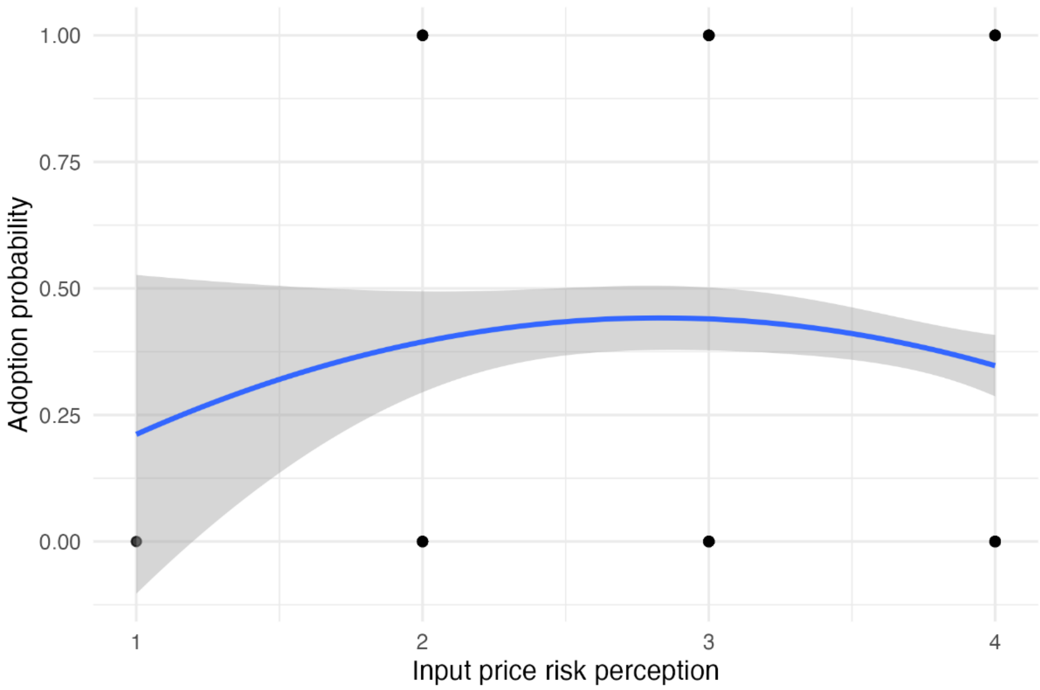

Figure A1. The graphical pattern for a potential inverted U-shape for input price risk perception.

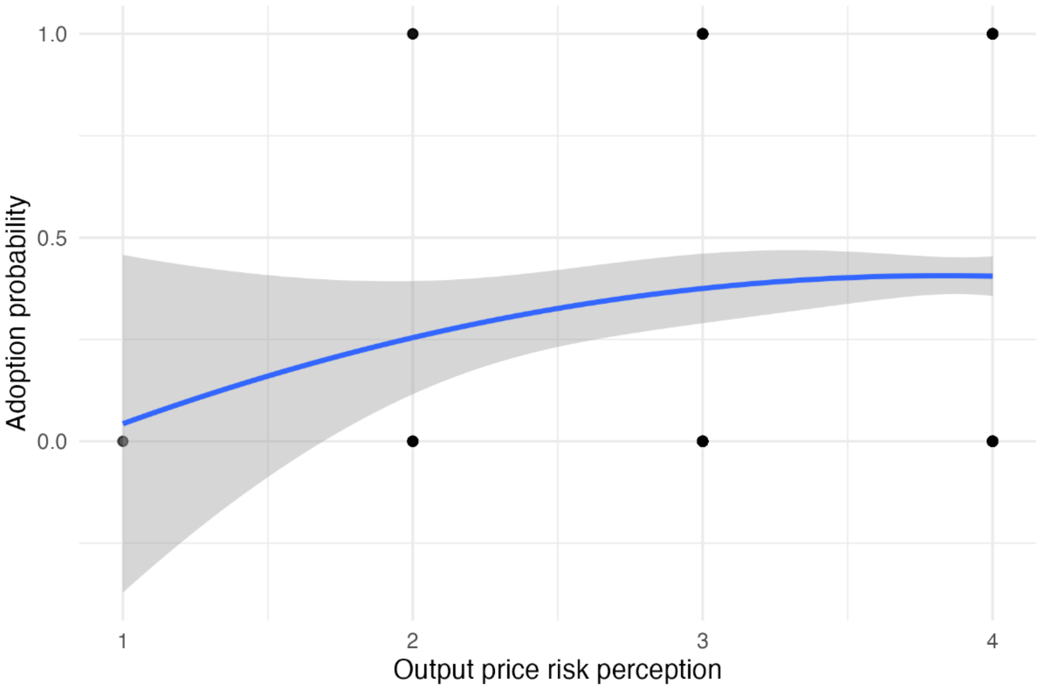

Figure A2. The graphical pattern for a potential inverted U-shape for output price risk perception.

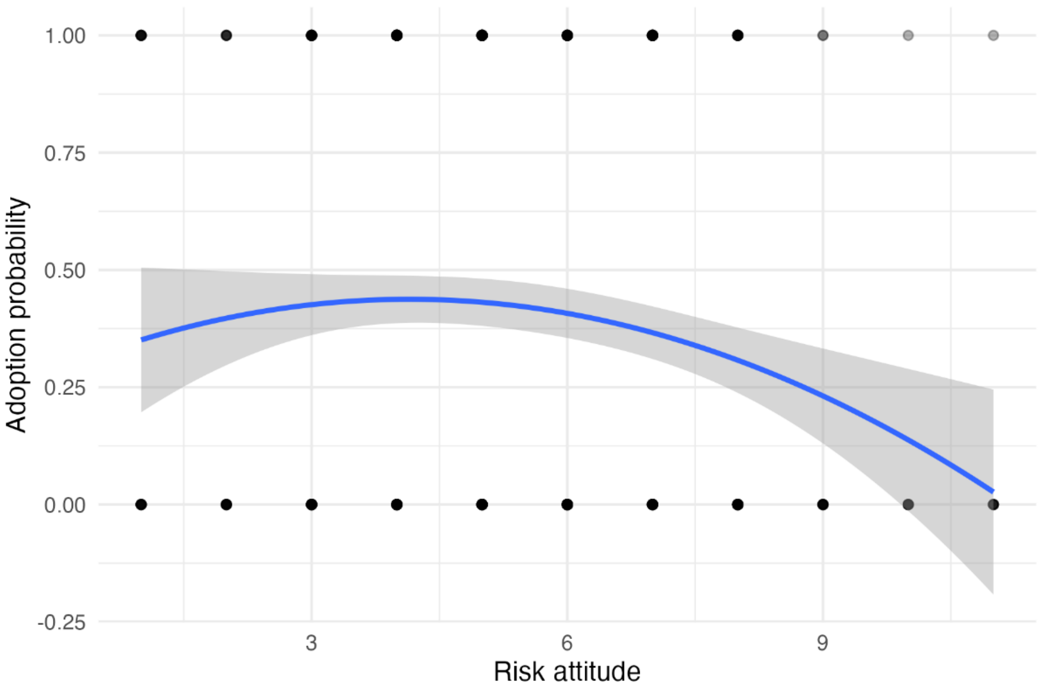

Figure A3. The graphical pattern for a potential inverted U-shape for risk attitude.

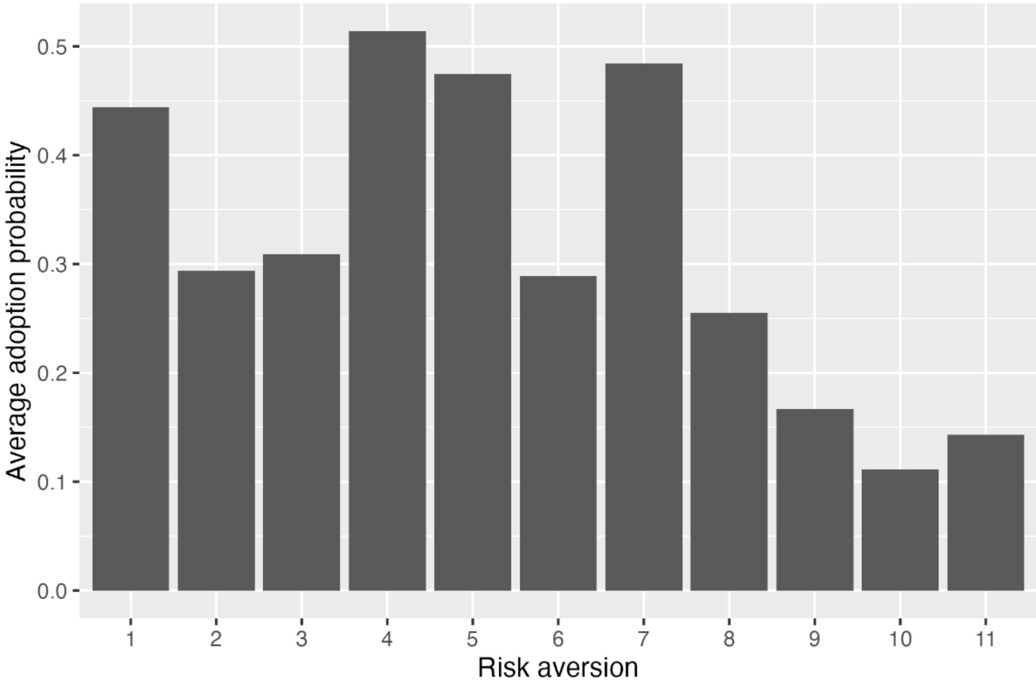

Figure A4. Average adoption probability by farmers' risk aversion. Note: higher values on the x-axis indicate higher risk aversion.

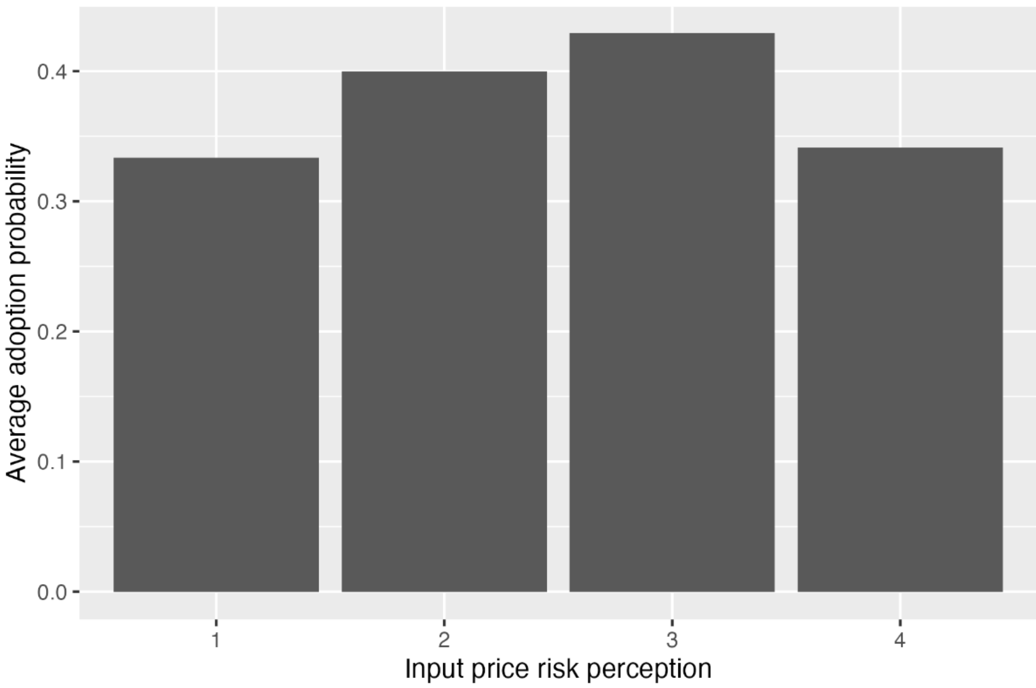

Figure A5. Average adoption probability by farmers' perceived input price risk.

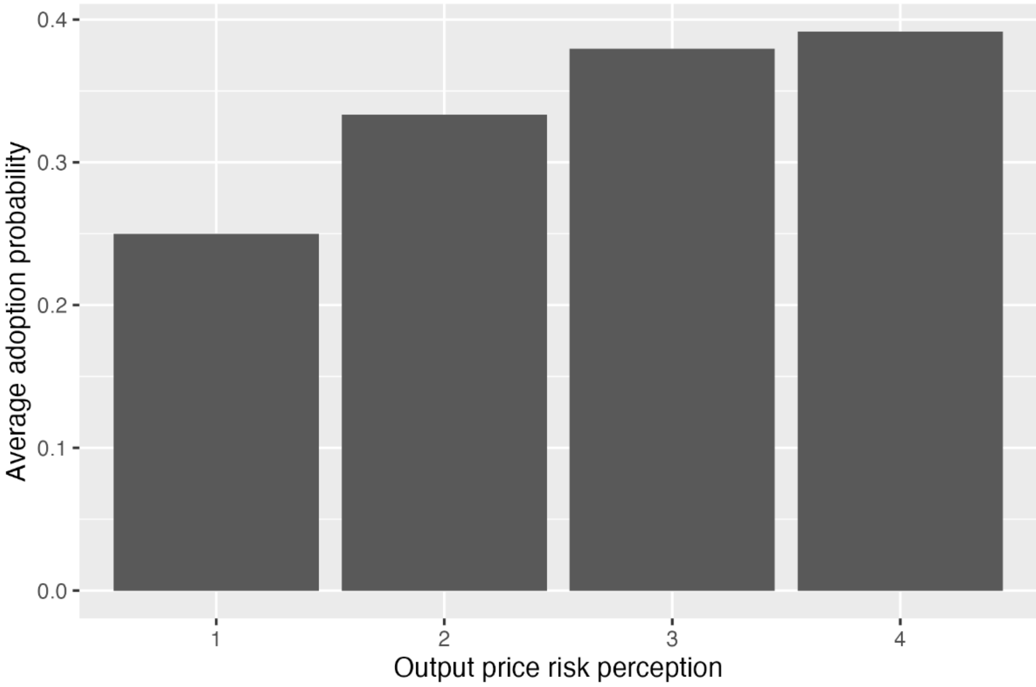

Figure A6. Average adoption probability by farmers' perceived output price risk.

Appendix 5: Correlation Matrix and Variance Inflation Factors (VIF)

Table A5.1. Correlation matrix comprising the independent and dependent variable used in the regression models

	Adoption	Input price risk perception	Output price risk perception	Risk aversion/attitude	Age	Gender	Education	Farm income	Household off-farm income	Farm size	Production system	Experience
Adoption	1	-0.050	0.076	-0.104	0.007	-0.024	0.133	0.181	0.104	0.196	-0.158	0.062
Input price risk perception	-0.050	1	0.356	0.029	-0.010	0.068	-0.036	-0.091	0.032	-0.031	-0.056	-0.002
Output price risk perception	0.076	0.356	1	0.012	-0.007	0.034	0.006	-0.069	0.006	0.126	-0.114	0.010
Risk attitude	-0.104	0.029	0.012	1	0.064	0.140	-0.059	-0.183	-0.011	-0.202	-0.003	-0.008
Age	0.007	-0.010	-0.007	0.064	1	-0.004	-0.103	-0.036	0.052	-0.010	0.052	0.803
Gender	-0.024	0.068	0.034	0.140	-0.004	1	0.027	-0.155	-0.029	-0.112	0.113	-0196
Education	0.133	-0.036	0.006	-0.059	-0.103	0.027	1	0.135	-0.158	0.266	0.141	-0.128
Farm income	0.181	-0.091	-0.069	-0.183	-0.036	-0.155	0.135	1	0.119	0.602	-0.031	0.087
Household off-farm income	0.104	0.032	0.006	-0.011	0.052	-0.029	-0.158	0.119	1	0.115	0.059	0.102
Farm size	0.196	-0.031	0.126	-0.202	-0.010	-0.112	0.266	0.602	0.115	1	0.021	0.073
Production system	-0.158	-0.056	-0.114	-0.003	0.052	0.113	0.141	-0.031	0.059	0.021	1	-0.036
Experience	0.062	-0.002	0.010	-0.008	0.803	-0.196	-0.128	0.087	0.102	0.073	-0.036	1

Note: The interaction terms are not comprised, as they per definition will be highly correlated to their components, which is expected and does not provide further information. The categorical variable "Farm type" with multiple categories is also excluded, since its inclusion would require the use of several dummy variables, thereby complicating the interpretation and reducing the clarity of the matrix.

Table A5.2. Variance Inflation Factors (VIF) across OLS regression specifications

Variables	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Risk attitude			1.063	1.284	1.036
Risk perception					
Input price risk perception		1.157		1.157	1.036
Output price risk perception		1.187		1.284	1.091
Age	1.015	1.015	1.018	1.020	1.091
Gender (ref: male)					
Female	1.029	1.034	1.045	1.062	1.024
Education (ref: low)					
High level	1.132	1.134	1.132	1.134	1.064
Farm income (EUR)	1.340	1.357	1.340	1.368	1.170
Household off-farm income	1.052	1.054	1.053	1.054	1.027
Farm size (hectares)	1.420	1.469	1.455	1.508	1.227

*Note: Variance inflation factors (VIF) are reported for all variables. For categorical variables with more than two levels, generalized VIF (GVIF) is reported and transformed using GVIF^(1/2*Df) to ensure comparability with standard VIF values. Values > 10 is commonly interpreted as indicating high multicollinearity. All values are below conventional thresholds, indicating no multicollinearity concerns. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception.*

Table A5.3. Variance Inflation Factors (VIF) across robustness tests for the main regression models 2-5

Variables	Regression 2	Regression 3	Regression 4	Regression 5
Risk attitude		1.039	1.049	1.042
Risk perception				
Input price risk perception	1.077		1.077	1.042
Output price risk perception	1.098		1.049	1.099
Interaction term risk perception × risk attitude				
Age	1.800	1.802	1.805	1.814
Gender (ref: male)				
Female	1.072	1.074	1.086	1.079
Education (ref: low level)				
High level	1.085	1.085	1.085	1.085
Farm income (EUR)	1.191	1.181	1.192	1.193
Household off-farm income	1.034	1.033	1.034	1.034
Farm size (hectares)	1.237	1.232	1.251	1.251
Farm type	1.035	1.036	1.040	1.038
Production system (organic vs non-organic)	1.053	1.045	1.055	1.057
Experience	1.830	1.831	1.834	1.839

*Note: Variance inflation factors (VIF) are reported for all variables. For categorical variables with more than two levels, generalized VIF (GVIF) is reported and transformed using GVIF^(1/2*Df) to ensure comparability with standard VIF values. Values > 10 is commonly interpreted as indicating high multicollinearity. All values are below conventional thresholds, indicating no multicollinearity concerns. In the Regression 4 interaction term, output price variability represents risk perception, while in the Regression 5 interaction term, input price variability represents risk perception.*

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