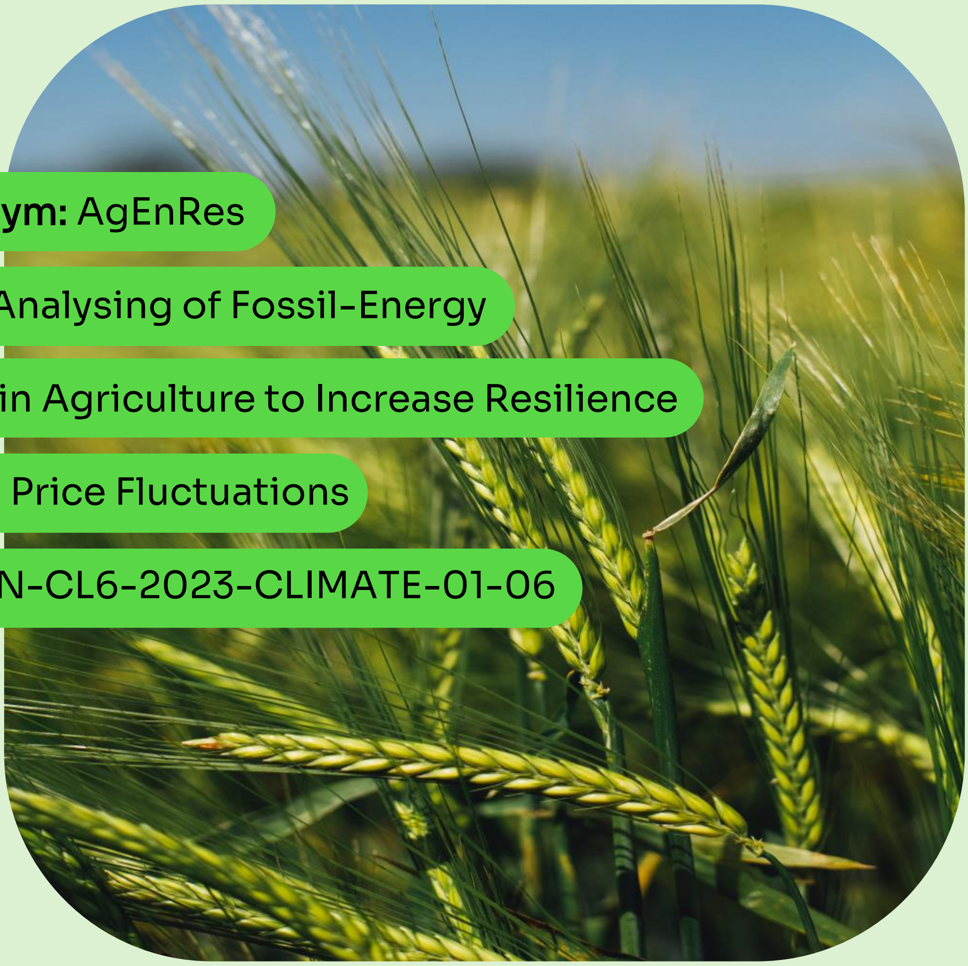
AgEnRes

D2.2 EU-wide database on risk parameters

Increasing Fossil Energy Independence and Resilience Against Input Price Fluctuations



Project acronym: AgEnRes

Project title: Analysing of Fossil-Energy Dependence in Agriculture to Increase Resilience Against Input Price Fluctuations

Call: HORIZON-CL6-2023-CLIMATE-01-06

Funded by the European Union

This work has received funding from the Swiss State Secretariat for Education, Research and Innovation (SERI)

Project no.	101136474
Project acronym:	AgEnRes
Project title:	Analysing of Fossil-Energy Dependence in Agriculture to Increase Resilience against Input Price Fluctuations
Call:	HORIZON-CL6-2023-CLIMATE-01-06
Start date of project:	01.01.2024
Duration:	48 months
Deliverable title:	D2.2 Database of risk parameter
Due date of deliverable:	30.06.2025
Actual date of submission:	09.07.2025
Deliverable Lead Partner:	Wageningen University
Dissemination level:	Public

Author list

Name	Organization
Kexin Wang	Wageningen University
Tobias Dalhaus	Wageningen University
Frederic Ang	Wageningen University

Document History			
Version	**Date**	**Note**	**Revised by**
01	27.06.2025	Deliverable Submission	Kexin Wang
02	04.07.2026	Revision of the Descriptive Table 2	Kexin Wang

Disclaimer

Executive Summary

Deliverable 2.2 systematically investigates the revealed risk preferences of European farmers using the moment-based approach. We evaluate the heterogeneity of preferences across farm types, countries, time, and methodological choices. We use the Farm Accountancy Data Network (FADN) for 121,433 crop and dairy farms during the period 2004-2022. We find that revealed risk preferences are heterogeneous with respect to farm type, country, and time periods. Furthermore, we find that the revealed risk preferences differ substantially depending on the choice of input variables, functional form, and estimator. Our findings suggest that the term 'revealed preferences' may overstate the clarity with which the risk attitudes of European farmers can be revealed in practice.

Table of Contents

List of Acronyms

2SLS	Two-stage Least Square
3SLS	Three-stage Least Square
AP	Arrow-Pratt Absolute Risk Aversion
CAP	Common Agricultural Policy
DBSCAN	Density-based Clustering Nonparametric Algorithm
DS	Downside Risk Aversion
EU	European Union
FADN	Farm Accountancy Data Network
FIML	Full Information Maximum Likelihood
GL	Generalised Leontief
GLS	Generalised Least Square
GMM	Generalised Method of Moments
IV	Instrumental Variable
KNN	K-nearest Neighbour
LOESS	Locally Weighted Regression
MSE	Mean Squared Error
NUTS2	Nomenclature of Territorial Units for Statistics-2
OLS	Ordinary Least Squares
RCM	Random Coefficient Model
SUR	Seemingly Unrelated Regression Equation
TL	Transcendental Logarithm
WP	Work Package

List of Figures

List of Tables

1. Introduction

European agriculture is exposed to various risks, such as volatile input and output prices and extreme weather events (Finger et al., 2022; Rippo & Cerroni, 2023). Climate change and recent global crises exacerbate these risks, making risk management even more essential for decision makers (European Commission, 2023; Meuwissen et al., 2018). To support farmers' decision-making under risk and develop risk management policies, a systematic understanding of farmers' risk attitudes is crucial. Although recent synthesising studies focus on the experimental elicitation of risk attitudes in this context, a systematic estimation of risk attitudes using observational data from the European agricultural sector is hitherto lacking (Finger et al., 2023; Garcia et al., 2024; Iyer et al., 2020).

In Deliverable 2.2, we systematically estimate the revealed risk attitudes of farmers in the entire European Union (EU) to conduct the risk parameter database. In doing so, we quantify the heterogeneity in risk attitudes between member states, the instability of risk attitudes over time, and the sensitivity to methodological choices. We use the seminal approach developed by Antle to estimate absolute Arrow-Pratt risk aversion and downside risk aversion (Antle, 1983, 1987). These revealed risk attitudes are of interest to this database for two reasons. First, revealed risk attitudes, which underpin the production decisions of farmers, predict real-world responses better than elicited risk attitudes (Just & Just, 2011; Rommel et al., 2019). Second, the elicitation of risk attitudes from rich EU-wide panel data complements that from experiments in a specific setting in a specific region in the EU (Garcia et al., 2024), which is relevant for effective policy-making (Finger et al., 2023; Groom et al., 2008).

Deliverable 2.2 contributes in three ways. First, in contrast to the previous literature focusing on specific case studies, we construct a comprehensive analysis of risk attitudes for all the EU countries, covering multiple sectors over a long time period. For instance, Gardebroek (2006) analyses the distribution of risk attitudes among Dutch conventional and organic arable farmers, and Bozzola & Finger (2021) and Groom et al. (2008) investigate the association between policy implementation and farmers' risk attitudes in Italy and Cyprus, respectively. These studies show that revealed risk attitudes can differ across regions, farm sectors, and over time (Iyer et al., 2020).

Second, we evaluate the temporal stability of risk attitudes before and after price spikes of fossil fuels and fertilisers. Such an evaluation is relevant, given the recent dramatic price spikes of fossil fuels and fertilisers in the aftermath of the COVID-19 pandemic and Russia's invasion of Ukraine (Meuwissen et al., 2021; Zhou & Wang, 2023), and the important role of input price risk in farmers' decision-making (Kuethe & Morehart, 2012). Our analysis complements previous studies that investigate the temporal stability of risk attitudes focusing on responses of farmers' risk attitudes to accession into the EU (Koundouri et al., 2009), Common Agricultural Policy (CAP) reforms, and severe climate change (Bozzola & Finger, 2021).

Third, we systematically evaluate the sensitivity to methodological choices of the revealed risk attitudes approach. An important limitation of assessing revealed risk attitudes using the method of moments (Antle, 1983, 1987) is the omission of unobserved variations, which could lead to significant bias in the estimation (Bozzola & Finger, 2021; Iyer et al., 2020). In addition, Just & Just (2011) criticise that the estimation of risk attitudes relies on the arbitrary parametric specification of risk and input variables, which indeed differs substantially across empirical studies (Bozzola & Finger, 2021; Mulungu et al., 2024). Our work addresses this gap by critically investigating the methodological choices and model specifications of the method of moments approach and proposing a sensitivity procedure to improve future studies that estimate stochastic production functions.

To this end, we systematically assess the revealed risk attitudes of farmers, i.e. the Arrow-Pratt absolute risk aversion and downside risk aversion, using the flexible moment-based approach developed by Antle (1983, 1987). We conduct the assessment of heterogeneous farm types, countries, periods split by energy price shocks, and methodological choices. Price shocks are identified as breaks in the autocorrelation structure of energy prices (Cottrell et al., 2019). We use the extensive Farm Accountancy Data Network (FADN, 2023) for 27 EU member states in the period of 2004-2022. The final FADN dataset used for deliverable 2.2 contains 667,046 observations of 121,433 crop and dairy farms. With identified energy price shocks, we split the FADN dataset into pre- and post-shock periods, and we compare whether farmers' risk attitudes are significantly stable ex-post (Bozzola & Finger, 2021). We further estimate revealed risk attitudes for all EU countries separately, and test for sensitivity of the results based on methodological choices in terms of functional form, estimator, and input choice.

We find that the revealed risk attitudes differ substantially between EU member states, farm types, periods divided by energy price shocks, and methodological choices (Bozzola & Finger, 2021; Finger et al., 2023). This change can be extremely large and can even shift the farmers' revealed risk preferences from risk-averse to risk-seeking, or vice versa. While preference heterogeneity across countries and over time might confirm earlier findings on context-specificity and temporal instability, we also find evidence that the revealed risk preferences depend critically on the choice of input variables, functional form, and estimator in the empirical estimation. The approach of revealed risk attitudes is an established method that has been applied in agricultural economic research for many years. However, these findings suggest that it is difficult to draw conclusions about the revealed risk attitudes. We therefore conclude to critically reflect on the overall usefulness of this approach and call for a better justification of empirical choices in future research. It appears that, based on such choices, a wide range of Arrow-Pratt coefficients of absolute risk aversion (from risk taking to risk-averse) and downside risk aversion can be inferred.

2. Theoretical Framework

2.1 Risk Parameter Assessment

The revealed risk attitude assesses how farmers make production decisions in the presence of risks. To evaluate it, we assume that farmers' economic behaviour is consistent with expected utility maximisation based on their profit distribution, and that farmers in the same country and the same sector have the same production technology. The choice of profit distribution allows us to relate energy price shocks with individual outputs, because the stochastic prices are also components involved in the profit function (Antle, 1987). Subsequently, the profit distribution differs before and after an energy price shock and, therefore, reveals different risk preferences. We assume that the profit distribution is conditional on the use of variable and quasi-fixed inputs and structural characteristics, as shown in the moment-based approximation (Antle, 1987). Therefore, to obtain moments, we first estimate the conditional expectation of profit as follows:

$$\pi_{csj} = f(X_{csj}, Z_{csj}, \alpha_{cs}) + \epsilon_{csj}, \tag{1}$$

where π_{csj} denotes the actual profit of farm j in sector s and country c, X_{csj} and Z_{csj} are a vector of variable inputs and quasi-fixed inputs, respectively, α_{cs} is the country- and farm-type-specific parameter, and ϵ_{csj} is the residual that is independently and identically distributed (i.i.d.) with a mean of zero. As shown in Equation (1), a farmer's profit consists of the conditional expected profit $f(\cdot)$ and a stochastic component ϵ_{csj}. This stochastic component can be used to proxy the higher moments, such as the second moment (variance) referring to the variability of the profit. Therefore, these moments accommodate risks. According to Antle (1983, 1987), we approximate the higher moments as functions of input and quasi-fixed inputs:

$$\mu_{csj,i} = {\epsilon_{csj}}^{i} = h(X_{csj}, Z_{csj}, \beta_{cs,i}) + \varepsilon_{csj,i}, i \geq 2, \tag{2}$$

where $\mu_{csj,i}$ denotes the ith moment of profit and $\varepsilon_{csj,i}$ is the residual that is i.i.d. with a mean of zero. We assume the farmers in the same country and farm type have similar structures of risk, denoted by a general parameter vector $\beta_{cs,i}$. For a utility function that is analytic in a finite interval, the expected utility can be characterised as (Antle, 1987):

$$E(U) = \int U(\pi_{csj}) dF[\pi_{csj} | \mu_{csj,1}, \mu_{csj,2}, \ldots, \mu_{csj,m}] \\ \equiv u(\mu_{csj,1}, \mu_{csj,2}, \ldots, \mu_{csj,m}), \tag{3}$$

where $\mu_{csj,1}$ denotes the first moment (i.e., the expected profit), and $F[\cdot]$ denotes the distribution of profit conditional on the moments. Therefore, the expected utility can be further identified as a function of moments (i.e., $u(\cdot)$). By taking the first-order condition of Equation (3) and applying a Taylor series expansion to the utility function (Antle, 1987; Chavas, 2004), we obtain revealed risk attitudes $r_{csj,i}$ with respect to different moments as follows:

$$\frac{\partial \mu_{csj,1}}{\partial x_k} = r_{csj,2} \cdot \frac{\partial \mu_{csj,2}}{\partial x_k} + \cdots + r_{csj,m} \cdot \frac{\partial \mu_{csj,m}}{\partial x_k}, \tag{4}$$

$$r_{csj,i} = -\frac{1}{i!} \cdot \frac{U^i}{U^1}, i \geq 2, \tag{5}$$

where x_k denotes the kth input, and U^i denotes the ith order derivative of the utility function with respect to the expected profit. This revealed risk attitude can be related to Arrow-Pratt absolute risk aversion (AP) and downside risk aversion (DS), as shown in Equation (6). The AP and DS reflect the farmer's aversion to a wider spread of their potential income (that is, variance) and extreme downside potential (that is, negative skewness), respectively.

$$AP_{csj} = 2! \cdot r_{csj,2} \text{ and } DS_{csj} = -3! \cdot r_{csj,3}. \tag{6}$$

According to Equation (6), farmers' revealed risk attitudes, as expressed by the AP and the DS measures, are unique to specific variable inputs and quasi-fixed inputs. Therefore, we hypothesise that farmers' risk attitudes differ across countries and farm types.

2.2 Temporarily Unstable Risk Attitudes during Energy Price Shock

Risk attitudes can fluctuate over time. For example, farmers' revealed attitudes may change in response to significant natural or policy shocks (Bozzola & Finger, 2021; Finger et al., 2023). These adverse shocks impact farmers through various channels, including emotions, financial stability, and alterations in their utility functions (Cohn et al., 2015; Di Falco & Vieider, 2022; Koundouri et al., 2009). When faced with an adverse shock, farmers often experience a sense of situational control, which can lead to increased fear and increased risk aversion, making their circumstances feel 'safer'. Additionally, a decline in wealth during such shocks can influence farmers' risk attitudes, particularly if those risk attitudes are closely linked to their financial status (Koundouri et al., 2009). Although natural or policy changes are evident to significantly affect farmers' risk attitudes, most existing evidence is limited to a single country or based on a few selected countries in specific case studies. Beyond production or institutional risks, energy price shocks likely have broader implications for the agricultural sector across all nations, given that various farm types heavily depend on energy (Heller & Keoleian, 2003). With the food system consuming 15-30% of global primary energy (Rosa et al., 2021), an energy price shock can influence farmers in multiple ways.

Both specialised crop and livestock farms in Europe are dependent on (fossil) energy. Regarding the former, particularly mineral fertilisers and fuels are essential energy-intensive inputs to produce food in sufficient quantities (Srivastava et al., 2023). For livestock farmers, fossil fuels are important because of their direct usage, such as the heating of stables or the cooling of livestock products (such as dairy). Indirectly, other inputs, such as externally purchased feeds, can also be energy-intensive.

To conclude, given the essential nature of energy, we perceive it as being sufficiently important across farm types to be used as a universal shock indicator for high price exposure that might affect risk attitudes. We hypothesise that farmers' revealed risk attitudes change during an energy price shock, and that this change is different between farm types, due to the differential role of energy.

2.3 Method Specification

Among the studies assessing revealed risk attitudes of farmers, most of them employ the flexible moment-based approach developed by Antle (1983, 1987) or the stochastic production function by Just & Pope (1978, 1979). However, these studies differ in their choice of estimator and input variables, as shown in Table 1. Most studies focus on crop farms, with most implementing quadratic profit, revenue, or production moment functions for flexibility. Other studies estimating these moment specifications use the Generalised Leontief (GL) and the Transcendental Logarithmic (TL) functional forms (Tveterås et al., 2011; Tveterås & Wan, 2000). The Cobb-Douglas specification is less commonly found in other literature. It has the advantage of involving fewer unknown parameters and converges effectively when estimating the risk function. Therefore, Koundouri et al. (2009) specify the Cobb-Douglas functional form for the variance function. However, it is also more restrictive than the quadratic functional form, imposing strong restrictions on the production technology/risk function being analysed (Koundouri et al., 2009; Tveterås & Wan, 2000).

We find heterogeneous estimator or specification choices in estimating the moment functions, as shown in column (4). Most studies assume only time-invariant farm-fixed effects. Mulungu et al. (2024) further argue that the input variables are still endogenous due to omitted variable bias. Therefore, they use instrumental variables in the moment specification functions. Koundouri et al. (2009) use a Full Information Maximum Likelihood (FIML) estimator with a farm fixed effect to estimate the complete system of mean, variance, and risk attitude equations. The FIML provides specific advantages in managing missing data and thus tackles the issue of absent yield information for some farms (Koundouri et al., 2009). Antle (1987) and Kakumanu et al. (2016) estimate the moments using Feasible Generalised Least Squares (Feasible GLS) and GLS estimators to account for heteroskedasticity and autocorrelation.

Table 1. Relevant studies that assessed risk attitudes from observable data using the moment-based approach.

Reference	Application	Profit/revenue/production moment specification		Revealed risk attitude specification/estimator	Inputs
		Functional form	Specification/estimator		
(1)	(2)	(3)	(4)	(5)	(6)
Bozzola & Finger (2021)	Field crop, Italy	Quadratic	Fixed effect	3SLS	Fertilisers, labour, seeds, crop protection
Mulungu et al. (2024)	Maize, Zambia	Quadratic	Instrumental variable-fixed effect	3SLS	Fertilisers and seeds
Koundouri et al. (2009)	Wheat and barley, Finland	Quadratic and Cobb-Douglas	FIML	FIML	Fertiliser, labour, plant protection, and fixed capital
Groom et al. (2008)	Vegetable and cereal, Cyprus	Quadratic	-	2SLS	Fertilisers, water, and labour
Antle (1987)	Rice, India	Quadratic	FGLS	2SLS	Labour, fertiliser, animal labour, and land
Gardebroek (2006)	Arable crop, The Netherlands	Quadratic	Fixed effect	Bayesian RCM	Fertiliser, seeds, pesticides, contractor work, hired labour, and other variable inputs
Kakumanu et al. (2016)	Crop, India	Quadratic	GLS	2SLS	Fertiliser, seed, labour, use of machine labour, and irrigation water

*Note that FIML=Full Information Maximum Likelihood, 3SLS=Three Stage Least Squares, 2SLS=Two Stage Least Squares, FGLS=Feasible Generalised Least Squares; RCM=Random Coefficient Model; OLS=Ordinary Least Squares.

Additionally, the estimators used for assessing risk attitudes are heterogeneous, as shown in column (5). To estimate revealed risk attitudes, the Generalised Method of Moments Three- and Two-Stage Least Squares Estimators (GMM-3/2SLS) have been used most frequently. Choices between these two are based on the assumption of whether risk attitudes are input-specific and whether correlations between error terms across equations are considered. Both estimators account for endogeneity in the marginal input variables of farmers. Other estimators, such as FIML (Koundouri et al., 2009) and the Bayesian Random Coefficient Model (RCM; Gardebroek, 2006), are used to estimate a full system of equations and estimate individual risk attitudes, respectively.

Lastly, the choice of input variables differs substantially by study, as shown in column (6). This heterogeneity is suggested depending on the context (e.g., farm type, regions, and dependent variables). Although fertiliser is the common input in every study, each study defines a different choice of input variables in general.

To conclude, we observe different functional forms of production functions in the studies that assess risk exposure. Moreover, we observe heterogeneity in the choice of estimators and regression specifications, as well as input variables in the studies that assess revealed risk attitudes. Therefore, we test the sensitivity of AP and DS with respect to the choice of (i) functional form, (ii) estimator, and (iii) input variables for field crop farmers.

3. Methods

3.1 Assessing Revealed Risk Attitudes

We discuss the empirical implementation in this Section. First, we start by regressing the profit on variable inputs, quasi-fixed inputs, and farm characteristics with a quadratic functional form, as shown in Equation (7). It is chosen as the baseline functional form because it is the most flexible and most frequently observed functional form in the corresponding literature (Bozzola & Finger, 2021; Groom et al., 2008). In addition to the quadratic functional form, we also discuss the robustness check for the alternative functional form in Section 3.2.2.

$$\begin{aligned}\pi_{csjt} = \alpha_{csj} + \sum_{k=1}^{K} \beta_{csk} x_{csjtk} \\ + \frac{1}{2} \sum_{h=1}^{K} \sum_{k=1}^{K} \beta_{cskh} x_{csjtk} x_{csjth} \\ + \sum_{l=1}^{L} \beta_{csl} z_{csjtl} + \epsilon_{csjt},\end{aligned} \tag{7}$$

where t denotes the time, k and h both denote the indices for variable input x, $k, h \in \{fertilisers,\ crop\,protection,\ etc.\}$, l denotes the index for quasi-fixed inputs and farm characteristics, and α_{csj} denotes the time-invariant farm-specific effect of farm j in sector s and country c, which is included to remove time-invariant unobserved heterogeneity. Equation (7) assesses a country- and farm-sector-specific relationship, which means that we assume a country- and farm-sector-specific production technology. Then, we use the residual from Equation (7) to calculate the higher moments of profit, which are regarded as measurements of risks, as discussed in Section 2.1. We regress these moments on the same explanatory variables, also with a quadratic functional form, as shown in Equation (8).

$$\begin{aligned}\mu_{csjt,i} = {\epsilon_{csjt}}^{i} = \alpha_{csj,i} + \sum_{k=1}^{K} \beta_{csk,i} x_{csjtk} \\ + \frac{1}{2} \sum_{h=1}^{K} \sum_{k=1}^{K} \beta_{cskh,i} x_{csjtk} x_{csjth} \\ + \sum_{l=1}^{L} \beta_{csl,i} z_{csjtl} + \varepsilon_{csjt,i}\end{aligned} \tag{8}$$

where $\alpha_{csj,i}$ is the farm-specific effect on the moment i, and the estimated parameter vector β is assumed to be moment-specific. We correct the standard errors for the moment specifications by Conley spatial standard errors, as the farmers within one region potentially correlate with each other (Conley, 1999). Furthermore, since estimation at the fourth moment or above has less meaningful interpretations (Gardebroek, 2006; Groom et al., 2008), we assume that three moments suffice to describe the profit distribution.

Then, we compute the derivatives of these three moments with respect to the input k. These derivatives assess the marginal effect of the input considered on risk. For example, the derivative of skewness with respect to fertilisers assesses the marginal effect of adjusting fertiliser usage on downside risks. As discussed in Section 2.1, we regress the derivative of the first moment on the derivatives of the higher moments, as shown in Equation (9):

$$D_{csjtk,1} = \theta_{csk,1} + \theta_{csk,2} D_{csjtk,2} + \theta_{csk,3} D_{csjtk,3} + v_{csjtk}, \tag{9}$$

where the $D_{csjtk,i}$ denotes the first-order derivatives of moment i with respect to input k for farm j in the sector s and country c at time t, θ denotes the parameter vectors to be estimated and equals the populational average of $r_{csj,i}$ in Section 2.1, and v denotes the residual that is i.i.d. Since risk attitudes are derived from the utility function with respect to wealth, we assume that they are not input-specific. Therefore, we pose restrictions forcing the coefficients to be equivalent across equations for different inputs (that is, $\theta_{csk,2} = \hat{\theta}_{cs,2}$ and $\theta_{csk,3} = \hat{\theta}_{cs,3}$). We follow a bootstrap procedure for the Seemingly Unrelated Regression Equations (SUR) estimation to obtain heteroskedasticity-robust coefficients and standard errors (Bozzola & Finger, 2021).

Following Antle (1987), GMM-2SLS can be used to estimate consistent risk attitudes, because (i) it estimates the first-order condition that is in an implicit form, (ii) it is suitable for large sample sizes, and (iii) it deals with endogeneity arising from restrictions on the technology parameter embedded in $D_{csjtk,i}$. Instrumental Variables (IVs) need to be relevant (that is, impact the endogenous variable) and fulfil the exclusion restriction (that is, affect the dependent variable only through the endogenous variable). Although the relevance of IVs can be tested, the fulfilment of the exclusion restriction cannot. To fulfil the exclusion restriction, the IVs should affect the dependent variable only through the endogenous variable. The econometrician bears the responsibility of intuitively justifying such a relationship (Bellemare et al., 2017; Henningsen et al., 2024; Mellon, 2024). However, we cannot find any intuitive IVs that affect the derivative of the profit mean equation with respect to a specific input only through their effects on the derivative of the profit variance equation with respect to the same input rather than effects on the derivative of profit skewness with respect to the same input, particularly since the latter two regressors both represent marginal effects of the same inputs on risk. Therefore, for assessing risk attitudes, we implement the SUR as the main estimator specification (Bozzola & Finger, 2021), and further discuss the feasibility of GMM-3SLS with IVs applied in literature as a heterogeneity analysis in Section 3.2.2.

3.2 Heterogeneity Analysis

3.2.1 Input Choices

We analyse heterogeneous input specifications by analysing risk attitudes based on multiple combinations of variable inputs. For all input choices, we specify profit as the dependent variable for the field crop and dairy sectors.

The main input specification is as follows. We use three variable inputs for the field crop farms: fertilisers, crop protection, and other inputs. The first two are adjustable in the short term and used to control for the production risk (Antle, 2010; Di Falco, 2006). Therefore, they reflect farmers' production decisions that aim to cope with risks. The other input, consisting of seeds and irrigation water, is used to simplify the empirical estimation in the current study and includes all relevant variable inputs for the estimation. For the dairy sector, we include five variable inputs: veterinary expenditure, purchased concentrate feeds, fertilisers, energy, and other inputs (Tveterås et al., 2011). For fixed inputs and structural characteristics, we specify three variables for the field crop sector: land, labour, and fixed assets (building and machinery). These variables are less adjustable in the short term to respond to risks, but become more adjustable over the long run. We also include livestock units specifically for the dairy sector, as the herd size plays a key role in its risk exposures from two perspectives. First, the aggregation of idiosyncratic risks, which affect the overall risk only through individual animals, increases when having a larger herd size. Second, the systematic risk for the entire herd also increases when having a larger herd size (Finger et al., 2018).

To further check the robustness of the risk attitudes with respect to input choices, we verify the results using the input choices of Bozzola & Finger (2021) for crop farms. Bozzola & Finger (2021) focus on field crop farmers' revealed risk attitudes in Italy, with their input variables including (i) fertilisers, (ii) seeds, (iii) labour hours, (iv) crop protection, and (v) covariates: land, fixed assets value, irrigation ratio, rented land ratio, and a dummy variable indicating a family-owned farm[1]. However, the variable referring to the ownership type is available in the Farm Accountancy Data Network (FADN) only until 2013. Therefore, we exclude it from the analysis. We know that a profit function should include all inputs and an adequate yield. However, in empirical settings, collecting all the data for the profit function is not always possible and, therefore, input sets differ in different studies (Bozzola & Finger, 2021; Groom et al., 2008). Therefore, we systematically alter the input variables for crop farmers to show how such changes affect estimates of farmers' risk attitudes. Thus, we provide the first comprehensive information on the sensitivity of the revealed risk attitudes approach with respect to methodological choices.

3.2.2 Functional Forms and Estimators

Heterogeneous functional forms. Quadratic, Generalised Leontief (GL), and Transcendental Logarithm (TL) are commonly employed in the risk exposure analysis using the moment-based approach because they are flexible and yield similar results. Among these functional forms, TL has the least flexibility in handling negative and zero values in both dependent and independent variables. Since we estimate the conditional profit mean, assuming it to be positive significantly reduces the number of observations and results in a truncated profit distribution. In contrast, the GL function only requires the independent variables to be non-negative and does not pose restrictions on the dependent variable. Therefore, we use GL as the alternative functional form specified in Equations (10) and (11):

$$\begin{aligned}\pi_{csjt} = \alpha_{csj} &+ \sum_{k=1}^{K} \beta_{csk}\sqrt{x_{csjtk}} \\ &+ \frac{1}{2}\sum_{h=1}^{K}\sum_{k=1}^{K} \beta_{cskh}\sqrt{x_{csjtk}}\sqrt{x_{csjth}} \\ &+ \sum_{l=1}^{L} \beta_{csl} z_{csjtl} + \epsilon_{csjt}\end{aligned} \tag{10}$$

[1] The variables (i)-(iv) are all considered as variable inputs which are used for revealed risk preference estimation (Bozzola & Finger, 2021).

$$\mu_{csjt,i} = \epsilon_{csjt}{}^{i} = \alpha_{csj,i} + \sum_{k=1}^{K} \beta_{csk,i}\sqrt{x_{csjtk}} + \frac{1}{2}\sum_{h=1}^{K}\sum_{k=1}^{K} \beta_{cskh,i}\sqrt{x_{csjtk}}\sqrt{x_{csjth}} + \sum_{l=1}^{L} \beta_{csl,i} z_{csjtl} + \varepsilon_{csjt,i} \tag{11}$$

Note that all notations are the same as for the quadratic function. The input variables remain the same as the main input specification for crop farmers, that is, fertilisers, crop protection, other inputs, and other quasi-fixed inputs (land, fixed assets, and labour). Therefore, the results reveal only the heterogeneity in results caused by the functional form.

Heterogeneous estimator choice. In this section, we discuss the GMM-3SLS estimator and the IVs used for the analysis. As discussed in Section 3.1, most instrumental variables used in earlier studies likely violate the exclusion restriction, as it cannot be argued that they affect the dependent variable only through the endogenous variable. Therefore, we specify the available IVs based on the literature (as shown in Appendix Table A1). However, we include the results of GMM-3SLS only to provide a comprehensive view of heterogeneity caused by estimators, but call for caution in interpreting the GMM-3SLS results: if the exclusion restriction is violated, the results using IVs can become more biased than those using the OLS estimation.

The IVs are specified as follows. For the crop farmers, we follow Antle (1987) and Bozzola (2014) and use the output price of the crop (excluding vegetables and fruits), annual rainfall during the growing seasons, and the annual maximum and minimum temperature during the growing season to instrument the marginal contribution of the use of fertiliser and crop protection to variance and skewness. As argued by Bozzola (2014), these IVs are assumed to be exogenous to risk attitudes, but correlated with irrigation, plant protection, and fertiliser choices. We do not specify IVs for the dairy sector, as to the best of our knowledge, no one has done so before when estimating revealed risk attitudes for the livestock sector.

We conduct the analysis retaining the same input variables as shown in the main specification using a quadratic functional form. Therefore, we provide information on heterogeneity in revealed risk attitudes caused by estimator choice.

3.2.3 Shock Identification

We define an energy price shock as a sudden peak in a time series. To detect it, we follow Cottrell et al. (2019) by using a smoothing algorithm and identifying local instabilities. First, we employ a locally weighted regression (LOESS), introduced by Cleveland (1979), to predict the energy price based on a moving time window. The LOESS predicts the energy price at the centre of each time window using a weighted least squares estimator, with higher weights assigned to the data points that are closer to the centre. It is a non-parametric approach and does not require an overall functional form for the energy price. Two parameters are required for a LOESS, including a polynomial degree parameter p and a smooth span q. The polynomial degree denotes the functional form of the local regression, such as linear, quadratic, and tricube specifications. The smoothing span defines how much data is included in each time window. With bigger p and smaller q, the LOESS can lead to unwanted variance in the predicted curve in which these parameters and data are overfitted (Simpson & Haggard, 2018). To avoid this, we apply leave-one-out cross-validation to detect the minimum mean squared error (MSE; Lettenmaier et al., 1991). In the end, we find an optimised parameter set of {p = 2 and q = 0.25}.

Based on the prediction from LOESS, we derive residuals and detect the autocorrelation therein. More specifically, we regress those residuals on the residual of the previous period (lagged residuals) using the ordinary least squares (OLS) estimator. Lastly, we use Cook's distance to detect outliers that do not follow the autocorrelation structure. The critical value used is the 90% quantile Cook's distance. In addition, we define these outliers as energy price shocks only when the actual energy prices are higher than the average price of the last five periods (Gephart et al., 2017).

4. Data

We use the Farm Accountancy Data Network (FADN) dataset to assess revealed risk attitudes. The FADN dataset contains a large and unbalanced panel with accounting data at the farm level. We focus on the period of 2004-2022. We include all EU member states for analysis, particularly for two farm types: field crops (including cereals, protein crops, and oilseeds) and dairy. The initial FADN sample consists of 122,055 farms and 671,116 observations, with an average of 5.498 observations per farm.

We clean the FADN data with several steps as follows. First, as our data points spread over a long time range, we consider price development by deflating the monetary values. In line with Tveterås et al. (2011), we deflate costs and expenditures by the price indices of specific agricultural inputs for the 2015 base year (Eurostat, 2024b)[2]. We replace the missing or zero values of the price indices using their own price at other years as the base, and multiply it by the trend at the EU level. For the missing or zero price indices that do not have the price indices in other corresponding years, we replace them with the price index at the EU level. Furthermore, we construct the Törnqvist price index for the other inputs, including seeds and water. Inflation in profit is removed by the harmonised consumer price index with the 2015 base year (European Commission, 2024). Second, we detect outliers using the density-based clustering nonparametric algorithm (DBSCAN; Ester et al., 1996). The DBSCAN has the advantage of distinguishing outliers based on a multidimensional combination of farm features, rather than focusing on the extreme values within one specific variable. All data points that are too distant from the cluster centre within one country and one farm type are identified as outliers[3]. We set the set of characteristics as follows: profit, fertilisers, crop protection (for the field crop sector), seeds, water, veterinary expenses, concentrated feeds

[2] We use other goods and services as a substitute for the water price index since we do not find the price indices of agricultural products that specifically refer to the irrigation water price index, and the price index of other direct inputs is related to the water price index.

[3] Two parameters are required for the DBSCAN algorithm, including a maximum distance *Eps* and the minimum data points for a cluster. Before selecting the parameters, we first normalise all the features between [0,1] (not for the final analysis), because cluster-based methods are sensitive to the different scales of the features. We set the minimum data points within one cluster (*MinPts*; denoting the threshold of the density of a neighbourhood) to the dimension of the dataset plus one (Ester et al., 1996). Subsequently, we obtain the country- and sector-specific *Eps* by taking the maximum value between the optimal cluster distance defined by the "knee" in the k-nearest neighbour (KNN) plot (setting k to the dimension of the dataset) and the 99% quantile value of the distance to the cluster centre in the same KNN plot. This ensures that we remove 1% of the data *at most*.

(for the dairy sector), energy, labour, land, fixed assets (including land value), land value, and livestock units (for the dairy sector). Third, all variables are rescaled by the corresponding country- and sector-specific standard deviations (Bozzola & Finger, 2021; Groom et al., 2008), which allows comparison between countries. In addition, we also removed 10 observations that do not have information for the nomenclature of territorial units for statistics-2 (NUTS2) code or have the NUTS2 code that cannot match with aggregated spatial coordinates from 2003 to 2024 (Eurostat, 2024c)[4], which is required by the Conley standard error.

Regarding the price shock identification procedure described in 3.2.3, we aim for extreme energy price shocks at the EU level[5] that are common for all European countries. To this end, we use quarterly nominal price indices throughout 2004-2022 for EU-15 (2004), EU-25 (between 2005 and 2006), EU-27 (between 2007 and 2012, and after 2020), and EU-28 (between 2013 and 2019; Eurostat, 2009, 2015, 2018, 2023) to identify. Furthermore, we also use the annual output price index at the national level, the cumulated rainfall, the maximum temperature and the minimum temperature during the growing seasons for Instrumental Variables (Cornes et al., 2018; Eurostat, 2024a).

Table 2. Summary statistics of the variables selected in the final sample.

Variable	Field crop		Dairy	
	Mean	**SD**	**Mean**	**SD**
Income (in €1000)	42.600	106.251	49.987	98.687
Fertiliser (in €1000)	19.671	43.771	8.165	19.736
Crop protection (in €1000)	13.204	31.502	3.261	11.585
Seed (in €1000)	12.193	27.766	4.618	12.647
Water (in €1000)	0.797	3.077	1.119	2.640
Veterinary (in €1000)	0.471	5.313	14.292	30.704
Purchased concentrated feed (in €1000)	0.559	7.911	44.184	87.038
Energy (in €1000)	14.063	32.259	15.168	35.601
Labour (in 1000 hours)	5.218	10.203	6.248	12.945
Land (ha)	135.231	297.097	89.597	214.262
Livestock Unit	4.949	30.513	105.596	155.667
Fixed assets (in €1000)	159.479	379.442	366.729	649.488
Number of observations	423,791		243,255	

SD denotes the standard deviation; The final sample is the deflated and outlier-removed dataset. Note that all monetary values are deflated to the base of 2015; Seeds: including seeds and plants, but new plantations of permanent crops are considered as investments.

The final sample consists of 121,433 farms and 667,046 observations, with an average of 5.493 observations per farm. This cleaning process removes 0.606% of the data. In the final sample, 11,401 observations from the crop sector do not use fertilisers, and 7,732 observations from the crop sector do not purchase seeds. The summary statistics of the final sample before rescaling are provided in Table 2.

[4] We match FADN data to the average coordinate of the NUTS code, because (i) the NUTS-2 centre only shifts in a small range throughout the years, which encourages us to assume using the average is a good approximation, and (ii) the FADN for each year contains more NUTS code than the NUTS regulation at that year. Therefore, merging the data by each year causes severe loss of observations in specific years.

[5] The EU is formed by different countries at different periods. We identify relative shocks at the EU level regardless of how many member states are included.

5. Results

5.1 Energy Price Shocks

In this section, we present the results of our analysis of energy price shock identification. We identify two distinct energy price shocks between 2004 and 2022, as illustrated in Figure 1. Figure 1a shows the nominal energy price index in different phases of the EU during this period, while Figure 1b shows the results of regressing residuals from a LOESS analysis on the lagged one-period residuals. Additionally, Figure 1c presents Cook's distance from the regression illustrated in Figure 1b, with the dashed line indicating the 90% quantile of Cook's distance for this sample.

The first energy price shock occurred during the 2008 financial crisis, beginning during the second quarter and lasting until the end of the year. As evidenced by Figure 1a, energy prices gradually increased from 2007 to 2008, reaching a peak in 2008. We also observe the second-highest Cook distance in the third quarter of that year. Following the 2008 energy price shock, prices fluctuated moderately. However, in the second quarter of 2020, there was a dramatic decrease in energy prices. This decline results in a relatively high Cook's distance, exceeding 0.15, resulting from a negative price shock, which we here do not consider further.

The second upward energy price shock began at the beginning of the fourth quarter of 2021 and continued until the second quarter of 2022. At the end of 2022, we observe another positive price shock, which we consider a continuation of the energy price shock from 2021 to 2022 as the aftermath of Russia's war on Ukraine.

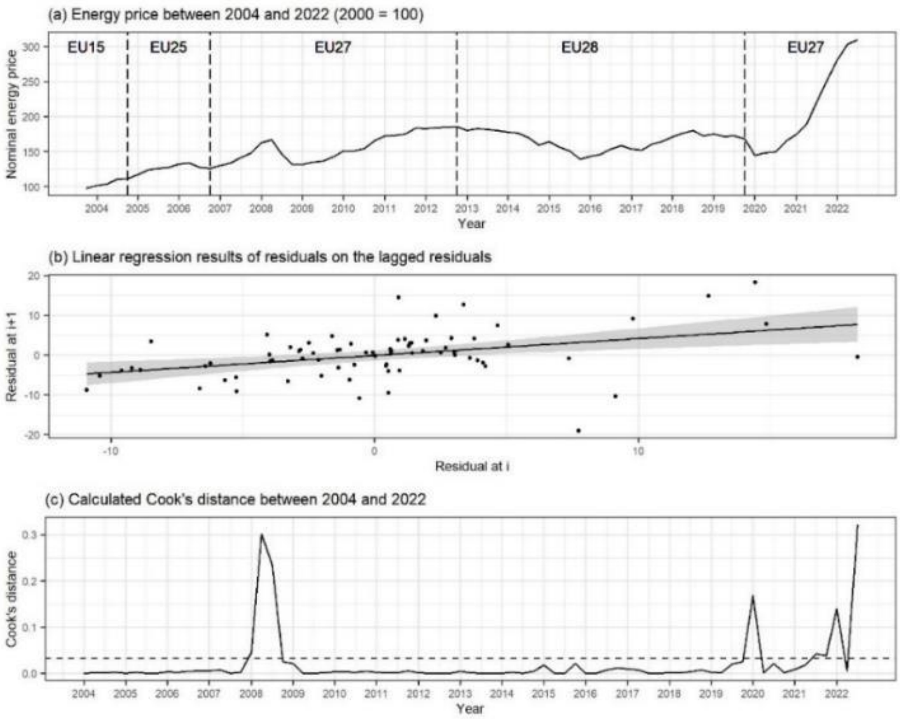


Figure 1. An illustration of the nominal energy price index (2000 = 100), the autocorrelation structure, and Cook's distance.

5.2 Heterogeneous Revealed Risk Attitudes

5.2.1 Revealed Risk Attitudes by Country and Farm Types

The results of the revealed risk attitudes of field crop farms and dairy farms across various countries from 2004 to 2022 are presented in Table A2 (in the Appendix). Overall, there is significant variation in risk attitudes between countries and types of farms. For field crop farms, the average Arrow-Pratt absolute risk aversion (AP) ranges between -1.690 and 5.347, with an average of 0.356. The downside risk attitude (DS) ranges from -1.366 to 13.505, with an average of 0.380. Dairy farms show an AP range of -1.488 to 3.172, with an average of 0.194. The DS of dairy farms ranges from -1.150 to 7.609, with an average of 0.275. In particular, in most countries except Denmark, Estonia, Ireland, Cyprus, Slovenia, Slovakia and Croatia, both types of revealed risk preferences of farmers differ significantly between farm types at the 0.1% significance level.

A comparison of revealed risk attitudes in EU countries from 2004 to 2022 shows that field crop farms in France, Cyprus, Luxembourg, the Netherlands, Slovenia, and Finland exhibit a relatively higher risk aversion (AP; as shown in Figure 2), indicating a greater aversion to profit variability. In contrast, crop farms in Germany, Ireland, and Austria show negative and lower AP values, suggesting a tendency toward risk-seeking behaviour. Regarding downside risks, farms in Luxembourg and France display a higher level of aversion, as indicated by their larger positive DS values, while crop farmers in Latvia and Austria are more inclined towards downside-risk-seeking behaviour, reflected in their smaller negative DS measures.

Dairy farms also reveal heterogeneous risk attitudes. As indicated in Figure 2c, dairy farms in Greece show the highest aversion to profit variance compared to other countries, followed by those in Cyprus and Slovenia, which also exhibit a relatively higher aversion. In contrast, farmers in Malta, the Netherlands, Austria, and Romania tend to seek profit variability. Regarding the downside risk, dairy farms in Cyprus demonstrate the highest aversion, with those in Ireland and Greece being relatively risk-averse. However, farmers in Lithuania and Croatia show a greater inclination toward downside risk-seeking behaviour.

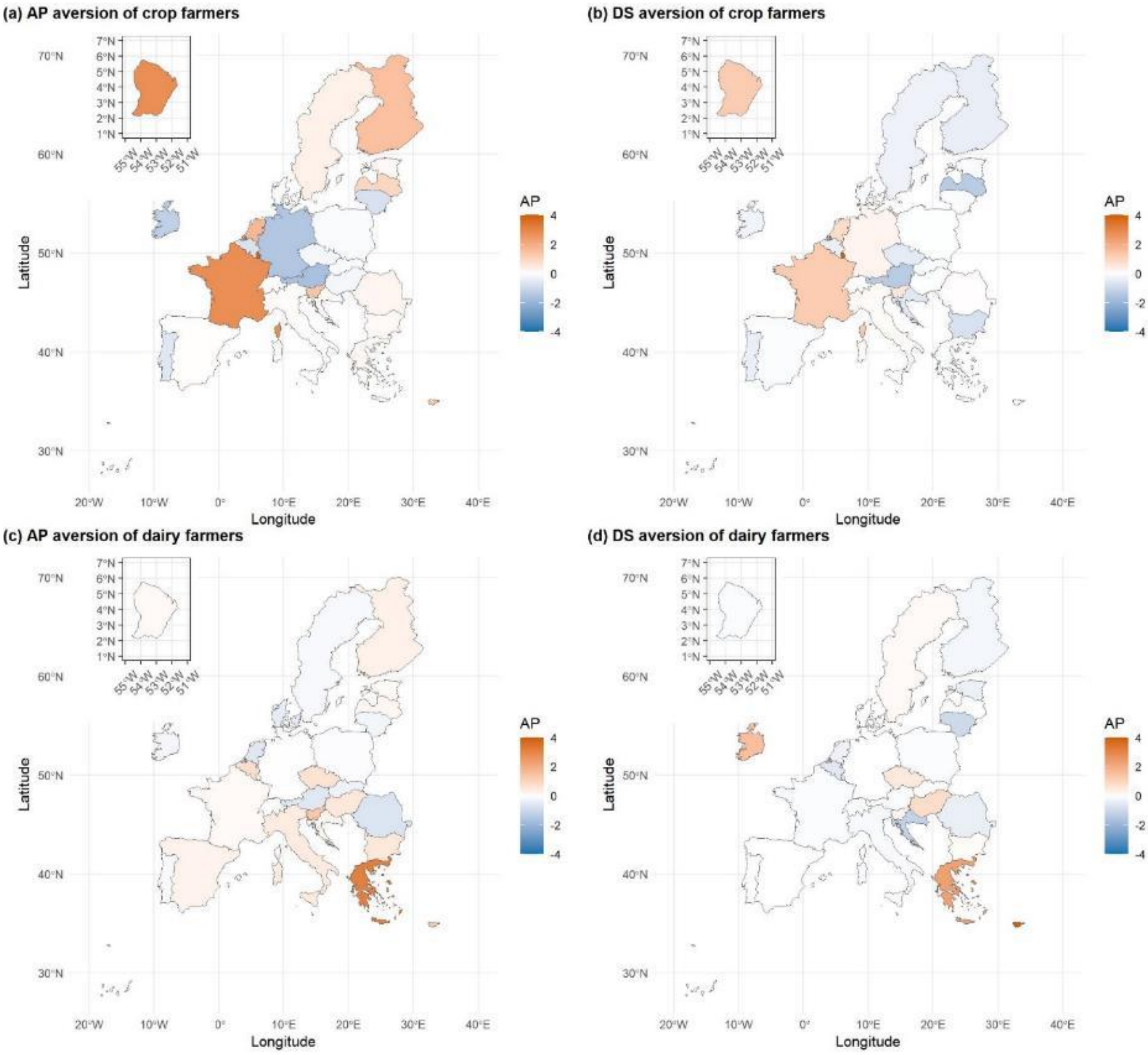


Figure 2. An illustration of the national average revealed risk attitudes from 2004 to 2022.

The orange colour refers to risk aversion, whereas the blue colour refers to risk-seeking. Note that Cyprus and Luxembourg have the AP or DS that is out of range. For visualisation, they are coloured on the map the same as maximum or minimum AP or DS; Other enclaves are not shown on the map due to space limitations.

5.2.2 Temporal Instabilities in Revealed Risk Attitudes

Temporal instabilities in risk attitudes of field crop farmers. The risk attitudes of crop producers in different time periods are shown in Table A3 (in the Appendix) and Figure 3a-b. The time periods are divided by the detected shocks, as indicated in Section 5.1. Since our farm-level dataset lasts only until 2023 and the revealed preferences approach requires panel data, we must neglect the 2022 energy price-shock for time period differentiation since the remaining post-shock period is too short. Furthermore, for the 2004–2007 era, we do not include Bulgaria, Luxembourg, Romania, and Croatia in our analysis because these country-period datasets only provide one year of observations, or the number of observations is too small (≤30) for analysis.

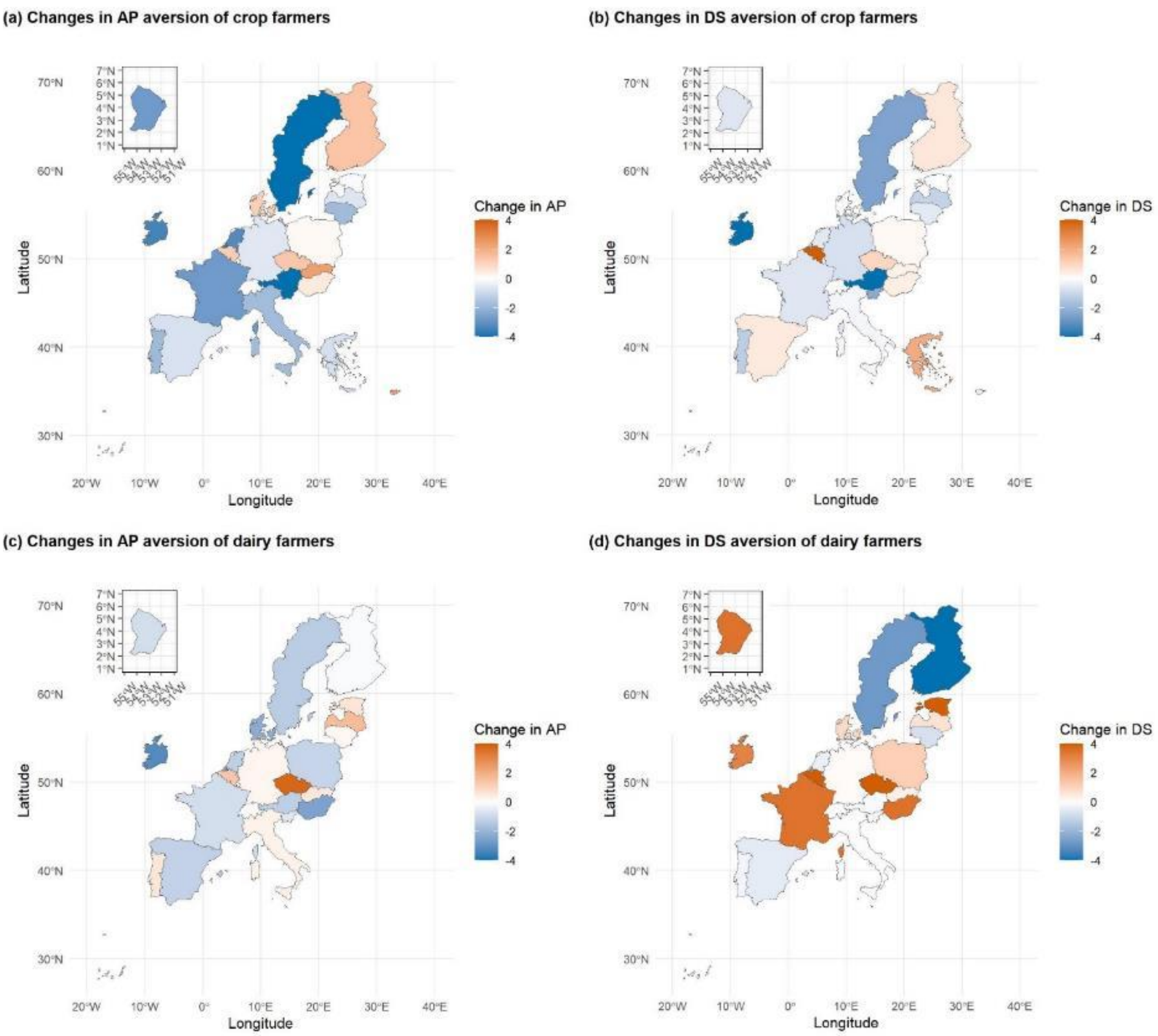


Figure 3. An illustration of the changes in the revealed risk attitudes during the 2008 energy price shock.

The orange colour indicates a positive change in the revealed risk attitudes at the national average, while the blue colour represents a negative shift in the revealed risk attitudes for a specific type of farm. We limit the change range to between -4 and 4 to provide a clear overview; however, in some countries, the shift in risk attitudes exceeds this range. Additionally, due to space limitations, certain enclaves are not shown on the map.

We identify two major findings here. First, farmers' attitudes towards risk are temporally unstable during the 2008 energy price shock at the 0.1% significance level across most of the countries, except Denmark, Estonia, Ireland, Poland, and Slovakia. Yet, the instabilities do not show a clear pattern.

Second, these shifts in risk attitudes vary between countries. The average risk attitudes of crop farms in a country can shift from being risk averse to risk seeking after experiencing the 2008 energy price shock, and vice versa. We illustrate this variation in Figures 3a-b for crop farms: the areas marked in orange indicate a positive change (a shift towards greater risk aversion), while the areas in blue indicate a negative change (a shift towards increased risk-seeking). We observe that crop farms in Denmark, Estonia, Cyprus, Poland, Romania, Slovakia, and Finland became more risk-seeking. In contrast, farms in other countries exhibit increased risk aversion or reduced risk-seeking behaviour.

Regarding downside risks, crop farms in Belgium, Czechia, Estonia, Greece, Spain, Hungary, Poland, Slovenia, Slovakia, and Finland display increased risk aversion or a reduction in their risk-seeking behaviour. Conversely, farms in other countries become more tolerant of downside risk.

Temporal instabilities in the risk attitudes of dairy farmers. The results of the risk attitudes of dairy farms over the periods divided by the 2008 energy price shock are shown in Table A4 (in the Appendix). Changes in risk attitudes for dairy farms are depicted in Figures 3c-d. The null hypothesis that dairy farmers have stable revealed risk preferences during the 2008 energy price shock is significantly rejected at the 0.1% significance level for a majority of nations, except Estonia, Italy, Lithuania, Luxembourg, Malta, Austria, Slovenia, Slovakia, and Finland. This is largely consistent with the results for the crop farms (as indicated in column z-value in Table A4). Furthermore, these shifts in risk perception vary by nation. For example, following the 2008 energy price shock, dairy farmers in Belgium, Czechia, Germany, Estonia, Italy, Latvia, Luxembourg, Portugal, and Slovakia either became more averse or sought less profit variance. Farmers also become more averse to downside risk, except for Spain, Italy, Malta, Netherlands, Austria, Portugal, Finland, and Sweden.

5.2.3 Revealed Risk Attitudes Under Alternative Input Options, Functional Forms, and Estimators

Revealed risk attitudes for alternative input choices. Table 3 presents the revealed risk attitudes of crop farmers from 2004 to 2022, based on the alternative input variables: fertilizers, seeds, labour, and crop protection, and covariates including land, fixed assets, irrigation ratio, and rented land ratio[6] (Bozzola & Finger, 2021).

First, the null hypothesis, assuming that the revealed risk preferences are equal between the alternative input variables and our primary specification above, can be rejected at the 0.1% significance level for most countries, except Ireland, Hungary, Malta, Austria, and Romania. Not only are those coefficients significantly different, but different input choices even lead to sign flips in coefficients. For example, crop farmers in Bulgaria demonstrate positive average preferences (AP) under the main input specification, which considers fertilisers, crop protection, and other inputs as variable inputs and land, fixed assets, and labour as quasi-fixed inputs (details available in Appendix Table A2).). In the alternative input variable specification, including labour as a variable input and incorporating irrigation and rented land ratios as covariates, the results indicate that these farmers show a negative AP at the national average level.

Second, the impact of changing input variables varies by country (as reflected in the Difference column of Table 3). For instance, Belgian farmers exhibit a shift towards less variance-seeking behaviour under the alternative input variables, while Bulgarian farmers appear to be more variance-seeking in this context. Additionally, a smaller sample size may amplify changes in revealed risk attitudes, as seen in Luxembourg (N = 239).

---

[6] The dummy indicating family-owned farm as used in Bozzola & Finger (2021) is excluded from the analysis due to the variable is only available until 2013.

Table 3. Estimates of the revealed risk attitudes based on alternative input choices throughout 2004-2020 for field crop farmers (dependent variable: derivative of the profit means with respect to inputs).

Country	AP	S.E.	Difference	z-value	DS	S.E.	Difference	z-value
Belgium	-0.438***	0.007	0.281***	-7.157	-1.120***	0.004	-0.742***	-13.491
Bulgaria	-0.015*	0.003	-0.128***	13.439	-0.207***	0.001	0.564***	33.488
Czechia	0.826***	0.008	1.012***	-36.141	0.117***	0.001	0.589***	26.411
Denmark	-0.503***	0.003	-0.471***	23.943	-0.367***	0.001	-0.327***	-18.590
Germany	-0.187***	0.003	1.312***	-11.665	-0.034***	0.001	-0.273***	-29.068
Estonia	0.007	0.002	-0.122***	23.740	-0.057***	0.001	0.034***	6.835
Ireland	-3.224***	0.206	-1.989***	3.829	0.016	0.140	0.272	0.210
Greece	-0.020	0.006	-0.119***	9.452	-0.158***	0.000	-0.122***	-18.041
Spain	0.460***	0.002	0.431***	-60.554	0.050***	0.000	0.137***	80.839
France	1.685***	0.009	-1.105***	36.355	0.581***	0.001	-0.639***	-45.029
Italy	-0.090***	0.003	-0.141***	20.726	-0.001	0.001	-0.098***	-27.076
Cyprus	0.390***	0.011	-0.966***	33.161	-0.467***	0.004	-0.615***	-22.964
Latvia	0.264***	0.009	-0.700***	14.907	-0.341***	0.002	1.025***	20.896
Lithuania	0.019***	0.001	0.783***	-114.472	-0.274***	0.001	-0.201***	-57.210
Luxembourg	-3.954***	0.365	-9.301***	11.903	-14.959***	0.232	-28.464***	-18.346
Hungary	-0.331***	0.004	-0.112***	6.101	-0.054***	0.001	-0.022**	-2.657
Malta	0.256	0.126	-0.410	1.084	0.153.	0.014	-0.319**	-2.860
Netherlands	0.783***	0.011	-0.955***	41.171	0.343***	0.003	-0.471***	-29.991
Austria	-1.640***	0.020	0.050	-1.234	-1.390***	0.002	-0.039*	-2.457
Poland	-0.172***	0.001	-0.074***	16.471	-0.202***	0.000	-0.165***	-122.248
Portugal	1.124***	0.015	1.706***	-52.346	-0.134***	0.002	0.252***	21.982
Romania	0.217***	0.005	-0.003	0.093	-0.078***	0.000	-0.118***	-24.040
Slovenia	-0.324***	0.007	-1.650***	27.867	-0.110***	0.001	-0.611***	-30.274
Slovakia	0.049**	0.009	0.154***	-8.294	-0.335***	0.001	-0.250***	-64.713
Finland	0.141**	0.022	-1.385***	25.831	-0.543***	0.002	-0.102***	-7.183
Sweden	-0.356***	0.014	-0.666***	14.344	-0.411***	0.003	-0.094***	-5.068
Croatia	-0.133***	0.007	-0.205***	5.426	-0.232***	0.001	0.332***	17.998

., *, **, and *** indicate significance levels at 10, 5, 1, and 0.1 per cent, respectively. AP refers to Arrow-Pratt absolute risk aversion, while DS represents downside risk aversion. S.E. denotes bootstrap standard errors. The "*Difference*" column indicates the change in risk attitudes compared to the corresponding risk attitude in Appendix Table A2. Dependent variables: fertilisers, seeds, crop protection products, and labour hours, along with covariates such as land, fixed assets, irrigation ratio, and rent ratio. We exclude the family-owned farm dummy from the analysis, as this variable is only available until 2013. The z-values are calculated based on the *bootstrapped* coefficients ($\frac{AP}{2}$ and $\frac{DS}{-6}$) and their corresponding standard errors (Clogg et al., 1995).

Revealed risk attitudes for alternative function specification. Table 4 presents the results of the revealed risk attitudes of crop farmers, assessed by specifying moments according to the Generalised Leontief (GL) functional form. The input variables and estimators used are the same as those in the main specification outlined in Appendix Table A2. Similar to the results when adjusting input variables in the former section, both AP and DS are sensitive to the chosen functional form for the moment specification. We observe significant differences between the results in Table 4 (As shown in the Difference and z-value column) and those in Appendix Table A2, at the 0.1% significance level for both types of risk preferences for the majority countries, except Belgium, Estonia, Ireland, Italy, Luxembourg, Netherlands, Austria, Slovakia, Finland, and Sweden.

Additionally, this effect may be more pronounced in cases with smaller sample sizes; for instance, Luxembourg exhibits the largest difference among all countries analysed. However, it is noteworthy that the revealed risk attitudes of field crop farmers in France, Germany, and Denmark also show substantial changes under the GL specification, despite having much larger sample sizes.

Table 4. Results of risk attitudes of field crop farmers throughout 2004-2022 under the Generalised Leontief functional form (dependent variable: derivative of the profit means with respect to inputs).

Country	AP	S.E.	Difference	z-value	DS	S.E.	Difference	z-value
Belgium	-1.427***	0.339	-0.707	1.043	-1.221***	0.053	-0.843**	-2.609
Bulgaria	0.477***	0.016	0.364***	-11.340	-0.541***	0.002	0.230***	11.621
Czechia	0.077***	0.008	0.264***	-9.389	-0.317***	0.001	0.155***	7.074
Denmark	2.585***	0.021	2.618***	-56.792	0.598***	0.006	0.639***	16.551
Germany	1.163***	0.245	2.662***	-5.286	-0.070	0.007	-0.309***	-7.498
Estonia	0.132***	0.002	0.002	-0.511	-0.028***	0.000	0.064***	39.594
Ireland	-5.647***	0.522	-4.413***	4.042	2.753***	0.072	3.010**	2.785
Greece	1.136***	0.028	1.037***	-18.435	0.499***	0.004	0.534***	19.638
Spain	0.732***	0.008	0.702***	-41.106	-0.026***	0.001	0.062***	6.895
France	6.978***	0.198	4.188***	-10.540	5.707***	0.048	4.487***	15.554
Italy	0.015***	0.003	-0.037***	5.996	0.096***	0.001	-0.001	-0.251
Cyprus	1.015***	0.031	-0.341***	5.269	-0.544***	0.002	-0.693***	-39.721
Latvia	0.103*	0.023	-0.861***	13.461	-0.264**	0.022	1.102***	7.963
Lithuania	-1.756***	0.044	-0.991***	11.138	-0.180***	0.001	-0.107***	-13.763
Luxembourg	-6.387*	1.845	-11.734**	3.172	-2.764**	0.207	-16.269***	-11.493
Hungary	-0.075***	0.007	0.144***	-6.787	-0.113***	0.002	-0.081***	-6.741
Malta	-0.961**	0.131	-1.627***	4.218	-0.639***	0.023	-1.111***	-7.049
Netherlands	1.491***	0.107	-0.247	1.155	1.246***	0.035	0.432*	2.049
Austria	-1.934***	0.036	-0.244***	3.333	-0.887**	0.034	0.464*	2.253
Poland	-0.521***	0.013	-0.422***	15.697	-0.062***	0.001	-0.025***	-3.947
Portugal	0.340***	0.037	0.922***	-12.340	-0.158***	0.003	0.229***	11.921
Romania	1.289***	0.001	1.069***	-34.570	-0.018***	0.000	-0.057***	-12.461
Slovenia	-0.004	0.025	-1.330***	17.464	0.021	0.003	-0.480***	-18.247
Slovakia	0.196***	0.017	0.300***	-8.956	-0.086***	0.001	-0.001	-0.116
Finland	1.271***	0.108	-0.255	1.163	0.110	0.020	0.551***	4.679
Sweden	-0.052	0.152	-0.362	1.180	-0.960***	0.060	-0.643.	-1.796
Croatia	-0.644***	0.034	-0.715***	9.332	-0.767***	0.001	-0.203***	-10.338

., *, **, and *** indicate significance levels at 10, 5, 1, and 0.1 per cent, respectively. AP refers to Arrow-Pratt absolute risk aversion, while DS represents downside risk aversion. S.E. denotes bootstrap standard errors. The "*Difference*" column indicates the change in risk attitudes compared to the corresponding risk attitude in Appendix Table A2. The dependent variables: fertilisers, crop protection products, other inputs, and covariates: land, fixed assets (without land value), and labour. The z-values are calculated based on the *bootstrapped* coefficients ($\frac{AP}{2}$ and $\frac{DS}{-6}$) and their corresponding standard errors (Clogg et al., 1995).

Revealed risk attitudes for alternative estimators. We evaluate the revealed risk attitudes of field crop farmers using the GMM-3SLS estimator. The findings are presented in Table 5. We observe instances of sign flips in the revealed risk attitudes for certain countries, such as Germany. However, the differences between the results produced by various estimators (noted in the Difference columns in Table 5) are relatively minor compared to the variability arising from differences in input and functional form choices. As indicated in the z-value column in Table 5, the null hypothesis of equality between the revealed risk attitudes assessed by GMM-3SLS and SUR is still significantly rejected at the 0.1% significance level for Germany, Spain, Latvia, Netherlands, Austria, Poland, and Romania.

Table 5. Results of risk attitudes of field crop farmers throughout 2004-2022 using the GMM-3SLS estimator (dependent variable: derivative of the profit means with respect to inputs).

COUNTRY	AP	S.E.	Difference	z-value	DS	S.E.	Difference	z-value
Belgium	-1.082	0.329	-0.363	0.551	-0.990	0.111	-0.612	-0.920
Bulgaria	-0.830***	0.084	-0.943***	5.613	-0.725	0.079	0.046	0.096
Czechia	2.567	1.283	2.753	-1.073	1.399	0.268	1.871	1.165
Denmark	-0.028	0.041	0.004	-0.046	0.040	0.010	0.080	1.240
Germany	0.331***	0.020	1.830***	-15.325	0.199***	0.000	-0.041***	-4.795
Estonia	0.113***	0.010	-0.016	0.827	-0.100***	0.004	-0.008	-0.316
Ireland	-1.903.	0.427	-0.669	0.735	1.778	0.421	2.035	0.750
Greece	0.173**	0.036	0.074	-1.029	-0.008	0.006	0.027	0.806
Spain	0.178***	0.020	0.149***	-3.627	-0.160***	0.002	-0.073***	-6.742

COUNTRY	AP	S.E.	Difference	z-value	DS	S.E.	Difference	z-value
France	2.677***	0.043	-0.113	1.258	1.039***	0.004	-0.181***	-6.268
Italy	0.001	0.013	-0.051.	1.887	0.028***	0.001	-0.069***	-9.477
Cyprus	1.928***	0.266	0.572	-1.076	0.534*	0.073	0.386	0.875
Latvia	1.492***	0.061	0.528***	-4.095	-1.941***	0.020	-0.575***	-4.523
Lithuania	-0.416	0.303	0.348	-0.574	-0.024	0.025	0.049	0.328
Luxembourg	5.770***	0.321	0.423	-0.604	13.480***	0.226	-0.025	-0.017
Hungary	0.033	0.019	0.252***	-6.164	-0.036***	0.001	-0.004	-0.426
Malta	3.718**	0.774	3.053.	-1.941	1.047	0.142	0.575	0.675
The Netherlands	1.394***	0.038	-0.344***	4.544	0.640***	0.009	-0.174***	-3.359
Austria	-1.454***	0.024	0.236***	-4.782	-1.128***	0.006	0.223***	6.455
Poland	-0.166***	0.006	-0.068***	5.820	-0.054***	0.000	-0.017***	-7.428
Portugal	-1.403***	0.107	-0.821***	3.818	-0.288***	0.008	0.099*	2.022
Romania	-1.540***	0.045	-1.760***	18.468	-0.131***	0.002	-0.170***	-14.439
Slovenia	1.527***	0.179	0.201	-0.554	0.566***	0.021	0.065	0.510
Slovakia	-0.534*	0.146	-0.430	1.475	-0.060	0.009	0.026	0.448
Finland	0.036	0.238	-1.490**	3.120	-0.861***	0.029	-0.420*	-2.414
Sweden	0.411***	0.044	0.101	-1.060	-0.250***	0.004	0.067**	2.872
Croatia	-0.159	0.553	-0.231	0.209	-1.333***	0.113	-0.769	-1.132

., *, **, and *** indicate significance levels at 10, 5, 1, and 0.1 per cent, respectively. AP refers to Arrow-Pratt absolute risk aversion, while DS represents downside risk aversion. S.E. denotes bootstrap standard errors. The column "Difference" indicates the change in risk attitudes compared to the corresponding risk attitude in Appendix Table A2. The dependent variables: fertilisers, crop protection products, other inputs, and covariates: land, fixed assets (without land value), and labour. The instrumental variables are annual rainfall during the growing season, the maximum and minimum temperatures during the growing season, and the output price of crops (excluding vegetables and fruits, deflated to the base of 2015). The z-values are calculated based on the *bootstrapped* coefficients ($\frac{AP}{2}$ and $\frac{DS}{-6}$) and their corresponding standard errors (Clogg et al., 1995).

6. Discussion

In deliverable 2.2, we provide the first systematic evidence of the revealed risk attitudes of farmers in the entire European Union (EU). We quantify the heterogeneity in risk attitudes between member states, the instability of risk attitudes over time, and the sensitivity to methodological choices. We have three main findings. First, our results suggest that the revealed risk preferences are context-specific, varying by both the farm type and the country. Our results further show that revealed risk preferences range from risk-averse to risk-seeking for Arrow-Pratt absolute risk aversion and downside risk aversion, which aligns with the findings of other experimental and econometric studies (Garcia et al., 2024; Koundouri et al., 2009). However, our results indicate a broader range of values of Arrow-Pratt (AP) absolute risk aversion and downside (DS) risk aversion than previously reported. Specifically, field crop farms exhibit AP values from -1.690 to 5.347 and DS values from -1.366 to 13.505, which contrasts with the ranges of -0.900 to 3.119 for AP and -3.031 to 2.951 for DS among crop farmers in the literature (Bozzola & Finger, 2021; Groom et al., 2008; Koundouri et al., 2009; Kakumanu et al., 2016). This divergence may stem from the larger geographical scope of deliverable 2.2. For different types of farmers, the heterogeneity of risk attitudes can be attributed to different production technologies, farm characteristics, and risk exposures. For instance, while fossil fuel-related fertilisers are crucial for production (Srivastava et al., 2023), they also introduce production and energy price risks that threaten crop farmers' income (Di Falco et al., 2014; Erisman et al., 2007). Being subject to varying weather conditions, crop farmers also face greater production risk (Di Falco et al., 2014). Consequently, this can lead them to become more averse to risks to secure their financial situation (Cohn et al., 2015). Our findings suggest that, at the EU average level, crop farmers exhibit a slightly higher aversion to both variance and downside risks than dairy farmers. For example, Swedish crop farmers are risk-averse, while dairy farmers in Sweden show risk-seeking behaviour regarding profit variance. Regarding differences between countries, Garcia et al. (2024) suggest that educational level, farm size, farmer age, and other characteristics influence the degree of risk aversion. This potentially drives the geographical heterogeneity in the risk preferences revealed in our findings.

Second, we observe temporal instabilities in revealed risk attitudes before and after the energy price shock in 2008. This finding aligns with other studies observing temporally unstable risk preferences (Bozzola & Finger, 2021; Finger et al., 2023; Koundouri et al., 2009). However, in contrast to other studies, our results reveal larger changes in farmers' revealed risk preferences, which even lead to sign flips that indicate farmers switching from risk-averse to risk-seeking behaviour and vice versa when experiencing an energy price shock. For crop farmers at the national average level, we note that more than half of the countries become more risk-tolerant during an energy price shock, particularly those located in the northwest. Finger et al. (2023) show a similar finding in the aftermath of unfavourable natural shocks, such as the combination of pest and severe frost events, for Swiss farmers. This could be explained by the heterogeneous degrees to which farmers depend on energy-related inputs, since those in the northwest, on average, rely more on fossil fuel inputs to cope with local weather conditions. Therefore, an unfavourable energy price shock can lead to farmers buffering more risk-tolerant behaviour, and degrees of magnitude for risk tolerance might be explained by such geographical differences (Finger et al., 2023). In contrast, we find that dairy farmers do not exhibit clear geographical patterns in their risk attitude changes regarding profit variance, but farmers located in the centre are more averse to downside risks during an energy price shock. In particular, Estonian crop farmers and Lithuanian dairy farmers demonstrate relatively stable risk attitudes during the 2008 energy price shock.

Third, we find substantial variation in estimated revealed risk attitudes, driven by different choices of input variables, the functional form of the production function, and estimators. We employ alternative assessment methods according to the literature that focuses on revealed risk preferences (Antle, 1987; Bozzola, 2014; Bozzola & Finger, 2021). Our findings demonstrate that the results are more sensitive to the selection of input variables and functional forms than to the choice of estimator. For example, only Swedish crop farmers display relatively robust revealed risk preferences when the functional form varies. All other countries possess at least one type of revealed risk preference that is significantly sensitive to changes in both functional form and input variables. In terms of estimator adjustments, slightly more countries exhibit stable revealed risk preferences, further suggesting that the choice of estimator introduces less heterogeneity than the other two choices. Heterogeneity can be introduced through various channels. First, we strictly follow Antle (1987) in assuming consistency of farmer behaviour with Expected Utility Theory. However, other theories, such as Cumulative Prospect Theory, might better reflect farmers' actual decision-making (Just & Just, 2011). Second, endogeneity might exist in the stage where risk attitudes are assessed and the IVs used in earlier studies do not satisfy the exclusion restriction. Therefore, the econometric estimates here and in former studies might be biased. All in all, given the evidence that revealed risk preferences are very sensitive to the assessment method, econometricians must justify and critically reflect on empirical choices made and provide extensive robustness checks to underpin their results. Former studies do not always justify and critically reflect on the econometric choices made.

We close this discussion with two remarks. First, we assume that farmers within the same region are subjected to the same weather conditions and input/output prices due to a lack of exact farm coordinates and data on farm-level prices. However, in practice, these values may vary at the farm level. Second, the 2008 energy price shock was confounded by many other market disruptions caused by the global financial crisis. However, deliverable 2.2 aims only to investigate the correlational evidence between a market disruption and the instability of revealed risk preferences, with an energy price shock as an example, which is directly associated with farm production.

7. Concluding Remarks

Using FADN data, deliverable 2.2 systematically assesses the risk attitudes revealed by European farmers for the period 2004-2022 in the dairy sector and the arable sector. We do so by estimating Arrow-Pratt absolute risk aversion and downside risk aversion with the flexible moment-based approach developed by Antle (1983, 1987). Furthermore, we analyse these risk attitudes before and after energy price shocks in the studied period and further investigate the heterogeneity of these risk attitudes to method adjustments.

Our findings indicate that the revealed risk preferences vary significantly across different types of farms, countries, time periods, and assessment methods. Among farm types, crop farmers across all 27 EU nations demonstrate, on average, a greater aversion to profit variance and downside risks. This suggests that they may adopt more risk mitigation strategies compared to dairy farmers. In response to energy price shocks, crop farmers also appear to become more tolerant of profit variances, particularly in western countries. Conversely, dairy farmers do not exhibit clear geographical patterns in their shifts in risk attitudes to profit variance, although those in central regions become more averse to downside risks. Furthermore, our analysis suggests that the revealed risk preferences in most countries are notably sensitive to the choice of input variables and the functional form of the specifications of the profit moments. While both types of risk preferences are less affected by changes in estimator choice, there are still significant instances of sign flips attributable to the selection of the estimator. Therefore, our results suggest that the term 'revealed preferences' may overstate the clarity with which farmers' risk attitudes can be revealed in practice. Since all choices are in line with the theoretical model, our study seems to reveal potential researchers’ degrees of freedom rather than farmers’ preferences.

Deliverable 2.2 has important implications for policy. First, the heterogeneity of revealed risk preferences among farmers, ranging from highly risk averse to very risk-seeking across various types of farms, countries, and time periods, suggests that the general belief of farmers being risk-averse may not truly represent their actual behaviour concerning risk. In fact, this assumption may even be contradicted at the national average level. Considering the current Common Agricultural Policy, which aims to support and stabilise farmers' income, it is essential to address that farmers may not favour insurance. Second, since the methods of assessment can influence revealed risk preferences and sometimes lead to conflicting results, policymakers must be cautious when interpreting revealed risk preferences.

Lastly, deliverable 2.2 suggests one future avenue. Since the moment-based approach is rooted in Expected Utility Theory, exploring how revealed risk preferences can be assessed under different theoretical frameworks may better predict farmers' actual behaviour. To date, however, no econometric applications have investigated this with alternative frameworks. Addressing other theoretical pathways in combination with empirical implementations could provide more robust evidence to assess farmers’ risk preferences using secondary data.

Reference

Antle, J. M. (1983). Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach. *Journal of Business & Economic Statistics*, *1*(3), 192–201. https://doi.org/10.1080/07350015.1983.10509339

Antle, J. M. (1987). Econometric Estimation of Producers' Risk Attitudes. American Journal of Agricultural Economics, 69(3), 509–522. https://doi.org/10.2307/1241687

Antle, J. M. (2010). Asymmetry, Partial Moments, and Production Risk. American Journal of Agricultural Economics, 92(5), 1294–1309. https://doi.org/10.1093/ajae/aaq077

Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged Explanatory Variables and the Estimation of Causal Effect. Source: The Journal of Politics, 79(3), 949–963. https://doi.org/10.2307/26551051

Bozzola, M. (2014). Farmers' Risk Preferences and the Role of Irrigation. https://doi.org/10.22004/ag.econ.182771

Bozzola, M., & Finger, R. (2021). Stability of risk attitude, agricultural policies and production shocks: evidence from Italy. European Review of Agricultural Economics, 48(3), 477–501. https://doi.org/10.1093/erae/jbaa021

Chavas, J.-P. (2004). *Risk analysis in theory and practice*. Elsevier. https://books.google.nl/books?id=3o40_dNLYcEC&lpg=PP1&ots=oGaTA-eGSl&dq=Risk%20analysis%20in%20theory%20and%20practice&lr&pg=PP1#v=onepage&q=Risk%20analysis%20in%20theory%20and%20practice&f=false

Cleveland, W. S. (1979). Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association*, *74*(368), 829. https://doi.org/10.2307/2286407

Clogg, C. C., Petkova, E., & Haritou, A. (1995). Statistical Methods for Comparing Regression Coefficients Between Models. In *Source: American Journal of Sociology* (Vol. 100, Issue 5, pp. 1261–1293). https://www.jstor.org/stable/2782277

Cohn, A., Engelmann, J., Fehr, E., & Maréchal, M. A. (2015). Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals. *American Economic Review*, *105*(2), 860–885. https://doi.org/10.1257/aer.20131314

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics*, *92*(1), 1–45. https://doi.org/10.1016/S0304-4076(98)00084-0

Cornes, R. C., van der Schrier, G., van den Besselaar, E. J. M., & Jones, P. D. (2018). An Ensemble Version of the E-OBS Temperature and Precipitation Data Sets. *Journal of Geophysical Research: Atmospheres*, *123*(17), 9391–9409. https://doi.org/10.1029/2017JD028200

Cottrell, R. S., Nash, K. L., Halpern, B. S., Remenyi, T. A., Corney, S. P., Fleming, A., Fulton, E. A., Hornborg, S., Johne, A., Watson, R. A., & Blanchard, J. L. (2019). Food production shocks across land and sea. *Nature Sustainability*, *2*(2), 130–137. https://doi.org/10.1038/s41893-018-0210-1

Di Falco, S. (2006). Crop genetic diversity, farm productivity and the management of environmental risk in rainfed agriculture. *European Review of Agricultural Economics*, *33*(3), 289–314. https://doi.org/10.1093/eurrag/jbl016

Di Falco, S., Adinolfi, F., Bozzola, M., & Capitanio, F. (2014). Crop Insurance as a Strategy for Adapting to Climate Change. *Journal of Agricultural Economics*, *65*(2), 485–504. https://doi.org/10.1111/1477-9552.12053

Di Falco, S., & Vieider, F. M. (2022). Environmental Adaptation of Risk Preferences. *The Economic Journal*, *132*(648), 2737–2766. https://doi.org/10.1093/ej/ueac030

Erisman, J. W., Bleeker, A., Galloway, J., & Sutton, M. S. (2007). Reduced nitrogen in ecology and the environment. In *Environmental Pollution* (Vol. 150, Issue 1, pp. 140–149). https://doi.org/10.1016/j.envpol.2007.06.033

Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. www.aaai.org

European Commission. (2023). *The common agricultural policy at a glance*. https://agriculture.ec.europa.eu/common-agricultural-policy/cap-overview/cap-glance_en

European Commission. (2024). *AMECO database*. https://dashboard.tech.ec.europa.eu/qs_digit_dashboard_mt/public/sense/app/667e9fba-eea7-4d17-abf0-ef20f6994336/sheet/f38b3b42-402c-44a8-9264-9d422233add2/state/analysis/

Eurostat. (2009). Price indices of the means of agricultural production, input (2000 = 100) - quarterly data. https://doi.org/10.2908/APRI_PI00_INQ

Eurostat. (2015). Price indices of the means of agricultural production, input (2005 = 100) - quarterly data. https://doi.org/10.2908/APRI_PI05_INQ

Eurostat. (2018). Price indices of the means of agricultural production, input (2010 = 100) - quarterly data. https://doi.org/10.2908/APRI_PI10_INQ

Eurostat. (2023). Price indices of the means of agricultural production, input (2015 = 100) - quarterly data. https://doi.org/10.2908/APRI_PI15_INQ

Eurostat. (2024a). Price indices of agricultural products, output (2015 = 100) - annual data. https://doi.org/10.2908/APRI_PI15_OUTA

Eurostat. (2024b). *Price indices of the means of agricultural production, input (2015 = 100) - annual data*. https://ec.europa.eu/eurostat/databrowser/view/apri_pi15_ina__custom_14116122/default/table

Eurostat. (2024c). *Territorial units for statistics (NUTS)*. https://ec.europa.eu/eurostat/web/gisco/geodata/statistical-units/territorial-units-statistics

FADN. (2023). Farm accounting data network: an A to Z of methodology.

Finger, R., Dalhaus, T., Allendorf, J., & Hirsch, S. (2018). Determinants of downside risk exposure of dairy farms. European Review of Agricultural Economics, 45(4), 641–674. https://doi.org/10.1093/erae/jby012

Finger, R., Vroege, W., Spiegel, A., de Mey, Y., Slijper, T., Poortvliet, P. M., Urquhart, J., Vigani, M., Nicholas-Davies, P., Soriano, B., Garrido, A., Severini, S., & Meuwissen, M. P. M. (2022). The Importance of Improving and Enlarging the Scope of Risk Management to Enhance Resilience in European Agriculture. In *Resilient and Sustainable Farming Systems in Europe* (pp. 18–37). Cambridge University Press. https://doi.org/10.1017/9781009093569.003

Finger, R., Wüpper, D., & McCallum, C. (2023). The (in)stability of farmer risk preferences. *Journal of Agricultural Economics*, *74*(1), 155–167. https://doi.org/10.1111/1477-9552.12496

Garcia, V., McCallum, C., & Finger, R. (2024). Heterogeneity of European farmers' risk preferences: an individual participant data meta-analysis. *European Review of Agricultural Economics*. https://doi.org/10.1093/erae/jbae012

Gardebroek, C. (2006). Comparing risk attitudes of organic and non-organic farmers with a Bayesian random coefficient model. *European Review of Agricultural Economics*, *33*(4), 485–510. https://doi.org/10.1093/erae/jbl029

Gephart, J. A., Deutsch, L., Pace, M. L., Troell, M., & Seekell, D. A. (2017). Shocks to fish production: Identification, trends, and consequences. *Global Environmental Change*, *42*, 24–32. https://doi.org/10.1016/j.gloenvcha.2016.11.003

Groom, B., Koundouri, P., Nauges, C., & Thomas, A. (2008). The story of the moment: risk averse cypriot farmers respond to drought management. *Applied Economics*, *40*(3), 315–326. https://doi.org/10.1080/00036840600592916

Heller, M. C., & Keoleian, G. A. (2003). Assessing the sustainability of the US food system: a life cycle perspective. In *Agricultural Systems* (Vol. 76). www.elsevier.com/locate/agsy

Henningsen, A., Low, G., Wuepper, D., Dalhaus, T., Storm, H., Belay, D., & Hirsch, S. (2024). *Estimating Causal Effects with Observational Data Guidelines for Agricultural and Applied Economists*. https://ifro.ku.dk/english/

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M., & Finger, R. (2020). Measuring Farmer Risk Preferences in Europe: A Systematic Review. *Journal of Agricultural Economics*, *71*(1), 3–26. https://doi.org/10.1111/1477-9552.12325

Just, R. E., & Just, D. R. (2011). Global identification of risk preferences with revealed preference data. *Journal of Econometrics*, *162*(1), 6–17. https://doi.org/10.1016/j.jeconom.2009.10.004

Just, R. E., & Pope, R. D. (1978). Stochastic specification of production functions and economic implications. *Journal of Econometrics*, *7*(1), 67–86. https://doi.org/10.1016/0304-4076(78)90006-4

Just, R. E., & Pope, R. D. (1979). Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics*, *61*(2), 276–284. https://doi.org/10.2307/1239732

Kakumanu, K. R., Kuppanan, P., Ranganathan, C. R., Shalander, K., & Amare, H. (2016). Assessment of risk premium in farm technology adoption as a climate change adaptation strategy in the dryland systems of India. *International Journal of Climate Change Strategies and Management*, *8*(5), 689–717. https://doi.org/10.1108/IJCCSM-10-2015-0149

Koundouri, P., Laukkanen, M., Myyra, S., & Nauges, C. (2009). The effects of EU agricultural policy changes on farmers' risk attitudes. *European Review of Agricultural Economics*, *36*(1), 53–77. https://doi.org/10.1093/erae/jbp003

Kuethe, T. H., & Morehart, M. (2012). The profit impacts of risk management tool adoption. *Agricultural Finance Review*, *72*(1), 104–116. https://doi.org/10.1108/00021461211222178

Lettenmaier, D. P., Hooper, E. R., Wagoner, C., & Faris, K. B. (1991). Trends in stream quality in the continental United States, 1978–1987. *Water Resources Research*, *27*(3), 327–339. https://doi.org/10.1029/90WR02140

Mellon, J. (2024). Rain, rain, go away: 194 potential exclusion-restriction violations for studies using weather as an instrumental variable. *American Journal of Political Science*. https://doi.org/10.1111/ajps.12894

Meuwissen, M. P. M., de Mey, Y., & van Asseldonk, M. (2018). Prospects for agricultural insurance in Europe. *Agricultural Finance Review*, *78*(2), 174–182. https://doi.org/10.1108/AFR-04-2018-093

Meuwissen, M. P. M., Feindt, P. H., Slijper, T., Spiegel, A., Finger, R., de Mey, Y., Paas, W., Termeer, K. J. A. M., Poortvliet, P. M., Peneva, M., Urquhart, J., Vigani, M., Black, J. E., Nicholas-Davies, P., Maye, D., Appel, F., Heinrich, F., Balmann, A., Bijttebier, J., … Reidsma, P. (2021). Impact of Covid-19 on farming systems in Europe through the lens of resilience thinking. *Agricultural Systems*, *191*, 103152. https://doi.org/10.1016/j.agsy.2021.103152

Mulungu, K., Kimani, M. E., & Sarr, M. (2024). Do farmers' risk preferences remain stable in the face of climatic shocks? Evidence from smallholder farmers in Zambia. *Applied Economics*, *56*(15), 1784–1800. https://doi.org/10.1080/00036846.2023.2177599

Rippo, R., & Cerroni, S. (2023). Farmers' participation in the Income Stabilisation Tool: Evidence from the apple sector in Italy. *Journal of Agricultural Economics*, *74*(1), 273–294. https://doi.org/10.1111/1477-9552.12508

Rommel, J., Hermann, D., Müller, M., & Mußhoff, O. (2019). Contextual Framing and Monetary Incentives in Field Experiments on Risk Preferences: Evidence from German Farmers. *Journal of Agricultural Economics*, *70*(2), 408–425. https://doi.org/10.1111/1477-9552.12298

Rosa, L., Rulli, M. C., Ali, S., Chiarelli, D. D., Dell'Angelo, J., Mueller, N. D., Scheidel, A., Siciliano, G., & D'Odorico, P. (2021). Energy implications of the 21st century agrarian transition. *Nature Communications*, *12*(1). https://doi.org/10.1038/s41467-021-22581-7

Simpson, Z. P., & Haggard, B. E. (2018). Optimizing the flow adjustment of constituent concentrations via LOESS for trend analysis. *Environmental Monitoring and Assessment*, *190*(2), 103. https://doi.org/10.1007/s10661-018-6461-5

Srivastava, N., Saquib, M., Rajput, P., Bhosale, A. C., Singh, R., & Arora, P. (2023). Prospects of solar-powered nitrogenous fertilizers. *Renewable and Sustainable Energy Reviews*, *187*, 113691. https://doi.org/10.1016/j.rser.2023.113691

Tveterås, R., Flaten, O., & Lien, G. (2011). Production risk in multi-output industries: estimates from Norwegian dairy farms. *Applied Economics*, *43*(28), 4403–4414. https://doi.org/10.1080/00036846.2010.491461

Tveterås, R., & Wan, G. H. (2000). Flexible panel data models for risky production technologies with an application to salmon aquaculture. *Econometric Reviews*, *19*(3), 367–389. https://doi.org/10.1080/07474930008800477

Zhou, E., & Wang, X. (2023). Dynamics of systemic risk in European gas and oil markets under the Russia–Ukraine conflict: A quantile regression neural network approach. *Energy Reports*, *9*, 3956–3966. https://doi.org/10.1016/j.egyr.2023.03.030

Annex 1: Supplementary Documents

Annex 1 consists of 4 Tables:

1. The relevant studies investigating revealed risk preferences (Table A1),
2. The estimated revealed risk preferences of the crop and dairy farmers at the national average level between 2004 and 2022 (Table A2)
3. The temporal revealed risk preference of the crop farmers with the 2008 energy price shock as an example (Table A3).
4. The temporal revealed risk preference of the dairy farmers with the 2008 energy price shock as an example (Table A4).

Table A1. The relevant studies assessing revealed risk preferences from observable data.

Literature	Farm type	Profit/revenue/production moment specification		Revealed risk attitude estimator/specification		Inputs
		Functional form	Estimator/specification	Estimator/specification	Instrument	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bozzola & Finger (2021)	Field crop	Quadratic	Fixed-effect	3SLS	Lagged fallow land, less favoured area	Fertilisers, labour, seeds, crop protection
Mulungu et al. (2024)	Maize	Quadratic	Instrumental variable-fixed effect	3SLS	Distance to agro-dealer, distance to fertiliser depot, access to extension (information), average district maize prices, lagged rainfall	Fertilisers and seeds
Koundouri et al. (2009)	Wheat and barley	Quadratic and Cobb-Douglas	FIML	FIML	-	Fertiliser, labour, plant protection and fixed capital
Groom et al. (2008)	Vegetable and cereal	Quadratic	-	2SLS	Well on the parcel (i.e., representative part of the land), distance to nearest town and river, access to the water reservoir, and whether the parcel belongs to an agricultural zone	Fertilisers, water, and labour
Antle (1987)	Rice	Quadratic	FGLS	2SLS	Output price, rainfall, farmer education, variety, seasonal and annual dummy	Labour, fertiliser, animal labour, and land
Gardebroek (2006)	Arable	Quadratic	Fixed-effect	Bayesian RCM	-	Fertiliser, seeds, pesticides, contractor work, hired labour, and other variable inputs
Bozzola (2014)	Vegetable and cereal	Quadratic	Fixed-effect	3SLS	Maximum and minimum average temperature, cumulated precipitation during the growing season	Irrigation water, fertilisers, and plant protection
Kakumanu et al. (2016)	Crop	Quadratic	GLS	2SLS	Distance to the market, investment in farm machinery, investments in new infrastructure, and awareness of technology	Fertiliser, seed, labour, use of machine labour, and irrigation water

Note that FIML=Full information maximum likelihood, 3SLS=Three stage least squares, 2SLS=Two stage least squares, FGLS=feasible generalised least squares; RCM=Random coefficient model.

Table A2. The results of the estimate revealed risk attitudes for field crop and dairy farmers per country throughout 2004-2022 (dependent variable: derivative of the profit means with respect to inputs).

Country	Field crop				Dairy				z-value	
	AP	DS	Intercept	N	AP	DS	Intercept	N	Difference of AP between types	Difference of DS between types
Belgium	-0.719***	-0.378***	-0.059***	2,219	0.755***	-0.551***	-0.096***	4,582	-32.792	-3.418
	(0.018)	(0.008)	(0.003)		(0.013)	(0.002)	(0.002)			
Bulgaria	0.113***	-0.771***	-0.422***	15,343	0.543***	0.076***	-0.212***	3,310	-5.710	43.248
	(0.004)	(0.003)	(0.001)		(0.037)	(0.002)	(0.008)			
Czechia	-0.186***	-0.472***	0.041***	8,321	0.667***	0.516***	-0.039***	2,709	-34.793	38.152
	(0.012)	(0.004)	(0.009)		(0.004)	(0.002)	(0.004)			
Denmark	-0.032.	-0.041**	-0.201***	8,471	-0.435***	0.000	-0.020***	6,904	20.203	2.443
	(0.009)	(0.003)	(0.003)		(0.003)	(0.001)	(0.001)			
Germany	-1.499***	0.239***	-0.026**	36,788	-0.014*	-0.011***	-0.087***	41,667	-13.207	-30.997
	(0.056)	(0.001)	(0.010)		(0.003)	(0.000)	(0.001)			
Estonia	0.129***	-0.092***	-0.275***	3,873	0.095***	-0.365***	0.219***	2,818	2.509	-6.459
	(0.001)	(0.000)	(0.002)		(0.007)	(0.007)	(0.009)			
Ireland	-1.234***	-0.257	-0.259***	831	-0.203***	1.565***	-0.049***	5,964	-3.232	1.839
	(0.158)	(0.165)	(0.091)		(0.018)	(0.009)	(0.001)			
Greece	0.099***	-0.035***	-0.108***	33,837	3.172***	2.312***	-0.074***	173	-16.962	13.018
	(0.002)	(0.001)	(0.000)		(0.091)	(0.030)	(0.024)			
Spain	0.029***	-0.088***	-0.002***	44,727	0.290***	0.005***	-0.033***	18,122	-45.965	95.481
	(0.003)	(0.000)	(0.001)		(0.000)	(0.000)	(0.000)			
France	2.790***	1.220***	-0.185***	32,390	0.113***	-0.076***	-0.126***	19,345	109.855	-94.155
	(0.012)	(0.002)	(0.000)		(0.002)	(0.001)	(0.000)			
Italy	0.052***	0.097***	-0.010***	66,983	0.434***	-0.122***	-0.037***	20,681	-12.971	-41.071
	(0.002)	(0.000)	(0.000)		(0.015)	(0.001)	(0.001)			
Cyprus	1.356***	0.148***	-0.057***	2,609	1.345***	7.609***	-0.148*	125	0.069	5.960
	(0.009)	(0.002)	(0.006)		(0.080)	(0.209)	(0.074)			
Latvia	0.964***	-1.366***	0.097***	6,466	0.184***	-0.010**	0.074***	6,172	17.266	28.298
	(0.022)	(0.008)	(0.013)		(0.006)	(0.001)	(0.001)			
Lithuania	-0.764***	-0.073***	-0.507***	9,335	-0.243***	-0.953***	-0.119***	5,005	-9.877	-10.176
	(0.003)	(0.000)	(0.001)		(0.026)	(0.014)	(0.001)			
Luxembourg	5.347***	13.505***	-0.152***	239	0.094	-0.712***	-0.019***	3,705	18.476	-20.774
	(0.139)	(0.114)	(0.007)		(0.032)	(0.007)	(0.001)			
Hungary	-0.219***	-0.032***	-0.244***	19,311	0.557***	0.803***	-0.535***	1,952	-6.717	7.607
	(0.008)	(0.001)	(0.002)		(0.057)	(0.018)	(0.054)			
Malta	0.666*	0.472***	0.050	1,327	-1.488***	-0.664***	-0.026***	1,237	7.497	-13.666
	(0.142)	(0.012)	(0.032)		(0.024)	(0.006)	(0.002)			
Netherlands	1.738***	0.814***	-0.091***	4,157	-0.576***	-0.301***	-0.093***	6,551	62.815	-130.966
	(0.005)	(0.001)	(0.001)		(0.018)	(0.001)	(0.002)			
Austria	-1.690***	-1.351***	-0.173***	6,934	-0.596***	-0.080***	-0.106***	14,481	-89.392	145.973
	(0.004)	(0.001)	(0.000)		(0.004)	(0.000)	(0.000)			
Poland	-0.099***	-0.037***	-0.410***	64,085	-0.066***	-0.073***	-0.121***	45,059	-4.511	-11.201
	(0.002)	(0.000)	(0.000)		(0.003)	(0.001)	(0.000)			
Portugal	-0.582***	-0.387***	0.247***	5,092	-0.072***	-0.066***	0.057***	6,225	-31.394	45.641
	(0.007)	(0.001)	(0.004)		(0.004)	(0.001)	(0.002)			
Romania	0.220***	0.039***	-0.082***	32,440	-0.697***	-0.393***	-0.122***	6,454	9.453	-17.297
	(0.015)	(0.001)	(0.003)		(0.046)	(0.004)	(0.004)			
Slovenia	1.326***	0.501***	0.033***	1,701	1.309***	0.204***	-0.214***	3,994	0.281	-15.551
	(0.029)	(0.003)	(0.007)		(0.007)	(0.001)	(0.001)			
Slovakia	-0.104***	-0.085***	-0.025***	5,052	-0.279***	-0.029.	-0.115***	1,255	7.741	3.277
	(0.000)	(0.000)	(0.001)		(0.011)	(0.003)	(0.010)			
Finland	1.526***	-0.441***	-0.247***	4,205	0.319***	-0.225***	-0.138***	5,627	37.071	19.829
	(0.016)	(0.002)	(0.001)		(0.004)	(0.001)	(0.000)			
Sweden	0.309***	-0.317***	-0.231***	3,836	-0.151***	0.134***	-0.134***	7,305	12.020	27.585
	(0.019)	(0.001)	(0.004)		(0.004)	(0.002)	(0.002)			
Croatia	0.072*	-0.565***	-0.281***	3,219	0.182*	-1.150***	-0.133***	1,833	-1.350	-19.980
	(0.018)	(0.003)	(0.006)		(0.037)	(0.004)	(0.007)			

Please note that ., *, **, and *** indicate significance levels of 10, 5, 1, and 0.1 per cent, respectively. The risk attitudes for Croatia, Malta, and Denmark do not include information for 2022 due to insufficient data. AP represents the Arrow-Pratt absolute risk aversion; DS denotes the downside risk aversion; N represents the number of observations, with bootstrap standard errors provided in parentheses. The intercept refers to the intercept of the fertiliser equation. The z-values are calculated based on the bootstrap coefficients and standard errors.

Table A3. The results of temporal risk attitudes of field crop farmers per country per period (dependent variable: derivative of the profit means with respect to inputs).

Country	Period	AP	S.E.	z-values for AP change	DS	S.E.	z-values for DS change	Country	Period	AP	z-values for AP change	S.E.	DS	S.E.	z-values for DS change
Belgium	2004-2007	-2.134***	0.053	-10.296	-10.691***	0.034	49.029	Luxembourg	2004-2007	-	-	-	-	-	-
	2008-2021	-0.977***	0.020		-0.312***	0.007			2008-2021	-0.539***		0.063	-2.712***	0.134	
Bulgaria	2004-2007	-	-	-	-	-	-	Hungary	2004-2007	-0.529***	-12.681	0.019	-0.544***	0.003	18.342
	2008-2021	-0.007	0.005		-0.483***	0.001			2008-2021	-0.033***		0.002	-0.163***	0.000	
Czechia	2004-2007	-1.048***	0.032	-17.731	-1.020***	0.032	4.887	Malta	2004-2007	-9.064***	-7.281	0.246	2.669*	0.180	-4.507
	2008-2021	0.296***	0.020		-0.072***	0.003			2008-2021	-4.314***		0.214	-2.355***	0.047	
Denmark	2004-2007	-0.589***	0.002	-54.514	0.404***	0.003	-2.041	Netherlands	2004-2007	4.005***	20.547	0.073	0.754***	0.017	-5.114
	2008-2021	0.543***	0.010		0.370***	0.001			2008-2021	0.806***		0.028	0.213***	0.005	
Germany	2004-2007	1.506***	0.019	11.660	0.572***	0.004	-22.787	Austria	2004-2007	3.911***	95.328	0.007	4.616***	0.005	-111.810
	2008-2021	0.901***	0.018		-0.227***	0.005			2008-2021	-1.366***		0.027	-0.887***	0.007	
Estonia	2004-2007	0.207***	0.033	1.009	-0.128	0.024	-0.089	Poland	2004-2007	0.184***	-2.672	0.025	-0.050.	0.004	6.145
	2008-2021	0.140***	0.001		-0.140***	0.000			2008-2021	0.320***		0.001	0.104***	0.000	
Ireland	2004-2007	3.410*	0.570	2.836	10.784***	0.440	-3.757	Portugal	2004-2007	1.088***	25.900	0.022	-0.115***	0.000	-24.378
	2008-2021	-0.014	0.198		0.368	0.140			2008-2021	-0.771***		0.029	-1.393***	0.009	
Greece	2004-2007	1.553***	0.030	13.267	-1.886***	0.006	52.329	Romania	2004-2007	-	-	-	-	-	-
	2008-2021	0.747***	0.002		0.143***	0.001			2008-2021	0.224***		0.008	0.066***	0.001	
Spain	2004-2007	0.983***	0.008	37.692	-0.502***	0.002	34.446	Slovenia	2004-2007	19.987***	7.995	1.191	2.675	0.539	-0.696
	2008-2021	0.216***	0.006		0.013***	0.000			2008-2021	0.936***		0.004	0.426***	0.001	
France	2004-2007	1.001***	0.017	44.401	0.483***	0.001	-30.965	Slovakia	2004-2007	-2.094***	-9.389	0.124	-0.432***	0.010	5.129
	2008-2021	-1.771***	0.026		-0.144***	0.003			2008-2021	0.243***		0.011	-0.128***	0.000	
Italy	2004-2007	1.430***	0.094	9.457	0.299***	0.007	-4.973	Finland	2004-2007	-0.230***	-29.214	0.006	-1.448***	0.003	25.763
	2008-2021	-0.356***	0.002		0.090***	0.000			2008-2021	1.193***		0.024	-0.871***	0.001	
Cyprus	2004-2007	-2.076***	0.049	-11.820	-0.560***	0.004	-3.700	Sweden	2004-2007	4.287***	9.836	0.238	2.097***	0.033	-12.706
	2008-2021	0.396*	0.092		-0.908***	0.015			2008-2021	-0.441***		0.033	-0.402***	0.003	
Latvia	2004-2007	0.840***	0.018	17.946	-0.049	0.011	-17.359	Croatia	2004-2007	-	-	-	-	-	-
	2008-2021	0.206***	0.001		-1.208***	0.000			2008-2021	0.072*		0.018	-0.565***	0.003	
Lithuania	2004-2007	1.422***	0.063	14.377	0.499***	0.015	-6.021								
	2008-2021	-0.396***	0.002		-0.028***	0.000									

., *, **, and *** indicate significance levels at 10, 5, 1, and 0.1 per cent, respectively; AP represents the Arrow-Pratt absolute risk aversion, DS represents Downside risk aversion, S.E. denotes Bootstrap standard errors, Bulgaria, Luxembourg, Romania, and Croatia do not have enough observations (≤30) or the corresponding dataset is only available for 1 year. We therefore exclude these specific country-period datasets from the analysis; The periods are split by the identified energy shock described in Section 5.1 in the text; Input variables: fertilisers, crop protection, other inputs, and covariates: land, total fixed assets value (without land value), and labour; z-value: testing for the null hypothesis: the corresponding revealed risk preference is stable during the 2008-energy-price-shock. The z-values are calculated based on the bootstrap coefficients and the standard errors.

Funded by the European Union

Table A4. The results of temporal risk attitudes of dairy farmers per country per period (dependent variable: derivative of the profit means with respect to inputs).

Country	Period	AP	S.E.	z-values for AP change	DS	S.E.	z-values for DS change	Country	Period	AP	S.E.	z-values for AP change	DS	S.E.	z-values for DS change
Belgium	2004-2007	-1.129***	0.012	-13.480	-14.643***	0.003	128.161	Luxembourg	2004-2007	0.001	0.159	0.388	-3.747***	0.107	5.381
	2008-2021	0.229*	0.049		-0.871***	0.003			2008-2021	-0.123***	0.019		-0.287***	0.011	
Bulgaria	2004-2007	-	-	-	-	-	-	Hungary	2004-2007	1.351***	0.050	11.058	-3.832***	0.025	17.419
	2008-2021	0.631***	0.017		0.065***	0.012			2008-2021	-1.152***	0.102		-0.322*	0.022	
Czechia	2004-2007	-3.195***	0.210	-8.907	-8.669***	0.045	6.180	Malta	2004-2007	-0.957*	0.203	1.871	9.996***	0.276	-6.475
	2008-2021	0.551***	0.003		0.186***	0.003			2008-2021	-1.719***	0.013		-0.731***	0.003	
Denmark	2004-2007	1.816***	0.104	10.854	-1.069***	0.006	11.051	Netherlands	2004-2007	0.351***	0.028	21.162	-0.022	0.003	-20.166
	2008-2021	-0.434***	0.003		-0.199***	0.001			2008-2021	-0.892***	0.008		-0.391***	0.001	
Germany	2004-2007	-0.073.	0.021	-5.345	-0.156***	0.004	3.678	Austria	2004-2007	1.064***	0.050	12.683	-0.260***	0.012	-1.337
	2008-2021	0.155***	0.001		-0.062***	0.001			2008-2021	-0.201***	0.005		-0.357***	0.001	
Estonia	2004-2007	-0.863**	0.147	-2.081	-5.899***	0.006	10.208	Poland	2004-2007	0.575***	0.013	40.458	-1.400***	0.004	52.146
	2008-2021	-0.251***	0.007		-0.164***	0.003			2008-2021	-0.543***	0.004		-0.239***	0.001	
Ireland	2004-2007	1.737***	0.044	33.995	-2.943***	0.004	24.231	Portugal	2004-2007	-0.592***	0.019	-15.504	0.099***	0.002	-17.074
	2008-2021	-1.455***	0.015		0.140***	0.001			2008-2021	0.000	0.003		-0.141***	0.000	
Spain	2004-2007	0.546***	0.042	14.321	0.461***	0.001	-8.545	Romania	2004-2007	-	-	-	-	-	-
	2008-2021	-0.653***	0.004		-0.033***	0.000			2008-2021	-0.694***	0.040		-0.378***	0.004	
France	2004-2007	1.116***	0.017	25.265	-3.408***	0.001	173.149	Slovenia	2004-2007	0.789***	0.036	7.531	-0.138*	0.011	1.771
	2008-2021	0.252***	0.002		0.053***	0.000			2008-2021	0.210***	0.013		-0.023***	0.000	
Italy	2004-2007	0.159	0.076	-1.993	0.097**	0.004	-1.006	Slovakia	2004-2007	-0.261	0.118	-2.210	-0.616***	0.010	4.464
	2008-2021	0.461***	0.006		0.056***	0.001			2008-2021	0.268***	0.020		-0.317***	0.004	
Cyprus	2004-2007	-	-	-	-	-	-	Finland	2004-2007	0.419**	0.075	0.751	6.159***	0.054	-20.716
	2008-2021	3.370***	0.188		12.239***	0.113			2008-2021	0.306***	0.003		-0.506***	0.000	
Latvia	2004-2007	-1.695***	0.042	-18.317	-0.866***	0.019	25.370	Sweden	2004-2007	1.139***	0.145	4.685	3.072***	0.095	-4.871
	2008-2021	-0.093**	0.011		-0.200***	0.004			2008-2021	-0.215***	0.004		0.282***	0.002	
Lithuania	2004-2007	-0.164	0.100	-0.697	-0.282	0.016	-1.059	Croatia	2004-2007	-	-	-	-	-	-
	2008-2021	0.002	0.065		-1.071***	0.008			2008-2021	0.182*	0.037		-1.150***	0.004	

., *, **, and *** indicate significance levels at 10, 5, 1, and 0.1 per cent, respectively; AP represents Arrow-Pratt absolute risk aversion, DS represents Downside risk aversion, S.E. denotes the bootstrap standard error, Bulgaria, Cyprus, Romania, and Croatia do not have enough observations (≤30) or the corresponding dataset is only available for 1 year. We therefore excluded these specific country-period datasets from the analysis; The periods are split by the identified energy shock; Greece is not included because collinearity occurs in its first stage; Input variables: fertilisers, veterinary products, purchased concentrated feeds, energy, other inputs, and covariates: land, fixed assets value (without land value), labour, and livestock units; z-values: testing for the null hypothesis: the corresponding revealed risk preference is stable during the 2008-energy-price-shock. The z-values are calculated based on the *bootstrap* coefficients and the standard errors

Funded by the European Union

Annex 2: Models Quality Checklist

DESCRIPTION OF MODELS AND DATASETS	
The technical implementation and environment of the model/dataset is documented (coding practices, code commenting, motivated (modular) design, code review, computer language, version control, computation time, multiple-processor use)	Yes. The theoretical framework and the empirical methods are discussed in Section 2 and 3 in the current report. The code are publicly available at the **Github online repository** and internally checked by the internal reviewers. The programming language is r, and all analysis mentioned in Section 3 are conducted in **R studio** version 4.4.1. The computational time is approximately **1 hour** for every heterogeneity check, i.e., described in Section 3.2.
Documentation: ○ **General model description** ○ **Formal model documentation (mathematical model))**	Yes. The documentation of both theoretical and empirical model are described in detail in Section 2 and 3.
Provision of data and metadata	Yes. The data used for the current report is the European Farm Accountancy Data Network (FADN), including all 27 member states. The data can be retrieved upon the request to the European Commission.
Description for model testing.	Yes. The model is carefully tested under multiple **robustness (sensitivity) check** as described in Section 3.2.

DESCRIPTION OF PARAMETERS, VARIABLES, INPUTS AND OUTPUT OF THE MODEL/DATASET	
The parameters and variables of the model/dataset are documented	Yes. The parameter and variable selection are discussed in detail in Section 3.
Calibration of parameters is described when relevant	Yes. The calibration of parameter is described in Section 3.
The inputs and outputs are described	Yes. The input, output variables, and the motivation of involving these specific variables are described in Section 3.2.1.
The origin of input data is described	Yes. The origin of input data is described in Section 4.

THE FUNCTIONING OF THE MODEL/DATASET IS EVALUATED	
A sensitivity analysis is performed	Yes. The details of sensitivity analysis is discussed in Section 3.2, and the results of the sensitivity analysis is provided in Section 5.2.

The model/dataset is validated e.g. 'trace specific variables' correctness', 'face validity test', 'correctly present input-output levels for a given activity', 'visualization techniques for visual goodness of fit', 'data validation', 'sensitivity analysis' and 'statistical validation'.	Yes. The current report provides robustness check at several aspects as shown in Section 3.2 and 5.2. Moreover, in describing the results, the current report also provide the statistical validation using the bootstrap technique.

RELIABILITY	
Version control	Yes. The backup of the original code are stored in the GitHub repository, which will be publicly available.
Modular structure	Yes. The analysis is done by modulars in the code.

TRANSPARENCY	
Is the model input data / underlying database (i.e. the database the model runs are based on) **made publicly available?**	Yes. The input data used for the current report includes the FADN, the agricultural input and output price indices from Eurostat, and weather information from E-OBS dataset. The latter two are publicly available, while the FADN is only retrievable upon proper request to the European Commission.
Can model outputs be made publicly available?	Yes. The model outputs will be available in the form of the current report and the scientific paper.
Are model equations and data base transparently documented and are these documents available to the general public?	Yes. The model equations and database are transparently documented in the current report, and will also be available in a scientific paper.
Is the model source code publicly accessible?	Yes. The model code will be publicly accessible in an open access GitHub repository upon publication. The code will first be submit to the European Commission in the form of zip files.

Funded by the European Union

AgEnRes

@AgenresEU

@AgenresEU

www.agenres.eu

Funded by
the European Union