Assessing Risk Attitudes and Their Stability to Mineral Fertilizers Price Shocks for European Farmers

Research Report Research Practice at the Business Economics Group

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Disclaimer

Preface

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In the beautiful Zakynthos, 7 May 2024,

Coco (Kexin) Wang

Abstract

This research practice investigates farmers' risk attitudes and their (in)stabilities during a mineral fertilizers price shock across 27 European member states. To this end, we use the flexible moment-based approach (Antle, 1983) to assess the populational average Arrow-Pratt (AP) and Downside (DS) risk aversion coefficients of farmers. Further, we use Wald statistics to test risk attitudes' (in)stabilities during a mineral fertilizers price shock and equalities across farm types and countries. We use a well-established method to identify the price shocks, combining local polynomial regression (LOESS) and detecting local outliers in the autocorrelation coefficient (Anselin, 1995; Cottrell et al., 2019). We use a sub-sample of the Farm Accountancy Data Network (FADN), covering 115,500 field crop or dairy farms during 2004 and 2020. Moreover, we use world urea price data (World Bank Prospects Group, 2024) to identify shocks.

We find on average, farmers are averse to variance in profit, but they also slightly seek left-skewed profit in the entire period (2004-2020). This indicates that farmers are averse to risk in general, but still, they seek to tolerate extremely bad income with compensation of receiving profit higher than their expectation with greater likelihood. Besides, we find evidence supporting farmers' risk attitudes instabilities during a urea price shock and heterogeneity in their risk attitudes across farm types and countries. Given this evidence, we suggest policymakers consider context-specific risk attitudes and further investigate individual farmers' risk premiums to precisely help farmers cope with mineral fertilizer price risks.

Keywords: risk attitudes, panel data, risk, price shock, mineral fertilizer

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List of Abbreviations

Abbreviations	Meanings
3SLS	Three Stage Least Square
AP	Arrow-Pratt
DS	Downside
EU	European Union
FADN	Farm Accountancy Data Network
IARA	Increasing Absolute Risk Aversion
LOESS	Local Polynomial Regression
MSE	Mean Squared Error
OLS	Ordinary Least Square
SURE	Seemingly Unrelated Regression Equations
VNM	Von Neumann Morgenstern

1 Introduction

Influenced by the interruption of COVID-19 and Russia's invasion of Ukraine, the fossil fuel price shock threats European agriculture through the direct energy price spikes (e.g., gas and diesel) and mineral fertilizer price shocks (Galiana-Carballo et al., 2024; Pinsard & Accatino, 2023; Zhou & Wang, 2023). Subsequently, farm income, consumer affordability, and food security are all affected (Martín et al., 2020; Uçak et al., 2022; Youn et al., 2011), calling for the development of price risk management approaches to help farmers. However, farmers' aversion to risk strongly affects their risk management approach adoption, and particularly, their attitudes are non-stable when encountering a shock (Bozzola & Finger, 2021; Isik & Khanna, 2003; Kakumanu et al., 2016; Koundouri et al., 2009). In this case, ignoring farmers' risk attitudes in formulating risk-oriented policies results in inappropriate designs and a waste of resource allocation (Groom et al., 2008; Mukasa, 2018; Vollmer et al., 2017). This ends up in a need for measuring farmers' risk attitudes and their changes to price shock before formulating post-price shock policies, with one major challenge of unstable results between risk attitude-eliciting approaches and risk attitudes' heterogeneities (Finger et al., 2023; Iyer et al., 2020).

To this extent, this research practice report delves into assessing farmers' historical risk attitudes, including the Arrow-Pratt (AP) and downside (DS) measures of risk aversion, and their (in)stabilities to urea price shocks across the entire European Union (EU) and two farm types using econometrics. We contribute to this specific research interest by (i) assessing the risk attitude of farmers, (ii) identifying the urea price shocks, (iii) test farmers' risk attitudes' (in)stability to urea price shocks, and (iv) comparing the risk attitudes of farmers across countries and farm types.

This research practice report extends the previous research, criticized for focusing mainly on production risk (Iyer et al., 2020), by measuring the association between farmers' risk attitudes and urea price shocks. Similar studies include research by Sckokai & Moro (2006), taking Italian arable farmers' risk aversion and output price fluctuation into consideration, and by Bozzola & Finger (2021) and Koundouri et al. (2009), investigating the association between policy shocks and farmers' risk attitude changes. However, none of the previous studies overlaps with our interests in mineral fertilizers' price shocks' correlations with farmers' risk attitudes. Moreover, this research practice contributes to assessing farmers' risk attitudes across farm types and countries, especially covering farmers in all 27 EU countries. This fulfills the need for farm-type-specific risk attitude analysis (Iyer et al., 2020). Lastly, as none of the methods among econometrics, self-reporting surveys, and mathematical calculation to incentivize lotteries dominates the other two (Finger et al., 2023), the use of observable production data and econometrics allows this research practice to combine farm-level data with the mineral fertilizers price data in a long period, offering new evidence on (in)stability of farmers' risk attitudes.

To this end, we use a subset of the Farm Accountancy Data Network (FADN, 2023) covering 115,500 field crop or dairy farms in 27 EU member states over 17 years (2004-2020). This subset is an unbalanced panel dataset, including 601,809 farm-year observations. We also import world urea price data for price shock identification (World Bank Prospects Group, 2024). To assess the farmers' risk attitudes, we employ the flexible moment-based approach (Antle, 1983, 1987) to disentangle farmers' AP and DS risk attitudes. For price shock identification, we use an established, standardized approach to identify certain peaks, as seen in the study by Cottrell et al. (2019). With the identified shocks, we split our dataset into groups by time, farm type, time-farm type, and countries, and we test equalities between risk attitudes in different groups.

We find from 2004 to 2020, farmers exhibit positive AP aversion (AP = 0.075) and negative DS aversion (DS = -0.122). This positive AP aversion suggests that farmers are on average averse to variabilities in their profit. From a downside risk perspective, they bear to receive extremely low profit with a lower likelihood and compensate for this with a higher chance of receiving profit higher than their expectations with greater likelihoods. Second, we find farmers' AP risk aversion slightly increases after a urea price shock, suggesting that they are more averse to overall variance in their profit after a shock. However, their DS aversion also slightly decreases, indicating their tolerance to extremely low-income grows. Moreover, we find risk attitudes are heterogeneous between farm types, and their temporary changes during a shock are also heterogeneous. This supports the previous studies' argumentation on farm-type-specific risk attitudes (Gardebroek, 2006; Iyer et al., 2020). Lastly, we assess farmers' risk attitudes in every EU member state and find mostly heterogeneous risk aversion across countries. To conclude, our findings suggest instabilities to urea price shocks and context-specific heterogeneities in farmers' risk attitudes among 27 EU member states.

The remainder of this research practice report is structured as follows. Section 2 describes the theoretical background of mineral fertilizer price shock and farmers' risk attitudes. Section 3 describes the data and methodology used in this research practice. Section 4 discusses the results of shock identification, risk attitude assessment, and risk attitudes' instabilities. Section 5 concludes and discusses the limitations, future avenues, and policy implications of this research practice.

2 Theoretical Framework

This section discusses the mineral fertilizers price shock and its relationship with farmers' risk attitudes from their theoretical backgrounds. Then, Section 2.2 derives farmers' AP and DS risk aversion from the expected utility theory and moment-based approach.

2.1 Urea Price Shock and Its Effects on Risk Attitudes

Nitrogen is an essential element for human beings and plant growth. It usually occurs in an unreactive form, such as gaseous nitrogen, which cannot be absorbed by most organisms. Thus, nitrogenous fertilizers are necessary for crop production to feed animals and humans. Among many types of nitrogenous fertilizers, urea has the highest nutrient concentrations (46% of nitrogen) and is the most commonly used nitrogenous fertilizer worldwide, demanding direct ammonia input in its production (Fertilizers Europe, 2014; Srivastava et al., 2023). However, ammonia production requires intensive fossil fuel usage. For instance, the Haber-Bosch process, widely used for industrial ammonia production since 1913, fixes atmospheric nitrogen at high temperatures and pressure. This results in nearly 2% of the global fossil fuel flows to ammonia production, with 70-80% of ammonia being used for nitrogenous fertilizer production every year (Erisman et al., 2007; IEA, 2021; Yang, 2018). Because of the dependency on energy usage, ammonia and urea prices are highly coupled to fossil fuels' prices (Erisman et al., 2007). Hence, a sudden peak (i.e., a shock) in fossil fuel prices results in a shock in urea prices.

The effect of this price shock also threatens the stability of farmers' risk attitudes. In neo-classical economics, the risk attitude of an individual is assumed to be stable over time, but this has been challenged by a growing number of research (Luo et al., 2023). Especially when an exogenous shock occurs, changes appear in individuals' risk attitudes. For instance, farmers' risk attitudes change after a policy change (Bozzola & Finger, 2021; Koundouri et al., 2009), because from a farmers' perspective, policy change can lead to considerable risks to investments, especially in the introduction phase of the policy. Likewise, the sudden outbreak of a pandemic also leads to risk attitude instability. Luo et al., (2023) and Mussio et al. (2023) document that individuals are more averse to variance in wealth after COVID-19. Financial crises, such as the Great Recession in 2008, also result in a higher aversion for individuals to take risks (Cohn et al., 2015; Dohmen et al., 2016; Guiso et al., 2018; Necker & Ziegelmeyer, 2016).

Mechanisms on how an exogenous shock affects an individual's risk attitude remain ambiguous, because a shock triggers many possible channels, and they affect risk attitude simultaneously in the real world (Finger et al., 2023; Schildberg-Hörisch, 2018). One potential channel is that a macroeconomic boom or bust affects individuals' risk attitudes through its effect on their beliefs (Malmendier & Nagel, 2011). The other potential channel suggests risk attitude changes because an individual's wealth condition changes during a shock. This channel is reasonable under the context of expected utility theory or prospect theory, but it is conflicted by many empirical studies (Bucciol & Miniaci, 2018; Sahm, 2012). One of the counter channels suggests that emotional changes during a shock—specifically the fear—affect individuals' risk attitudes, even if those individuals don't experience any losses in their wealth during a shock (Cohn et al., 2015; Guiso et al., 2018; Lemer & Keltner, 2001). To explain this, Lemer & Keltner (2001) suggest that individuals fear because they sense situational control and uncertainty, leading them to be more averse to risk and tend to make their situation "surer".

In all, based on the prior discussions, we formulate three hypotheses:

H_1. Regarding field crops and dairy farmers as a whole, farmers' risk attitudes are unstable during a global urea price shock. In our FADN sample, dairy farmers are allowed to input fertilizers in their production, meaning that both field crops and dairy farmers have a part of their income threatened by fertilizer price risk. Hence, with both sectors' incomes being at risk when a urea price shock occurs, we assume in general the farmers' risk attitudes are unstable during a urea price shock.

H_2. Risk attitudes and their changes are heterogeneous between field crop and dairy farmers. That is, the field crop farmers heavily depend on urea in their production compared to dairy farmers, leading to a larger proportional income of theirs being at risk when a urea price shock occurs. This results in a temporary (larger) change in crop farmers' wealth[1] and produces more fear. With these income and emotional changes, we assume their risk attitudes are different to dairy farmers, and their attitudes changes are also different.

H_3. Farmers' risk attitudes vary geographically in the EU. That is, due to the geographical differences, the cultural and political background varies between countries, which results in differences in farmers' risk attitudes (Alesina & Fuchs-Schündeln, 2007). Besides, different quantities and quality of natural resources also lead to farmers being exposed to nitrogenous fertilizer price risk differently in their cost allocation.

2.2 Risk Attitudes of Farmers

To investigate instabilities in farmers' risk attitudes after a shock, we need first to assess the farmers' risk attitudes. In the expected utility theory, risk attitude refers to the curvature of the individual's utility function. To measure this curvature, we start with the assumption that a risk-averse individual aims to maximize expected utility under a risky situation, represented by the distribution of the individual's wealth. In production economics, the flexible moment-based approach (Antle, 1983, 1987) proxies the expected utility maximization problem to maximize a function of moments of error term u in profit. To uncover this error term, also called the stochastic component, Antle (1987) describes a profit function with this stochastic component, as shown in Equation (2.1).

$$\pi = f(Z, \alpha) + u \tag{2.1}$$

Where π is the profit of the farm, Z is the set containing input choices and farm characteristics, α is the parameter to be estimated, $f(Z, \alpha)$ gives the expected farm income

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[1] Even though output price also changes accordingly in the harvest season leading to unobvious changes in income (and potentially even higher income at the end of the year compared to other accounting years), the sudden growth in cost before the harvest season results in temporary lower wealth and liquidity for farmers.

given Z and α, and u is the stochastic component of farm income. According to Antle (1983), the moments of the error can be described by a function of input and farm characteristics set Z, as shown in Equation (2.2).

$$\mu_i = u^i = h(Z, \beta) + \varepsilon_i, \qquad \forall i \in \{2,3,\dots,m\} \tag{2.2}$$

Where μ_i denotes the ith moment of error distribution, β is the parameter to be estimated, and ε_i is the econometric error term. Solving the utility maximization problem for each specific farm, which is equivalent to maximizing the cumulative distribution function of error in profit (Equation (2.3)), the first-order condition gives the farmers' risk attitude parameters[2] (Equation (2.4)).

$$\max_Z E[U(\pi)] = \max_Z F(\mu_1(Z), \mu_2(Z), \dots, \mu_m(Z)) \tag{2.3}$$

$$\begin{aligned}\frac{\partial \mu_1(Z)}{\partial x_k} = -\frac{1}{2!} \times \underbrace{\frac{\partial F(\cdot)}{\partial \mu_2(Z)} \times \frac{\partial \mu_1(Z)}{\partial F(\cdot)}}_{-\mathrm{r}_{AP}} \times \frac{\partial \mu_2(Z)}{\partial x_k} - \frac{1}{3!} \times \underbrace{\frac{\partial F(\cdot)}{\partial \mu_3(Z)} \times \frac{\partial \mu_1(Z)}{\partial F(\cdot)}}_{r_{DS}} \times \frac{\partial \mu_3(Z)}{\partial x_k} \dots \\ - \frac{1}{m!} \times \frac{\partial F(\cdot)}{\partial \mu_m(Z)} \times \frac{\partial \mu_1(Z)}{\partial F(\cdot)} \times \frac{\partial \mu_m(Z)}{\partial x_k}\end{aligned} \tag{2.4}$$

Where $F(\cdot)$ gives the cumulative distribution function, $E[U(\cdot)]$ is the expected utility operator for the von Neumann Morgenstern (VNM) utility function, r_{AP} is the AP absolute risk aversion measure, r_{DS} is the DS risk attitude measure, and x_k denotes the input k in set Z. The AP absolute risk aversion coefficient denotes how averse a farmer is to variabilities in farm income. A positive, zero, and negative AP coefficient means the farmer is risk-averse, risk-neutral, and risk-loving, respectively. Likewise, a positive, zero, and negative DS coefficient shows the farmer is downside risk-averse, downside risk-neutral, and downside risk-loving, respectively (Menezes et al., 1980).

[2] Equation (2) only holds for restricted utility functional forms, as seen in the study by Antle (1987).

3 Methodology and Data

3.1 Econometric Implementation

Measuring the risk attitudes As shown in Equation (2.4), it is necessary to measure moments of the error term in profit, and their first-order derivatives to inputs for risk attitude estimation. Hence, we regress profit on a set of explanatory variables using a linear quadratic functional form to obtain deterministic and stochastic components, as shown in Equation (3.1).

$$y_{ht} = \alpha_h + \sum_k^K \alpha_k x_{kht} + \frac{1}{2}\sum_k^K \sum_j^K \alpha_{jk} x_{kht} x_{jht} + \sum_n^N \alpha_n s_{nht} + u_{ht} \tag{3.1}$$

Where y_{ht} denotes farm h's profit at time t, α_h denotes the farm-specific effect on profit and assumed to be time-invariant, α_n and α_{jk} are the parameters to be estimated, x_{kht} denotes variable input k of farm h at time t, s_{nht} is the extra shifter, and u_{ht} is the econometric residual. Among options of functional forms, such as generalized Leontief function, linear quadratic function, and translog function, the linear quadratic functional form is chosen considering its flexibility, particularly regarding its ability to deal with the potential negative values in dependent and independent variables (e.g., profit). Raising residuals in Equation (3.1) to the power of two and three, we regress variance and skewness on the same set of explanatory variables, as shown in Equation (3.2).

$$\mu_{iht} = \beta_{ih} + \sum_k^K \beta_{ik} x_{kht} + \frac{1}{2}\sum_k^K \sum_j^K \beta_{ijk} x_{kht} x_{jht} + \sum_n^N \beta_k s_{nht} + \epsilon_{iht}, \forall i \in \{2,3\} \tag{3.2}$$

Where μ_{iht} denotes the ith moment of farm profit, β_{ih} denotes the farm-specific effect on variance and skewness and is assumed to be time-invariant[3], β_{ijk} and β_k are parameters to be estimated, and ϵ_{iht} is the econometric residual. Argued by some studies, moments above skewness only add insignificant precision to the approximation of profit distribution (Antle, 1983; Groom et al., 2008), while considering solely mean-variance analysis also lacks insights into farmers' risk behavior toward downside risks (Chavas, 2004). Hence, we focus on variance and skewness in profit distribution, referring to the second and the third moments.

After regressing the mean, variance, and skewness of farmers' profit, the AP and DS measures of risk aversion are estimated through a system of regression equations, as shown in Equation (3.3). These equations estimate the correlations between the dependent variables (i.e., the first-order derivatives of mean function) and first-order derivatives of variance and skewness to inputs (fertilizers, seeds, crop protection, feeds, and veterinary expenditure). In

[3] Unobservable heterogeneity is for sure a problem causing endogeneity. We assume we eliminate (most) of the endogeneity with the use of a fixed effect model, accounting for time-invariant unobserved variables' effect in α_h and β_{ih}. Besides, considering Equations (3.1) and (3.2) are intermediate steps of assessing risk attitude, the causal effect in Equations (3.1) and (3.2) is out of interest in this research practice.

Equation (3.3), θ_{ik}, θ_{ij}, and $\hat{\theta}_i$ denote the parameters to be estimated, D_{ihkt} and D_{ihjt} denote the obtained first-order derivatives in Equations (3.1) and (3.2), and ε_{kh} and ε_{jht} denote the residuals. We assume that the farmers' risk attitudes are not input-specific, and therefore pose restrictions on equality between risk attitude coefficients across equations.

It is noticeable in Equation (3.3) that the dependent variables are simultaneously determined by the same mean profit function in Equation (3.1). Besides the simultaneity, the residuals in Equation (3.3), ε_{kht} and ε_{jht}, are potentially correlated since they come from the same farm[4]. In this sense, treating these equations independently results in suboptimal estimations. Hence, we employ the seemingly unrelated regression equations (SURE) approach to improve estimation efficiency (Zellner, 1962).

$$D_{1hkt} = \theta_{1k} + \theta_{2k} D_{2hkt} + \theta_{3k} D_{3hkt} + \varepsilon_{kht} \tag{3.3}$$

$$D_{1hjt} = \theta_{1j} + \theta_{2j} D_{2hjt} + \theta_{3j} D_{3hjt} + \varepsilon_{jht}$$

$$s.t. \theta_{ik} = \theta_{ij} = \hat{\theta}_i, \forall i \in \{2,3\}, \forall j, k = 1 \dots K$$

Where according to Antle (1987), the AP absolute risk aversion and DS risk coefficients for the entire sample are proxied as:

$$AP \cong 2\hat{\theta}_2, DS \cong -6\hat{\theta}_3 \tag{3.4}$$

Additionally, the occurrence of heteroskedasticity provides a base for risk attitude analysis but also causes inefficient coefficient estimations in Equations (3.1) and (3.2) (Wooldridge, 2019). Besides heteroskedasticity, the assumption of *conditionally uncorrelated observations* may be violated because of two-dimensional correlations in our estimation (Cameron & Trivedi, 2022). First, the autocorrelation for one farm's observations potentially presents, that is, the u_{ht} (and ϵ_{iht}) is correlated for farm h across time $t \in \{1, \dots, T\}$. Second, the unobserved geographic characteristics, such as weather conditions, war, and trade volume, induce spatial correlations between farms in the same period. That is, the u_{ht} (and ϵ_{iht}) is correlated across farm $h \in \{1, \dots, H\}$ at the time t. Thus, we employ the two-way cluster-robust standard error to account for both two-dimensional correlations and heteroskedasticity in Equations (3.1) and (3.2).

Identifying price shocks Based on the obtained AP and DS measures of risk aversion, we test the hypothesis that these risk attitudes are unstable before and after price shocks, between farm types, and across countries. To this end, we identify significant urea price shocks in the past according to the deviations in the serial correlations (Anselin, 1995; Cottrell et al., 2019).

[4] The effect of kurtosis and higher moments are omitted because we assume the first three moments can well-proxy the profit distribution. Potentially, higher moments' effects are included in the econometric error term ε_{kht} and ε_{jht}, and therefore lead to correlations between these errors.

More specifically, we use a local polynomial regression (LOESS) to fit into price serial data and apply Cook's distance to identify sudden disruption (i.e., a shock) in autocorrelation coefficients. LOESS is a smoothing algorithm, pioneered by Cleveland (1979) and further developed by Cleveland & Devlin (1988). It predicts the deterministic curve of the data by moving smoothly across time windows, employing a weighted least square estimation with higher weights assigned to the "neighbors" that are closer to each time window center.

One of the main advantages of LOESS is that it is non-parametric, meaning there is no need to pre-determine a global function between urea price and time indices. Two parameters are needed for the LOESS, including a proportional period q and a polynomial degree p. Span q describes the proportion of the entire dataset in each time window (i.e., a subset) for estimation. Therefore, it controls the flexibility of the approach. In our design, we select two values for span, the first is 0.15, obtained from minimizing the mean squared error (MSE) of LOESS among different span grids[5] under k-fold cross-validation (k = 5). The other one is 0.60, the value that other shock identification studies use for controlling the total number of shocks (Cottrell et al., 2019; Gephart et al., 2017). The other parameter, polynomial degree p, indicates whether the function is locally linear or locally quadratic. We fix it to 2 because a higher polynomial degree results in the overfitting of the model and a lower polynomial degree leads to flatting out the sharp peaks (Simonoff, 1996, p. 145).

We regress residuals from LOESS against the lag-1 residuals to estimate localized autocorrelation coefficients using an ordinary least square (OLS) regression, in which a high value of Cook's (1986) distance points to an outlier[6]. The shock, in our case referring to a positive outlier, is detected when satisfying two restrictions: (i) it is an outlier having a high Cook's distance, and (ii) the actual price at this point is greater than the average price of the past 5 periods.

Instability in risk attitude After identifying the price shocks, we investigate the consistency of farmers' risk attitudes by Wald tests. More precisely, we use the data in each time window (i.e., a subset) split by shocks to assess the risk attitudes of farmers and test various hypotheses. These hypotheses include whether (i) the farmer's attitude is stable during a price shock, with the null hypothesis of H_0: $\hat{\theta}_{i,\tau} = \hat{\theta}_{i,\tau+1}$, where τ and τ+1 denote time window τ and the following time window, (ii) the risk attitudes are the same between field crop and dairy farmers in each sub-period, with the null hypothesis of H_0: $\hat{\theta}_{i,\tau,crop} = \hat{\theta}_{i,\tau,dairy}$, where *dairy* and *crop* refers to dairy and field crop farmers, (iii) the changes in risk attitudes are the same for field

[5] The timespan is gridded from 0.15 to 0.95, with grid = 0.05. The minimum value of 0.15 is set based on the minimum observations used in each subset, i.e., approximately 30 observations.

[6] There is no specific answer on what Cook's distance should be considered as a "high value". For example, Wang et al. (2018) use the critical value at a 96% confidence interval of Cook's distance as a cutoff point for outliers, while other studies e.g., Cottrell et al. (2019), use a cutoff point of 0.30 according to the total number of shocks identified. In our case, we grid the confidence interval from 95% to 99% and count the number of shocks at each confidence interval (in Appendix Table A1). In the range of 96% to 98% confidence interval, all the shocks were concentrated in the years 2008 and 2011. Since results show that yearly shocks are not extremely sensitive to parameter settings, we roughly set the cutoff point at the 98% confidence interval.

crop and dairy farmers, with the null hypothesis of H$_0$: $\hat{\theta}_{i,\tau,crop} - \hat{\theta}_{i,\tau+1,crop} = \hat{\theta}_{i,\tau,dairy} - \hat{\theta}_{i,\tau+1,dairy}$, and (iv) the farmers' risk attitudes are equal across countries, with the null hypothesis of H$_0$: $\hat{\theta}_{i,a} = \hat{\theta}_{i,b}$, where a and b represent two different countries.

We acknowledge no causalities of price shocks on risk attitude instabilities can be derived from this research practice. A urea price shock can be accompanied by other shocks, such as wars or policy changes, and these shocks cannot be distinguished by our Wald test. Therefore, we can only conclude whether a risk attitude change happens during a urea price shock but cannot factor out other sources' effects on this risk attitude change.[7]

3.2 Data

This research practice uses the Farm Accountancy Data Network (FADN, 2023) for individual farmers' risk attitude estimation. The FADN contains a cross-sectional and a time series dimension, consisting of mostly monetary values. We take a subset of initial FADN, consisting of 601,809 observations for 115,500 field crop and dairy farms over 17 years (2004-2020). Besides the FADN, the data of the consumer price index (Eurostat, 2023) is used for FADN monetary value deflation[8], and the monthly world urea price data (World Bank Prospects Group, 2024) is used for shock identification. This world urea price data spans from 2004 to 2020 (17 years), ranging from 128.375 (\$/mt) to 785.000 (\$/mt) with an average price of 284.225 (\$/mt).

According to many other empirical studies (Bozzola & Finger, 2021; Groom et al., 2008), our explanatory variable set includes (i) labor (both paid and family labor, in hours), (ii) costs for seeds (in EUR), (iii) costs for fertilizers (in EUR), (iv) costs for crop protection (in EUR), (v) costs for feeds (in EUR), (vi) veterinary expenditures (in EUR), and (vii) other shifters (e.g., land ownership)[9]. Table 3-1 provides the summary statistics and explanatory variable definitions of the initial data sample.

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[7] All the codes used for analysis in this research practice are publicly available through a GitHub repository (https://github.com/wangcocooo/Shock_risk_attitude).

[8] Many studies deflate monetary variables to avoid confounding results (El Benni et al., 2012; Tveteras et al., 2011). In line with these studies, we remove price fluctuation in monetary variables by deflating them with the consumer price index. This allows us to transfer this profit distribution problem into an output distribution problem. Besides pure production risk, we still account for price fluctuation by analyzing price shocks and detecting correlations between risk attitude changes and the occurrence of a shock.

[9] In line with Bozzola & Finger (2021) and Groom et al. (2008), we rescale all variables with their standard deviations.

Table 3-1. Summary statistics of the initial sample for field crop and dairy sectors.

Variable	Definition	Crop		Dairy		Total	
		Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Dependent variable							
Profit	Farm total net income (in 1000 €)	45.538	939.196	48.928	112.289	46.785	749.868
Explanatory variables							
Land	Utilized agricultural area (UAA, in ha)	144.512	364.169	92.134	235.920	125.248	323.961
Seed	Total seeds and plants costs (in 1000 €)	13.363	36.154	4.947	17.787	10.267	30.971
Labor	Annual labor hour, including both hired and family (in 1000 hours)	5.625	13.253	6.508	14.947	5.950	13.906
Fertilizers	Total fertilizers costs (in 1000 €)	20.371	52.716	7.953	22.240	15.804	44.437
Crop protection	Total costs of crop protection products (in 1000 €)	14.121	37.916	3.384	14.189	10.172	31.777
Total assets	Farm total assets (in 1000 €)	678.028	1,851.859	946.597	1,665.973	776.806	1,790.430
Feeds for grazing livestock	Costs of livestock feeds (in 1000 €)	1.933	21.050	75.030	170.879	28.818	110.734
Livestock unit	Weighted average number of livestock (LU)	5.499	36.846	108.069	179.443	43.224	123.075
Veterinary	Veterinary and medicine expenditure (in 1000 €)	0.096	1.694	2.872	11.141	1.117	7.019
Land ownership	Owned or shared land/UAA (%)	49.905	38.669	53.408	34.652	51.186	37.288
Current ratio	Current assets/total assets (%)	23.521	22.458	18.814	14.355	21.790	19.995
Irrigation ratio	Irrigated land area/UAA (%)	8.982	24.970	3.347	16.445	6.921	22.399
N		380,467		221,342		601,809	

Note that the values are calculated for all 27 EU member states; S.D. = Standard deviation; All monetary values are deflated by the consumer price index by the base of 2015.

4 Results and Discussion

In this section, we start with discussing the detected urea price shocks in the 17 years and the backgrounds of these shocks. Then, we assess farmers' risk aversion in general, across periods, across farm types, and countries in Section 4.2. Besides, we also report temporary instabilities, farm type differences, farm type-time differences, and country-wise differences in risk aversion.

4.1 Global Urea Price Shocks Between 2004 and 2020

This section discusses the detected price shocks and potential mechanisms. Figure 4-1 plots LOESS fitted to urea price data (in (a-b)), autocorrelation between residuals and lag-1 residuals (in (c-d)), and shocks that have a Cook's distance larger than the 98% confidence interval critical values (in (e-f)).

In Figure 4-1 (a-b), we find the urea price shows minor variation between 2005 and 2008, with price points generally located within 95% of the confidence interval of LOESS. From July 2008, the urea price rises dramatically above the prediction of LOESS, leading to a peak in the figure. Then, from October 2008, the urea price rapidly decreases and begins to fluctuate moderately until June 2011. From June 2011, the price jumps above the 95% confidence interval prediction in both span settings again, lasting until August 2012. After this decrease, the urea price fluctuates smoothly until the end of 2020.

Figure 4-1 (c-d) uses the residual obtained from (a-b) as the Y-axis, and the lag-1 residual as the X-axis. This figure reflects the overall pattern of association between residual and lag-1 residuals. The information from this figure is the points that are located remotely from the trendline—in our case, the solid line with a 95% confidence interval in the grey area—do not follow the same trend as other points. Hence, these points potentially refer to local instabilities in price.

Figure 4-1 (e-f) confirms the findings in Figure 4-1 (a-b) and detects the sudden peaks in price. With parameter sets and restrictions defined in Section 3.1, we find urea price shocks in August 2008, September 2008, and June 2011 when the span parameter q is 0.15, and we find shocks in July 2008, August 2008, and June 2011 when the span parameter q is 0.60. Both parameter settings reveal distinct shocks in 2008 and 2011, with the only differences in the flatness of the Cook's distance curve and the exact month where a shock occurs in a year. Hence, both 2008 and 2011 are considered candidate shocks. To complement this shock detection, we reason the (likely) causes for the urea price shocks in 2008 and 2011 as follows.

The urea price shock in 2008 potentially comes from two perspectives. First, the global urea demand increases because of the increasing food needs in emerging countries and the farmers' desire to produce more grains, which is incentivized by high record grain prices in early 2008. Consequently, the global urea fertilizer supply fails to meet its sharply rising demand, leading to a dramatic increase in its price (Lécuyer et al., 2014; Paulson & Sherrick, 2009). Second, the financial crisis of 2008 causes a growth in urea suppliers' input (e.g., fossil fuels) prices, which increases their costs in producing urea (Lécuyer et al., 2014).

Then, in 2011, the strong demand for the livestock sector and biofuel production leads to a decrease in the global grain stock, which pushes the grain price to rise again. Consequently, this grain price increase incentivizes farmers' willingness to demand more urea, similar to the causes of the 2008 urea shock. This unbalances between urea supply and demand pushes urea prices upwards. Besides, the unrest in the Middle East impacts the urea export availability in Egypt. Similarly, China extends its periods of high tariffs for urea export in early 2011, contributing to the rapid increase in urea prices in June 2011 (IFA, 2011; Silva, 2011).

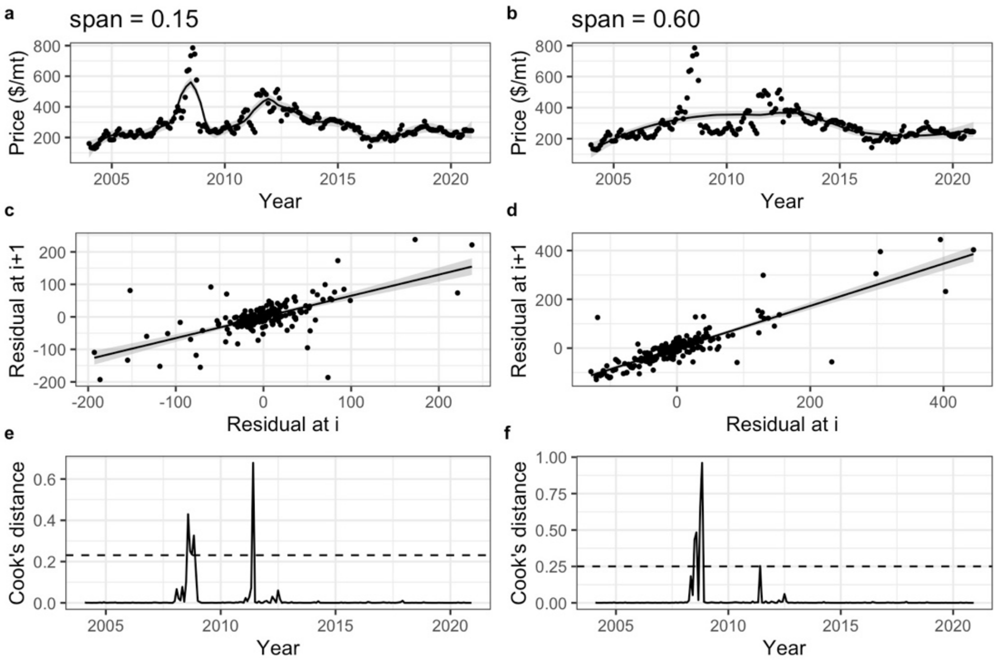

Figure 4-1. Steps to identify price shocks using monthly global urea price between 2004 and 2020.
(a-b) The LOESS (degree = 2, span = 0.15 and 0.60, respectively) fitting to the urea price data, with the grey area denoting the 95% confidence interval. (c-d) OLS regression fitting to residuals against lag-1 residuals obtained from (a-b). (e-f) Cook's distance in OLS regression in (c-d). The dashed lines represent the cutoff values at a 98% confidence interval.

4.2 Empirical Results and Discussion of Risk Attitude Instabilities

In this section, we provide the results of risk attitude assessment from three dimensions: (i) before and after a urea price shock, (ii) between farm types, and (iii) between the EU-27 member states. Before delving into these tests, we start with the overall risk attitudes of all types of farmers in the entire period (2004-2020). Besides risk attitudes, the estimated coefficients of mean, variance, and skewness regressions for the entire sample are reported in Appendix Table A2.

Overall risk attitudes from 2004 to 2020 In Table 4-1, we provide the estimation of AP absolute risk aversion and DS risk coefficients of all farmers between 2004 and 2020. According to Table 4-1, we find the overall AP coefficient is 0.075 for all types of farms at a 1 percent significance level. This positive AP coefficient shows that farmers are generally averse to the variability in profit. However, we find the farmers have a negative DS risk aversion coefficient of -0.122 at a 1 percent significance level, revealing that they are risk-loving towards downside risks. To be clear, this downside risk refers to a reduction in skewness when fixing the mean and variance of profit. This indicates that the farmers prefer to bear extremely low incomes with a low possibility, but they also tend to receive profits above their expectations with a greater likelihood.

Table 4-1. Estimated risk coefficients of all types of farmers between 2004 and 2020.

AP	Std. Err.	DS	Std. Err.
0.075***	0.000	-0.122***	0.000

***,**, and * denote significance at 1, 5, and 10 percent, respectively; Std. Err = original standard error of $\hat{\theta}_i$; AP = $2\hat{\theta}_2$; DS = -$6\hat{\theta}_3$; Original values of $\hat{\theta}_i$ are shown in Appendix Table A3. Estimations are obtained regarding all countries, all farm types, and all periods as a whole.

However, our findings are slightly in contrast to empirical studies, especially regarding the value of the DS aversion coefficient. Table 4-2 provides a summary of the results in literature focusing on risk aversion coefficients using the flexible moment-based approach. As shown, our positive AP coefficient is consistent with most of the findings. Still, some studies (e.g., Antle, 1989) find negative AP coefficients, meaning the farmers love to take greater variabilities in their profit. On the other hand, most studies obtain positive DS aversion, meaning that on average, the farmers are averse to a left shift in their profit distribution. These results are in contrast to our findings. Some studies also obtain negative but insignificant DS coefficients. Only Kakumanu et al. (2016) find negative and significant DS aversion, with the assumption that farmers' risk attitudes can be input-specific.

To further check the sensitivity of our results, we also estimate coefficients after trimming the upper and bottom 1 percent of our inputs. This procedure helps remove potential outliers. The comparison between using trimmed and untrimmed data is provided in Appendix Table A3, and the year-by-year estimations (using untrimmed data) are provided in Appendix Table A4. According to Table A3, we find a -0.003 for $\hat{\theta}_2$ (AP = -0.006) using trimmed data, meaning the farmers are on average neutral or slightly loving the variability in profit. For DS coefficients, we find an extremely small value ($\hat{\theta}_3$ = 0.000, DS = -0.003) using trimmed data. These different results show that after removing the potential outliers, farmers are on average risk risk-neutral or slightly risk-loving to both variance and downside risks.

Table 4-2. Estimated risk aversion coefficients in empirical studies.

Literature	Location	Farm type	AP	DS
Bozzola & Finger (2021)	Italy	Cereal	0.289 ~ 0.446	-0.003 ~ 0.011[a]
Groom et al. (2008)	Cyprus	Vegetable and cereal	0.073 ~ 0.340	-0.088 ~ 0.293[a]
Antle (1987)	India	Rice	3.272 (2.644)	4.254 (3.786)
Antle (1989)	India	Crop	-0.10 ~ 1.40	0.04 ~ 0.26
Kumbhakar & Tveterås (2003)[b]	Norway	Salmon	0.308 ~ 0.441	0.425 ~ 0.490
Koundouri et al. (2009)	Finland	Wheat and barley	-0.900 ~ 0.247	-0.034 ~ 1.106[a]
Kakumanu et al. (2016)	India	Crop	0.370 ~ 3.119	-3.031 ~ 2.951
Mulungu et al. (2024)	Zambia	Crop	0.798	0.021
Simtowe et al. (2006)	Malawi	Maize	4.111	8.517
Vollenweider et al. (2011)	Ireland	Dairy	2.23	3.07

AP = Arrow-Pratt risk aversion; DS = Downside risk aversion; [a] The negative DS is not significant; [b] The DS in Kumbhakar & Tveterås's (2003) study is derived from AP, instead of obtained from -$6\hat{\theta}_3$; Standard deviations reported in parenthesis; most studies assume risk aversion coefficients are constant across inputs, but studies e.g., Antle (1987) and Kakumanu et al. (2016) assume differently.

Risk attitudes in different periods After estimating the risk attitudes taking all countries, all farm types, and the entire period as a whole, we then estimate risk attitudes by sub-periods. We report risk attitudes and Wald statistics across pre- and post-shock periods in Table 4-3. We first treat the field crop and dairy sectors as a whole, and split the sub-periods by urea price shocks, referring to 2008 and 2011. As shown in Table 4-3, we find AP risk aversion coefficients are positive and significant in all sub-periods, with a gradually increasing trend of aversion over time. Besides, DS risk aversions are negative and significant in all sub-periods, with a slightly decreasing trend over time.

We use the Wald statistics to test the equality of risk attitudes between two periods split by a shock. This indicates whether the farmers' risk attitudes are consistent during a shock. The results show significant differences in risk attitudes between every two periods split by a shock. This confirms that farmers' risk attitudes were significantly unstable during shocks in 2008 and 2011.

Table 4-3. Estimated risk coefficients and Wald test statistics for the equality of risk coefficients across periods.

Period	AP	Wald test $\hat{\boldsymbol{\theta}}_{2,\tau} = \hat{\boldsymbol{\theta}}_{2,\tau+1}$	DS	Wald test $\hat{\boldsymbol{\theta}}_{3,\tau} = \hat{\boldsymbol{\theta}}_{3,\tau+1}$
2004-2007	0.071***		-0.121***	
	(0.000)	$\chi^2(1) = 260.11$ Prob > chi2 = 0.000	(0.000)	$\chi^2(1) = 88.45$ Prob > chi2 = 0.000
2008-2010	0.073***		-0.122***	
	(0.000)	$\chi^2(1) = 605.44$ Prob > chi2 = 0.000	(0.000)	$\chi^2(1) = 260.12$ Prob > chi2 = 0.000
2011-2020	0.076***		-0.122***	
	(0.000)		(0.000)	

***, **, and * denote significance at 1, 5, and 10 percent, respectively; The results are reported for average risk attitudes in every sub-sample, including both field crop and dairy farmers; Original standard errors of $\hat{\theta}_i$ are in parenthesis; AP = $2\hat{\theta}_2$; DS = -$6\hat{\theta}_3$; Estimations are obtained regarding all countries and farm types as a whole.

Risk attitudes of different farm types in different periods After treating field crop and dairy sectors as a whole, we split our sample by farm types. The estimated risk attitudes and Wald statistics of different farm types and time ranges are reported in Table 4-3. For AP absolute risk aversion, the field crop farmers show slightly higher aversion to risk in 2004-2007 and 2008-2011. After the urea price shock in 2011, dairy farmers are more averse to variance in profit than field crop farmers. For the DS risk aversion coefficient, the field crop farmers are more downside risk-loving than dairy farmers every period. This shows that on average, compared to dairy farmers, the field crop farmers slightly prefer to bear extremely bad income at some times but also to receive profits that are higher than their expectations most of the time.

We provide Wald test statistics for two null hypotheses in Table 4-3. First, we test the null hypothesis that risk attitudes are equal between field crop and dairy sectors in every period. This is rejected at a 1 percent significance level in every period, meaning that farmers' risk attitudes are different between the field crop and dairy sectors. Besides, we test the null hypothesis that the changes in risk attitudes are equal between farm sectors across periods. We fail to reject the hypothesis of equality of AP risk attitude differences during the 2008 urea price shock between two types of farms. This indicates that during the 2008 urea price shock, the changes in farmers' aversion to profit variance were similar in the field crop and dairy sectors. All other hypotheses are significantly rejected, indicating that all risk attitudes' changes are different between field crop and dairy sectors during the 2011 urea price shock, and farmers' DS risk aversion coefficient changes significantly different between farm types in 2008.

Table 4-4. Estimated risk coefficients and Wald test statistics for different farm types and sub-periods.

Period	Risk coefficients		Wald test	
	Field crop	**Dairy**	$\hat{\boldsymbol{\theta}}_{i,\tau,crop} = \hat{\boldsymbol{\theta}}_{i,\tau,dairy}$	$\hat{\boldsymbol{\theta}}_{i,\tau,crop} - \hat{\boldsymbol{\theta}}_{i,\tau+1,crop} = \hat{\boldsymbol{\theta}}_{i,\tau,dairy} - \hat{\boldsymbol{\theta}}_{i,\tau+1,dairy}$
AP				
2004-2007	0.063*** (0.000)	0.062*** (0.000)	$\chi^2(1) = 10.11$ Prob > chi2 = 0.002	$\chi^2(1) = 0.27$ Prob > chi2 = 0 0.601
2008-2010	0.064*** (0.000)	0.063*** (0.000)	$\chi^2(1) = 13.75$ Prob > chi2 = 0.000	
2011-2020	0.065*** (0.000)	0.068*** (0.000)	$\chi^2(1) = 618.48$ Prob > chi2 = 0.000	$\chi^2(1) = 231.75$ Prob > chi2 = 0.000
DS				
2004-2007	-0.123*** (0.000)	-0.122*** (0.000)	$\chi^2(1) = 88.31$ Prob > chi2 = 0.000	$\chi^2(1) = 16.67$ Prob > chi2 = 0.000
2008-2010	-0.123*** (0.000)	-0.122*** (0.000)	$\chi^2(1) = 9.54$ Prob > chi2 = 0.002	
2011-2020	-0.123*** (0.000)	-0.122*** (0.000)	$\chi^2(1) = 661.27$ Prob > chi2 = 0.000	$\chi^2(1) = 88.83$ Prob > chi2 = 0.000

***,**, and * denote significance at 1, 5, and 10 percent, respectively; Standard errors of $\hat{\theta}_i$ are in parenthesis; AP = $2\hat{\theta}_2$; DS = $-6\hat{\theta}_3$; Estimations are obtained regarding all countries as a whole.

Risk attitudes across countries Finally, we separate the dataset by country but regard the periods (2004-2020) and farm types as a whole. The AP and DS risk aversion coefficients and their standard errors for the EU-27 member states are reported in Table 4-5, the original estimated coefficients are reported in Appendix Table A6, and an illustration of farmers' average risk attitudes by countries is shown in Figure 4-2.

As shown in Table 4-5, all AP and DS risk attitudes are significant at a 1 percent significance level. The Arrow-Pratt risk aversion of EU-27 member states ranges from 0.059 to 0.092, showing that the farmers are averse to variance in their profit at different levels in every country. Besides AP aversion, farmers show downside risk-loving attitudes in every country, with their DS risk aversion ranging from -0.129 to -0.116.

From a geographical perspective, Figure 4-2 (a) shows that farmers' AP risk aversion coefficients vary heterogeneously. Fewer countries in Figure 4-2 (a) are filled with the same color, indicating that farmers hardly show similar AP risk aversion across countries. Remarkably, farmers in Germany, Slovakia, and Denmark show a comparatively high value of AP risk aversion, whereas farmers in Greece and Croatia show a lower value of AP risk aversion. Figure 4-2 (b) shows that DS risk aversion does not vary much across countries. Most of the countries are filled in similar colors, meaning the farmers in these countries have (potentially) similar attitudes toward downside risk. Even though we cannot conclude any similar risk attitude patterns by countries, interestingly, some countries (e.g., Germany) show a relatively high AP value but also a relatively low DS value, which suggests the farmers in these countries are comparatively more averse to risk in the context of variance, but also love to have left-skewed income distribution more.

Lastly, we test for equality between risk aversion coefficients across countries in the entire 17-year period, shown in Figure 4-3. Detailed Wald statistics are reported in Appendix Table A9 and Table A10. As shown in Figure 4-3, the Wald tests are implemented between every pair of countries, and a darker grid indicates the more likely the risk aversion coefficients are similar between the two countries. Overall, we find more dark grids for DS aversion (Figure 4-3 (b)) than AP aversion (Figure 4-3 (a)), suggesting that the farmers' downside risk aversion is potentially homogeneous between countries. Noticeably, farmers in Croatia, Czechia, Denmark, Germany, and Romania hardly reveal similar risk aversion to any other member states, in the context of both AP and DS aversion. This finding supports previous literature arguing that risk attitudes are rather context-specific (Iyer et al., 2020). Besides, as risk aversion plays an essential role in determining farmers' risk premium (Groom et al., 2008), our finding also suggests a need for measuring context-specific risk aversion coefficients before formulating national policies.

Table 4-5. Estimated risk coefficients for different countries in the entire period (2004-2020).

Country	AP	Std. Err.	DS	Std. Err.
Belgium	0.067***	0.000	-0.119***	0.000
Bulgaria	0.077***	0.000	-0.121***	0.000
Cyprus	0.059***	0.000	-0.118***	0.000
Czechia	0.092***	0.000	-0.129***	0.000
Denmark	0.079***	0.000	-0.121***	0.000
Germany	0.078***	0.000	-0.123***	0.000
Greece	0.059***	0.000	-0.117***	0.000
Spain	0.062***	0.000	-0.118***	0.000
Estonia	0.076***	0.000	-0.124***	0.000
France	0.071***	0.000	-0.119***	0.000
Croatia	0.058***	0.000	-0.116***	0.000
Hungary	0.074***	0.000	-0.123***	0.000
Ireland	0.066***	0.000	-0.119***	0.000
Italy	0.062***	0.000	-0.119***	0.000
Lithuania	0.075***	0.000	-0.123***	0.000
Luxembourg	0.066***	0.000	-0.119***	0.000
Latvia	0.073***	0.000	-0.122***	0.000
Malta	0.063***	0.000	-0.120***	0.000
Netherlands	0.064***	0.000	-0.120***	0.000
Austria	0.059***	0.000	-0.118***	0.000
Poland	0.064***	0.000	-0.120***	0.000
Portugal	0.061***	0.000	-0.118***	0.000
Romania	0.069***	0.000	-0.122***	0.000
Finland	0.062***	0.000	-0.118***	0.000
Sweden	0.074***	0.000	-0.124***	0.000
Slovakia	0.086***	0.000	-0.121***	0.000
Slovenia	0.060***	0.000	-0.118***	0.000

***, **, and * denote significance at 1, 5, and 10 percent, respectively; Std. Err. = Standard error; AP = $2\hat{\theta}_2$; DS = $-6\hat{\theta}_3$; Estimations are obtained aggregating field crop and dairy farms.

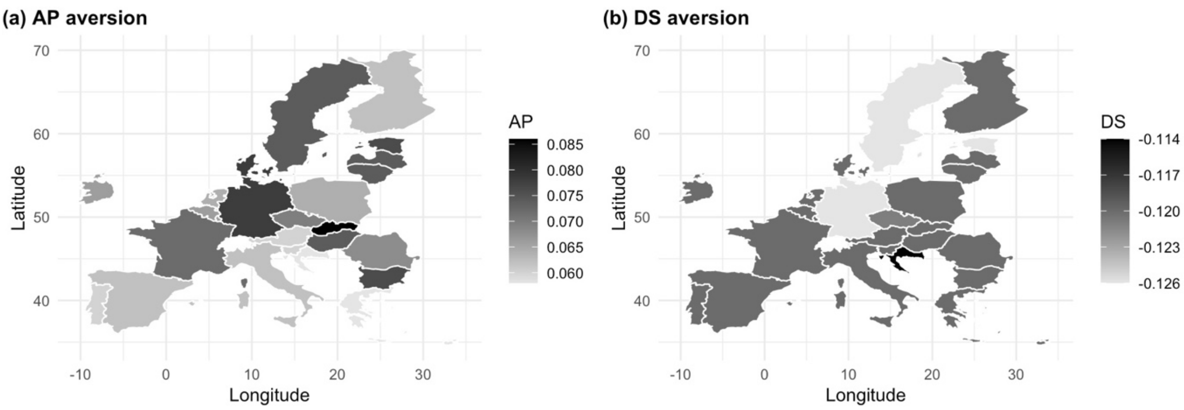

Figure 4-2. An illustration of farmers' average AP and DS risk attitudes in 27 EU countries in the entire period (2004-2020).

(a) Average AP risk aversion by countries; (b) Average DS risk aversion by countries; Note that colors are given relatively: darker color refers to a greater value of risk attitudes (i.e., AP and DS), and brighter color refers to the opposite. More precisely, in (a), farmers in the darker-colored countries have a higher aversion to risk in the context of variance, and brighter-colored countries are more "variance-loving" on average; And in (b), farmers in darker-colored countries are less downside-risk-loving, and in brighter-colored countries are more downside-risk loving.

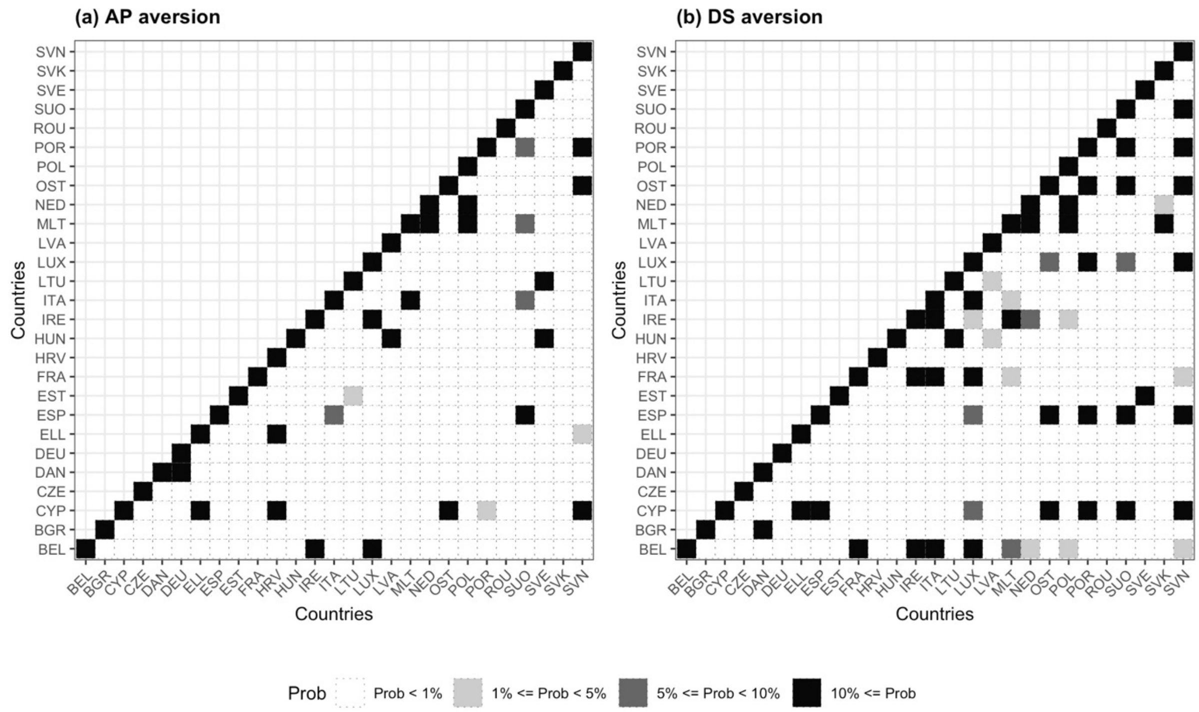

Figure 4-3. An illustration of Wald test statistics of risk aversion equality across countries in the entire period (2004-2020).

(a) Wald statistics of AP risk aversion coefficients' equality across countries; (b) Wald statistics of DS risk aversion coefficients' equality across countries; Note that the darker color in the figure shows a higher probability > Chi-square, indicating the risk aversion coefficients are not significantly different between two countries; BEL = Belgium, BGR = Bulgaria, CYP = Cyprus, CZE = Czechia, DAN = Denmark, DEU = Germany, ELL = Greece, ESP = Spain, EST = Estonia, FRA = France, HRV = Croatia, HUN = Hungary, IRE = Ireland, Republic of EIRE, ITA = Italy, LTU = Lithuania, LUX = Luxembourg, LVA = Latvia, MLT = Malta, NED = Netherlands, OST = Austria, POL = Poland, POR = Portugal, ROU = Romania, SUO = Finland, SVE = Sweden, SVK = Slovakia, and SVN = Slovenia.

5 Summary and Concluding Remarks

5.1 Summary

This research practice contributes to assessing farmers' risk attitudes and their instabilities during a mineral fertilizer price shock. More specifically, we restrict the mineral fertilizers in this research practice to urea, which is both essential for production and highly sensitive to fossil fuel price shock. Using the Farm Accountancy Data Network (FADN), we employ the flexible-moment-based approach (Antle, 1983) to assess overall farmers' Arrow-Pratt (AP) absolute risk aversion and downside (DS) risk aversion coefficients, proxying these two coefficients as an aversion to the second and third moments in profit. Then, we compare instabilities in farmers' risk attitudes during a urea price shock. To this end, we use world urea price data to identify urea price shocks. We employ a local polynomial regression (LOESS) and detect outliers in the autocorrelation regression (Anselin, 1995; Cottrell et al., 2019), and this combination of approaches helps us find urea price shocks in 2008 and 2011. Then, we split the FADN data into subsets by the shocks and use Wald statistics to test risk attitude equalities between periods, farm types, and countries.

Our results suggest that, first, the farmers are on average risk averse to variance in profit, with their AP aversion equaling 0.075. However, regarding their DS aversion being -0.122, farmers are slightly seeking downside risk, meaning they tend to bear a low chance of receiving an extremely bad income but compensate it with a higher chance of receiving an income that is higher than their expected income. Second, our finding highlights that after a urea price shock, farmers' AP aversion temporarily increases, suggesting they are more averse to variabilities in their income. On the other hand, farmers' DS aversion decreases after a shock, indicating their tolerance towards extremely low income slightly grows. However, note that this decrease in DS is close to zero in both the 2008 and 2011 shocks, meaning that farmers' DS aversion coefficients are nearly the same as they were before the shock. Third, we also provide evidence of risk aversion differences between field crops and dairy farmers, accepting our hypothesis that risk attitudes differ between farm types. Besides, the instabilities of risk aversion coefficients also differ between farm types during a urea price shock, i.e., field crop and dairy farmers' risk aversion coefficients change heterogeneously during a urea price shock. Lastly, we assess and compare country-level risk attitudes, showing that on average, farmers pose heterogeneous risk aversion attitudes between countries (e.g., Croatia, Czechia, Denmark, Germany, and Romania), suggesting that national policymakers should carefully consider their own farmers' risk aversion to correctly help farmers to cope with urea price shocks.

5.2 Limitations, Future Avenues, and Policy Implications

Limitations of this research practice This research practice exposes the following limitations.

Firstly, in risk attitude assessment, we only use limited inputs that are normally considered variable inputs, e.g., fertilizers. However, this is (likely) incorrect since a long-term-running farm potentially reallocates its fixed inputs, e.g., land (Just & Just, 2011). Moreover, knowing that Antle (1987) claims misspecification appears in the first-order condition of fertilizers in his setting, we assume there is no misspecification in our set. However, if such an assumption is violated, our first-order condition is then incorrect. Such as, if farmers do not have credit to access fertilizers, they then adjust other inputs for compensation (Just & Just, 2011). Additionally, this research practice merely focuses on profit and ignores other outputs, assuming covariances between profit and other outputs are unaffected by inputs (Just & Just, 2011). These three assumptions help us set up a simple first-order condition for analysis, but they may be so restrictive that they are violated in reality.

Secondly, in line with Antle (1987), we assume the farmers' utility function is analytic in a finite interval on a real line, and farmers' profit is defined on a bounded interval (Antle, 1987, p. 522). This assumption allows us to obtain farmers' risk attitude using a moment-based approach, but it is invalid if farmers have other utility function forms, e.g., a quadratic form (Antle, 1987; Loistl, 1976). Moreover, we assess farmers' risk attitudes on a populational average base, assuming that farmers exhibit similar risk attitudes. However, this is also potentially violated in reality.

Thirdly, there are limitations to generalizing our results into reality. For instance, we cannot distinguish between statistical or theoretical differences in risk attitude instability tests, even if we find significant Wald statistics results. Besides, as a continuation of the prior paragraph, we only test for equality of risk attitudes for the populational average. Hence, we cannot interpret our results as individual farmers' risk attitudes change during a shock. Moreover, as we also replicate the results of Bozzola & Finger (2021) (as shown in Appendix Table A7 for mean, variance, skewness regression and Table A8 for risk attitudes assessment), we find very similar results to ours using the three-stage least square approach (3SLS). Hence, this drives us to carefully interpret results in correlational thinking, other than causalities to avoid any misleading conclusion. However, we lack insight into whether a mineral fertilizer price shock drives a change in farmers' attitudes.

Lastly, the use of FADN also adds limitations to this research practice. For instance, FADN lacks available qualitative information on reasons that farmers quit (Slijper et al., 2022), which is relevant for this research practice because farmers may drop out due to their risk attitudes changes during a price shock. Moreover, information on farmers' time-varying data, e.g., changes in relatives' numbers on a farm, are not included in FADN. The lack of this information limits precisely proxying farmers' technology and behavioral models. For example, with a relative number change in a farm, the farm's risk attitudes are likely to change, but this change cannot be distinguished from a change associated with a price shock in this research practice.

Avenues for future research This research practice opens several avenues for future research.

Firstly, as a continuation of limitations on assessing farmers' risk attitudes on an average level, we encourage future research to assess individual farmers' risk attitudes, detect changes in these risk attitudes, and derive farmers' risk premiums. Future research can also classify farmers by their attitudes and therefore help construct policies with clearer targets. However, investigating individual farmers' attitudes needs to be prudent to account for ethical problems.

Secondly, in contrast to many studies regarding DS aversion (i.e., skewness preference, see Chiu (2005) and Menezes et al. (1980)), we find farmers love left-skewed profit on average. This suggests the farmers exhibit increasing absolute risk aversion (IARA, see Appendix B), which is not commonly found in other prior studies. Considering the potential causes for this, we suggest future research investigate multiple outputs and their covariance in using the moment approach. Besides, future studies can carefully check the robustness of the results by varying input sets, such as adding "fixed" inputs into first-order conditions. Further, and importantly, future studies can investigate the feasibility of adding group-wise restrictions. As seen in Appendix B, if some farmers in the population have an exponential utility function, these groups of farmers should at least exhibit positive downside risk aversion. Hence, considering additional restrictions or analyzing risk attitudes by groups, if possible, may overcome unreasonable results from assuming the overall population has similar AP and DS attitudes.

Thirdly, as mentioned in prior studies, the reliability of using production data and econometrics to assess risk attitudes remains doubtful. Hence, we in line with Antle (1987) encourage future studies to implement systematic comparisons between alternative methods. Moreover, seeing the risk attitude differences between farm types, we suggest further investigating other farm types (e.g., horticulture) for a more comprehensive view of risk attitudes. Lastly, future studies can delve into disentangling shock, time, and other potential channels' causal effects on risk attitude instabilities, which can offer more specific information.

Policy implications from this research practice This research practice provides the following suggestions for policymaking. For instance, we find farmers are on average variance-averse but downside risk-loving. We suggest policymakers derive our results into farmers' risk premiums to know how much the farmers tend to pay to eliminate their risks. As suggested by Groom et al. (2008), without this information or simply assuming farmers are risk-neutral results in a bad design of policy. Second, we suggest policymakers consider farmers' risk attitude change during a price shock, but not to take this change as a huge difference in farmers' attitudes. Third, after assessing farmers' risk attitudes on an average level and discussing potential limitations caused by it, we suggest policymakers support research focusing on individual farmers' attitudes and classify farmers. This helps precisely target and predict policy responses. Last but not least, given the many limitations of this research practice, we suggest policymaking be cautious in generalizing our results, especially considering realistic constraints in farmers' production, such as credit constraints or environmental restrictions, that are not accounted for in this research practice.

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Appendix

Appendix A. Tables of Shock Identification, Risk Attitude Estimations, and Risk Attitude Instability Check

In Appendix A, we provide shock identification results for different confidence interval settings in Table A1, estimated coefficients of mean, variance, and skewness using Antle's (1983) moment-based approach in Table A2, overall risk aversion estimations for all farms and countries (2004-2020) in Table A3, year-by-year risk aversion estimations in Table A4, risk aversion estimations across farm types and shock periods in Table A5, risk aversion estimations across countries between 2004-2020 in Table A6, estimated coefficients of mean, variance, and skewness using fixed effect estimator for Italian field crop farmers in Table A7, Italian field crop farmers' risk attitudes in Table A8, and Wald statistics testing equality between risk attitudes across countries in Table A9 and Table A10.

Table A1. Detected shocks at different timespan parameters and confidence intervals.

<table>
<tr><th colspan="4">Span = 0.15</th><th colspan="4">Span = 0.60</th></tr>
<tr><th>Confidence interval</th><th>Number of shocks</th><th>Cut-off value</th><th>Year of shocks</th><th>Confidence interval</th><th>Number of shocks</th><th>Cut-off value</th><th>Year of shocks</th></tr>
<tr><td>0.95</td><td>5</td><td>0.057</td><td rowspan="5">2008, 2011</td><td>0.95</td><td>8</td><td>0.016</td><td>2008, 2011, 2012</td></tr>
<tr><td>0.96</td><td>5</td><td>0.072</td><td>0.96</td><td>6</td><td>0.019</td><td></td></tr>
<tr><td>0.97</td><td>4</td><td>0.101</td><td>0.97</td><td>4</td><td>0.061</td><td>2008, 2011</td></tr>
<tr><td>0.98</td><td>3</td><td>0.231</td><td>0.98</td><td>3</td><td>0.250</td><td></td></tr>
<tr><td>0.99</td><td>2</td><td>0.325</td><td>0.99</td><td>1</td><td>0.483</td><td>2008</td></tr>
</table>

Span = timespan parameter q in LOESS; Confidence interval: quantile of Cook's distance, Cut-off value = critical value for Cook's distance.

Table A2. Estimated coefficients of profit mean, variance, and skewness regression for all farm types and all countries.

Variables	Mean (profit)	Variance	Skewness
Land	0.132***	0.033	0.159
	(0.013)	(0.044)	(0.450)
Ownership	0.002	-0.002	-0.011
	(0.001)	(0.003)	(0.019)
Irrigation ratio	0.001*	-0.000	0.006
	(0.001)	(0.001)	(0.006)
Assets	0.012	0.017*	0.103
	(0.007)	(0.009)	(0.106)
Labor	-0.021*	0.048	-0.244
	(0.011)	(0.033)	(0.330)
LSU (livestock unit)	0.040***	0.003	-0.073
	(0.010)	(0.010)	(0.081)
Current ratio	0.017***	0.000	0.008
	(0.002)	(0.001)	(0.008)
Fertilizers	-0.006	-0.080*	0.176
	(0.008)	(0.044)	(0.209)
Seeds	-0.017***	-0.006	-0.201**
	(0.005)	(0.019)	(0.081)
Feeds	-0.025***	-0.007	0.025
	(0.008)	(0.010)	(0.059)
Crop protection	-0.005	-0.001	-0.470
	(0.008)	(0.017)	(0.306)
Veterinary	-0.002	-0.002	-0.023
	(0.005)	(0.005)	(0.032)
Labor x Labor	0.000**	-0.000	0.001
	(0.000)	(0.000)	(0.001)
Labor x Fertilizers	0.001	0.005	-0.053
	(0.002)	(0.005)	(0.058)
Labor x Seeds	0.001	-0.010	0.059
	(0.002)	(0.008)	(0.078)
Labor x Feeds	0.000	-0.003	-0.003
	(0.002)	(0.002)	(0.016)
Labor x Crop protection	-0.000	-0.000	0.072
	(0.002)	(0.006)	(0.066)
Labor x Veterinary	0.001	0.001	0.006
	(0.001)	(0.001)	(0.009)
Fertilizers x Fertilizers	-0.001	-0.007***	-0.018
	(0.001)	(0.002)	(0.030)
Fertilizers x Seeds	0.002**	0.016*	0.002
	(0.001)	(0.009)	(0.026)
Fertilizers x Feeds	-0.001	-0.005	0.027
	(0.002)	(0.004)	(0.036)
Fertilizers x Crop protection	0.001	0.013**	0.044
	(0.001)	(0.005)	(0.063)
Fertilizers x Veterinary	-0.002	-0.001	0.002
	(0.002)	(0.002)	(0.009)
Seeds x Seeds	0.000	-0.002*	-0.004
	(0.000)	(0.001)	(0.009)
Seeds x Feeds	-0.004	0.008	-0.071
	(0.003)	(0.009)	(0.090)
Seeds x Crop protection	-0.000	0.004	-0.001
	(0.002)	(0.004)	(0.053)
Seeds x Veterinary	-0.001	-0.002	0.025

Variables	Mean (profit)	Variance	Skewness
	(0.001)	(0.003)	(0.027)
Feeds x Feeds	-0.000	0.001*	0.002
	(0.001)	(0.001)	(0.004)
Feeds x Crop protection	0.003	-0.004	0.016
	(0.003)	(0.005)	(0.049)
Feeds x Veterinary	0.001	0.000	0.001
	(0.001)	(0.001)	(0.003)
Crop protection x Crop protection	-0.001*	-0.007***	-0.013
	(0.000)	(0.001)	(0.028)
Crop protection x Veterinary	0.002	0.001	-0.010
	(0.001)	(0.002)	(0.020)
Veterinary x Veterinary	-0.000	-0.000	-0.002
	(0.000)	(0.000)	(0.003)
Constant	-0.006	-0.004	0.125
	(0.006)	(0.025)	(0.173)
N	575,589	575,589	575,589
Adjusted R-squared	0.577	0.423	-0.051

Two-way clustered standard errors in parenthesis, i.e., clustered by farm id and year; ***, **, and * denote significance at 1, 5, and 10 percent, respectively; Observation N (i.e., 575,589) is smaller than N (i.e., 601,809) in summary statistics, due to that some observations of one farm with only one year's record are removed for clustered standard error.

Table A3. Estimated risk aversion coefficients for the trimmed and untrimmed dataset.

Coefficients	**Untrimmed**	**Trimmed**
$\hat{\theta}_2$	0.038***	-0.003***
	(0.000)	(0.000)
$\hat{\theta}_3$	0.020***	0.000***
	(0.000)	(0.000)
$\hat{\theta}_{1,fertilizer}$	-0.007***	-0.118***
	(0.000)	(0.000)
$\hat{\theta}_{1,seed}$	-0.013***	-0.073***
	(0.000)	(0.000)
$\hat{\theta}_{1,feed}$	-0.026***	-0.135***
	(0.000)	(0.000)
$\hat{\theta}_{1,protection}$	0.004***	0.030***
	(0.000)	(0.000)
$\hat{\theta}_{1,veterinary}$	-0.002***	0.031***
	(0.000)	(0.000)
N	575,589	532,073

Standard errors in parenthesis; ***, **, and * denote significance at 1, 5, and 10 percent, respectively; $\hat{\theta}_2$ and $\hat{\theta}_3$ are coefficients associated with AP and DS aversion, respectively; Untrimmed = using the original dataset for estimation, excluding farms with only one farm-year observation and missing data; Trimmed = removing the upper and bottom 1 percent observations in variable set: land, labor, assets, fertilizers, seed, crop protection, livestock unit, veterinary expenditure, feeds in every farm type and country; Additionally, changing the input set for SURE from {veterinary expenditure, fertilizers, seeds, feeds, and crop protection } to {labor, fertilizers, seeds, feeds, and crop protection} only changes little in the results.

Table A4. Year-by-year estimated risk aversion.

Year	**AP**	**DS**
2004	0.084***	-0.087***
	(-0.000)	(0.000)
2005	0.092***	-0.108***
	(0.000)	(0.000)
2006	0.089***	-0.104***
	(0.000)	(0.000)
2007	0.080***	-0.105***
	(0.000)	(0.000)
2008	0.093***	-0.119***
	(0.000)	(0.000)
2009	0.101***	-0.080***
	(0.000)	(0.000)
2010	0.090***	-0.106***
	(0.000)	(0.000)
2011	0.090***	-0.115***
	(0.000)	(0.000)
2012	0.098***	-0.114***
	(0.000)	(0.000)
2013	0.096***	-0.117***
	(0.000)	(0.000)
2014	0.091***	-0.124***
	(0.000)	(0.000)
2015	0.079***	-0.121***
	(0.000)	(0.000)
2016	0.073***	-0.137***
	(0.000)	(0.000)
2017	0.073***	-0.152***
	(0.000)	(0.000)
2018	0.068***	-0.161***
	(0.000)	(0.000)
2019	0.078***	-0.171***
	(0.000)	(0.000)
2020	0.079***	-0.184***
	(0.000)	(0.000)

Standard errors in parenthesis; ***, **, and * denote significance at 1, 5, and 10 percent, respectively; AP = $2\hat{\theta}_2$; DS = $-6\hat{\theta}_3$.

Table A5. Estimated risk aversion coefficients for field crop and dairy farmers across time range.

	Overall	**Crop**	**Dairy**
$\hat{\theta}_{2,2004-2007}$	0.035***	0.031***	0.031***
	(0.000)	(0.000)	(0.000)
$\hat{\theta}_{2,2008-2010}$	0.037***	0.032***	0.032***
	(0.000)	(0.000)	(0.000)
$\hat{\theta}_{2,2011-2020}$	0.038***	0.032***	0.034***
	(0.000)	(0.000)	(0.000)
$\hat{\theta}_{3,2004-2007}$	0.020***	0.020***	0.020***
	(0.000)	(0.000)	(0.000)
$\hat{\theta}_{3,2008-2010}$	0.020***	0.020***	0.020***
	(0.000)	(0.000)	(0.000)
$\hat{\theta}_{3,2011-2020}$	0.020***	0.021***	0.020***
	(0.000)	(0.000)	(0.000)
$\hat{\theta}_{1,fertilizers}$	-0.007***		
	(0.000)		
$\hat{\theta}_{1,seed}$	-0.013***		
	(0.000)		
$\hat{\theta}_{1,feed}$	-0.026***		
	(0.000)		
$\hat{\theta}_{1,protection}$	0.004***		
	(0.000)		
$\hat{\theta}_{1,veterinary}$	-0.002***		
	(0.000)		
N	575,589	575,589	

Standard errors in parenthesis; ***, **, and * denote significance at 1, 5, and 10 percent, respectively; $\hat{\theta}_2$ and $\hat{\theta}_3$ are coefficients associated with AP and DS aversion, respectively.

Table A6. Estimated risk aversion coefficients for all farm types across countries.

	$\hat{\boldsymbol{\theta}}_2$	$\hat{\boldsymbol{\theta}}_3$
Belgium	0.033***	0.020***
	(0.000)	(0.000)
Bulgaria	0.038***	0.020***
	(0.000)	(0.000)
Cyprus	0.029***	0.020***
	(0.000)	(0.000)
Czechia	0.046***	0.021***
	(0.000)	(0.000)
Denmark	0.039***	0.020***
	(0.000)	(0.000)
Germany	0.039***	0.021***
	(0.000)	(0.000)
Greece	0.029***	0.020***
	(0.000)	(0.000)
Spain	0.031***	0.020***
	(0.000)	(0.000)
Estonia	0.038***	0.021***
	(0.000)	(0.000)
France	0.036***	0.020***
	(0.000)	(0.000)
Croatia	0.029***	0.019***
	(0.000)	(0.000)
Hungary	0.037***	0.020***
	(0.000)	(0.000)
Ireland, Republic of EIRE	0.033***	0.020***
	(0.000)	(0.000)
Italy	0.031***	0.020***
	(0.000)	(0.000)
Lithuania	0.037***	0.020***
	(0.000)	(0.000)
Luxembourg	0.033***	0.020***
	(0.000)	(0.000)
Latvia	0.037***	0.020***
	(0.000)	(0.000)
Malta	0.032***	0.020***
	(0.000)	(0.000)
Netherlands	0.032***	0.020***
	(0.000)	(0.000)
Austria	0.030***	0.020***
	(0.000)	(0.000)
Poland	0.032***	0.020***
	(0.000)	(0.000)
Portugal	0.030***	0.020***
	(0.000)	(0.000)
Romania	0.034***	0.020***
	(0.000)	(0.000)
Finland	0.031***	0.020***
	(0.000)	(0.000)
Sweden	0.037***	0.021***
	(0.000)	(0.000)
Slovakia	0.043***	0.020***
	(0.000)	(0.000)
Slovenia	0.030***	0.020***
	(0.000)	(0.000)
N	575,589	575,589

Standard errors in parenthesis; ***, **, and * denote significance at 1, 5, and 10 percent, respectively; $\hat{\theta}_2$ and $\hat{\theta}_3$ are coefficients associated with AP and DS aversion, respectively.

Table A7. Estimated coefficients of profit, variance, and skewness for Italian field crop farms in the period from 2004 to 2020: a replication of Bozzola & Finger's (2021) study.

Variables	std_se420	Variance	Skewness
std_se295	-0.007	-0.170***	-0.531
	(0.030)	(0.053)	(1.374)
std_se010	-0.039	-0.049	-0.780
	(0.036)	(0.074)	(1.287)
std_se285	-0.038	0.290	-1.805
	(0.114)	(0.216)	(4.486)
std_se300	0.043	-0.115	-1.073
	(0.058)	(0.085)	(2.002)
std_se295_sq	-0.004*	-0.008**	-0.047
	(0.002)	(0.004)	(0.099)
std_se010_sq	-0.007	-0.016	0.046
	(0.004)	(0.012)	(0.136)
std_se285_sq	0.006	0.017	0.294
	(0.006)	(0.018)	(0.221)
std_se300_sq	-0.006	-0.011	-0.159
	(0.006)	(0.017)	(0.209)
std_se010_se295	0.025*	0.047**	0.302
	(0.014)	(0.022)	(0.585)
std_se295_se285	-0.011	-0.042	-1.044
	(0.017)	(0.040)	(0.709)
std_se295_se300	0.003	0.066***	0.309
	(0.009)	(0.014)	(0.368)
std_se010_se285	0.013	-0.004	-0.527
	(0.019)	(0.037)	(0.701)
std_se010_se300	-0.004	0.021	-0.028
	(0.008)	(0.017)	(0.276)
std_se300_se285	-0.001	-0.079**	0.698
	(0.018)	(0.038)	(0.836)
std_se025	0.245***	0.343*	2.511*
	(0.050)	(0.176)	(1.370)
std_se441	-0.004	-0.016	-0.153
	(0.005)	(0.018)	(0.154)
family	0.027	0.004	1.187
	(0.024)	(0.054)	(0.733)
share_irrig	0.031***	-0.024	-0.084
	(0.011)	(0.044)	(0.430)
shareRented	-0.006	0.021	-0.050
	(0.013)	(0.026)	(0.228)
2004.year	0.000	0.000	0.000
	(.)	(.)	(.)
2005.year	0.010	-0.006	0.100
	(0.009)	(0.021)	(0.248)
2006.year	-0.001	-0.021	-0.587
	(0.011)	(0.021)	(0.480)
2007.year	0.060***	-0.017	-0.258
	(0.010)	(0.017)	(0.361)
2008.year	0.041***	0.046*	-0.232
	(0.010)	(0.026)	(0.279)
2009.year	0.025**	0.006	-0.090
	(0.010)	(0.022)	(0.222)
2010.year	0.044***	-0.001	-0.220
	(0.010)	(0.015)	(0.241)
2011.year	0.045***	-0.006	-0.027
	(0.011)	(0.016)	(0.242)
2012.year	0.046***	0.018	0.494
	(0.012)	(0.018)	(0.488)
2013.year	0.037***	0.005	-0.217
	(0.013)	(0.017)	(0.652)
2014.year	0.083***	0.001	1.297
	(0.032)	(0.062)	(0.990)
2015.year	0.092***	0.019	1.677
	(0.034)	(0.085)	(1.227)

Variables	std_se420	Variance	Skewness
2016.year	0.092***	0.042	1.836
	(0.034)	(0.092)	(1.365)
2017.year	0.079**	0.013	1.175
	(0.032)	(0.074)	(1.013)
2018.year	0.091***	-0.012	1.238
	(0.031)	(0.066)	(1.034)
2019.year	0.089***	-0.010	1.079
	(0.030)	(0.069)	(0.969)
2020.year	0.107***	-0.012	1.218
	(0.031)	(0.067)	(1.043)
Constant	-0.006	-0.079	-1.257
	(0.045)	(0.130)	(1.312)
N	60,596	60,596	60,596
adj. R-sq	0.212	0.082	0.012

Clustered standard errors in parenthesis; ***, **, and * denote significance at 1, 5, and 10 percent, respectively; std = rescaled variables by their standard deviations in the Italian sample; se295 = fertilizers; se010 = labor units; se285 = seeds; se300 = crop protection; se420 = net income; se025 = utilized agricultural area; se441 = total assets; family = a dummy denoting whether the farm is controlled by family; share_irrig = share of the land that is irrigated; shareRented = share of the land that is rented; sq = squared tern; Note that variables with two different variables denote the interaction terms.

Table A8. Estimated risk aversion coefficients of Italian field crop farms from 2005 to 2020: a replication of Bozzola & Finger's (2021) study.

Coefficients	Estimations	Std. Err.
$\hat{\theta}_2$	0.308***	0.010
$\hat{\theta}_3$	0.018***	0.001
$\hat{\theta}_{1,fertilizer}$	0.052***	0.001
$\hat{\theta}_{1,labor}$	-0.010***	0.001
$\hat{\theta}_{1,seed}$	-0.069***	0.004
$\hat{\theta}_{1,crop\ protection}$	0.082***	0.001
AP	0.616	
DS	-0.107	
N	56,528	

***, **, and * denote significance at 1, 5, and 10 percent, respectively; The estimation is obtained using 3SLS, setting exogenous variables of a dummy indicating a less favorable area, and the ratio of farmland that is not cultivated in the previous year. Bozzola & Finger (2021) argue these variables are associated with farmers' decisions on fertilizers, seeds, labor, and crop protection product choices but are exogenous to risk attitudes; Std. Err. = Standard error; Note that due to the use of lag-1 period variables, the results show Italian farmers' risk attitudes from 2005 to 2020.

Table A9. Wald statistics for AP aversion coefficient equality across countries.

	BEL	BGR	CYP	CZE	DAN	DEU	ELL	ESP	EST	FRA	HRV	HUN	IRE	ITA	LTU	LUX	LVA	MLT	NED	OST	POL	POR	ROU	SUO	SVE	
	357.51***																									
CYP	74.70***	492.44***																								
CZE	1888.34***	2071.18***	1511.30***																							
DAN	405.01***	22.83***	542.74***	913.50***																						
DEU	492.48***	31.52***	583.89***	1941.91***	2.03																					
ELL	234.98***	3951.42***	0.05	8914.78***	2721.60***	6037.72***																				
ESP	82.44***	3436.56***	17.35***	8622.40***	2153.27***	6078.04***	178.28***																			
EST	211.32***	9.91***	379.06***	1291.98***	40.53***	45.91***	1712.22***	1229.60***																		
FRA	74.75***	436.20***	240.98***	3785.38***	400.41***	953.32***	2128.15***	1532.53***	118.40***																	
HRV	163.39***	1299.23***	0.84	3564.17***	1246.78***	1578.44***	1.59	66.39***	862.92***	659.00***																
HUN	155.58***	109.17***	324.64***	2407.76***	152.73***	263.14***	2167.69***	1589.56***	20.99***	60.37***	828.44***															
IRE	0.31	440.37***	70.80***	2192.59***	479.67***	607.37***	243.69***	80.39***	254.23***	100.37***	161.72***	195.72***														
ITA	71.01***	3672.91***	21.86***	9048.00***	2167.74***	6901.39***	242.92***	3.62*	1217.69***	1596.48***	81.38***	1614.29***	68.44***													
LTU	197.99***	45.66***	364.54***	1991.30***	90.27***	137.55***	2229.90***	1661.42***	4.49**	110.89***	906.64***	8.19***	244.80***	1683.49***												
LUX	0.34	245.24***	55.44***	1281.16***	294.42***	324.68***	131.83***	40.91***	160.76***	56.48***	108.78***	114.19***	0.02	34.19***	144.73***											
LVA	132.21***	140.09***	301.62***	2482.86***	176.85***	301.18***	1917.67***	1362.17***	31.81***	35.98***	766.56***	1.83	167.34***	1375.65***	16.97***	98.66***										
MLT	13.43***	271.15***	17.12***	1106.42***	317.83***	336.48***	34.34***	2.49	198.51***	95.68***	34.55***	153.52***	11.11***	1.20	182.55***	8.36***	138.51***									
NED	22.50***	1074.30***	36.18***	3924.80***	972.69***	1475.80***	173.86***	23.32***	566.57***	360.54***	101.09***	528.88***	18.86***	15.18***	613.75***	10.70***	469.09***	0.42								
OST	170.16***	2686.61***	0.74	6843.91***	2090.24***	3820.27***	6.77***	71.13***	1319.84***	1348.95***	7.83***	1516.16***	172.34***	100.64***	1604.88***	97.19***	1351.94***	21.83***	103.35***							
POL	25.01***	3174.09***	47.76***	8520.11***	1788.27***	6312.32***	552.42***	123.97***	947.37***	1127.84***	159.35***	1227.57***	21.07***	101.13***	1309.56***	9.97***	1026.30***	1.23	0.81	266.40***						
POR	92.51***	1483.39***	6.16**	4463.23***	1337.14***	1974.38***	30.73***	9.13***	843.08***	663.96***	24.24***	847.38***	89.52***	16.79***	933.80***	54.03***	761.22***	8.03***	36.43***	10.10***	77.57***					
ROU	11.21***	1048.86***	146.09***	5055.72***	746.11***	1826.34***	1255.40***	712.95***	323.01***	117.55***	415.67***	287.62***	18.85***	712.06***	370.76***	11.22***	225.09***	40.52***	139.58***	770.62***	399.86***	352.21***				
SUO	64.32***	1243.09***	12.29***	3999.35***	1152.39***	1657.16***	56.12***	0.49	713.08***	519.91***	40.01***	693.03***	60.54***	2.85*	774.94***	36.67***	620.13***	3.15*	17.13***	25.64***	38.46***	3.02*	257.19***			
SVE	158.51***	41.55***	327.89***	1538.28***	85.08***	109.69***	1547.12***	1072.50***	6.85***	62.03***	756.57***	2.59	193.67***	1057.64***	0.67	121.74***	7.31***	161.27***	464.55***	1172.93***	792.70***	728.30***	224.65***	607.60***		
SVK	851.07***	383.86***	901.40***	145.88***	174.90***	296.10***	3414.13***	2860.03***	342.73***	1013.83***	1878.01***	630.23***	969.19***	2868.38***	502.30***	633.84***	69.15***	613.21***	1626.28***	2819.59***	2525.62***	2019.29***	1471.09***	1808.81***	442.43***	
SVN	91.63***	921.45***	1.59	2842.90***	935.24***	1145.71***	5.93**	15.88***	621.40***	429.32***	8.15***	569.57***	87.92***	22.65***	635.77***	59.83***	521.18***	13.16***	40.95***	0.65	65.99***	2.33	243.81***	8.55***	536.63***	1489.66***

Numerical values: $\chi^2(1)$; ***, **, and * denote probability larger than chi-square is at 1, 5, and 10 percent level; respectively; BEL = Belgium, BGR = Bulgaria, CYP = Cyprus, CZE = Czechia, DAN = Denmark, DEU = Germany, ELL = Greece, ESP = Spain, EST = Estonia, FRA = France, HRV = Croatia, HUN = Hungary, IRE = Ireland, Republic of EIRE, ITA = Italy, LTU = Lithuania, LUX = Luxembourg, LVA = Latvia, MLT = Malta, NED = Netherlands, OST = Austria, POL = Poland, POR = Portugal, ROU = Romania, SUO = Finland, SVE = Sweden, SVK = Slovakia, and SVN = Slovenia.

Table A10. Wald statistics for DS aversion coefficient equality across countries.

	BEL	BGR	CYP	CZE	DAN	DEU	ELL	ESP	EST	FRA	HRV	HUN	IRE	ITA	LTU	LUX	LVA	MLT	NED	OST	POL	POR	ROU	SUO	SVE	SVK
BGR	60.93***																									
CYP	11.01***	79.73***																								
CZE	1197.83***	1892.74***	743.88***																							
DAN	50.34***	0.17	72.44***	1418.99***																						
DEU	274.41***	243.89***	208.84***	1235.90***	172.23***																					
ELL	52.51***	655.98***	0.98	4253.84***	463.52***	2316.74***																				
ESP	22.31***	563.54***	0.64	4485.51***	367.36***	2656.44***	29.70***																			
EST	250.83***	157.42***	226.33***	301.21***	142.28***	19.62***	837.63***	741.26***																		
FRA	0.81	250.63***	10.40***	3429.44***	166.96***	1493.21***	147.18***	66.50***	513.67***																	
HRV	92.67***	412.10***	15.13***	2187.65***	351.18***	884.71***	27.38***	68.03***	673.71***	140.73***																
HUN	181.95***	90.33***	162.67***	1053.05***	73.35***	12.01***	1164.04***	1097.17***	35.98***	640.44***	660.79***															
IRE	0.10	52.71***	12.53***	1134.22***	43.61***	250.05***	56.76***	25.65***	234.58***	1.71	96.90***	165.51***														
ITA	0.31	283.37***	12.26***	894.97***	174.87***	2006.44***	202.90***	108.29***	531.68***	0.70	158.58***	725.41***	0.96													
LTU	157.87***	63.38***	152.06***	793.19***	55.95***	8.09***	202.90***	725.44***	31.12***	436.76***	572.52***	0.00	144.09***	466.99***												
LUX	2.20	61.69***	3.32*	858.83***	54.17***	209.03***	15.03***	3.30*	219.32***	1.19	44.69***	152.65***	3.04**	1.94	139.24***											
LVA	124.59***	34.35***	127.77***	1022.78***	30.44***	35.62***	765.62***	667.69***	57.04***	376.39***	521.15***	6.41**	112.42***	406.94***	4.79**	112.73***										
MLT	2.89*	11.26***	17.70***	492.29***	9.45***	78.17***	46.30***	25.79***	102.02***	6.56**	81.45***	53.24***	2.09	5.52**	49.49***	7.49***	35.16***									
NED	4.76**	49.18***	26.03***	1650.86***	36.00***	359.06***	160.25***	95.38***	263.45***	20.44***	176.72***	202.17***	3.17*	18.15***	162.38***	11.60***	123.41***	0.08								
OST	18.74***	347.58***	0.61	3101.03***	258.21***	1273.01***	17.81***	0.00	610.19***	35.91***	57.71***	708.74***	21.67***	50.39***	532.37***	2.94*	472.75***	23.80***	71.50***							
POL	6.16**	129.66***	29.65***	3429.71***	75.68***	1487.60***	435.10***	343.79***	397.40***	61.84***	247.20***	484.62***	3.99**	71.62***	307.42***	13.76***	249.93***	0.14	0.03	154.03***						
POR	12.96***	222.60***	1.02	2222.28***	177.09***	747.25***	15.88***	0.35	485.46***	18.03***	53.89***	474.24***	15.33***	24.45***	384.29***	1.74	331.92***	19.44***	48.48***	0.25	81.16***					
ROU	93.24***	8.27***	101.81***	1894.02***	7.80***	209.30***	985.77***	938.47***	126.90***	444.79***	506.64***	58.10***	82.04***	537.32***	38.80***	85.39***	15.04***	19.87***	90.17***	517.56***	290.98***	316.05***				
SUO	16.55***	220.47***	0.34	2073.33***	179.58***	694.10***	8.68***	0.09	480.10***	23.16***	42.89***	456.82***	19.10***	29.96***	377.55***	3.12*	326.53***	22.65***	54.04***	0.08	85.67***	0.45	305.93***			
SVE	300.42***	217.80***	248.46***	402.04***	189.28***	29.07***	1190.23***	1095.73***	0.00	746.94***	805.40***	49.30***	279.91***	796.52***	40.40***	248.19***	75.17***	112.29***	338.66***	832.03***	599.25***	621.77***	182.31***	604.48***		
SVK	14.93***	14.06***	39.11***	1210.66***	9.67***	184.00***	183.58***	121.65***	173.55***	42.07***	204.90***	105.13***	12.05***	39.94***	86.62***	22.77***	59.48***	1.16	4.68**	97.31***	8.09***	71.69***	32.70***	77.28***	214.08***	
SVN	5.88**	109.01***	2.00	1289.23***	93.08***	354.23***	14.34***	1.62	316.88***	5.23**	47.44***	249.94***	7.35***	7.27***	219.70***	0.40	182.78***	12.51***	23.53***	1.36	31.60***	0.52	150.24***	1.57	374.50***	39.89***

Numerical values: $\chi^2(1)$; ***, **, and * denote probability larger than chi-square is at 1, 5, and 10 percent level; respectively; BEL = Belgium, BGR = Bulgaria, CYP = Cyprus, CZE = Czechia, DAN = Denmark, DEU = Germany, ELL = Greece, ESP = Spain, EST = Estonia, FRA = France, HRV = Croatia, HUN = Hungary, IRE = Ireland, Republic of EIRE, ITA = Italy, LTU = Lithuania, LUX = Luxembourg, LVA = Latvia, MLT = Malta, NED = Netherlands, OST = Austria, POL = Poland, POR = Portugal, ROU = Romania, SUO = Finland, SVE = Sweden, SVK = Slovakia, and SVN = Slovenia.

Appendix B.   Mathematical Notes

Increasing Absolute Risk Aversion

Assume the farmers' utility function is three times differentiable, and farmers' Arrow-Pratt (AP) absolute risk aversion is differentiable to wealth. Let U', U'', U''' denote farmers' first, second, and third-order derivatives of utility function to wealth, the farmers' AP absolute risk aversion and downside (DS) risk aversion are shown in Equations (B.1) and (B.2).

$$A(w) = -\frac{U''}{U'} \tag{B.1}$$

$$DS = \frac{U'''}{U'} \tag{B.2}$$

Where $A(w)$ denotes the AP absolute risk aversion given wealth w. Taking the first-order derivative of Equation (B.1), we get

$$A'(w) = -\frac{U'''U' - (U'')^2}{(U')^2} = -\frac{U'''}{U'} + \left(\frac{U''}{U'}\right)^2 \tag{B.3}$$

Hence, assuming farmers' first order derivative of the utility function is positive, i.e., $U' > 0$, and giving our average result of $A(w) > 0, DS < 0$, we easily see that U'' and U''' are both negative. This further means that $A'(w)$ in Equation (B.3) is positive, indicating farmers exhibit increasing absolute risk aversion (IARA).

Negative Exponential Utility Function

If a farmer exhibits a negative exponential utility function, as Antle (1983) assumed as an example, then this farmer's utility function is written as:

$$u(\pi) = a - be^{-c\pi} \tag{B.4}$$

Where a, b, and c are positive parameters, and π denotes the profit of the farm. Deriving this utility function to wealth gives the first, second, and third-order derivatives, and we obtain equation (B.5) to (B.7).

$$u' = bce^{-c\pi} \tag{B.5}$$

$$u'' = -bc^2e^{-c\pi} \tag{B.6}$$

$$u''' = bc^3e^{-c\pi} \tag{B.7}$$

Combining Equations (B.1), (B.2), (B.5), (B.6), and (B.7), we substitute AP and DS to Equation (B.8) and (B.9).

$$AP = -\frac{u''}{u'} = c \tag{B.8}$$

$$DS = \frac{u'''}{u'} = c^2 \tag{B.9}$$

Given the assumption of $c > 0$, it can be found both DS and AP are restricted to be positive. If $c < 0$, the farmer still exhibits a positive DS aversion, but AP is negative. In analysis, we do not classify or give any restrictions to the signs of AP and DS aversion, aligning with prior studies.

Appendix C. Use of AI

No artificial intelligence has been used in this research practice.