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Impact of the adoption of chemical inputs on crop yield downside risk

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Abstract: The study aims to analyse the impact of application of chemical inputs like fertilisers or crop protection products on farm crop yield productivity in Estonian and Slovenian agriculture. We combined the propensity score matching (PSM) method with an inverse probability weighted regression (IPWRA) model to derive treatment effects of the adoption of these critical inputs using Farm Accountancy Data Network data. Results exhibit consistency across estimation techniques. Estimates of both IPWRA and PSM models showed that adoption of at least one of the chemical inputs decreases volatility of crop yield output and downside risk. The results are more robust for Estonian than for Slovenian farms suggesting on possible impacts of other exogenous factors such as climate change on mitigating the crop yield downside risk.

Keywords: chemical input adoption; Estonia; fertilisers; food security; household crop yield; crop protection products; productivity; Slovenia

Unexpectedly lower crop yield outcomes or downside risks challenge farmers' use of external inputs that can enhance crop productivity (Möhring et al. 2020). Agriculture crop farm income risk is determined by various factors particularly crop yield instability, price volatility and cost risk (El Benni and Finger 2014). The bibliometric analysis regarding risk in agriculture has revealed that literature has focused on the impacts of climate and food security, and the insurance schemes in agriculture (Novickytė 2019). Most recently the farm sector has been affected by a changing set of risk sources including more unusual and extremely adverse weather patterns. This induces the need for assessments and adjustments in risk management tools.

Our focus is on crop yield downside risks, which can be caused by various factors related to input uses, agricultural natural factor endowments, climate change and risk management in crop production and agriculture. The conditions for crop production are negatively determined by a high level of risk in agriculture, particularly in crop production, due to climate change and the resulting extreme weather conditions. They increase the likelihood of natural disasters, which is reflected in the quantity and quality of crop production. The ability of early detection and effective management of the risks at the farm level is important for crop market trends in monitoring and decision-making of the price risk, production or income risk with the diversification as the farm's risk management strategy (Jankelova et al. 2017).

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This article aims to investigate the impacts of chemical input adoption on crop yield downside risk by applying propensity score matching (PSM) and inverse probability weighted regression adjustment (IPWRA) estimation procedures. Estonia and Slovenia are selected as the case studies, both being members of the Common Agricultural Policy (CAP) of the European Union. Both countries aim to prevent the impacts of climate change by reducing crop yields' sensitivity to climate change. Slovenian agriculture has suffered the greatest damage from drought, heavy rainfall, floods, hail and windstorms, frost, snow, glaze ice, and weather-related diseases and pests (MAFF 2023). The natural-climatic conditions regarding drought in Estonia as a Northern EU country might be better than in Slovenia as the latter is situated in the Central-Southern EU geographic area in the mixture between Pannonian and Mediterranean and partly Alpine climatic conditions. The cross-country comparison represents a novel contribution to mitigation or reduction measures addressing the crop yield risks and adaptation of crop production to changing conditions. Stabilisation of crop yields can be important for the stability of the income situation of farms.

The CAP considers risk management by promoting and co-financing the implementation of climate change adaptation and mitigation measures through the Rural Development Programme (Ministry of Agriculture, Forestry and Food 2024) or other programmes or projects in the field of agriculture (European Commission 2017). Among the main challenges is the introduction of new, innovative approaches to maintain or increase productivity levels while also successfully adapting to climate change and its vulnerability (Gancheva et al. 2020).

Technology adoption on reducing crop yield risk has been investigated in agricultural economics, most recently particularly with climate change (Santeramo et al. 2024). The econometric modelling of frontier production functions has been an important area of research in agricultural economics (Battese 1992; Battese and Coelli 1992; Čechura et al. 2022). While there are studies on the productivity and efficiency of crop farms (Błażejczyk-Majka et al. 2012; Biagini et al. 2023; Makieła et al. 2025), to our knowledge, there have not been any quantitative farm-level micro-econometric studies that examined whether crop yield output has been impacted with the adoption of agricultural technologies such as fertilisers and/or pesticides in Estonia and Slovenia. From a policy perspective, this is crucial since crop yield output is expected to require improvement in the level of farming practices adoption in agriculture. However, the literature does not provide straightforward answer both for risk preferences from crop protection products use in agriculture (Bontemps et al. 2021) and the welfare effects of crop biodiversity (Bozzola and Smale 2020).

This paper attempts to fill this gap by assessing the effect of the adoption at least one chemical input (ALOCI) like crop protection products or fertilisers on crop yield productivity using micro-level panel data obtained from Farm Accountancy Data Network (FADN) in two EU countries. Precisely, we use the PSM and the doubly robust IPWRA models to estimate the average treatment effects.

MATERIAL AND METHODS

Estimating the moments of the stochastic production function

The probability distribution of the stochastic production function is evaluated by using a moment-based approach (Antle 1983), allowing for flexible representation of production risks, considered the following specification for y:

$$Y_i = f\left(X_i, \beta_i\right) + u_i \tag{1}$$

where: Y_i – eligible crop yield output; X_i – a vector of production inputs (i.e. fertilisers, crop protection products, other intermediate consumption, labour, capital and land); β_i – a vector of parameters, u_i – the identically independently distributed error term; i = 1, ..., N – individual farms in the sample.

Econometrically, the translog production function is specified as follows:

$$\ln\left(Y_i\right) = \beta_0 + \sum_{n=1}^{6}\beta_n \ln\left(X_{in}\right) + 0.5\sum_{n=1}^{6}\sum_{m=1}^{6}\beta_{nm}\ln\left(X_{in}\right)\ln\left(X_{im}\right) + u_i \tag{2}$$

where: $\ln(Y_i)$ – the natural logarithm of the total crop yield output for farmer i; $\ln(X_{in})$ – the natural logarithm of n input for farmer i; $\ln(X_{in})\ln(X_{im})$ – the interaction between inputs n and m, the inputs include other intermediate consumption, total assets, land, labour, fertilisers, and crop protection.

Because some farmers in our sample did not purchase fertilisers and crop protection products in the 2013–2021 years, the two input variables have zero-value observations. Since zero values are unsuitable for modelling in logarithm form [Equation(2)], we follow Villano et al. (2015), Zheng et al. (2021) and Ma et al. (2022)

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by replacing zero values with one to deal with zero values. Because ln(1) = 0, this allows not to omit such values from the analysis. Since prices and crop yields are key factors influencing farmers' decisions, out-of-range values (including negative or extreme outliers) or zeros are unsuitable for modelling (Louhichi 2018). Therefore, in our analysis, we excluded negative crop output values as outliers. Equation (2) is estimated by an ordinary least squares (OLS) regression model to calculate the first three moments, i.e. expected crop yield, its variance and skewness (Huang et al. 2015; Issahaku and Abdulai 2020). Specifically, the expected crop yield is predicted as $E(\ln(Y_i))$.

The second moment represents the variance of crop yield, which is measured by the squared term of the error term, that is, $E(\varepsilon_i)^2$. The third moment represents the downside risk (skewness) of crop yield, which is measured by the third power of the error term, that is, $E(\varepsilon_i)^3$ (Ma et al. 2022).

Estimation strategy

We assume that a risk-neutral and utility-maximising crop farmer i chooses to adopt at least one from critical inputs if the utility derived from using them exceeds that of otherwise (Olagunju et al. 2023). We can express farmer's i adoption decision by a latent variable F_i^* as:

$$F_i^* = \theta_i Z_i + \varepsilon_i \text{ with } F_i = \begin{cases} 1, \textit{ if } F_i^* > 0 \\ 0, \textit{ otherwise} \end{cases} \tag{3}$$

where: F_i – a binary variable representing adoption status (1 = adopters, 0 = non-adopters); Z_i – a set of farmer characteristics and farm-level factors hypothesised to influence input use decisions; ε_i – the error term assumed to be normally distributed; θ_i – the unknown parameters.

To estimate the impact of ALOCI on the crop yield productivity we explored the propensity score matching (PSM) and inverse probability weighted regression adjustment (IPWRA) to produce unbiased and consistent estimates. The PSM controls for selection bias by controlling for observable confounding factors. However, an important shortcoming of the PSM method is its inability to deal with biases resulting from unobservable characteristics of sampled units. Thus, we employed IPWRA estimator. According to Imbens and Wooldridge (2009), IPWRA contributes to research which isolates the effects of exposure, as the technique adjusts both for the predictors of intervention and for the effects of these predictors.

Propensity score matching (PSM)

The propensity score matching method (PSM) is a quasi-experimental technique often used in observational causal studies (Adjin et al. 2020). We estimate the average treatment effect on the treated (*ATT*) of critical inputs used on the expected crop yield, crop yield variance and crop yield skewness using the PSM model (package 'MatchIt', Sekhon 2011). Following Sseguya et al. (2020), the ATT can be defined as:

$$ATT = E(\Phi_{1i} | F_i = 1) - E(\Phi_{0i} | F_i = 1) \tag{4}$$

where: E(.) – the expectation operator; Φ_{1i}– the outcome of the household's crop yield that is adopted; Φ_{0i}– the outcome of a household's crop yield that did not adopt.

However, *ATT* from PSM can still produce biased results in the presence of misspecification in the propensity score model (Robins et al. 2007; Wooldridge, 2010; Wossen et al. 2017). A potential remedy for such misspecification bias is to use IPWRA.

Inverse probability weighted regression (IPWRA) model

IPWRA (using packages 'twang' and 'survey' in R) estimator has the double-robust property that ensures consistent results as it allows the outcome and the treatment model to account for misspecification. *ATT* in the IPWRA model was estimated in two steps (Imbens and Wooldridge 2009). In the first step, we estimated the propensity scores using multinomial logit regression and in the second step, linear regression was used to estimate the *ATT* which was computed as follows (Kazal et al. 2020):

$$ATT = \frac{1}{N_A} \sum_{i=1}^{n} \left((\gamma_1 + \eta_1 X_i) - (\gamma_0 + \eta_0 X_i) \right) \tag{5}$$

where: γ_1, η_1 – estimated inverse probability-weighted parameters for adopters; γ_0, η_0 – estimated inverse probability-weighted parameters for non-adopters; N_A – the total number of adopters.

To evaluate how sensitive the estimated treatment effects are to potential hidden bias, sensitivity analysis was conducted using the 'psens' function from the 'rbounds' package in R to assess the robustness of treatment effects to unobserved confounders. The 'psens' function implements the Rosenbaum bounds approach to evaluate how sensitive the estimated

https://doi.org/10.17221/298/2024-AGRICECON

treatment effects are to potential hidden bias. To test for heterogeneity in treatment effects (*HTE*), we conducted an analysis using interaction terms in our regression models.

Data and descriptive statistics

Data. The analysis is based on the Estonian and Slovenian FADN panel datasets. FADN is a database for a stratified sample of farms across EU countries. This paper focuses on specialist crop farms. The EU Types of crop farms are: (15) specialist cereals, oilseeds and protein crops (COP); (16) specialist other field crops; (20) specialist horticulture; (36) specialist orchards – fruits; (38) permanent crops combined; (60) mixed crops (European Commission 2022).

We used FADN SE variables codes: SE010 – labour hours used on the farm, measured as total number of hours worked; SE025 – total utilised agricultural area (*UAA*) in hectares (ha); SE030 – leased *UAA* in ha; SE131 – total crop production; SE275 – total intermediate consumption; SE436 – total assets; SE295 – fertiliser expenditures; SE300 – crop protection expenditures; SE410 – gross farm income. For deflation of monetary data in EUR, the agricultural input price index (IA148) and agricultural output price index (IA146) were taken from Statistics Estonia (2021) and the Statistical Office of the Republic of Slovenia (2021); 2015 is a base year.

The crop yield output is calculated as the ratio of total crop production over total *UAA* (SE131/SE025, SE131 is deflated by index IA146 output). Other intermediate consumption (*OIC*) was calculated as the difference between total intermediate consumption and both critical inputs: fertilisers and pesticides (*OIC* = SE275 – SE295 – SE300) and deflated by index IA148 input. Total assets (*TA*), SE436, is deflated by index IA148 input. Land is SE025, total *UAA* in ha. Labour is calculated as the ratio of SE010 over total *UAA*: SE010/SE025. The use of fertilisers is calculated as a ratio SE295 deflated by index (IA148 input) for fertilisers over SE025 (ha). The use of pesticides is calculated as a ratio SE300 deflated by index IA148 input for pesticides over SE025 (ha).

In the FADN database, the farm type and economic size of farm households is determined based on the value of the standard output (*SO*) (Eurostat 2023). In the empirical estimation, economic size classes (that range from 3 to 14) are used as an indicator of farm size. Farms with *SO* EUR 4 000–8 000 belong to size class 3, and farms with *SO* above EUR 3 000 000 belong to size class 14.

We used the age of the farm owner or farm manager if the head of a farm or farm owner was not a manager.

Tenure is calculated as a ratio of difference between total *UAA* (SE025) and leased *UAA* (SE030) to total *UAA* (SE025). Income per ha is calculated as a ratio of gross farm income SE410 over SE025.

The major outcome indicator was crop yield output, which is expressed in natural logarithm.

Descriptive statistics. Table 1 presents the variables' means and compares these for the adopters and non-adopters. The *t*-test values indicating the mean differences between adopters and non-adopters suggest that there are – except for land tenure in both countries and head of farm age and farm income in Slovenia – statistically significant differences between adopters and non-adopters in crop yield output and the used inputs concerning terms of observed characteristics. These notable differences are largely in favour of adopters' farms, which denotes that the adoption would generate a selection bias issue in our estimation.

RESULTS AND DISCUSSION

Following Ma et al. (2022), we utilised the likelihood ratio test (LR) and Akaike Information Criterion (AIC) value to identify the most appropriate functional form. The production functions are estimated by the translog specification [Equation (2)] and Cobb–Douglas specification. The results indicate that the translog specification is preferred (Supplementary Table S1).

Table 2 presents the logit regression model estimates of Equation (3), reporting the determinants of critical inputs used. Labour resources and assets increase the likelihood of ALOCI for Estonian and Slovenian farmers. Whereas the head of farm age decreases the likelihood of ALOCI for Estonian farmers.

Following (Ma et al. 2022), we estimate the treatment effects of the critical inputs using on expected crop yield, crop yield variance and crop yield skewness using the PSM and IPWRA models. Since the PSM methods are sensitive to the exact specification and matching method (Imbens 2004; Caliendo and Kopeinig 2008), we use three different matching techniques: nearest neighbour matching (NNM), optimal matching (OM) and radius matching (RM) as a robustness check. Supplementary Tables S2 and S3 present the matching quality test results, confirming the superior performance of OM for Estonia, and RM for Slovenia.

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Table 1. The descriptive statistics of variables used: adopters vs. non-adopters and statistical t-test for Estonia and Slovenia

Variables	Estonia			Slovenia		
	adopters	non-adopters	mean difference	adopters	non-adopters	mean difference
Crop yield output	207.590	13.780	193.800***	37.156	15.3197	21.840***
OIC	1 219.800	397.450	822.350***	230.980	69.5600	161.420***
Total assets (*TA*)	6 813.260	2 436.930	4 376.330***	3157.170	1 722.5300	1 434.650***
Land (*UAA* in ha)	324.000	109.630	214.370***	14.390	7.2100	7.180***
Labour	0.270	0.060	0.210***	0.190	0.1600	0.030*
Head of farm age	52.050	53.310	–1.260*	53.980	52.0700	1.910
Land tenure	0.410	0.410	0.000	0.730	0.7700	–0.040
Farm income	83.15	7.640	75.510***	29.160	19.6500	9.500
Farm size (*SO*)	7.060	5.360	1.700***	5.610	4.6300	0.980***
Fertilisers (expenditures)	4.030	0.000	4.030***	2.120	0.0000	2.121***
Crop protection products (expenditures)	0.760	0.000	0.760***	2.220	0.0000	2.220***
Expected value	0.539	0.436	0.103*	0.519	0.4800	–0.039
Variance	0.313	1.075	–0.763***	–0.054	0.4660	–0.520***
Skewness	–0.467	–2.716	2.249***	5.763	3.3050	2.458***
n	2 106	537	–	1324	60	–

*** and *significance at 0.01 and 0.1 levels, respectively; *OIC* – other immediate consumption; *SO* – standard output; *UAA* – utilised agriculture area
Source: Authors' calculations based on FADN data

Table 2. Determinants of the use of the critical inputs: logit regression model estimates

Variables	Estonia		Slovenia	
	coefficients	marginal effects	coefficients	marginal effects
Head of farm age	–0.001* (0.001)	–0.001*** (0.001)	0.001 (0.000)	0.001 (0.000)
Income	–0.000 (0.000)	–0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
Assets	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000** (0.000)
Labour	0.018** (0.008)	0.018* (0.008)	0.046 (0.033)	0.046 (0.033)
Land tenure	0.009 (0.023)	0.009 (0.023)	–0.015 (0.021)	–0.015 (0.021)
Constant	0.819*** (0.033)	–	0.912*** (0.297)	–
Number of observations	2 643	2 643	1 384	1 384

***, ** and *significance at 0.01, 0.05 and 0.10 levels, resectively; robust SEs are presented in parentheses.
Source: Authors' calculations

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Tables 3 and 4 present the results for the treatment effects of ALOCI on the first three moments of crop yield output of the PSM (second column) and the IPWRA estimator for Estonia and Slovenia respectively. Our estimates show that ALOCI increases expected crop yield in Estonia but decreases that in Slovenia. For Estonia, sensitivity analysis indicates that the effect on variance is robust to hidden confounders, whereas the effect on skewness may be influenced by unobserved factors. The impact on expected crop yield is inconclusive, as PSM suggests no effect, while IPWRA finds a small but significant effect. For Slovenia, sensitivity analysis confirms that the effect on variance is highly robust to unobserved confounders, while the effect on skewness remains strong and reliable even in the presence of hidden bias. The insignificant effect on expected yield is also robust to potential confounders. The results for Slovenia suggest that the ALOCI is not sufficient for risk efficiency. For example, in northeast Germany risk efficiency was established for the relationship of irrigation of cereals with nitrogen fertiliser (Meyer-Aurich et al. 2016). In addition, Santeramo et al. (2024) argue that in Southern EU geographical areas drought risk is more frequent for spring-summer crops which points to the need to reform policies and strategies of crop insurance schemes to increase farms' resilience to weather shocks.

Table 3. PSM and IPWRA model estimates for Estonia

Outcomes	*ATT* (PSM)	*ATT* (IPWRA)	Sensitivity analysis	Heterogeneity treatment effect (HTE)
Expected crop yield	0.097 (0.113) (–0.023, 0.222)	0.278** (0.128) (0.026, 0.531)	no effect (P = 0.999)	varies by labour and tenure
Crop yield variance	–0.601*** (0.103) (–0.711, –0.494)	–0.545*** (0.098) (–0.740, –0.351)	strong effect (P = 0.000)	varies by income and labour
Crop yield skewness	1.868*** (0.347) (1.526, 2.211)	1.823*** (0.302) (1.228, 2.418)	no effect (P = 1.000)	varies by assets income and labour

*** and **significance at 0.01 and 0.05 levels, respectively; heteroskedasticity robust standard errors for PSM results and design-based standard errors for IPWRA results are presented in parentheses; the bootstrap 95% confidence intervals are in parentheses (n = 1 000); sensitivity analysis was conducted using $\gamma = 1.5$, which is considered a conservative assumption (γ – the odds of differential treatment assignment due to unobserved confounders); expected crop yield is measured at log-transformed forms; *ATT* – average treatment effects on the treated; IPWRA – inversed probability weighted regression adjustment; PSM – propensity score matching

Source: Authors' calculations

Table 4. PSM and IPWRA model estimates for Slovenia

Outcomes	*ATT* (PSM)	*ATT* (IPWRA)	Sensitivity analysis	Heterogeneity treatment effect (HTE)
Expected crop yield	–0.162 (0.130) (–0.383, 0.065)	–0.030 (0.107) (–0.242, 0.181)	no effect (P = 0.725)	varies by assets
Crop yield variance	–0.553***(0.123) (–0.726, –0.387)	–0.393*** (0.117) (–0.623, –0.163)	no effect (P = 1.000)	varies by assets and labour
Crop yield skewness	2.285*** (0.626) (1.477, 3.105)	1.736** (0.629) (0.499, 2.974)	strong effect (P = 0.000)	varies by assets and labour

*** and **significance at 0.01 and 0.05 levels, respectively; heteroskedasticity robust SEs for PSM results and design-based standard errors for IPWRA results are presented in parentheses; the bootstrap 95% confidence intervals are in parentheses (n = 1 000); sensitivity analysis was conducted using $\gamma = 1.5$, which is considered a conservative assumption (γ – the odds of differential treatment assignment due to unobserved confounders); expected crop yield is measured in log-transformed forms; *ATT* – average treatment effects on the treated; IPWRA – inversed probability weighted regression adjustment; PSM – propensity score matching

Source: Authors' calculations

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The negative and statistically significant *ATT* for crop yield variance for Estonia and Slovenia indicates that ALOCI reduces the volatility of crop yield output.

The results for both countries show that the estimated *ATT*s for skewness is positively and statistically significant. Thus, ALOCI reduces downside risk. Overall, the findings of both PSM and IPWRA model estimations (Tables 3 and 4) are like the results of Table 1, verifying that our *ATT* estimates are robust.

Heterogeneity treatment effect regression results (Supplementary Tables S4 and S5) show that the treatment effects vary based on factors like tenure, labour and income (for Estonia), and assets and labour (for Slovenia), suggesting that targeted interventions could be more effective than uniform policies. This finding is supported by the literature, e.g. Nilsson (2017) and Carter et al. (2019) found that the effect of the investment support varied with the size of the support relative to firm/farm income and had a positive impact on productivity. The policymakers can design more efficient and equitable agricultural programs by focusing resources on specific subgroups, ultimately enhancing the overall impact and contributing to sustainable development goals. To mitigate agricultural yield risks in Slovenia due to exceptional weather conditions such as droughts and floods, a combination of short-term and long-term strategies and policy measures is essential. Among them is water management with implementation of efficient irrigation systems and investment in water reservoirs to store excess rainfall for dry periods. Irrigation plays a relatively limited but increasingly important role for high-value crops such as vegetables, orchards, and vineyards. Many crops traditionally rely on natural precipitation (Mavsar et al. 2025). However, climate changing weather patterns, including prolonged droughts, are making irrigation more crucial, especially in the Pannonian region in north-eastern Slovenia.

It is also important to adjust crop rotation types to climate change over the hot summer period, for ensuring stable yields, food security, and agricultural sustainability. Resilient crops can encourage the use of drought- and flood-resistant crop varieties tailored to local conditions through research and government supports. This can be supported with early warning systems with develop and expand meteorological forecasting tools to provide timely alerts for extreme weather conditions. It is likely to require up-to-date education and training of farmers on climate-smart agriculture and support research into precision farming and adaptive technologies.

Soil health management promoting integrated and sustainable farming practices with intercropping and crop rotation, including to mitigate the impacts of high temperature in the summer period, reduced tillage, and organic matter enrichment to improve soil structure and water retention can improve crop yields and increase crop production while reducing environmental footprint (Li et al. 2021; Chai et al. 2021).

Proper fertilisation can enhance soil fertility and crop growth, helping plants withstand stress from drought, pests, and diseases. Balanced fertilisation (nitrogen, phosphorus, potassium) can improve yields. However, excessive use of fertiliser can lead to soil degradation, water pollution, and reduced biodiversity. Precision farming and organic fertilisers can optimise benefits while minimising environmental risks (Čechura et al. 2021).

Crop protection (pesticides and fungicides) protect crops from pests, diseases, and weeds, reducing yield losses. While chemical crop protection improves reliability, overuse can cause pesticide resistance, harm pollinators, and contaminate water sources. Integrated Pest Management, which combines biological controls with minimal chemical use, can be a more sustainable approach.

By combining these measures, Slovenia and Estonia can improve efficiency in use of chemical fertilisers and crop protection products that can help mitigate crop yield risks and enhance agricultural resilience, but carefully managed to ensure sustainability and environmental protection, ensuring stable crop production and food security despite changing climate patterns.

CONCLUSION

This paper investigated the inspirations of farmers' decisions to apply ALOCI on downside risk exposure using FADN farm-level data from Estonia and Slovenia. We used a combination of propensity score matching and the doubly robust inverse probability weighted regression models to achieve our objective.

The results indicate that assets and labour sources were some of the important determinants of ALOCI in both countries. The results reveal that ALOCI increases the expected crop yield in Estonia but decreases that in Slovenia. The latter result and finding are surprising but might indicate less efficient use of chemical agricultural inputs in mitigating downside risk exposure in crop farming. It can be also

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linked to changing climatic conditions with adverse weather conditions, particularly frequent severe droughts with prolonged extremely high daily temperatures when efficiency in use of chemical inputs in terms of fertilisers and pesticides might be limited without complementary use of irrigation to cereals to fertiliser.

Whereas the results for crop yield variance and crop yield skewness are the same for both countries: ALOCI reduces the volatility of crop yield output and reduces downside risk. In particular, the average treatment effect on the treated (*ATT*) estimates shows that ALOCI increases expected crop yield in Estonia by 10% and reduces expected crop yield in Slovenia by 16.2%. At the same time, the ALOCI decreases crop yield skewness for Estonia and Slovenia by 19% and 22% respectively.

The results and findings are robust to alternative matching algorithms and to bias. The results point to the need for policies to encourage financial investment in technology adoption reducing crop yield risk, crop rotation and diversification strategies to mitigate the climate change effects and to adopt eco-friendly farming practices. Farmer organisations models supported with the most recent developments and adoption of artificial intelligence, drone, sensor, and robotic technologies can act as agents for more efficient and sustainable adoption of fertilisers and crop protection on crop yield downside risk.

REFERENCES

Adjin, K.C., Goundan, A., Henning, Ch.H.C.A., Sarr, S. (2020): Estimating the impact of agricultural cooperatives in Senegal: Propensity score matching and endogenous switching regression analysis, Working Papers of Agricultural Policy: No. WP2020-10.

Antle J.M. (1983): Testing the stochastic structure of production: A flexible moment-based approach. Journal of Business and Economic Statistics, 1: 192–201.

Battese G.E. (1992): Frontier production functions and technical efficiency: A survey of empirical applications in agricultural economics. Agricultural Economics, 7: 185–208.

Battese G.E., Coelli T.J. (1992): Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. Journal of Productivity Analysis, 3: 153–169.

Biagini L., Antonioli F., Severini S. (2023): The impact of CAP subsidies on the productivity of cereal farms in six European countries: A historical perspective (2008–2018). Food Policy, 119: 102473.

Błażejczyk-Majka L., Kala R., Maciejewski K. (2012): Productivity and efficiency of large and small field crop farms and mixed farms of the old and new EU regions. Agricultural Economics – Czech, 58: 61–71.

Bontemps C., Bougherara D., Nauges C. (2021): Do risk preferences really matter? The case of pesticide use in agriculture. Environmental Modeling and Assessment, 26: 609–630.

Bozzola M., Smale M. (2020): The welfare effects of crop biodiversity as an adaptation to climate shocks in Kenya. World Development, 135: 105065.

Caliendo M., Kopeinig S. (2008): Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22: 31–72.

Carter M.R., Tjernström E., Toledo P. (2019): Heterogeneous impact dynamics of a rural business development program in Nicaragua, Journal of Development Economics, 138: 77–98.

Chai Q., Nemecek T., Liang C., Zhao C., Yu A.Z., Coulter J.A., Wang Y.F., Hu F.L., Wang L., Siddique K.H.M., Gan Y.T. (2021): Integrated farming with intercropping increases food production while reducing environmental footprint. Proceedings of the National Academy of Sciences of the United States of America, 118: e2106382118.

Čechura L., Žáková Kroupová Z., Kostlivý V., Lekešová M. (2021): Productivity and efficiency of precision farming: The case of Czech cereal production. AGRIS on-line Papers in Economics and Informatics, 13: 15–24.

Čechura L., Žáková Kroupová Z., Lekešová M. (2022): Productivity and efficiency in Czech agriculture: Does farm size matter? Agricultural Economics – Czech, 68, 1–10.

El Benni N., Finger R. (2014): Where is the risk? Price, yield and cost risk in Swiss crop production. Revue d'études en Agriculture et Environnement, 95: 299–326.

European Commission (2017): Risk Management Schemes in EU Agriculture: Dealing with Risk and Volatility. Brussels, European Commission. Available at https://agriculture.ec.europa.eu/system/files/2019-10/agri-market-brief-12_en_0.pdf. (accessed July 19, 2024).

European Commission (2022): Directorate – General for agriculture and rural development. Directorate A – Strategy and policy analysis, A2 - Analysis and Outlook. Brussels, European Comission. Available at https://agriculture.ec.europa.eu/system/files/2023-04/agricultural-outlook-2022-report_en_0.pdf. (accessed Aug 27, 2024).

Eurostat (2023): Glossary: Standard Output (SO). Luxembourg, Eurostat. Available at https://ec.europa.eu/eurostat/statisticsexplained/index.php?title=Glossary:Standard_output_(SO) (accessed Nov 15, 2023).

Gancheva M., O'Brien S., Tugran T., Borrett C. (2020): Adapting to climate change: Challenges and opportunities for

https://doi.org/10.17221/298/2024-AGRICECON

the EU local and regional authorities. Brussels, European Committee of Regions.

Huang J., Wang Y., Wang J. (2015): Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China. American Journal of Agricultural Economics, 97: 602–617.

Imbens G. (2004): Nonparametric estimation of average treatment effects under exogeneity: A review. The Review of Economics and Statistics, 86: 4–29.

Imbens G.W., Wooldridge J.M. (2009): Recent developments in the econometrics of program evaluation. Journal of Economic Literature, 47: 5–86.

Issahaku G., Abdulai A. (2020): Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. Australian Journal of Agricultural and Resource Economics, 64: 396–420.

Jankelova N., Masar D., Moricova S. (2017): Risk factors in the agriculture sector. Agricultural Economics – Czech, 63: 247–258.

Kazal M.M.H., Rahman Md.S., Rayhan S.J. (2020): Determinants and impact of the adoption of improved management practices: Case of freshwater prawn farming in Bangladesh. Aquaculture Reports, 18: 100448.

Li X., Wang Z., Bao X., Sun J., Yang S., Wang P., Wang C., Wu J., Liu X., Tian X., Wang Y., Li J., Wang Y., Xia H., Mei P., Wang X., Zhao J., Yu R., Zhang W., Che Z., Gui L., Callaway R.M., Tilman D., Li L. (2021): Long-term increased grain yield and soil fertility from intercropping. Nature Sustainability, 4: 943–950.

Louhichi K., Espinosa M., Ciaian P., Perni A., Vosough Ahmadi B.L., Colen S., y Paloma G. (2018): The EU-Wide Individual Farm Model for Common Agricultural Policy Analysis (IFM-CAP v.1). Economic Impacts of CAP Greening European Commission, Joint Research Centre. JCR10869. Available at https://op.europa.eu/en/publication-detail/-/publication/13480ce0-803e-4ec4-9f88-24d44d565eab/language-en#:~:text=To%20guarantee%20the%20highest%20representativeness,(more%20than%20%E2%80%9310%20%25) (accessed July 24, 2024).

Ma W., Zheng H., Yuan P. (2022): Impacts of cooperative membership on banana yield and risk exposure: Insights from China. Journal of Agricultural Economics, 73: 564–579.

MAFF (2023): Agriculture Commissioner in Slovenia on Damage in Agriculture. Ljubljana, Slovenia, Ministry of Agriculture, Forestry and Food. Available at https://www.gov.si/en/news/2023-11-24-agriculture-commissioner-in-slovenia-on-damage-in-agriculture/ (accessed July 19, 2024).

Makieła K., Marzec J., Pisulewski A., Mazur B. (2025): Are European farms equally efficient? What do regional FADN data on crop farms tell us? Journal of Agricultural and Applied Economics, 57: 157–181.

Mavsar S., Grčman H., Turniški R., Mihelič R. (2025): Organic carbon sequestration potential of Slovenian agricultural soil and the impact of management practices on SOC stock. Cogent Food & Agriculture, 11: 2437574.

Meyer-Aurich A., Gandorfer M., Trost B., Ellmer F., Baumecker M. (2016): Risk efficiency of irrigation to cereals in northeast Germany with respect to nitrogen fertilizer. Agricultural Systems, 149: 132–138.

Möhring N., Dalhaus T., Enjolras G., Finger R. (2020): Crop insurance and pesticide use in European agriculture. Agricultural Systems, 184: 102902.

Nilsson P. (2017): Productivity effects of CAP investment support: Evidence from Sweden using matched panel data. Land Use Policy, 66: 172–182

Novickytė L. (2019): Risk in agriculture: An overview of the theoretical insights and recent development trends during last decade – A review. Agricultural Economics – Czech, 65: 435–444.

Olagunju K.O., Olagunju K.A., Ogunniyi A.I., Omotayo A.O., Oyetunde-Usman Z. (2023): To own or not to own? Land tenure security and production risk in small-scale farming. Land Use Policy, 127: 106584.

Ministry of Agriculture, Forestry and Food (2024): Measures - Common Agricultural Policy. Ljubljana, Slovenia. Available at: skp.si. (accessed July 23, 2024).

Robins J., Sued M., Lei-Gomez Q., Rotnitzky A. (2007): Comment: Performance of double robust estimators when 'inverse probability' weights are highly variable. Statistical Science, 22: 544–559.

Santeramo F.G., Lamonaca E., Maccarone I., Tappi M. (2024): Extreme weather events and crop insurance demand. Heliyon, 10: e27839.

Sekhon J.S. (2011): Multivariate and propensity score matching software with automated balance optimization: The matching package for R. Journal of Statistical Software, 42: 1–52.

Sseguya H., Robinson D.S., Mwango H.R., Flock J.A., Manda J., Abed R., Mruma S.O. (2021): The impact of demonstration plots on improved agricultural input purchase in Tanzania: Implications for policy and practice. PLoS ONE 16: e0243896.

Statistical Office of the Republic of Slovenia (2021): Prices in agriculture. Available at: https://pxweb.stat.si/SiStat/en/Podrocja/Index/85/agriculture-forestry-and-fishery. (accessed July 23, 2024).

Statistics Estonia (2021): Prices in agriculture. Available at: https://www.stat.ee/et/avasta-statistikat/valdkonnad/rahandus/hinnad. (accessed July 23, 2024).

https://doi.org/10.17221/298/2024-AGRICECON

Villano R., Bravo-Ureta B., Solís D., Fleming E. (2015): Modern rice technologies and productivity in the Philippines: Disentangling technology from managerial gaps. Journal of Agricultural Economics, 66: 129–154.

Wooldridge J.M. (2010): Econometric Analysis of Cross Section and Panel Data. Cambridge, The MIT Press: 603–620.

Wossen T., Abdoulaye T., Alene A., Haile M.G., Feleklanrewaju A., Manyong V. (2017): Impacts of extension access and cooperative membership on technology adoption and household welfare. Journal of Rural Studies, 54: 223e233.

Zheng H., Ma W., Wang F., Li G. (2021): Does internet use improve technical efficiency of banana production in China? Evidence from a selectivity-corrected analysis. Food Policy, 102: 102044.

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