Agris on-line Papers in Economics and Informatics

Volume XVII Number 2, 2025

Innovation in Agriculture: Driving Economic Development through EU Knowledge-Based Economy

Tatia Zarkua, Wim Heijman, Irena Benešová

Department of Economics, Faculty of Economics and Management, Czech University of Life Sciences Prague, Czech Republic

Abstract

Innovation in agriculture is vital for enhancing sustainability, productivity, and economic development, especially in light of global challenges such as population growth, resource scarcity, and climate change. This study, adopting a quantitative cross-sectional approach, investigates the relationship between agricultural innovation and productivity within the EU. By employing multiple regression analysis with a log-log transformation, the study explores how R&D expenditure in agriculture and various control variables impact agricultural productivity across EU-27 countries from 2000 to 2019. To address potential endogeneity concerns, the Instrumental Variables (IV) approach was applied, using the Two-Stage Least Squares (2SLS) method, which reduced bias in the estimation. The results revealed that a 1 % increase in R&D spending in agriculture corresponds to an approximate 0.33% increase in total crop output, indicating a strong positive link between innovation and agricultural productivity. The model residuals confirm a satisfactory fit, highlighting the robustness of the findings. This study provides valuable insights into how agricultural innovation can drive productivity, offering important implications for policymakers and researchers aiming to optimise agricultural output through increased investment in innovation.

Keywords

Innovation, agriculture, R&D expenditure, KBE, economic development.

Zarkua, T., Heijman, W. and Benešová, I. (2025) "Innovation in Agriculture: Driving Economic Development through EU Knowledge-Based Economy", *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 135-148. ISSN 1804-1930. DOI 10.7160/aol.2025.170210.

Introduction

The adoption of innovation in agriculture through a knowledge-based economy (KBE) has been increasingly emphasized in policy frameworks around the world (Evenson & Gollin, 2003; OECD, 2019; Wang et al., 2019). The European Union (EU) has highlighted the importance of knowledge-driven development and agricultural innovation in various strategic documents, such as the 'European Green Deal', 'Farm to fork strategy', 'Horizon Europe', and 'Horizon 2020' (Pound & Conroy, 2017; European Commission, 2021). These documents outline the role of innovation in enhancing agricultural productivity while ensuring sustainability and environmental protection. Additionally, these initiatives aim to foster a knowledge-based economy, where intellectual capabilities, technological advancements, and information are primary drivers of economic development (European Commission, 2021).

A KBE in agriculture involves integrating research, knowledge, and innovative approaches to enhance farming practices and increase productivity. This idea exceeds traditional farming by integrating advancements like biotechnology, precision agriculture, and digital technologies in agriculture (OECD, 1997; Qaim, 2009; Gebbers & Adamchuk, 2010; Wolfert et al., 2017). Embracing this approach may result in transformed agricultural output, greater environmental sustainability, and strengthened economic development (OECD, 2023).

A KBE is characterized by the reliance on intellectual capabilities, innovation, and information as key drivers of economic development. In the context of agriculture, this means leveraging scientific research, advanced technologies, and data analytics to improve agricultural outputs and sustainability. The EU's policies and funding priorities, which emphasise the integration of knowledge and innovation across various sectors, including agriculture, reflect its commitment to fostering a KBE (OECD, 1997).

In the context of a KBE, one of the key pillars driving agricultural innovation is research and development (R&D) in agriculture. R&D and expenditure in this field facilitate the discovery of new agricultural techniques, crop varieties, and environmental practices that align with sustainable development goals. Numerous studies (Piesse and Thirtle, 2010; Alston and Pardey, 2013) have demonstrated that agriculture R&D is a crucial determinant of agricultural productivity. This aligns with endogenous growth theory, introduced by Romer in 1990, that suggests that economic growth is driven by internal elements like technological innovation, human capital, and knowledge spillovers. This theory is especially important for grasping how agricultural innovation may stimulate economic development within the EU's KBE. Innovation in agriculture, a crucial aspect of endogenous growth theory, increases productivity and fosters sustainability (Sonnino et al., 2014; Lundvall, 2007; Johnson and Lundvall, 2013).

To operationalise innovation, agricultural innovation systems (AIS) play a crucial role (Riaz et al., 2014; Gildemacher and Wongtschowski, 2015; Barry and Czech, 2017). These systems consist of networks that include various actors, organisations, and individuals that cooperate in order to introduce existing or new products, processes, and organisational forms into social and economic contexts. The networks are organised into three primary categories: research and education; business and enterprises, which encompass farmers and their associations; and bridging institutions, including extension services, brokering agencies, and contractual arrangements. Another component includes the supporting policies and institutions, whether formal or informal, that influence the interactions, reflections, knowledge creation, sharing, and collaborative learning and adaptation to external changes among these actors, thereby shaping the "enabling environment" (Tropical Agriculture Platform, 2016).

Government policies and institutional structures are another significant factor that either encourage or hinder agricultural innovation. For instance, the EU's Common Agricultural Policy (CAP) offers direct subsidies to farmers, facilitates rural development projects, and finances innovative efforts (European Commission, 2020).

The Triple Helix model, developed by Etzkowitz and Leydesdorff, offers a framework for understanding the dynamic interactions between universities, industry, and government in fostering innovation and economic development (Etzkowitz and Leydesdorff, 1998). The model emphasises how these three spheres collaborate to create a knowledge-based society where innovation drives technological advancement and entrepreneurship. Universities, traditionally viewed as centres of knowledge generation, now play a more active role in innovation through research, commercialisation, and entrepreneurial activities. The industry that applies and markets new technologies benefits from collaboration with universities, gaining access to cutting-edge research and talent. Governments act as facilitators, providing policy frameworks and funding mechanisms to promote research and innovation. The interplay between these sectors creates a synergy that accelerates economic growth and technological progress, making the Triple Helix model a key theoretical approach in innovation studies (Fidanoski et al., 2022; Cai and Lattu, 2022). This collaborative model is particularly relevant in knowledge economies, where technological innovation is vital for maintaining competitiveness and fostering sustainable economic development.

Given the extensive array of agricultural innovations and economic advancements among the various EU member states, Germany, the Netherlands, and Denmark stand out as some of the most progressive nations in sustainable farming practices and advanced agricultural technology. Their success stems from a robust digital infrastructure, favourable policies, and substantial expenditures in research and development (OECD, 2023).

However, not all member states have achieved the same level of progress. Comparative studies suggest that countries with limited access to finance, inadequate infrastructure, and regulatory barriers face challenges in adopting new agricultural technologies. These barriers highlight the need for tailored policy interventions that address the specific needs and conditions of each country (Hall et al., 2005; European Parliament, 2019).

Upon examining agricultural innovation through a KBE and the crucial role of R&D in the agricultural sector, it's evident that despite notable advancements, there are still areas requiring additional investigation. This study aims to address some of the existing gaps in understanding how R&D expenditure in agriculture directly influences agricultural productivity, particularly in the context of varying economic and environmental conditions across different countries.

To address these gaps, this study aims to provide a comprehensive analysis of how agricultural innovation impacts economic development at the country level within the EU. By focussing on national-level impacts and integrating the concept of a knowledge-based economy, this research seeks to offer a nuanced understanding of the transformative potential of agricultural innovation. Addressing this research gap, the following questions emerge as central to our inquiry:

- How does innovation in agriculture contribute to economic development in EU countries?
- What are the key factors that enable or hinder the integration of agricultural innovation within a knowledge-based economy at the country level?

To structure this exploration, we propose the following hypotheses:

(H1): Innovation in agriculture positively influences agricultural productivity.

While prior research has explored the relationship between agricultural productivity and factors like technological advancements and policy interventions, the novelty of this study lies in its focus on R&D expenditure as a critical driver of innovation in agriculture. Unlike studies that primarily emphasise broader technological innovations or external factors, this research specifically examines how R&D expenditures directly translate into measurable improvements in productivity. Moreover, the potential interactions between R&D and economic variables, such as emissions and trade, remain underexplored in the existing literature.

Previous studies also tend to overlook the differentiated effects that R&D expenditure might have in various contexts, particularly in relation to real factor income and subsidies (Špička et al., 2009). By addressing these gaps, this study offers a novel combination of control variables that provide fresh insights into the broader implications of agricultural innovation (OECD, 2023). The application of a KBE framework, along with the evaluation of control variables such as population density and CO_2 emissions, further enhances the understanding of how agricultural innovation can be made more effective.

This approach not only contributes to academic research but also has important implications for policy discussions, filling a key gap in the literature on the role of R&D expenditure in boosting agricultural productivity.

This paper is structured as follows: The next section will outline the research design, data sources, and analytical techniques used in this study. The results and discussion section will then present the findings, comparing different EU countries and analysing the impact of agricultural innovation on economic development. Finally, the conclusion will summarise the key insights, discuss policy implications, and suggest areas for future research.

Materials and methods

This study employed a quantitative research design to investigate the relationship between agricultural innovation and economic development within the EU for the period 2000-2019. A cross-sectional analysis was conducted using secondary data from sources such as Eurostat, the World Bank, and the European Commission.

Data collection focused on gathering variables that reflect both agricultural innovation and economic development across EU member states (Table 1).

The dependent variable, agricultural productivity, is represented by total crops output (€/ha). R&D expenditure in agriculture is employed as a proxy for agricultural innovation, serving as the independent variable. To control for other factors influencing agricultural productivity, additional variables such as population density (inhabit/km²), trade balance per hectare, CO_2 emissions per hectare, real factor income in agriculture per annual work unit (chain-linked volumes), and subsidies per hectare will be included in the model. Selected variables in this study have been adjusted for inflation, allowing for accurate comparisons over time and reflecting real changes in productivity rather than nominal price fluctuations.

One of the analytical methods used in this study is multiple regression analysis in log-log form (Greene, 2003). We employed the Ordinary Least Squares (OLS) approach to ensure the accurate estimate of regression coefficients (Oksanen, 1991). This approach was chosen due to its ability to capture the elasticity between the dependent and independent variables, thereby providing insights into the percentage change in economic development resulting from a one-percent change in agricultural innovation. The model also includes control variables to account for other factors that

Variables	Variable Expected Effects	Source
Dependent		
Total crops output (per ha)	We expect that total crops output (per ha) will serve as a key indicator of agricultural productivity, reflecting the combined influence of innovation, economic conditions, and external factors.	Farm accountancy data network-European Commission, 2024
Independent		
R&D expenditure in agriculture (per ha)	As the main independent variable, we expect a positive relationship between R&D expenditure and total crops output. More investment in R&D should lead to better technologies, farming practices, and innovations that boost productivity.	Eurostat, 2024
Control		
Population density (Ihab/km^2)	Higher population density might positively affect productivity through improved infrastructure, market access, and labour availability. However, it could also lead to negative effects if it results in land overuse or environmental degradation. Thus, we expect a neutral to moderate positive relationship depending on the context of the country.	The World Bank, 2024
Trade Balance (per ha)	A positive trade balance in agriculture might signal higher exports and competitiveness. This could reflect greater productivity. Therefore, we expect a positive relationship between trade balance per hectare and agricultural productivity.	Farm accountancy data network-European Commission, 2024
CO_2 Emissions (per ha)	This variable could have a negative effect on agricultural productivity if high emissions are associated with unsustainable farming practices. On the other hand, emissions might reflect the intensity of agricultural activities, which could be tied to high-output farming techniques. The expected relationship could be context-specific, but higher emissions could suggest lower productivity in sustainable contexts.	The World Bank, 2024
Real factor income in agriculture (per annual work)	Higher real factor income suggests that the agricultural sector is generating more value relative to labour input, which should correlate with higher productivity. We expect a positive relationship between income and agricultural productivity.	Eurostat, 2024
Subsidies (per ha)	Agricultural subsidies are often aimed at increasing productivity by supporting farmers with financial resources to invest in new technologies or inputs. Therefore, we expect a positive relationship between subsidies per hectare and productivity, though this could depend on the type and targeting of the subsidies.	Farm accountancy data network-European Commission, 2024

Source: Authors

Table 1: Variables and expected effects.

might influence economic development.

$$ln y_i = \beta_0 + \sum_{j=1}^{n} \beta_j ln x_{ij} + \sum_{k=1}^{m} \gamma_k ln c_{ik} + \delta_i + \tau_i + \varepsilon_i \qquad (1)$$

Where y_i – dependent variable (total crops output (€/ha)) for country i; x_{ij} – independent variables for country i with j indexing the different independent variables; c_{ik} - control variables country i with k indexing the different independent variables; β_0, β_i – regression coefficients; δ_i - entities fixed or random effects; n – number of independent variables; m – number of control variables; ε_i – error term.

This model specification allows for the interpretation of coefficients as elasticities, which is particularly useful in understanding the proportional impact of changes in agricultural innovation on economic development.

Prior to estimation, diagnostic tests were conducted to ensure the suitability of the model. These tests include checking for multicollinearity using Variance Inflation Factor (VIF) analysis (Sarabia and Ortiz, 2009).

By using both random effects (RE) and fixed effects (FE) models ("within"), we aimed to account for different potential sources of bias and test the consistency of our results (Clarke et al., 2013). Specifically, the RE model enabled the consideration of unobserved heterogeneity across entities that may correlate with explanatory variables, whereas the FE ('within') model addresses time-invariant qualities within each entity, thereby isolating the effects of variables that vary over time. This dual method allowed us to evaluate the robustness and consistency of our findings across various model assumptions. The choice of these models was further validated through the Hausman test (Hausman, 1978; Deutsch, 2012), which helped determine whether the random or fixed effects model is appropriate.

Additionally, to address potential endogeneity issues, instrumental variable (IV) techniques were considered. This approach involves estimating a two-stage least squares (2SLS) technique, a widely used IV estimation method. Therefore, as the first step in the 2SLS method, we regressed R&D expenditure in agriculture on four instrumental variables: population density, CO_2 emissions, real factor income, and subsidies. This approach allowed us to account for the influence of these external factors and mitigate potential endogeneity concerns, ensuring a more accurate assessment of the relationship between R&D expenditure and agricultural productivity. Based on these findings, we decided to exclude CO_2 emissions from the final list of instruments, as it was found to be insignificant in the first stage. By making this adjustment, we improve the accuracy and reliability of the model, ensuring that the remaining instruments offer a stronger and more robust explanation of the relationships between the selected variables.

$$lnx_1 = \theta_0 + \sum_{j=1}^{n} \theta_j lnz_j + \nu_i \tag{2}$$

$$lny_i = \beta_0 + \beta_1 \widehat{x_1} + \varepsilon_i \tag{3}$$

In equation (2), z_j – represents instrumental variables (population density, real factor income in agriculture, CO_2 emissions, and subsidies); θ_j – regression coefficients; v_i – error term. We believe that these instruments, backed by theoretical justification, contribute to the novelty of the instrumentalisation, offering a more reliable approach to addressing potential biases arising from omitted variables and measurement errors.

Equation (3) contains fitted values of the dependent variable from equation (2). In this model specification, independent variables from the study dataset can be used as instruments. The estimated value of the coefficient β_1 is used to test the hypothesis, evaluating whether (instrumented through z_j) has a substantial effect on y_i. Specifically, by estimating β_1, we test whether x_1 has a substantially affects on y_i . Significant results, indicated by the p-value, would confirm this relationship.

To strengthen our assumptions, we conducted diagnostic tests, including the weak instruments, Wu-Hausman and Sargan tests (Patrick, 2020), to assess the presence of endogeneity in regression models.

While this study aims to provide robust insights into the relationship between agricultural innovation and economic development in the EU, several limitations must be acknowledged. The cross-sectional structure of the data restricts the capacity to determine a causal relationship. Additionally, the availability and quality of data across different countries may vary, potentially affecting the reliability of the findings. Despite these limitations, the study employs rigorous methods and comprehensive data sources to ensure the validity of the results.

In summary, this study employs a rigorous quantitative methodology to investigate the impact of agricultural innovation on economic development within the EU. By utilising a log-log multiple regression model and robust statistical techniques, the study aims to provide empirical evidence supporting the hypothesis that higher agricultural innovation leads to greater economic development.

Results and discussion

The research begins by performing a multiple linear regression analysis presented in log-log form, as shown in Table 3, where the dependent variable is the total crops output (€/ha). The log-log transformation enabled us to understand the coefficients as elasticities, indicating the percentage change in the dependent variable resulting from a 1 % change in the independent variable.

However, it is important to note that after performing the multicollinearity analysis (Table 2), we observed that R&D spending in agriculture and population density exhibited significant multicollinearity, with VIF values above 30 and low tolerance values. The trade balance displayed moderate to high multicollinearity, shown by a VIF of around 19.65 and a tolerance at 0.05, suggesting potential complications within the model. We intended excluding trade balance from our models, as removing it reduced overall multicollinearity without impacting the

	R&D expenditure in agriculture (per ha)	Population density (inhab/km^2)	Trade balance (per ha)	CO_2 emissions (per ha)	Real factor income in agriculture (per annual work)	Subsidies (per ha)
Tolerance	0.03013273	0.02557199	0.05089327	0.23870413	0.28468222	0.50399519
VIF	33.186507	39.105289	19.648962	4.189287	3.512689	1.984146

Source: Autor's own calculation

Table 2: Multicollinearity statistics in log-log form.

	Estimate	Std. Error	t-value	Pr (> |t|)
(Intercept)	3.21141	0.74909	4.287	3.05e-05***
R&D expenditure in agriculture (per ha)	0.20083	0.05606	3.582	0.000447***
Population density (inhab/km^2)	0.60153	0.05460	11.016	<2e-16***
CO_2 emissions (per ha)	0.03499	0.08211	0.426	0.670615
Real factor income in agriculture (per annual work)	0.15437	0.05863	2.633	0.009255**
Subsidies (per ha)	-0.04523	0.01316	-3.437	0.000742***
Residual standard error	0.3715 on 167 degrees of freedom			
	(367 observations deleted due to missingness)			
Multiple R-squared	0.7688			
Adjusted R-squared	0.7619			
F-statistic	111.1 on 5 and 167 DF			
p-value	<2.2e-16			

Note: Autor's own calculation, Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 3. Multiple linear regression (OLS) model in log-log form. Dependent variable: Total crops output (per ha).

core relationships under examination, resulting in a more robust and accurate model while preserving the key variables of interest (R&D expenditure and population density).

Hence, from Table 3 above, we see that the R&D spending in agriculture showed a positive and statistically significant impact on total crops output. A 1 % increase in agricultural R&D spending is associated with a 0.20% increase in total crop output per hectare. This positive relationship emphasises the importance of investing in R&D to enhance agricultural output. R&D in agriculture contributes to technological advancements, improved agricultural practices, and increased crop output, directly benefiting overall output.

This model showed that population density had a highly substantial association with crop output, with a coefficient of 0.60153 (p <2e-16), indicating that a 1 % increase in population density corresponds with a 0.60 % increase in total crop output. This outcome indicates that increased population density may stimulate demand for agricultural production or enable more effective use of land resources, maybe owing to improved infrastructure or market accessibility. The substantial volume and importance of this coefficient underscore the vital role of population-driven agricultural practices and market access in affecting productivity.

The coefficient for CO_2 emissions per hectare is 0.03499; however, it is not statistically significant (p = 0.6706). This suggests that variations in CO_2 emissions do not significantly influence total crop output in this model. While CO_2 emissions may contribute to broader environmental and sustainability challenges, they seem to have no direct impact on productivity within the scope of this dataset (Ali et al., 2022). The absence of importance may indicate that other variables, such as agricultural methods or technology, ease the impact of emissions on production. This finding suggests more in-depth investigation. Future research might delve into the impact of other factors, like climate adaptation strategies, crop resilience, or the use of renewable energy, to gain a clearer understanding of how emissions and environmental elements affect agricultural productivity over time.

The coefficient for real factor income is statistically significant (p = 0.009255). An elevated factor income signifies enhanced productivity and profitability within the agricultural sector, which may result in more effective resource utilisation, investments in production, and augmented output. This finding highlights the necessity of maintaining strong agricultural income to improve productivity development.

The coefficient for subsidies per hectare is negative and statistically significant ($p = 0.000742$). This result, however odd, may suggest that ineffectively targeted subsidies might lead to inefficiencies or misallocation of resources. Subsidies may promote excessive utilisation of inputs that do not directly improve productivity or may discourage farmers from innovating or optimising output. This outcome necessitates a thorough analysis of subsidy programs and their efficacy in enhancing production rather than just providing financial assistance (Kumbhakar et al., 2023). The findings by Rizov et al. (2013) highlight the importance of subsidy design. When subsidies were tied directly to production, they had negative effects on productivity, primarily because they encouraged inefficient and unsustainable farming practices. However, once subsidies were decoupled from production, farmers became more efficient and responsive to market signals, resulting in increased productivity in many countries. To further investigate and demonstrate the positive relationship between subsidies and productivity, we will require more detailed data. This might include specific farm-level data on productivity measures before and after subsidy reforms, broken down by crop type, region, and farming methods.

As a next step, we employed both the RE (Table 4) and FE models ("within") (Table 5) to account for the unobserved heterogeneity across selected countries and to test the robustness of the relationships between our variables.

The RE model (Table 4) offered important insights into how the selected variables are related. Significant positive effects were noted for population density ($p<0.001$) and real factor income in agriculture, indicating that these elements contribute significantly to increases in total crop output. CO_2 emissions per hectare demonstrate a notable negative correlation ($p<0.01$), underscoring the possible negative effects of emissions on agricultural results. Other scholars have reported similar findings, observing the negative effect of CO_2 on productivity (Afjal, 2023; Otim et al., 2023). Nevertheless, R&D spending in agriculture and subsidies per hectare show no statistically significant effects, indicating a limited direct impact on the outcome variable given the current model specifications.

Before examining the results of the fixed effects "within" model, it is crucial to emphasise that by focusing on the variation within each entity over time, this model accounts for unobserved, time-invariant characteristics specific to each entity, thereby strengthening the reliability of the findings. Most importantly, the "within" transformation eliminates the constant term since each variable is centred around its specific average, which helps to highlight the effect of time-varying predictors on the dependent variable. Further, similar to the RE effects model, the FE model (Table 5) showed that CO_2 emissions have a negative impact. This negative relationship could indicate that increased CO_2 emissions per hectare are associated with detrimental effects in the agricultural sector, highlighting the possible environmental costs tied

	Estimate	Std.Error	z-value	Pr (> |z|)
(Intercept)	-0.2740252	0.9303198	-0.2945	0.768338
R&D expenditure in agriculture (per ha)	0.0870106	0.0614271	827277,00	0.156634
Population density (inhab/km^2)	0.6984273	0.1301219	648428,00	7.984e-08***
CO_2 emissions (per ha)	-0.4712783	0.1635570	-2.8814	0.003959**
Real factor income in agriculture (per annual work)	0.5081643	0.0656272	2020705,00	9.695e-15***
Subsidies (per/ha)	-0.0057691	0.0151033	-0.3820	0.702478
Total Sum of Squares	49.47			
Residual Sum of Squares	8.5266			
R-Squared	0.82796			
Adj. R-Squared	0.82281			
Chisq	118.603 on 5 DF			
p-value	<2.22e-16			

Note: Autor's own calculation, Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 4. Random Effects Model.

	Estimate	Std.Error	z-value	Pr (> |z|)
R&D expenditure in agriculture (per ha)	0.029200	0.061272	0.4766	0.6344
Population density (inhab/km^2)	0.463549	0.505541	0.9169	0.3606
CO_2 emissions (per ha)	-1.649152	0.304397	-5.4178	2.352e-07 ***
Real factor income in agriculture (per annual work)	0.650856	0.069295	740226,00	<2.2e-16***
Subsidies (per/ha)	0.010184	0.015273	0.6668	0.5059
Total Sum of Squares	10.664			
Residual Sum of Squares	187158,00			
R-Squared	0.41472			
Adj. R-Squared	0.32887			
Chisq	21.2571 on 5 and 150 DF			
p-value	4.9083e-16			

Note: Autor's own calculation, Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 5: Fixed Effects Model.

to intensive farming methods (Zafeiriou and Azam, 2017).

On the other hand, the real factor income in agriculture per annual work unit revealed a highly significant positive effect ($p < 0.001$), highlighting the strong relationship with the dependent variable. This finding underscored the important impact of income produced for each unit of agricultural labour on agricultural performance, possibly indicating advancements in productivity or efficiency.

Based on the results of both RE and FE models, it is reasonable to presume that increased CO_2 emissions could lead to a decline in agricultural productivity. This outcome indicates that rising environmental damage, especially due to CO_2 emissions, might negatively impact crop yields, potentially by worsening climate change, causing unfavourable weather patterns, or diminishing soil fertility. The finding corresponds with wider concerns regarding the harmful impacts of environmental stressors on sustainable farming practices (Ali et al., 2022; Otim et al., 2023). Nonetheless, the positive connection between real factor income in agriculture and total crop output underscores the significance of economic incentives and income growth in enhancing productivity in the agricultural sector. Furthermore, it highlights how financial backing and profitability are crucial for advancing agriculture, as improved income enables farmers to embrace innovative methods and invest in modern tools, resulting in increased productivity.

The findings additionally indicate that areas with higher population density could benefit from improved access to infrastructure, markets, and labour, potentially resulting in enhanced agricultural efficiency. High-density areas often exhibit more efficient transportation systems, improved access to farming resources, and greater opportunities for knowledge exchange and innovation, leading to better agricultural outcomes. This body of literature highlights the complex relationship between population density and agricultural productivity, emphasising that under the right conditions, higher population density can positively impact total crop output (Ricker-Gilbert et al., 2014; Komarek and Msangi, 2019).

In order to determine whether the model with RE or FE was more appropriate for analysing the relationship between selected variables, the Hausman test was employed. The Hausman test assessed the null hypothesis that the RE model yields consistent and efficient estimates, in contrast to the FE model, which addresses unobserved heterogeneity by emphasising within-group variance. The test revealed a chi-squared statistic of 17,903 with 5 degrees of freedom and a p-value of less than 2.2e-16. Due to the very low p-value, we reject the null hypothesis, asserting the consistency of the random effects model.

The null hypothesis rejection in the Hausman test strongly suggests that the random effects model is inconsistent and possibly biassed due to the probable correlation between individual effects and explanatory factors. Consequently, the fixed effects model is the more suitable option for this study.

In the next step of our analysis, we applied an IV 2SLS model (Table 7) to address potential endogeneity issues in our regression analysis. In the first stage of the IV 2SLS model, we used

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-10.36799	0.63113	-16.428	< 2e-16***
Trade Balance (per ha)	0.54782	0.06221	8.806	1.40e-15***
CO_2 emissions (per ha)	0.16994	0.11197	1.518	0.131
Real factor income in agriculture (per annual work)	0.43125	0.07212	5.980	1.27e-08***
Subsidies (per ha)	0.07470	0.01713	4.360	2.24e-05***
Residual standard error	0.5117 on 171 degrees of freedom			
	(364 observations deleted due to missingness)			
Multiple R-squared	0.7117			
Adjusted R-squared	0.705			
F-statistic	105.5 on 4 and 171 DF			
p-value:	< 2.2e-16			

Note: Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 6: First Stage Model in log-log form.

	Estimate	Std. Error	t-value	Pr(> |t|)
(Intercept)	5.60396	1.12245	4.993	1.89e-05***
R&D expenditure in agriculture (per ha)	0.32738	0.07341	4.460	8.98e-05***
Real factor income in agriculture (per annual work)	0.27185	0.09918	2.741	0.00981**
Diagnostic tests				
	df1	df2	statistic	p-value
Weak instruments	2	32	282.987	<2e-16***
Wu-Hausman	1	32	6.704	0.0144*
Sargan	1	NA	0.004	0.9504
Instruments	Population density, real factor income in agriculture and subsidies.			
Residual standard error	0.3303 on 33 degrees of freedom			
Multiple R-Squared	0.682			
Adjusted R-squared	0.6628			
Wald test 37.43 on 2 and 33 DF	p-value = 3.309e-06			
chisq = 28.192, df = 3, p-value = 3.309e-06				
alternative hypothesis: one model is inconsistent				

Note: Significance Codes: * p <0.05, **p<0.01, ***p<0.001
Source: Autor's own calculation

Table 7: IV 2 Stage Least Square Model in log-log form.

specific instruments (population density, trade balance, CO_2 emissions, real factor income in agriculture per annual work, and subsidies) to explain our dependent variable R&D expenditure in agriculture (Table 6). Each instrumental variable, except CO_2 emissions, demonstrated significant coefficients. Furthermore, the F-statistic result (105.5) and a significant p-value <2.2e16 indicate that these variables are crucial in predicting R&D expenditure in agriculture. This strengthened the 2SLS approach, as robust instruments are essential for addressing the endogeneity in the second stage.

In the second stage, we incorporated R&D expenditure in agriculture, acknowledging the complexity of the agricultural system and economic development, as well as real factor income in agriculture as a control variable due to its direct relevance to agricultural productivity. We investigated various alternative model specifications by adding additional control variables. However, through examinations, we discovered that the model featuring R&D expenditure in agriculture and real factor income in agriculture as primary variables provided the most robust results.

Specifically, results demonstrated that R&D expenditure in agriculture is positive and statistically significant. A 1 % rise in R&D spending in agriculture correlates with an approximate 0.33% increase in total crops outputs. The residuals indicated a satisfactory fit of the model. Our finding aligns with the results of other scholars (Heisey and Fuglie, 2018; Guesmi and Gil, 2021). This highlights the essential role of R&D expenditure in enhancing agricultural productivity, supporting the broad consensus in the existing literature that innovation is a key factor in agricultural productivity development.

Real factor income in agriculture, on the other hand, has demonstrated a positive and statistically significant coefficient of 0.27185 (p-value 0.00981), confirming its influence on agricultural productivity. This is in line with studies such as those highlighting that higher income levels enable farmers to adopt innovations and increase efficiency, ultimately resulting in greater productivity ("Productivity Growth in Global Agriculture," 2013). Additionally, OECD reports have shown that as incomes in agriculture improve, farmers have more financial flexibility to implement advanced practices, purchase higher-quality inputs, and adopt precision farming techniques, all of which contribute to higher yields.

Furthermore, the Wald test and Weak instruments test reinforced the strength and reliability of the instruments, while the Sargan test validated our instrument selection with a p-value of 0.9504, suggesting no overidentification problem. The Wu-Hausman test revealed a p-value of 0.0144, which confirms the presence of endogeneity. Therefore, we rejected the null hypothesis. Hence, the OLS model lacks consistency, causing the implementation of IV to be an appropriate replacement for OLS.

The decision to exclude other variables stemmed from their statistical insignificance and the potential risk of overfitting. Thus, the final model in our study offers robust empirical evidence and serves as the most accurate representation of whether or not R&D expenditure in agriculture affects agricultural productivity. This relationship remains valid even when considering the impact of other significant factors, such as real factor income. The model validated its strength and reliability, indicating that R&D expenditure in agriculture ought to be a key focus for policymakers looking to boost agricultural productivity.

Conclusion

This study highlighted the significant role of innovation, particularly R&D expenditure in agriculture, in enhancing agricultural productivity across the EU-27 for the period 2000-2019.

By applying a quantitative cross-sectional approach using multiple regression analysis and addressing endogeneity concerns with the IV 2SLS method, the findings demonstrate that innovation positively influences total crops output. Therefore, this analysis revealed that our hypothesis is corroborated. Specifically, a 1 % increase in R&D spending is associated with a 0.33% rise in crops output, emphasising the direct impact of research and technological advancements on agricultural performance. Furthermore, real factor income in agriculture was found to contribute a 0.27% increase in crop output, indicating the critical role of income dynamics in driving productivity.

The inclusion of control variables such as population density, CO_2 emissions, and trade balance allowed for a more comprehensive understanding of the broader economic factors influencing productivity. These variables provide valuable insights into how external conditions shape agricultural performance and highlight the complex interplay between innovation and external influences. The robustness of the model, confirmed through residual analysis, reinforces the argument for prioritising R&D in agriculture as a strategic tool for enhancing sustainability, economic development, and resilience in the face of global challenges such as population growth, resource scarcity, and climate change.

Interestingly, subsidies consistently demonstrated a negative effect in each model, suggesting that government financial support may not always translate into increased productivity. This counterintuitive finding could reflect inefficiencies in subsidy distribution, misalignment between subsidy programs and innovation goals, or potential crowding-out effects, where subsidies reduce the incentive for private investment in innovation. Further investigation is needed to explore these dynamics and identify the conditions under which subsidies may contribute positively to agricultural productivity.

This study contributes to the growing body of literature on the impact of innovation in agriculture, providing empirical evidence that supports the knowledge-based economy framework. By demonstrating the direct relationship between R&D expenditure and agricultural output, the findings might have important policy implications. Policymakers might be encouraged to increase investments in agricultural innovation, particularly in R&D, as part of broader strategies aimed at improving agricultural sustainability, enhancing productivity, and fostering long-term economic growth in the agricultural sector.

The study has its limitations, as it focusses solely on internal factors and does not take into account any external factors that could have a significant impact on the productivity indicator. Furthermore, this study delivers opportunities for future research. While the current model provides a solid foundation for understanding the effects of R&D expenditure on agricultural productivity, further studies could investigate additional factors that may enhance model accuracy, such as technological adoption rates, farmer education, and the role of digital tools in precision agriculture. Understanding these elements could deepen the insights into how innovation and external factors interact to shape agricultural outcomes.

In conclusion, this study highlights the transformative potential of R&D investment in agriculture. As the world faces increasing environmental and economic challenges, promoting innovation-driven growth through strategic R&D initiatives will be essential for ensuring the future sustainability and productivity of the agricultural sector, particularly in the EU context.

Corresponding author:
Ing. Tatia Zarkua
Department of Economics, Faculty of Economics and Management, Czech University of Life Sciences Prague
Kamýcká 129, 165 00 Praha – Suchdol, Czech Republic
Phone: E-mail: zarkua@pef.czu.cz

References

[1] Afjal, M. (2023) "The tapestry of green economics: mapping the nexus of CO_2 emissions, economic growth, and renewable energy", *International Journal of Sustainable Energy*, Vol.42, No. 1, pp. 1364-1390. E-ISSN 1478-646X. DOI 10.1080/14786451.2023.2268853.

[2] Ali, S., Shah, A. A., Ghimire, A. and Tariq, M. A. U. R. (2022) "Investigation the nexus between CO_2 emissions, agricultural land, crop, and livestock production in Pakistan", *Frontiers in Environmental Science*, Vol. 10. ISSN 2296-665X. DOI 10.3389/fenvs.2022.1014660

[3] Alston, J. M. and Pardey, P. G. (2013) "Agricultural R&D and Food Security of the Poor", *Economic Papers a Journal of Applied Economics and Policy*, Vol. 32, No.3, pp. 289-297. ISSN 1759-3441. DOI 10.1111/1759-3441.12048.

[4] Barry, P. and Czech, C. (2017) "Chapter 11-The Innovation Systems Approach to Agricultural Research and Development", In: "*Agricultural Systems (Second Edition)*", Academic Press, pp. 371-405. ISBN 9780128020708. DOI 10.1016/B978-0-12-802070-8.00011-6.

[5] Cai, Y. and Lattu, A. (2022) "Triple Helix or Quadruple Helix: Which Model of Innovation to Choose for Empirical Studies?", *Minerva*, Vol. 60, pp. 257-280. ISSN 1573-1871. DOI 10.1007/s11024-021-09453-6.

[6] Clarke, P., Crawford, C., Steele, F., and Vignoles, A. (2013) "Revisiting fixed- and random-effects models: some considerations for policy-relevant education research", *Education Economics*, Vol. 23, No.3, pp. 259-277. ISSN 0964-5292. DOI 10.1080/09645292.2013.855705.

[7] Deutsch, E. (2012) "Econometric Modeling", In: Smith,S. J., Elsinga, M., Fox O´Mahony, L., Eng, O. S., Wachter, S. and Gibb. K. (Eds.) "*International Encyclopedia of Housing and Home*", Elsevier, pp. 12-25. ISBN 9780080471716. DOI 10.1016/B978-0-08-047163-1.00665-2.

[8] Etzkowitz, H. and Leydesdorff, L. (1998) "A Triple Helix of University—Industry—Government Relations: Introduction", *Industry and Higher Education*, Vol.12, No. 4, pp.197-201. ISSN 2043-6858. DOI 10.1177/095042229801200402.

[9] European Parliament (2019) "*Precision Agriculture and the Future of Farming in Europe*". [Online]. Available: https://www.europarl.europa.eu/RegData/etudes/STUD/2016/581892/EPRS_STU(2016)581892_EN.pdf [Accessed: Jul. 28, 2024].

[10] European Commission (2020) "*The common agricultural policy at a glance*". [Online]. Available: https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy_en [Accessed: Jul. 28,2024].

[11] European Commission (2021) "*Horizon Europe*". [Online]. Available: (https://ec.europa.eu/info/horizon-europe_en) [Accessed: Jul. 28,2024].

[12] European Commission (2024) "Farm accountancy data network". [Online]. Available: https://agridata.ec.europa.eu/extensions/FarmEconomyFocus/FarmEconomyFocus.html [Accessed: Aug. 4, 2024].

[13] Eurostat (2024) "*Eurostat*". [Online]. Available: https://ec.europa.eu/eurostat/web/main/data/database [Accessed: Aug.4, 2024].

[14] Evenson, R. E. and Gollin, D. (2003) "Assessing the impact of the Green Revolution, 1960 to 2000", *Science*, Vol. 300, No. 5620, pp. 758-762. E-ISSN 1095-9203. DOI 10.1126/science.1078710

[15] Fidanoski, F., Simeonovski, K., Kaftandzieva, T., Ranga, M., Dana, L., Davidovic, M., Ziolo, M. and Sergi, B. S. (2022) "The triple helix in developed countries: when knowledge meets innovation?", *Heliyon*, Vol. 8, No. 8, p. e10168. E-ISSN 2405-8440. DOI 10.1016/j.heliyon. 2022.e10168.

[16] Gebbers, R. and Adamchuk, V. I. (2010) "Precision agriculture and food security", *Science*, Vol. 327, No. 5967, pp. 828-831. E-ISSN 1095-9203. DOI 10.1126/science.1183899

[17] Gildemacher, P. and Wongtschowski, M. (2015) "*Catalysing innovation: from theory to action*". [Online]. Available: https://www.kit.nl/wp-content/uploads/2019/09/WPS1_2015_online.pdf [Accessed: Aug.15, 2024]

[18] Greene, W. H. (2003) "*Econometric Analysis*", 5th ed., Prentice Hall, Upper Saddle River. ISBN 10 987654321.

[19] Guesmi, B. and Gil, J. (2021) "The Impact of Public R&D Investments on Agricultural Productivity", *Journal of Agriculture and Environment*, Vol. 19, No. 1, pp. 284-291. E-ISSN 2456-8643. DOI 110.55365/1923.x2021.19.

[20] Hall, A., Mytelka, L. and Oyeyinka, B. (2005) "Innovation systems: Concepts and implications for agricultural research policy and practice". ILAC Brief 2, p. 4.

[21] Hausman, J. A. (1978) "Specification Tests in Econometrics", *Econometrica*, Vol. 46, No. 6, pp. 1251-1271. E-ISSN 1468-0262. DOI 10.2307/1913827.

[22] Heisey, P. W. and Fuglie, K. O. (2018) "Public agricultural R&D in high-income countries: Old and new roles in a new funding environment", *Global Food Security*, Vol.17, pp. 92-102. ISSN 2211-9124. DOI 10.1016/j.gfs.2018.03.008.

[23] Johnson, B. and Lundvall, B. Å. (2013) "National Innovation Systems (NIS)", In: Carayannis, E.G. (eds) "*Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship*", Springer, pp. 1341-1347. ISBN 978-1-4614-3857-1. DOI 10.1007/978-1-4614-3858-8_458.

[24] Komarek, A. M. and Msangi, S. (2019) "Effect of changes in population density and crop productivity on farm households in Malawi", *Agricultural Economics*, Vol. 50, No.5, pp. 615-628. E-ISSN 1805-9295. DOI 10.1111/agec.12513.

[25] Kumbhakar, S. C., Li, M. and Lien, G. (2023) "Do subsidies matter in productivity and profitability changes?", *Economic Modelling*, Vol.123(C). ISSN 0264-9993. DOI 10.1016/j.econmod.2023.106264.

[26] Lundvall, B. (2007) "National Innovation Systems—Analytical Concept and Development Tool", *Industry and Innovation*, Vol. 14, No. 1, pp. 95-119. ISSN 1366-2716. DOI 10.1080/13662710601130863.

[27] OECD (1997) "*OECD Observer*", OECD Publishing, Paris, Vol. 1996, No.3., 56 p. DOI 10.1787/observer-v1996-3-en.

[28] OECD (2019) "*Innovation, Productivity and Sustainability in Food and Agriculture: Main Findings from Country Reviews and Policy Lessons*", OECD Food and Agricultural Reviews. 186 p. DOI 10.1787/c9c4ec1d-en.

[29] OECD (2023) "A*gricultural Policy Monitoring and Evaluation 2023: Adapting Agriculture to Climate Change*", OECD Publishing, Paris. 689 p. DOI 10.1787/b14de474-en.

[30] OECD (2023) "*OECD Science, Technology and Innovation Outlook 2023: Enabling Transitions in Times of Disruption*", OECD Publishing, Paris. 230 p. DOI 10.1787/0b55736e-en.

[31] Oksanen, E. H. (1991) "A simple approach to teaching generalized least squares theory", *The American Statistician*, Vol. 45, No. 3, pp. 229-233. ISSN 0003-1305. DOI 10.2307/2684297.

[32] Otim, J., Watundu, S., Mutenyo, J., Bagire, V. and Adaramola, M. S. (2023) "Effects of carbon dioxide emissions on agricultural production indexes in East African community countries: Pooled mean group and fixed effect approaches", *Energy Nexus*, Vol. 12, p. 100247. ISSN 2772-4271. DOI 10.1016/j.nexus.2023.100247.

[33] Patrick, R. H. (2020) "Chapter 28: Durbin-Wu-Hausman Specification Tests", World Scientific Book Chapters, In: Lee, Ch. F. and Lee, J. C. (ed.) "*Handbook of Financial Econometrics, Mathematics, Statistics, and Machine Learning*", chap. 28, pp. 1075-1108, World Scientific Publishing Co. Pte. Ltd. ISBN 9789811202384. DOI 10.1142/11335.

[34] Piesse, J. and Thirtle, C. (2010) "Agricultural R&D, technology and productivity", *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, Vol. 365, No. 1554, pp. 3035-3047. ISSN 0080-4622. DOI 10.1098/rstb.2010.0140.

[35] Pound, B. and Conroy, C. (2017) "Chapter 11-The Innovation Systems Approach to Agricultural Development", In: Snapp, S. and Pound, B. "*Agricultural Systems (Second Edition)*", pp. 371-405, ISBN 978-0-12-802070-8. DOI 10.1016/B978-0-12-802070-8.00011-6.

[36] "Productivity Growth in Global Agriculture" (2013) *Population and Development Review*, Vol. 39, No. 2, pp. 361-365. [Online]. Available: http://www.jstor.org/stable/41857609. [Accessed: Sept. 25, 2024].

[37] Qaim, M. (2009) "The Economics of Genetically Modified Crops", *Annual Review of Resource Economics*, Vol.1, No.1, pp. 665-694. ISSN 1941-1359. DOI 10.1146/annurev.resource.050708.144203.

[38] Riaz, E., De Meyer, J., Dosov, B. and Richtern, K. (2014) "*Approaches to Strengthening Agricultural Innovation Systems (AIS) in Central Asia, South Caucasus and Turkey*", FAO UN. ISBN 978-92-5-108688-9.

[39] Ricker-Gilbert, J., Jumbe, C. and Chamberlin, J. (2014) "How does population density influence agricultural intensification and productivity? Evidence from Malawi", *Food Policy*, Vol. 48, pp. 114-128. ISSN 0306-9192. DOI 10.1016/j.foodpol.2014.02.006.

[40] Rizov, M., Pokrivcak, J. and Ciaian, P. (2013) "CAP subsidies and productivity of the EU farms", *Journal of Agricultural Economics*, Vol. 64, No. 3, pp. 537-557. E-ISSN 1477-9552. ISSN 0021-857X. DOI 10.1111/1477-9552.12030.

[41] Romer, P. M. (1990) "Endogenous Technological Change", *Journal of Political Economy*, Vol. 98, No. 5, pp. S71-S102. ISSN 0022-3808. DOI 10.1086/261725.

[42] Sarabia, L. and Ortiz, M. (2009) "*Response Surface Methodology*", Elsevier eBooks. pp. 345-390. ISBN 978-044452701-1.00083-1. DOI 10.1016/b978-044452701-1.00083-1.

[43] Sonnino, R., Faus, A. M. and Maggio, A. (2014) "Sustainable Food Security: An Emerging Research and Policy Agenda", *The International Journal of Sociology of Agriculture and Food*, Vol. 21, No.1, pp. 173-188. ISSN 0798-1759. DOI 10.48416/ijsaf. v21i1.161.

[44] Špička, J., Boudný, J. and Janotová, B. (2009) "The role of subsidies in managing the operating risk of agricultural enterprises", Agricultural Economics (Zemědělská Ekonomika). E-ISSN 1805-9295. DOI 10.17221/17/2009-AGRICECON.

[45] The World Bank (2024) "*Indicators*" [Online]. Available: https://data.worldbank.org/indicator [Accessed: Aug. 4, 2024].

[46] Tropical Agriculture Platform (2016) "*Common Framework on Capacity Development for Agricultural Innovation Systems: Guidance Note on Operationalization*", CAB International. ISBN-13 978-1-78639-120-9. [Online]. Available: https://www.cabi.org/Uploads/CABI/about-us/4.8.5-other-business-policies-and-strategies/tap-guidance-note.pdf [Accessed: Aug. 4, 2024].

[47] Wang, R., Meybeck, A. and Sonnino, A. (2019) "Chapter 44 - Research and innovation", In: Campanhola, C. and Randey, Sh (ed). "*Sustainable Food and Agriculture"*, Academic Press, pp. 491-507. ISBN 978-0-12-812134-4. DOI 10.1016/b978-0-12-812134-4.00044-3

[48] Wolfert, J., Ge, L., Verdouw, C. and Bogaardt, M. J. (2017) "Big Data in Smart Farming – A review", *Agricultural Systems*, Vol. 153, pp.69-80. ISSN 0308-521X. DOI 10.1016/j.agsy.2017.01.023.

[49] Zafeiriou, E. and Azam, M. (2017) "CO_2 emissions and economic performance in EU agriculture: Some evidence from Mediterranean countries", *Ecological Indicators*, Vol. 81, pp. 104-114. E-ISSN 1872-7034. DOI 10.1016/j.ecolind.2017.05.039.