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SYSTEMIC ASPECTS OF AGRICULTURAL INVESTMENTS: REGIONAL VARIABILITY AND SECTOR-SPECIFIC CHARACTERISTICS IN COST EFFICIENCY

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Abstract

This paper explores whether the impacts of long-term investments on efficiency vary significantly across different regions and sectors of agricultural production. By delving into these complexities, this study seeks to determine if these factors should be integral considerations in the formulation of policies and strategies aimed at improving the efficiency and resilience of the European agricultural system.

To address this, the study employs mathematical and statistical analyses of data from the Farm Accountancy Data Network (FADN) covering 2014-2020.

The findings reveal that the diverse behaviors of agricultural systems across various regions and sectors present unique challenges in efficiency analysis. The results indicate that (i) incorporating regional and sector-specific variability provides a more comprehensive and nuanced understanding of the factors influencing the agricultural cost efficiency of EU farm groups; (ii) emphasizing the systemic aspects of agricultural investments and adopting a system thinking approach in evaluations ensures more accurate and meaningful assessments of investments, interventions, and their impacts.

Keywords: agricultural investments, system thinking, cost efficiency, DEA, model performance

INTRODUCTION

When we talk about a system, Schuster (2021) provides a comprehensive understanding of this concept in “The Art of Thinking in Systems.” The system is described as a unified set of interconnected elements that collectively exhibit characteristic behavior patterns over time. Systems are viewed as the cause of their own behavior, demonstrating consistency even when influenced by external forces. This inherent characteristic highlights the unique identity and response of the system to certain stimuli.

Hummelbrunner (2011) views systems theory as a specific approach to conceptualizing the world, emphasizing the relationships that connect elements into a whole. This perspective suggests that almost anything can be considered a system, ranging from natural ecosystems to social organizations.

Systems typically consist of subsystems, which are part of a larger system known as a suprasystem. The hierarchy between these systems should not be seen as strictly linear but rather as a network with various connections, reflecting the complexity and interdependency of the elements involved. The concept of systems thinking encourages us to see everything as interconnected, instead of viewing units as isolated components.

Systems are not only physical entities in the real world, but also mental constructs created by people to help us understand the world around us. These mental constructs can be highly subjective, and any representation of a system is inevitably a subjective simplification of relationships (systemic relationships) and may not fully capture the complexity of the real world.

In this context, agricultural systems encompass a broad framework of various interconnected components and processes. These systems can be represented in analyses as complex interactions between biological, ecological, social, economic, and other factors at different levels-from individual farms to entire regions and sectors. The multidisciplinary, multilevel, and multisectoral perspectives present the agricultural system as composed of various interconnected subsystems, collectively contributing to a more holistic view of agricultural systems.

Many factors driving the agricultural systems have been identified by Hendrickson et al. (2008), Walters et al. (2016), FAO (2021), and many others. Some researchers go beyond merely identifying the elements (factors) and describe the interactions between them, forming system characteristics such as feedback loops, trade-offs, synergies, and scale effects, highlighting the complex challenges facing modern agriculture (Lee-Gammage, 2017).

Identifying system relationships, characteristics, and dynamics, when comprehensive data is available allows for a more thorough assessment of agricultural activities, cost efficiency, and associated systemic risks. System relationships are fundamental to the emergence of systemic risks. However, system relationships are a more comprehensive concept that is not limited to causing solely systemic risks. Although the term "systemic risks" is widely used, emphasizing the negative consequences of system relationships, the term "complex systemic uncertainties" more adequately describes the diversity of different interactions between elements of complex systems. Therefore, understanding system relationships is crucial for addressing systemic risks and uncertainties in agriculture.

Systems thinking allows for a more nuanced understanding of the agricultural landscape by considering the various factors and their interdependencies, thus, organizations like the American Evaluation Association (AEA), the International Development Evaluation Association (IDEAS), the European Evaluation Society (EES), and the International Organization for Cooperation in Evaluation (IOCE) already promote the use of systems approaches by sharing best practices, developing professional standards, and fostering innovation in evaluation methodologies.

The endorsement of systems approaches underlines the value of methodologies in understanding complex, interlinked phenomena. Such approaches are critical in agriculture, where investments in fixed assets like machinery, equipment, and infrastructure are pivotal for boosting productivity and efficiency. However, the impact of these investments is not uniform.

These investments are heavily influenced by numerous factors that vary from region to region and even from sector to sector, necessitating a nuanced evaluation of their effectiveness within diverse contexts.

Socio-economic conditions play a critical role in determining the effectiveness and efficiency of investments. For example, developed economies may have easier access to modern technologies and financial resources, significantly affecting their opportunities for agricultural modernization. Meanwhile, developing regions face challenges such as limited access to capital, technology, and education, which restrict their ability to utilize the potential of investments in fixed assets.

Climate and ecological conditions also play a critical role, as they dictate the types of crops and production methods that can be productive and efficient in each region. Economic and social characteristics, including land ownership distribution and the social structure of the workforce, also have a significant impact on how investments in agriculture are utilized.

The specific combination and complex interrelationships of these factors manifest through regional differences and sectoral characteristics.

Different regions have different climatic and ecological conditions, different cultural and historical contexts, as well as different economic and social characteristics. Therefore, the specific combination of these factors will impact differently in each area, taking into account local conditions and context.

Each agricultural sector also has its specific characteristics that can influence the way various factors interact. As a result, each agricultural investment activity may have unique challenges and opportunities that vary depending on the specific conditions in the sector.

The impact of investments on efficiency varies based on contextual factors such as regional differences and sector-specific characteristics. This variation presents significant challenges in assessing investments and implementing uniform policies across different investment intervention areas. Therefore, achieving an optimal effect from investments in fixed assets in agriculture requires understanding the specific contextual factors. This necessitates a differentiated approach and flexibility in policies and programs to support investments, addressing the unique challenges and opportunities that arise in different regions and sectors of agriculture.

Purpose of the study

The primary objective of this research is to investigate whether differences in regional conditions and sector-specific characteristics influence the effectiveness of agricultural investments on efficiency.

Proving that the variation in investments' impacts on efficiency depends heavily on regional differences and sectoral characteristics of agriculture production will provide valuable insights that could guide strategic decision-making, thereby fostering policies that are better aligned with the diverse conditions across the European Union's agricultural landscape. By confirming the presence or absence of these nuanced impacts, the research aims to contribute insights for enhancing the resilience of the European agricultural system.

Research question

In order to investigate the influence of distinct regional disparities and specific sectoral characteristics on the effectiveness of investments in enhancing the efficiency of agricultural production the study aims to answer the following research question:

Q: Does reflecting regional differences and sectoral characteristics improve the model's ability to capture the complex and intricate relationships between annual distributed investment costs in fixed assets (depreciation) and relative cost efficiency?

Specifically, the study seeks to answer whether accounting for regional differences and sectoral characteristics enhances the model's ability to capture the complex relationships between annual investment costs in long-term fixed assets (depreciation) and relative cost efficiency.

MATERIALS AND METHODS

For the purpose of the research mathematical and many statistical analyses of data on investments in fixed assets (FA) and the comparative cost efficiency of farm groups in the European Union for the period 2014-2020 are conducted. The source of the data is the Farm Accountancy Data Network (FADN), which is a comprehensive database managed by the Directorate-General for Agriculture and Rural Development of the European Commission. FADN collects a diverse range of financial and economic data from agricultural farms throughout the member states of the European Union. This database is designed to provide a representative sample of farms across

Europe and is renowned for its reliability and comprehensive coverage in gathering crucial information related to farm incomes and operations.

Various quantitative methods are used to present comparative cost efficiency and its relationship with investments in long-term fixed assets (FA) in the following order:

1. Deriving the comparative cost efficiency using a mathematical programming model known as Data Envelopment Analysis (DEA),
2. Normalizing the comparative cost efficiency through nominalization,
3. Transforming the annual distributed investments in long-term fixed assets (depreciation cost) through logarithmic transformation,
4. Analyzing relationships between comparative cost efficiency and depreciation cost using maximum likelihood estimation parameters in binary logistic regression,
5. Evaluating model performance through:

5.1 Overall assessment tests based on likelihood ratio tests,

5.2 Pseudo R-squares calculated using methods like McFadden, Cox & Snell, and Nagelkerke,

5.3 Information-theoretic criteria based on methods from information theory,

5.4 Classification and predictive methods such as AUC and related ROC.

Deriving the comparative cost efficiency using a mathematical programming model known as Data Envelopment Analysis (DEA)

Seven technological boundaries are established using a mathematical model (Equation 1) known as Data Envelopment Analysis (DEA). Optimization tasks were tackled using the software application OpenSolver 2.9.3, following the methodologies outlined by Mason (2012). The method applied, known as basic DEA, evaluates Decision Making Units (DMUs) based on their ability to achieve the optimal ratio between inputs and outputs. DMUs that achieve the best efficiency score of 1 are considered fully efficient and are positioned on the 'efficiency frontier'. DMUs that fall short of this frontier receive scores below 1, indicating less efficiency. The difference between 1 and the efficiency score of each DMU quantifies its potential for improvement.

Equation 1

$$\min \theta$$

st.

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ij_0} \quad i = 1,2,\ldots\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj_0} \quad r = 1,2,\ldots\ldots,s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \qquad j = 1,2,\ldots\ldots,n$$

Since the groups of farms examined in this study may not operate at their optimal scale, the model used in this research assumes *variable returns to scale* (VRS), as proposed in the model by Banker, Charnes, and Cooper (1984).

The orientation applied in this study for calculating comparative efficiency *is input-oriented* for two main reasons: (1) because the resources used (inputs) are controlled variables, while outputs are uncontrollable variables, and (2) because this orientation aligns with the imperative of sustainability, aiming to reduce excessive resource use.

There is no specific predefined objective or imposed constraint, which is why a radial approach is used to derive the index of comparative cost efficiency.

The variables used to measure comparative cost efficiency, reflecting the cost structure of DMUs, are based on representative data from the Farm Accountancy Data Network (FADN) at the economic size level of farms across all EU member states during the period

2014–2020. All variables are expressed in financial measures (€).

The model uses three input variables (m = 3) representing the expenditure structure of farms:

SE281 Total specific costs

SE336 Total farming overheads

SE365 Total external factors

As an output (s = 1) for the model, a measure of production is used:

SE131 Total output

The number of DMUs varies over the years: 2014 (n=1296), 2015 (n=1271), 2016 (n=1313), 2017 (n=1336), 2018 (n=1325), 2019 (n=1315), and 2020 (n=1327).

These variables are detailed in the "Definitions of Variables Used in Standard Results of FADN" (AGRI DG, 2011).

Normalizing the comparative cost efficiency through nominalization

In order to satisfy the requirements for the target value of binary logistic regression the numerical value of comparative cost efficiency (DEA index) is transformed into a binary variable with two categories:

"0-50%" – DMUs with less than or equal to 50% comparative cost efficiency.

"50-100%" – DMUs with more than 50% comparative cost efficiency.

Transforming the annual distributed investments in long-term fixed assets (depreciation cost) through logarithmic transformation

One of the most widely used variables in Data Envelopment Analysis (DEA) in various research publications in the field of agriculture is depreciation. Depreciation SE360 from the publicly available FADN database denotes the decrease in the value of capital assets over the accounting year. Due to its non-normal distribution as confirmed by the Shapiro-Wilk test ($p < .001$) it is transformed logarithmically before using it as a factor variable in the logistic regression.

Analyzing relationships using maximum likelihood estimation parameters in binary logistic regression

In this research, binary logistic regression is employed to present the relationship between depreciation cost (a proxy for investments in long-term capital assets) and the comparative efficiency of costs. Assessing the investment effects is presented by two contrasting methodologies: the reductionist and systemic approaches.

The reductionist approach simplifies evaluation by focusing on isolated factors and measuring their individual impacts on outcomes. It breaks down complex scenarios into discrete elements, analyzing them independently to identify specific contributions.

Conversely, the systemic approach adopts a holistic perspective, acknowledging that investment outcomes are shaped by a web of interconnected factors. Understanding the impact of investments requires considering these multifaceted influences across diverse regions and sectors. The inclusion of the categorical variables (sector and member state) in interaction effects allows for modeling how the effect of the predictor variable (logarithm of depreciation expenses) on the logarithm of odds changes depending on the value of the dichotomous categorical variable (0;1).

Within the framework of this research the two models, A and B, (Equation 2 and Equation 3) illustrate these contrasting approaches. The reductionist model isolates and examines specific variables to quantify their direct effects, aiming for clarity and simplicity in analysis. In contrast, the systemic model portrays agricultural systems as intricate networks of interconnected subsystems. It captures the dynamic and nonlinear interactions within agriculture, emphasizing the interdependence of factors and context across diverse regions and sectors.

Model A reflecting reductionist approach:

Equation 2

$$Logit(p) = \beta 0 + \beta 1 \cdot Log\_Depreciation$$

Model B reflecting system approach:

Equation 3

$$Logit(p) = \beta 0 + \beta 1 \cdot Log\_Depreciation$$
$$+\beta 2 \cdot Sector$$
$$+\beta 3 \cdot EU\_Member$$
$$+\beta 4 \cdot (Log\_Depreciation \times Sector)$$
$$+\beta 5 \cdot (Log\_Depreciation \times EU\_Member)$$

$Logit(p)$ is the logit of the probability p.

β0,β1,β2,β3,β4,β5 are parameters of the model estimated during analysis

Log_Depreciation is the logarithm of depreciation

Sector is the categorical variable representing different sectors

EU_Member is the categorical variable representing different EU member states

Log_Depreciation×Sector and Log_Depreciation×EU_Member are interactions between the logarithm of depreciation and the categorical variables

By employing both models, the research seeks to provide a comprehensive understanding of how different methodological approaches can reveal insights into the ***systemic aspects of agricultural investments***.

Evaluating model performance

For evaluating the model performance the research goes through (i) Overall assessment tests based on likelihood ratio tests, (ii) Pseudo R-squares calculated using methods like McFadden, Cox & Snell, and Nagelkerke, (iii) Information-theoretic criteria based on methods from information theory, and (iv) Classification and predictive methods such as AUC and related ROC.

In the **Overall Model Test**, the considered model (A or B), referred to as the full model, which includes one or more factor variables, is compared with the null model (M0), which has no factor variables. It measures the improvement in model fit when transitioning from the null model to the considered model. This statistic is based on the χ^2 statistic. The larger the value of the χ^2 statistic, the better the proposed model fits the dataset.

Pseudo R-squared in logistic regression represents a measure of improvement in model fit compared to the null model (with no predictor variables). It assesses the model's goodness-of-fit for predicting probabilities, which is different from explaining variance in a continuous outcome as does R-squared in linear regression. A higher value of pseudo R-squared indicates a better fit of the model in terms of predicting probabilities. Measures used in this research are the pseudo R-squares of McFadden, Cox-Snell, and Nagelkerke (see Cox and Snell, 1989; McFadden, 1974; Nagelkerke, 1991). The higher the value, the better the proposed model fits the dataset.

AUC (Area Under the Curve) is another crucial metric for evaluating the performance of binary classifiers. AUC quantifies the ability of a binary classifier to distinguish between classes. It represents the area under the **Receiver Operating Characteristic (ROC) curve**, which plots the true positive rate (sensitivity) against the false positive rate (1-specificity) for different threshold values.

AUC values range from 0 to 1. AUC = 0.5 indicates that the classifier performs no better than random guessing (no discrimination ability), where the ROC curve is along the diagonal line (true positive rate = false positive rate). AUC = 1 represents a perfect classifier that achieves perfect discrimination between the classes without any misclassifications.

AUC values between 0.5 and 1 indicate varying levels of classifier performance. The closer the AUC is to 1, the better the classifier's ability to distinguish between the positive and negative classes. Higher AUC values indicate better overall performance of the classifier.

AUC is particularly useful because it provides a single scalar value that summarizes the classifier's performance across all possible threshold values. It is robust to class imbalance and is widely used in evaluating and comparing different classifiers.

In practical terms, when comparing classifiers, higher AUC values generally suggest that the classifier has better predictive power and can more effectively distinguish between the classes it is trained to identify.

When comparing models using **Information-theoretic criteria**, depending on the objectives, we can evaluate the models with absolute and relative measures. The *Akaike Information Criterion (AIC)* formulated by Hirotugu Akaike, a Japanese statistician, in his seminal paper "A New Look at the Statistical Model Identification" (Akaike, 1974) is an absolute measure, while so-called *evidence ratio (ER)* is a relative measure to make direct comparisons between normalized likelihoods using Akaike weights. They allow us to compare the relative strength of evidence (Akaike weights) in favor of one model against another. The ratio indicates which of the two models is better, in the context of Kullback-Leibler (K-L) information - a measure of good approximation.

Values of the evidence ratio higher than one indicate a stronger evidence in support of the model in the nominator compared to the model in the denominator. Conversely, lower values than one, indicate that the model in the nominator is less supported compared to the model in the denominator. A ratio close to 1 highlights that there is no strong evidence favoring one model over the other.

RESULTS AND DISCUSSION

In this section, the outcomes of the statistical analysis are presented comparing the performance of the two models, MA and MB, across a seven-year period from 2014 to 2020. The following results demonstrate the robustness of Model MB in capturing the nuanced dynamics of agricultural efficiencies, thus providing crucial insights for the impact of regional and sector-specific characteristics on the effectiveness of agricultural investments on efficiency.

Table 1. Summarizes the results of the performance metrics:

Table 1. Performance metrics

Performance metrics		Model	2014	2015	2016	2017	2018	2019	2020
LRT - Overall Model Test	χ^2	MA	0.1	9.96	0.12	2.07	1.5	21.6	7.96
		MB	805.27	840.85	868.88	896.48	674.39	812.7	721.4
	Df	MA	1	1	1	1	1	1	1
		MB	69	69	69	69	69	69	69
	P	MA	0.755	0.002	0.725	0.150	0.221	< .001	0.005
		MB	< .001	< .001	< .001	< .001	< .001	< .001	< .001
Pseudo Rs – squared	R^2_{McF}	MA	5.46e-5	0.00566	6.81e-5	0.00112	9.60e-4	0.0120	0.00433
		MB	0.450	0.47787	0.478	0.48410	0.432	0.4498	0.39275
	R^2_{CS}	MA	7.54e-5	0.00780	9.43e-5	0.00155	0.00113	0.0163	0.00598
		MB	0.463	0.48396	0.484	0.48881	0.39889	0.4610	0.41937
	R^2_N	MA	1.01e-4	0.0104	1.26e-4	0.00207	0.00163	0.0218	0.00798
		MB	0.618	0.6457	0.646	0.65179	0.57653	0.6172	0.55955
Information-theoretic criteria	AIC	MA	1794	1754	1823	1854	1562	1789	1833
		MB	1125	1059	1090	1095	1025	1134	1255
	ER aic	MA	1	1	1	1	1	1	1
		MB	1.87E+145	8.27E+150	1.48E+159	6.53E+164	4.06E+116	1.70E+142	3.24E+125
Classification metrics	AUC	MA	0.498	0.569	0.519	0.533	0.495	0.597	0.566
		MB	0.91	0.92	0.92	0.921	0.909	0.911	0.89

Source: Own research based on data from FADN

According to the Overall Model Test, our analysis underscores the superiority of Model MB as the more reliable and consistently fitting model over the seven-year period. This conclusion is drawn from its ability to consistently achieve high chi-square values (from 674,39 to 896,48) and significant p-values, thereby demonstrating its robustness and efficacy in model fitting.

According to the Pseudo R-squared metrics for two models (MA and MB) across different years (2014 to 2020), Model MB consistently outperforms Model MA. Model MA shows very low values in all three pseudo R-squared measures, indicating a poor fit to the data. In contrast, Model MB demonstrates high pseudo R-squared values across all metrics, suggesting a much better fit. Model MB is evidently the more reliable and better-fitting model over the years, as indicated by its higher pseudo R-squared values. This suggests that Model MB is much more effective in capturing the underlying patterns in the data compared to Model MA.

Across all the years, Model MB consistently has lower AIC values, ranging from 1025 in the 2018 year to 1255 in the 2020 year, compared to Model MA, indicating that Model MB provides a better fit for the data each year. The Evidence Ratios also strongly favor Model MB over Model MA, with values indicating an extremely high likelihood that Model MB is the better model compared to Model MA. The consistent pattern observed in both the AIC values and the Evidence Ratios clearly indicates that Model MB is superior to Model MA across all the years from 2014 to 2020.

The AUC values for Model MA range from 0.495 to 0.597 across the years. These values are close to 0.5, indicating that Model MA performs only slightly better than random guessing and has poor discriminatory power between the classes.

The AUC values for Model MB are consistently high, ranging from 0.89 to 0.921. These values are close to 1, indicating that Model MB has excellent discriminatory power and performs significantly better at distinguishing between the two classes.

Therefore, Model MB demonstrates superior performance in terms of classification accuracy compared to Model MA across all years from 2014 to 2020. The AUC values for Model MB are consistently high, indicating that it reliably and effectively distinguishes between the two classes. In contrast, Model MA's AUC values suggest that it struggles to differentiate between the classes, performing only marginally better than a random classifier, as is evident from the ROC curves from Figure 1 to Figure 7.

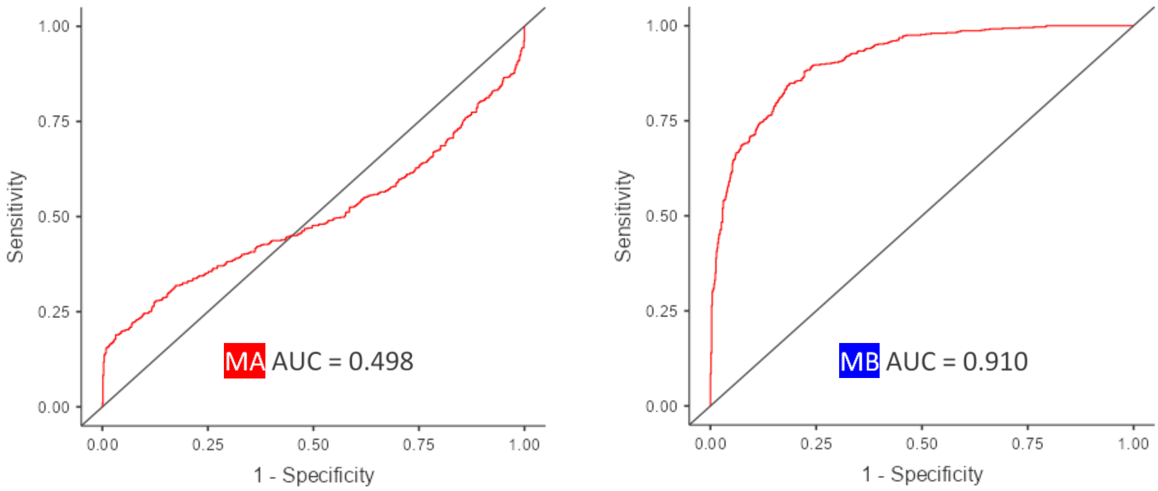

Figure 1. ROC and AUC 2014
Source: Author's elaboration on data from FADN

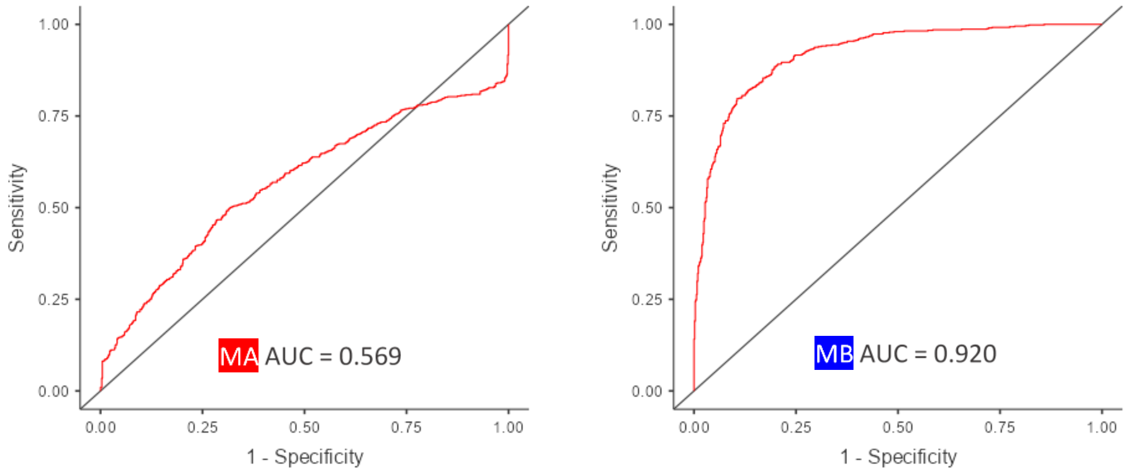

Figure 2. ROC and AUC 2015
Source: Author's elaboration on data from FADN

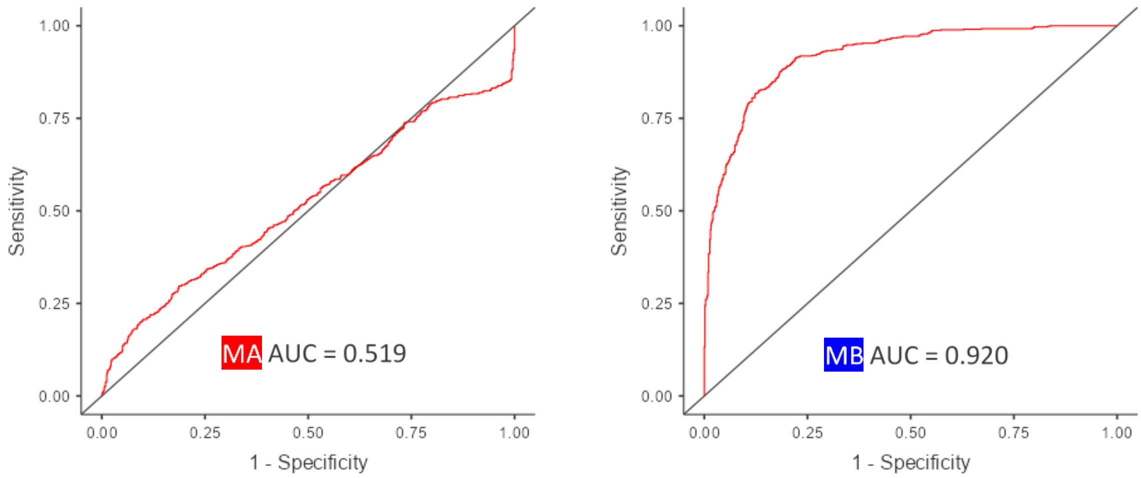

Figure 3. ROC and AUC 2016
Source: Author's elaboration on data from FADN

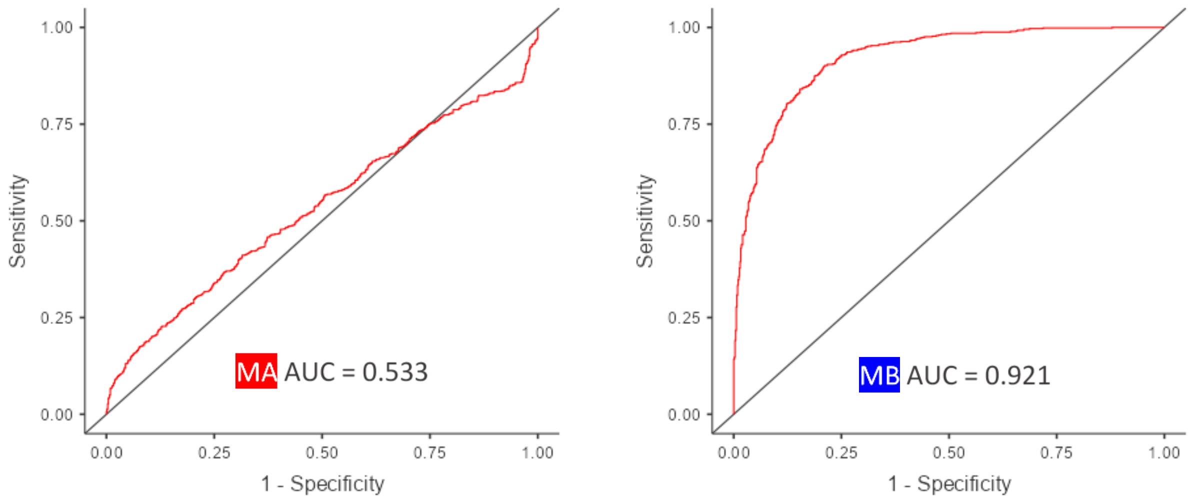

Figure 4. ROC and AUC 2017
Source: Author's elaboration on data from FADN

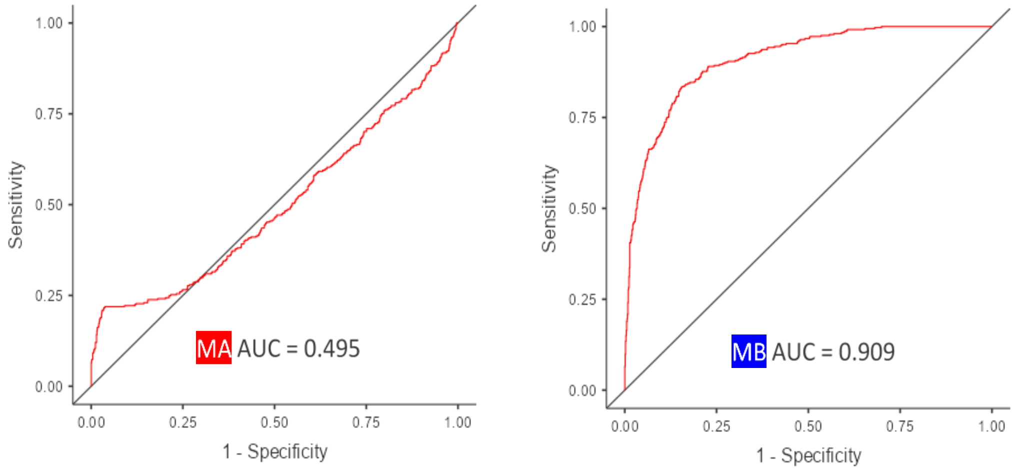

Figure 5. ROC and AUC 2018
Source: Author's elaboration on data from FADN

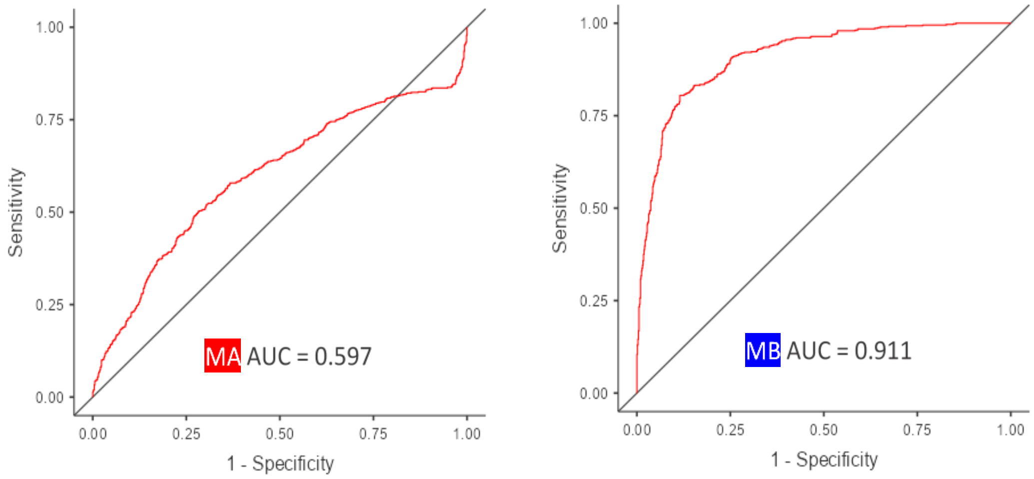

Figure 6. ROC and AUC 2019
Source: Author's elaboration on data from FADN

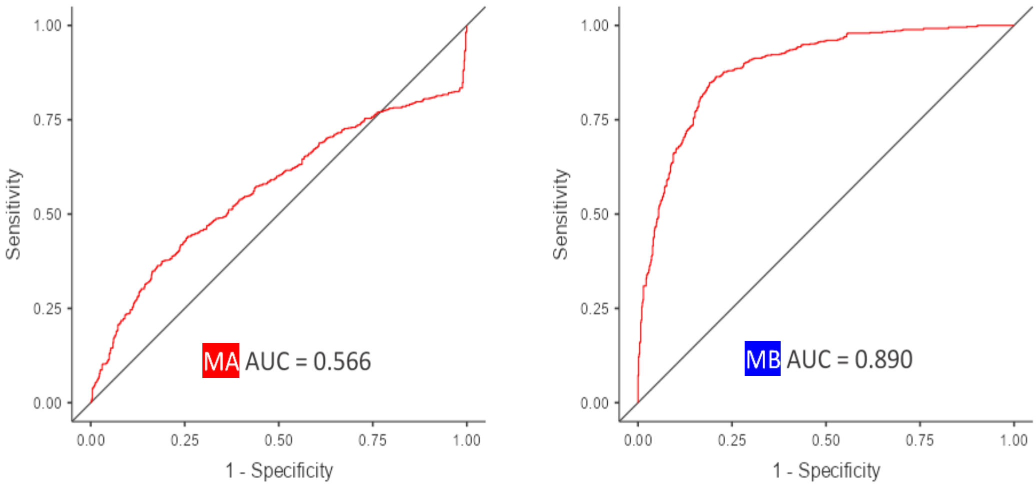

Figure 7. ROC and AUC 2020
Source: Author's elaboration on data from FADN

Overall, the AUC analysis and ROC curves reinforce the earlier findings from the Overall Model Test, Pseudo R-squared metrics, AIC, and Evidence Ratios, highlighting Model MB's robustness and effectiveness in classification tasks. Model MB is evidently the more reliable and accurate model for predicting outcomes in this context, indicating that Model MB is well-suited for analyzing cost efficiency with consideration of regional and sector-specific factors. This makes Model MB a valuable tool for policymakers and business analysts seeking to understand and improve EU agricultural cost efficiency in different regions and sectors.

The trends in the models' performance are observed across all considered years. The established patterns are not random but indicate the presence of systemic relationships. Knowledge of these systemic relationships and persistent patterns aids in strategic planning and informed decision-making. Incorporating moderator effects into statistical models like Model MB provides a rigorous way to confirm and delineate systemic relationships in agricultural investments. This approach is crucial for understanding how regional characteristics and sector-specific factors influence the effectiveness of investments in enhancing agricultural efficiency.

Delving deeper into the systemic aspects of agricultural investments, it is evident that the consistent performance trends of Model MB over a seven-year period underscore the importance of incorporating a systemic perspective into the analysis of agricultural efficiency. Unlike isolated evaluations, a systemic approach considers the interconnectedness and interdependencies of various factors within the agriculture.

Agriculture is inherently influenced by a multitude of interconnected factors that include ecological conditions, technological advancements, market dynamics, policy frameworks, socio-economic conditions, and others, which Hendrickson et al. (2008), Walters et al. (2016), FAO (2021) aim to identify. These factors, however, do not exist in a vacuum, rather, they interact in complex ways forming regional and sectoral influences that significantly impact investment outcomes.

CONCLUSION

This research underlines the intricate dynamics between regional and sector-specific characteristics and their impact on the efficiency of agricultural investments within the European Union. By embracing a systemic approach that incorporates variability across regions and sectors, this study demonstrates a more precise understanding of investments' impacts on comparative cost efficiency.

The robustness of these findings is underscored by rigorous statistical analyses, including Data Envelopment Analysis (DEA) and logistic regression, which have provided a comprehensive view of the efficiency dynamics within the agricultural sectors across the European Union. The high chi-square values and significant p-values observed in Model MB across multiple years indicate superiority of systemic approaches over reductionist ones.

By incorporating advanced metrics such as Pseudo R-squared values and the Area Under the Curve (AUC) analysis, this study has not only highlighted the disparities in agricultural efficiency but also quantified the extent to which regional and sector-specific factors influence these efficiencies. The consistent high AUC values close to 1 for Model MB illustrate its superior predictive power and discrimination ability, validating the impact of regional and sector-specific variations on comparative cost efficiency in agriculture.

These statistical insights have profound implications for policy-making. The analysis shows that adopting uniform agricultural policies may overlook critical regional and sector-specific nuances, potentially leading to suboptimal outcomes. Therefore, tailored strategies that account for the distinct characteristics of each region and sector are essential for enhancing agricultural efficiency. Such policies should support flexibility in investment, fostering adaptive strategies that align with specific regional and sectoral needs. Furthermore, the findings advocate for considering system aspects of agricultural investments and incorporating systems thinking into evaluation. Confirmed by the research outcomes, system approach in evaluation help ensure more accurate and meaningful assessments of investments, interventions, and their impacts. Ultimately, this study calls for a paradigm shift towards a more integrative and holistic approach in agricultural policy design and implementation.

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