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Systemic Competitiveness in the EU Cereal Value Chain: A Network Perspective for Policy Alignment

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Abstract: This research explores the systemic nature of competitiveness within the cereal sector of the European Union (EU) and addresses the structural interdependencies among key competitiveness drivers through a network-based model. The goal of this research is to offer policy alignment solutions based on the empirical findings derived from a sparse Gaussian graphical model that was operationalized to identify conditional dependencies, synergies, and decouplings across five dimensions: factor endowments, self-sufficiency, trade strategy, resource productivity, and environmental impact. The results showed systemic vulnerabilities, including the decoupling of factor endowments from strategic trade specialization, a pronounced East–West productivity divide, and the asymmetry between the economic valorization of harvested land and its environmental impact, reflected in land management practices. Research findings underscore the need for synergy-driven strategies to coherently align agricultural competitiveness outcomes with the economic and structural potential of each EU country. A critical policy incongruency has been identified: the current prioritization of ecological performance under the Common Agricultural Policy overlooks essential agricultural infrastructural disparities, thereby perpetuating competitiveness asymmetries across the Union. In response, this study introduces a systemic amelioration framework designed to reconcile environmental priorities with agricultural infrastructure development, fostering cohesive and resilient competitiveness throughout the EU cereal sector.

Keywords: network analysis; interdependencies; sustainability; value chain governance; trade strategy; structural alignment; sparse Gaussian graphical model

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1. Introduction

Competitiveness lies at the core of economic and policy debates, particularly within the European Union (EU), amid shifting global food supply dynamics, coupled with the trade-off-laden policy agendas of the Common Agricultural Policy (CAP). Policy design in the agri-food sector is inherently complex—it must reconcile global trade realignments, market volatility, sustainability exigencies, and other elements. Within this evolving and highly complex setting, the EU cereal market stands at a critical juncture—it serves as a key pillar of global food security, striving to meet the world's cereal demand, while also attempting to be competitive amid the imperatives of population growth, supply disruptions or reconfigurations, ecological commitments, and other factors of influence. As they are insufficiently understood, competitiveness drivers require more holistic analyses of systemic interdependence, focused on synergies and asymmetries. If not properly approached, they can lead to ineffective socio-economic outcomes and condition competitiveness, which is neither intrinsic nor static. Incoherence between legislation and disruptive market dynamics can also harm competitiveness by creating regulatory inconsistencies and misaligned incentives for divergent objectives, which can also be interpreted as ignoring systemic interdependency. Thus, conducting research on the systematic nature of the competitiveness drivers is imperative for fostering resilient, equitable, and sustainable cereal value chains.

The urgency of revisiting competitiveness in the EU cereal sector is justified by the confluence of global crises that have disrupted cereal supply chains globally. Particularly, the COVID-19 pandemic and geopolitical conflict in Ukraine have exposed the fragility of cereal supply networks [1], with high market volatility [2–4] being only one of the major consequences. The rerouting of Ukrainian cereal exports contributing to the downward pressure on cereal prices in global markets was observed, as well as the emergence of environmental regulatory disparities [5,6]. Intense price competition exacerbated market imbalances [7,8]. Beyond geopolitical pressures, structural transformations within the cereal sector are further reshaping its competitiveness dynamics. The emergence of biomass-driven businesses complicates conventional assessment frameworks, as trade-offs between food, energy, and environmental sustainability must also be accounted for in the framework [9]. Driven by the EU decarbonization policies, the biofuel and biomass industries have exacerbated price volatility in cereal markets [10–12]. New complexity layers have thus emerged, cereals being no longer considered for their food security contribution solely, but as critical inputs for the energy transition [13–15]. Consequently, this has profound implications for both competitiveness and food security.

The challenges briefly described thus far underscore the complexity of assessing competitiveness within the cereal sector. Traditionally, competitiveness was measured by resorting to metrics specific to trade specialization, export performance, trade balances, and productivity-based advantages [16–20], just to name a few. However, many research frameworks overlook systemic interdependencies, isolating competitiveness drivers and failing to capture the interconnectedness dimension. Although regression and structural equation modeling have been employed in the literature, these models often assume linear relationships between variables [21–26]. This is problematic because these types of models do not account for the systemic interdependence of the competitiveness drivers.

More recent studies have attempted to overcome the limitations of traditional regression-based modeling by employing network-based methodologies, agent-based modeling, and machine learning techniques, which respect the nonlinearities specific to the agri-food system's drivers of competitiveness [27]. For example, a Bayesian network was constructed to study crop area planning optimization for enhanced competitiveness, while also accounting for systemic influencing factors [28]. Similarly, other machine learning applications [29] were employed to analyze the synergies between physical, biological, and sensory-related indicators that influence crop productivity, in an attempt to maximize positive outcomes. Congruent with this type of approach, Mehra et al. [30] constructed Bayesian networks to predict the appropriate control actions for hydroponics systems to work in synergy with the crop agronomic characteristics.

However, despite significant methodological advancements, most research in this field remains fragmented. While some studies deliberately exclude systemic interactions due to their specific research scope, other competitiveness assessment frameworks are designed in a way that particular drivers tend to be isolated or even omitted, hence their synergies and trade-offs are not accounted for. This leads to limited dimensional assessments. Consequently, such research frameworks provide only partial insights, neglecting that competitiveness is not shaped only by intrinsic market parameters. From this shortfall, a research gap emerges: the need for a holistic research instrument capable of integrating the dynamic interconnections between competitiveness drivers—a tool that accounts for their synergies, trade-offs, and structural asymmetries.

In response to this gap, the goal of this research is to offer policy alignment solutions based on the empirical findings derived from a sparse Gaussian graphical model that was designed and operationalized for identifying conditional dependencies, synergies, and decouplings across five dimensions: factor endowments, self-sufficiency, trade strategy, resource productivity, and environmental impact. Moreover, this study contributes novel insights into the structural interdependencies among competitiveness drivers, revealing systemic misalignments that hinder the efficient integration of resources, trade strategies, productivity outcomes, and environmental sustainability across EU countries. Findings support decision-makers in formulating synergistic strategies that sustainably and resiliently enhance competitiveness. Informing CAP reforms, this research proposes targeted systemic policy interventions to address these structural distortions and mitigate competitiveness asymmetries, particularly those arising from policy inefficiencies.

The remainder of this paper is structured as follows: the Introduction continues with the development of the conceptual framework. Section 2 focuses, among other aspects, on data—its sources, structuring, and processing procedures. The rationale behind the research method selection is also presented, followed by the details concerning model operationalization. Section 3 covers the empirical research results, highlighting systemic interdependencies, decoupled relationships, and competitiveness asymmetries across the EU cereal sector. Section 4 was dedicated to the critical and analytical assessment of both the convergence and divergence of the findings in relation to existing literature. The study's methodological and empirical contributions are outlined, as well as key policy implications aimed at enhancing systemic competitiveness within the EU cereal sector. Finally, key insights are synthesized in Section 5, Conclusions, presenting the theoretical contributions of this study, its limitations, and potential future research avenues.

The Conceptual Framework

This subsection develops the conceptual framework of the proposed competitiveness model by mapping the key drivers of competitiveness within and across five categories of influence, critically justifying their inclusion in the analytical framework. Figure 1 was designed to offer a visual representation of the proposed competitiveness model.

At the core of this model are Factor endowments, which serve as a fundamental precondition, since adequate land resources and production capacity are indispensable to achieving sustainable competitiveness [31–34]. All other competitiveness drivers are contingent upon factor endowments. Other factors constraining competitiveness are self-sufficiency-related pressures (Category B) [35,36]. In an increasingly volatile global trade environment specific to the agri-food sector [37–39], self-sufficiency-driven policies condition competitiveness by shielding domestic supply chains from external shocks through various market positioning strategies.

The adjacent dimensions do shape competitiveness as well, but their effectiveness is conditioned by the performance of Categories A and B. To detail, Category C evaluates a country's ability to strategically leverage its cereal domestic production valuation system, even if complemented by imports. Then, Category D assesses competitiveness with the study of how efficiently available inputs are converted into outputs. Finally, Category E incorporates long-term environmental considerations, ensuring that competitiveness does not come at the expense of ecological stability. Although the visual representation of the model might suggest a strict multi-layered structure in which Category A appears more important than B, and B more important than C, D, and E, this framework does not impose a rigid hierarchical ordering in terms of relative importance. On the contrary, the aim was to highlight the sequential and interdependent nature of competitiveness drivers.

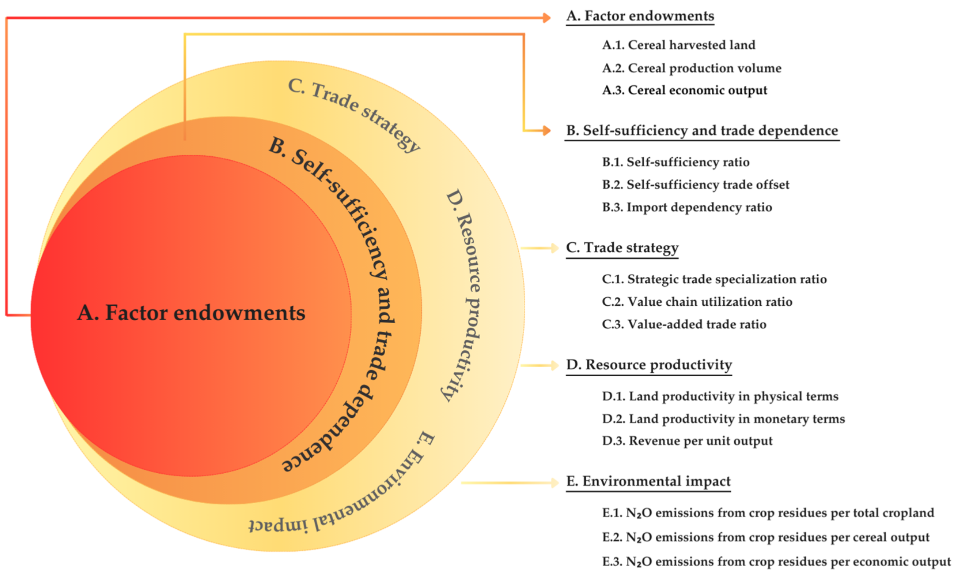


Figure 1. The author's conceptual design of the competitiveness model.

At the core of agricultural competitiveness resides Factor endowments (Category A), as, regardless of the availability of productive resources and output capacity, constructing a sustainable, competitive, and resilient agri-food system would be impossible [40,41]. Cereal harvested land (A.1) and production volume (A.2) stand as critical indicators of any agricultural system's capacity, shaping cereal availability and influencing the extent of development in the global market [42]. The assessment of cereal economic output (A.3) extends the scope of simple physical production counts by adding the gross production value of cereals into the competitiveness equation. This indicator reflects the alignment of domestic output levels with market conditions, price fluctuations, and value generation within the cereal sector [43,44]. The assessment of factor endowments covers land availability, output performance, and economic valuation, making it an appropriate evaluation framework for resource-based competitiveness. However, a limitation of this assessment framework is that it does not account for additional drivers of competitiveness from a factor-endowment-specific perspective. There is a growing body of literature assessing the influence of other factor endowments—such as labor availability, infrastructure, technological advancements, know-how, smart farming, and AI-driven automation techniques, among others—on delivering agricultural competitiveness [45–49]. Although they can be significant factors of influence, this framework is deliberately focused on land availability and production capacity as the fundamental drivers of competitiveness within the factor endowment category. The literature showed that achieving resilient and economically sustainable competitiveness is inseparable from strong market expansion prospects, which cannot be realized without adequate foundational resources [50–53]. In line with the literature, the indicator selection for Category A supports the premise that land and production capacity form the backbone of any healthy agricultural system, upon which other competitiveness drivers can build.

Complementing the Factor endowments category, Self-sufficiency and trade dependence (Category B) is the second category included in the research framework to assess competitiveness through the lens of the balance between domestic production and reliance on external markets. While factor endowments (especially the production capacity) can be viewed as the first layer of competitiveness that influences a country's potential for self-sufficiency, incorporating trade positioning elements into the model of competitiveness adds more profound layers. From this angle, competitiveness is assessed based on the agri-food system's capacity for the domestic output to be sufficient to meet the domestic demand without resorting to imports [54]. The self-sufficiency ratio (B.1) was included to measure the extent of self-reliance—higher ratios signal competitiveness achieved through greater domestic capacities, while lower ratios signal poor competitiveness due to the trade risks that emerge from the degree of import exposure. However, the economic reality is more complex. Production data alone does not account for the destination of surplus output: self-sufficiency or export, thus making it necessary for the inclusion of trade-based measures in Category B. The self-sufficiency trade offset (B.2) addresses this challenge by focusing on the net trade balance, computed as the difference between cereal exports and imports [55]. Positive offsets can suggest self-sufficiency potential, while negative offsets signal cereal import reliance, introducing competitiveness vulnerabilities as domestic production falls short of demand and external supply dependence can be observed. B.2 alone is not sufficient to measure self-sufficiency, as a country may have positive offsets while still relying on cereal imports for domestic consumption. Yet, B.2 assesses production surplus relative to trade flows and identifies competitiveness through the lens of the extent to which domestic output meets market needs beyond simple production ratios [56–58]. To further contextualize the second layer of competitiveness (Category B), the import dependency ratio (B.3) was included in the model to explicitly assess external market reliance. Competitiveness can be undermined by high import dependency ratios, which indicate greater exposure to global market fluctuations, trade restrictions, and supply chain risks. Lower ratios translate into stronger competitiveness. It is acknowledged in the literature that import reliance per se does not necessarily lead to weak competitiveness [59–61], as strategic imports can actually improve market efficiency, diversity, and trade specialization. With the integration of these indicators in the research framework, category B offers an all-around view of the dynamics between self-sufficiency and trade patterns, approached through the lens of competitiveness.

The competitiveness model is extended beyond factor endowments (Category A) and self-sufficiency dynamics (Category B) with the integration of the third category of influence (C), specific to strategic market positioning and value chain integration. A well-thought-out trade strategy enhances competitiveness by focusing on exporting high-value processed cereals utilizing domestic production resources and/or imports of raw cereal, which ensures internally retained economic benefits [62]. However, when processing capabilities are insufficient or absent, the potential economic benefits remain unrealized. The barriers are carefully examined in the literature: inefficient and/or outdated irrigation systems [63–65], lack of investments in technology [66–68], and weak logistic integration [69–71] are just a few of the deficiencies that hinder the maximization of value retention. On top of that, such challenges can even entertain vicious circles, such as exporting significant volumes of raw cereals while importing high-value processed cereal-based products [72], which deepens trade imbalances, limits value chain development, and ultimately causes competitiveness to leak in favor of exploitative trade patterns. To align with this vision, indicator C.1 was designed and integrated into the model as a proxy for strategic trade specialization, measuring the Balassa index of processed cereals relative to that of raw cereals. Subsequently, C.2 and C.3 were integrated to enlarge the trade strategy angle with value chain-oriented metrics. Specifically, C.2 quantifies a country's ability to retain value within its agricultural sector by capitalizing on domestic or imported raw cereals, while C.3 measures strategic trade prioritization (the ratio between high-margin cereal-based product exports to that of lower-value raw cereal exports). Thus, the third layer of the competitiveness model accentuates the fact that trade outcomes are not incidental, but that they rather reflect strategic choices [73,74]. Value-added-driven cereal chains are not competitive only due to production capabilities, but also through strategy. Failing to develop fruitful trade patterns in the spirit of strategic choices can cause countries to become vulnerable to market volatility and external dependencies. By integrating C.1, C.2, and C.3 in this research framework, competitiveness is assessed not only through trade outcomes but also through the strategic choices that shape them.

The first three layers of the competitiveness model are expanded with the analysis of resource productivity, which is specific to Category D. While resource availability, self-sufficiency patterns, and trade strategy shape competitiveness, converting resources into output and economic value in a highly efficient manner can also drive competitiveness [75,76]. Thus, indicator D.1 was introduced to measure cereal yield per hectare, capturing the physical efficiency of land use. Then, D.2 adds another dimension to the assessment of productivity by integrating market conditions into the research framework. D.2 quantifies the impact of technology, inputs, know-how, and agronomic practices on agricultural efficiency. More specifically, it looks at the gross production value per hectare. D.3 complements D.1 and D.2 by focusing on the revenue generated per ton of cereal, providing additional insight into the efficiency of monetizing domestic agricultural production. Consequently, Category D assesses the relationship between resource productivity and competitiveness, stressing that efficiency-related challenges limit the ability to capitalize on competitive advantages, reinforcing structural inefficiencies and market vulnerabilities [77,78].

Factor endowments, self-sufficiency, trade strategy, and productivity can all lead to competitiveness if approached optimally. However, it becomes more of a challenge when aiming for both sustainability and competitiveness–this requires the proper integration of another dimension into the model, specific to the measurement of Environmental impact (Category E). Adding this into the equation ensures that competitiveness aligns well with the three pillars of sustainability: social, economic, and environmental [79–82]. Competitive agri-food value chains must demonstrate the capacity to be resilient in the face of emerging environmental constraints, regulatory pressures, and ecological risks [83–86]. In harmony with the literature, indicators E.1–E.2 assess the trade-offs between agricultural productivity, economic performance and environmental impact. E.1 quantifies N_2O emissions from crop residues relative to harvested land, which is an approach focused on assessing the environmental impact of harvesting cereals. Lower indicator values signal competitiveness achieved through the environmentally sustainable manner of managing fertilizer use and crop residue disposal, which translates into minimizing their impact on greenhouse gas emissions and soil degradation. While other indicators could have been integrated into the framework of assessing the environmental sustainability dimension of cereal competitiveness, the selection of N_2O mainly resides in the following arguments: (1) among non-synthetic greenhouse gases, N_2O emissions are the most powerful in terms of their global warming potential on a per-molecule basis [87]; (2) agriculture generates 75% of total anthropogenic N_2O emissions, which accounts for utilizing nitrogen fertilizer, organic residue decomposition, and other livestock activities [88]; (3) by isolating crop residue emissions, it is ensured that variations in environmental performance are directly tied to cereal production rather than external farming inputs. Indicator E.2 refines the assessment by measuring N_2O emissions from crop residues per ton of cereal output. E.3 links N_2O emissions to the economic value generated from cereal production, therefore complementing Category C with an evaluation of cereal production systems to generate sufficient returns to justify their environmental costs. As cereal production might intensify to meet the growing market demands [89], it is imperative to raise sustainability concerns from an environmental perspective [90–92]. By integrating E.1, E.2, and E.3 into the competitiveness model, the research framework aligns with the directive lines instilled in the European Green Deal [93], which, among other environmental priorities, targets the ecological transformation of EU agri-food value chains. E.1, E.2, and E.3 are more than assessment instruments of environmental compliance; they construct a pillar of ecological competitiveness directly tied to agricultural factor endowments and the resilience of the cereal market. The previous four dimensions of competitiveness, rooted in traditional economic and market-driven literature perspectives, are now 'clothed' with an ecological dimension that ensures that competitiveness is pursued, minimizing environmental impact.

2. Materials and Methods

In line with the research objective, competitiveness was technically approached from the perspective of five main categories that shape it: (A) factor endowments, (B) self-sufficiency, (C) trade strategy, (D) resource productivity, and (E) environmental impact. Three indicators per category were included in the research framework, as described in Table 1. These indicators served as proxies for assessing the overall competitiveness at the level of each EU member state. Data required to integrate non-trade-related indicators (categories A, D, and E) into the research framework were extracted from FAOSTAT's database in February 2025, while trade-related data (for categories B and C) were retrieved from the International Trade Center (Intracen) during the same period. Regarding the data structure, three major cereal crops were included in the framework: wheat, barley, and maize, which collectively accounted for approximately 90% of the EU's total cereal export value in 2023. Spanning from 2012 to 2023, the datasets include all the EU member states.

Table 1. List of indicators utilized to assess competitiveness.

Category	Indicators	Technical Notes
A. Factor endowments	A.1. Cereal harvested land	Measured in hectares
	A.2. Cereal production volume	Measured in t (metric tons)
	A.3. Cereal economic output	Measured in gross production value (constant 2014–2016 US$)
B. Self-sufficiency and trade dependence	B.1. Self-sufficiency ratio	Computed as the ratio of cereal production (t) to the total domestic supply, defined as the sum of production (t) and imports (t) minus exports (t)
	B.2. Self-sufficiency trade offset	Computed as the difference between cereal exports (t) and cereal imports (t)
	B.3. Import dependency ratio	Computed as the ratio of cereal imports (t) to total domestic supply, defined as the sum of production (t) and imports (t) minus exports (t)
C. Trade strategy	C.1. Strategic trade specialization ratio	Computed as the ratio of the Balassa index (RCA) for processed cereals to the Balassa index (RCA) for raw cereals
	C.2. Value chain utilization ratio	Computed as the ratio of the export value of processed cereal products to the sum of the gross production value of raw cereals and their imports, minus their exports, all expressed in US$
	C.3. Value-added trade ratio	Computed as the ratio of the processed cereal exports and raw cereal exports in US$

Table 1. *Cont.*

Category		Indicators	Technical Notes
D.	Resource productivity	D.1. Land productivity in physical terms	Computed as the ratio of A.2 to A.1 (t per hectare)
		D.2. Land productivity in monetary terms	Computed as the ratio of A.3 to A.1 (US$ per hectare)
		D.3. Revenue per unit output	Computed as the ratio of A.3 to A.2 (US$ per t)
E.	Environmental impact	E.1. N_2O emissions from crop residues per total cropland	Measured in kt (kilotons) per total cropland
		E.2. N_2O emissions from crop residues per cereal output	Measured in kt (kilotons) per t
		E.3. N_2O emissions from crop residues per economic output	Measured in kt (kilotons) per US$

Raw data were extracted from FAOSTAT [94] and Trade Map [95].

Balassa's trade competitiveness index [96] was adapted to fit the specific needs of this research and computed as described in Equation (1). The refined version is focused on the study of EU member state competitiveness within the Union, aiming to capture structural asymmetries within the EU cereal value chain. Unlike the traditional Balassa index, which quantifies national export performance relative to the global market, the adapted version proposed in this paper is dedicated to the intra-EU competitiveness assessment.

$$Balassa\ Index = \frac{\left(X_{ij}/X_{EUj}\right)}{\left(X_{iAGRI}/X_{EUAGRI}\right)} \tag{1}$$

In Equation (1), X_{ij} represents the export of the cereal product *j* (wheat, barley, or maize) from the country *i*, X_{EUj} represents the total EU exports of product *j*, X_{iAGRI} represents the exports from country *i* of all agri-food products, and X_{EUAGRI} represents the EU's total agri-food exports. Indices values should be interpreted according to four competitiveness scales: (1) values below 1 indicate the absence of comparative advantage; (2) values scored between 1 and 2 signal marginal comparative advantage; (3) the 3 to 4 bracket is dedicated to moderate competitiveness; and (4) values greater than four demonstrate pronounced comparative advantage.

To ensure comparability across indicators with different units of measurement, the min–max normalization procedure was applied, thereby enabling competitiveness to be studied regardless of the inherent scale differences among indicators. Each of them was standardized for each cereal crop, country, and year by rescaling values within a range of zero (least competitive) to one (most competitive). Through this approach, discrepancies in terms of unit measurement were resolved. The normalized values ($X_{ycp}{'}$) were computed with the formula described in Equation (2):

$$X_{ycp}{'} = \frac{X_{ycp} - min\left(X_{ycp}\right)}{max\left(X_{ycp}\right) - min\left(X_{ycp}\right)} \tag{2}$$

where X_{ycp} represents the raw value of the indicator for a given year (*y*), country (*c*), and cereal product (*p*); min(X_{ycp}) and max(X_{ycp}) denote the minimum and maximum observed values of the indicator across the dataset. Following the normalization procedure, the research framework involved averaging $X_{ycp}{'}$ for each indicator, country, and cereal product. These averages were subsequently aggregated to derive category-specific scores for the five dimensions of competitiveness. An overall competitiveness score was later computed for each country and cereal product as the mean of all category-specific scores.

Serving as logical and essential precursors to the network-based analysis, the initial steps previously described facilitated the identification of a general competitiveness level among the EU member states. To align general competitiveness-related findings with the purpose of this study—to identify asymmetries between the key competitiveness drivers—a sparse Gaussian graphical model was operationalized. This statistical method effectively accommodates the high-dimensional nature of the data [97,98] and goes beyond enabling the analysis of direct relationships established between competitiveness drivers—it captures subtle interdependencies within the network [99]. Unlike conventional statistical techniques employed to study competitiveness drivers under the assumption of linear relationships among variables [100–104], the sparse Gaussian graphical model proposed in this paper differs and adds novel layers to the literature for many reasons. It filters out spurious correlations and identifies meaningful associations of competitiveness drivers by relying on conditional dependencies [105,106]. Aiming to mitigate the risk of model overfitting, a sparse precision matrix was computed, which is also ideal for detecting structural asymmetries and vector dependencies within the EU cereal sector [107].

Building on the research framework introduced above, the network was estimated using EBICglasso (the Extended Bayesian Information Criterion graphical lasso). The rationale behind this choice was that sparsity is enforced simultaneously with the optimization of the model selection through an extended Bayesian information criterion. More precisely, opting for EBICglasso involved inheriting a dual advantage: (1) filtering out spurious correlation through sparsity, and (2) model selection optimization through an extended Bayesian information criterion, thus creating a pathway between network interpretability and statistical robustness. A penalty term is introduced, which means that overfitting risks are mitigated by EBICglasso, preserving significant dependencies. These factors make the method well-suited for the high-dimensional data structure from Table 1.

To improve transparency and reproducibility, this research can be replicated or even extended by following similar data collection and processing techniques. Computations specific to the network analysis were performed using JASP, an open-source statistical software supported by the University of Amsterdam [108]. The network specifications are summarized in Table 2. Regarding possible model extensions or applications, alternative model specifications can be explored to assess different competitiveness dynamics. In addition, datasets can be expanded beyond those collected from the International Trade Center and FAOSTAT to incorporate broader variables and ensure robustness.

Table 2. The configuration summary of the operationalized sparse Gaussian graphical model.

Network Property	Specification
Estimation method	EBICglasso
Tuning parameter (γ)	0.1
Number of nodes	15
Number of non-zero edges	78/105 (74.2%)
Sparsity	0.257

The trade-offs between revealing meaningful relationships among competitiveness drivers and mitigating potential model overfitting risks were mitigated by setting the tuning parameter γ to 0.1. Through this research design, a sufficient level of sparsity was ensured, and the network structure benefits from an exploratory approach. This approach is particularly valuable, as it allows for the study of synergies and asymmetries among the competitiveness drivers with the methodological advantage that the model prevents the inclusion of redundant associations and preserves key interdependencies, balancing interpretability and structural flexibility.

The 15 nodes of the model represent the competitiveness indicators from Table 1. The model's edge density is relatively high (74.2%), suggesting retention of a substantial number of direct relationships while still enforcing sparsity. The moderate sparsity level (0.257) represents a methodological trade-off accepted to balance informativeness and parsimony. Higher sparsity could have potentially triggered the exclusion of meaningful interactions between competitiveness drivers, thereby leading to an overly fragmented representation that could have failed to capture the systemic nature of competitiveness in the EU cereal value chain. Therefore, the chosen sparsity level reflects a calibrated well-acknowledged compromise that facilitates the detection of asymmetries and structural interdependencies among the key influential factors of competitiveness while preventing overfitting and network over-saturation.

Betweenness, closeness, strength, and expected influence are the centrality measures computed for each influence factor of competitiveness. Betweenness reveals which nodes act as bridges for indirect network connections, closeness assesses the degree of integration based on proximity to all other nodes, strength refers to the total influence of a node (summing the weights of its direct connections), and expected influence extends strength measure by incorporating indirect effects, broadening a node's overall impact. Equations (3)–(6) present the mathematical expressions of the operationalized network measures.

$$Betweenness(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \quad (3)$$

$$Closeness(v) = \frac{N-1}{\sum_{u \neq v} d(v,u)} \quad (4)$$

$$Strength(v) = \sum_{u \in N(v)} \omega_{vu} \quad (5)$$

$$Expected\ influence(v) = \sum_{u \in V} \left[(A)_{vu} + \left(A^2\right)_{vu} \right] \quad (6)$$

In Equations (3)–(6), inspired by Freeman's betweenness centrality [109], σ_{st} represents the total number of shortest paths between nodes s and t; $\sigma_{st}(v)$ stands for the number of those shortest paths that pass through node v, N represents the total number of nodes, $d(v, u)$ is the shortest path distance from v to u, ω_{vu} is the weight of the edge between v and u, A captures the network's weight matrix, while A^2 captures the effects of all two-step paths from v. These centrality metrics are specific to network hierarchy, structural bottlenecks, and key leverage points, which translates into the relative influence and connectivity of competitiveness drivers. To complement the centrality measures, the Watts–Strogatz (WS), Barrat, Onnela, and Zhang clustering measures were computed, as presented in Equations (7)–(10). These measures specifically assess local connectivity patterns, weighted link formations, and node heterogeneity within the network.

$$WS(v) = \frac{2 \times number\ of\ links\ between\ neighbors\ of\ v}{k_v(k_v - 1)} \quad (7)$$

$$Barrat\ (v) = \frac{1}{s_v(k_v - 1)} \sum_{j,h} \frac{\omega_{vj} + \omega_{vh}}{2} a_{vj} a_{vh} a_{jh} \quad (8)$$

$$Onnela\ (v) = \frac{1}{k_v(k_v - 1)} \sum_{j,h} \left(\hat{\omega}_{vj} \hat{\omega}_{vh} \hat{\omega}_{jh} \right)^{1/3} \quad (9)$$

$$Zhang\ (v) = \frac{\sum_{j,h} \omega_{vj}\omega_{jh}\omega_{hv}}{\left(\sum_j \omega_{vj}\right)^2 - \sum_j \omega_{vj}^2} \quad (10)$$

In the clustering coefficient Equations (7)–(10), k_v represents the degree of node v (its total number of immediate neighbors), while $s_v = \sum_j \omega_{vj}$ defines the strength of node v. ω_{vj} refers to the weight of the edge between nodes i and j. For binary adjacency, a_{vj}, a_{vh}, and a_{jh} are used, where if it is equal to one, a connection exists between respective nodes, and zero otherwise. In the Onnela measure, normalized weights are used, scaled by the maximum observed weight, and combined through a geometric mean to emphasize strongly correlated triangles. The Zhang coefficient captures weighted clustering by summing the product of edge weights in closed triplets and normalizing this by the variance in the strength distribution of node v.

Beyond the centrality and clustering measures, the network's weight matrix was computed to quantify the strength of conditional dependencies between the drivers of competitiveness. The weight matrix encoded the magnitude of relationships and revealed how strongly each variable influences the others. Higher absolute values signify stronger conditional dependencies, while redundant associations can be observed if values are near zero. The network's topology is reflected in the weight matrix—it acts as a structured representation of the competitiveness network.

Lastly, the Gini index was used to measure competitiveness and dispersion among the countries, aiming to track structural asymmetries and the extent of competitiveness concentration per factor of influence. Equation (11) presents the employed formula:

$$Gini = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} \left| x_i - x_j \right|}{2n^2\overline{x}} \quad (11)$$

where n is the number of countries, x_i and x_j denote competitiveness scores of the i-th country and j-th country, respectively, and $\overline{x}$ is the mean competitiveness score across all countries. The double summation represents the sum of the absolute differences in competitiveness scores for all possible pairs of countries (i, j).

3. Results

3.1. Overview—Main Competitiveness Results

Figure 2 presents a general competitiveness overview of the EU cereal sector in an aggregated manner. The averaged scores are displayed per country and category. The overall mean is depicted by the red dashed line: 1.61, with nearly half of the EU-27 member states surpassing this threshold. Values above the mean indicate stronger competitiveness based on countries' performance across the categories (A–E) that shape competitiveness, while values below the red dashed line reflect deficiencies. The observed disparities highlight systemic asymmetries within the EU, suggesting that competitiveness is driven more by fragmented strengths than by a cohesive, well-aligned framework.

The associated Gini coefficient of the general competitiveness score was calculated to determine dispersion, and the result of 0.17 suggests a moderate degree of endowment in terms of competitiveness across the EU member states within the cereal sector. This dispersion stems from diverse complementarities across key competitiveness influence factors. This uneven performance across different categories is the outcome of underlying structural asymmetries among Union members and decoupled relationships among competitiveness drivers. More specifically, countries scoring high values in one category may not necessarily be as performant in others, hence showing signs of systemic incoherence. As a result, competitiveness in the EU cereal sector is constrained by fragmented strengths rather than competitiveness frameworks built on synergistic principles. Advancing this argument, a critical insight of this overview emerges: although competitiveness appears to be balanced overall at the aggregate level, asymmetric influence factors weaken the EU's cereal value chain in the global markets.

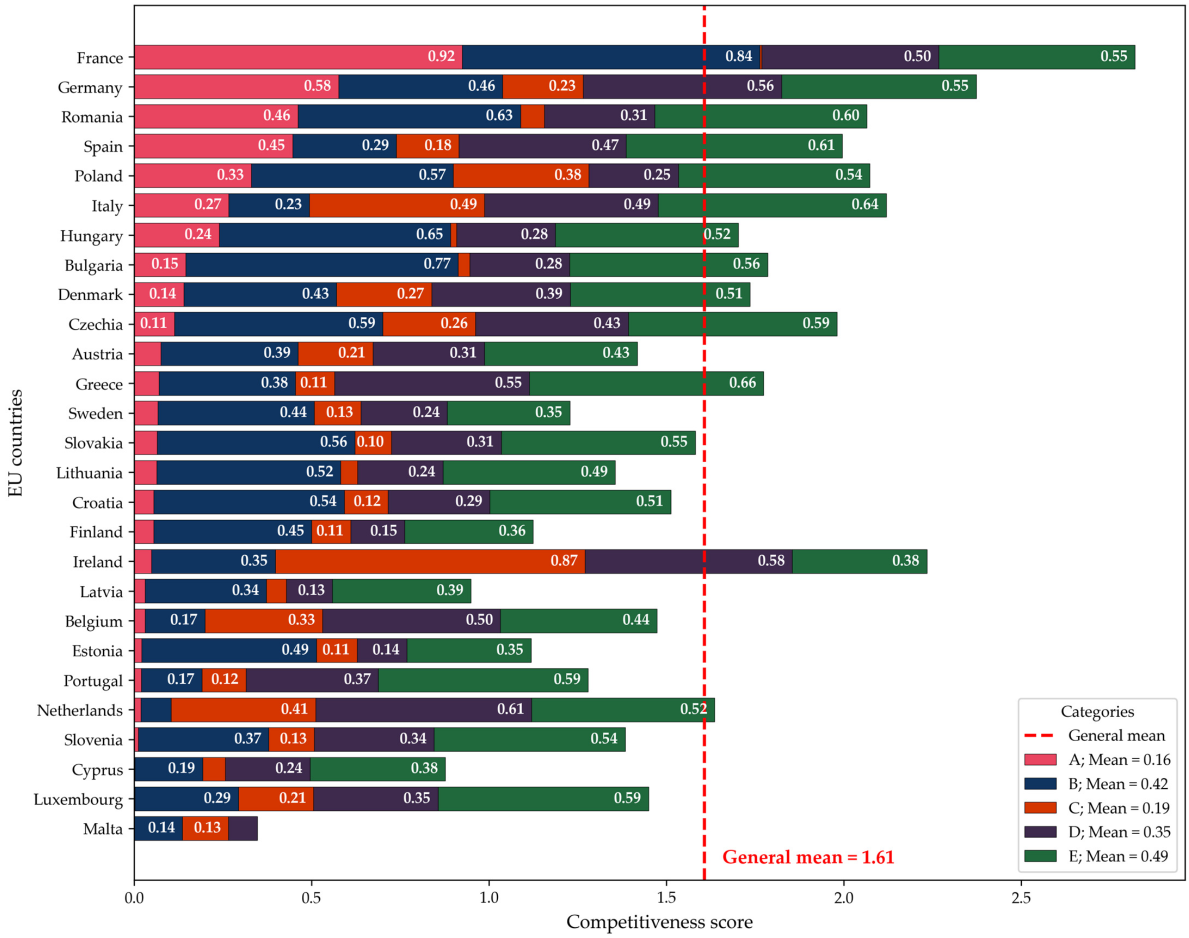


Figure 2. Competitiveness in the EU Cereal Sector: Country-Level Assessment across Five Dimensions of Influence.

Based on the competitiveness framework employed in this research, France emerged as the most competitive country in the EU, achieving the highest overall score, primarily driven by factor endowments (0.92) and a high level of self-sufficiency (0.84), yet with strategic trade representing its main weakness (0.01) within its cereal value chain. Germany benefits from consistent performance across all five competitiveness categories, suggesting a symmetrical alignment of influence factors. Conversely, countries like Ireland (0.77) and Italy (0.49) manifested different forms of competitiveness, which was heavily reliant on trade strategy despite limited raw agricultural endowments (0.05 and 0.27), indicating asymmetry between influence factors, a model dependent on external markets. An opposite pattern was observed in the case of Romania, Hungary, and Bulgaria, whose competitiveness is driven by raw agricultural endowments (0.46, 0.24, and 0,15) and self-sufficiency (0.63, 0.65, and 0.77), but hindered by myopic trade strategies (0.07, 0.02, and 0.03), revealing systemic asymmetries. This configuration translates into untapped agricultural potential and value chain deficiencies. The decoupling of cereal production capacity from strategic trade suggests structural issues in Eastern Europe countries. Poland, a notable exception from the same region, broke the competitiveness patterns of Romania, Hungary, and Bulgaria by better aligning its strategic trade patterns (0.38) with its cereal endowments

(0.33), self-sufficiency (0.57), and environmental impact (0.54), although productivity can still be improved (0.25). Such performance positions Poland closer to Germany's systemic alignment, rather than to its Eastern European counterparts.

Environmental impact registered the highest average score among all categories of influence (0.49), signaling congruence between the Union members in terms of aligning and respecting environmental standards in the cereal sector. These symmetrical results in terms of minimizing environmental impact can be largely attributed to the stringent and harmonized regulations imposed by the CAP. Moreover, these evenly distributed performances aligned through policy also demonstrate that consistency can be achieved despite differences in resource endowments or trade strategies. Thus, a unifying factor in the EU cereal sector's competitiveness landscape is environmental compliance.

Factor endowments scored the lowest overall competitiveness average (0.16), which underlines structural limitations in the EU related to land availability and production capacity. This deficiency represents a fundamental competitiveness limit of the Union, as the potential of productivity and strategic trade is inherently constrained by resource-based limitations. The results specific to the trade strategy category indicate that trade-related factors contribute to competitiveness asymmetries, as some countries outperform in terms of value chain integration and strategic export prioritization despite raw commodity availability. Other countries that possess these endowments fail to optimize their value chain and export strategic cereal-based products, hence missing value retention opportunities. These disparities reflect more than strategic choices; they reflect deeper systemic constraints faced by the EU, spanning logistical challenges, inefficient cereal processing infrastructure, and lack of adaptability. These constraints should gain the attention of decision-makers in an attempt to mitigate the competitiveness asymmetries noticed among the EU member states because they require prompt policy responses.

Resource productivity revealed a distinct East–West divide. Western EU countries (top performers: the Netherlands, Ireland, and Germany) exhibit higher productivity scores, which is the outcome of technological advancement and efficient farming practices. Conversely, Eastern EU countries (low-tier performers: Poland, Hungary, Bulgaria, and Romania), mostly former communist states, lag in productivity performance. As a result of different EU accession timelines and financing opportunities compared to the Western EU counterparts, former communist countries still suffer from agricultural infrastructure gaps. This translates to productivity deficiencies, leading to competitiveness leaks inside the Union. Thus, structural competitiveness asymmetries occur due to the limited capacity to efficiently convert the available agri-resources into high-added-value products at export. As a result, research findings support that the EU should design and implement financing programs for technological modernization in targeted regions. The purpose is to bridge the gap between two competitiveness drivers: resource availability and efficient valuation techniques; the Union could further reinforce resilience and economic sustainability.

While the general competitiveness landscape in the EU cereal value chain is covered in Section 3.1, more in-depth insight is required to comprehensively capture subtle socio-economic, environmental, and policy-level implications of the key alignments and asymmetries identified thus far. The observed complementarities and decouplings across competitiveness categories are proof of systemic interdependencies that cannot be fully revealed through descriptive statistical methods. To address this, in line with the research objective, a sparse Gaussian graphical model was introduced in Section 3.2 for a more nuanced analysis of conditional dependencies and systemic relationships among the drivers of competitiveness. By transitioning to a structural network-based perspective, Section 3.2 maps the complex architecture of competitiveness within the EU cereal sector, peeling back the layers of complexity (reference Figure 1).

3.2. The Sparse Gaussian Graphical Model

Figure 3 represents the network plot of competitiveness drivers, with computation for centrality measures in Table 3 and clustering measures in Table 4. The N_2O emissions from crop residues per total cropland (E.1) scored the highest strength (2.1) and closeness (1.3), which demonstrates that EU environmental regulations provide coherency among countries and competitiveness drivers. Together with land productivity (D.2), which also accounts for high strength (1.3) and expected influence (0.9), E.1 and D.2 are drivers that bring the competitiveness network together, suggesting complementarity, as well as the systemic alignment in terms of yield and environmental competitiveness. Conversely, self-sufficiency metrics are decoupled. Although with high betweenness centrality (1.9 for B.1: the self-sufficiency ratio, and 1.7 for B.2: the self-sufficiency trade offset), the expected influence is negative (−1.55) in the case of B.2. These findings suggest key insights: self-sufficiency facilitates network interactions between otherwise poorly linked drivers (e.g., factor endowments–trade strategy), and surpluses in cereal trade flows or domestic supply sufficiency are not a guarantee of competitiveness, especially if not strategically integrated into high-value trade flows with processed cereals. This decoupling suggests that trade surpluses result in competitiveness leaks, as top B.2 performers fail to capitalize on the potential for value-added cereal processing and high-margin export opportunities. Although CAP has historically fostered production and self-sufficiency, pursuing stable domestic supply, the policy's focus has not been sufficiently complemented by initiatives promoting high-value trade integration. This misalignment has led to cereals being often exported as raw commodities by factor-endowed countries, and the result is structural asymmetry, where resource-rich countries fail to retain value. To further articulate these findings, the moderate centrality (0.38) and expected influence (0.68) of C.3 (value-added trade ratio) contrast trade offsets (B.2), underscoring asymmetries between cereal export surpluses and strategic value retention. The strategic trade specialization ratio (C.1) shows negative strength (−0.25), hence adverse influence on the overall network connectivity.

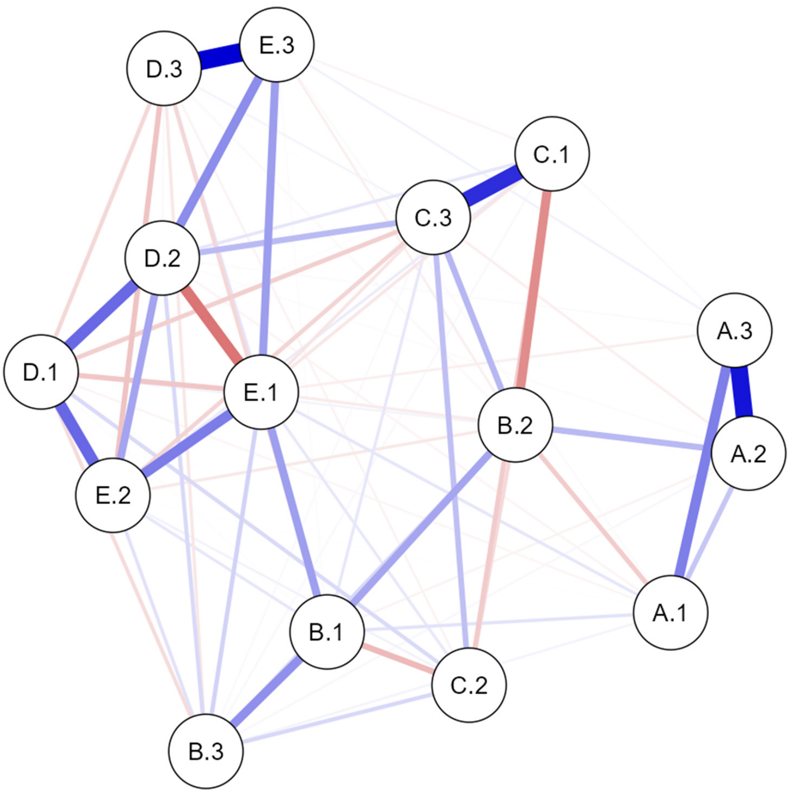


Figure 3. The network plot of competitiveness drivers.

Table 3. Centrality measures per variable.

Variable *	Network			
	Betweenness	**Closeness**	**Strength**	**Expected Influence**
A.1	−0.898	−1.646	−1.551	−0.304
A.2	0.125	−1.011	−0.637	0.83
A.3	−0.812	−1.435	−0.843	1.028
B.1	1.744	1.639	−0.012	0.189
B.2	1.915	0.903	0.336	−1.55
B.3	−0.898	−0.406	−0.96	0.315
C.1	0.295	0.738	−0.251	−1.16
C.2	−0.898	−0.688	−1.358	−1.565
C.3	0.381	0.811	0.765	0.68
D.1	−0.898	−0.231	0.387	−0.467
D.2	0.466	0.777	1.343	0.901
D.3	−0.898	−0.711	−0.19	−0.777
E.1	1.148	1.299	2.099	−0.563
E.2	−0.898	0.081	0.735	0.755
E.3	0.125	−0.12	0.137	1.687

* A.1. Cereal harvested land; A.2. Cereal production volume; A.3. Cereal economic output; B.1. Self-sufficiency ratio; B.2. Self-sufficiency trade offset; B.3. Import dependency ratio; C.1. Strategic trade specialization ratio; C.2. Value chain utilization ratio; C.3. Value-added trade ratio; D.1. Land productivity in physical terms; D.2. Land productivity in monetary terms; D.3. Revenue per unit output; E.1. N_2O emissions from crop residues per total cropland; E.2. N_2O emissions from crop residues per cereal output; E.3. N_2O emissions from crop residues per economic output.

To summarize the findings derived from the centrality measurements (Table 3), E.1 (N_2O emissions from crop residues per total cropland) and D.2 (Land productivity in monetary terms) exhibit the highest strength within the network, followed by C.3 (value-added trade ratio). Strategic trade nodes are decoupled from factor endowment-related nodes, highlighting a paradoxical incongruency: countries rich in cereal resources fail to develop strategic trade pathways, and vice-versa. Within the network, strategic trade specialization is structurally misaligned and functionally underutilized due to the decoupled relationship between factor endowments (A) and trade strategy categories (C).

Extending the insight derived from the centrality measurements, the clustering measurements explore local connectivity patterns. D.2 (Land productivity in monetary terms) and E.1 (N_2O emissions per total cropland) exhibit high clustering coefficients (Barrat: 1.49; WS: 2.29 for D.2), indicating strong local connectivity between nodes, hence competitiveness synergy between monetary-based land productivity and cropland-based environmental efficiency. This relationship is further comparatively explained in Section 3.3.3. Section 3.3.2 deals with another key network relationship C–A, characterized by the fact that cereal production performance is disconnected from strategic trade performance. In Section 3.3.1, C.1 is similarly approached in relation to the self-sufficiency trade offset (B.2), analyzing how misaligned cereal commodity surpluses are prematurely directed to export, instead of being strategically redirected into processing and efficient value chain valorization flows.

Table 4. Clustering measures per variable.

Variable *	Network			
	Barrat	**Onnela**	**WS**	**Zhang**
A.1	−1.005	−1.526	−0.888	1.647
A.2	−2.08	−1.805	−0.202	−0.415
A.3	−0.52	−0.493	0.484	−0.134
B.1	−0.209	0.529	−1.009	−0.239
B.2	1.137	1.53	0.764	1.206
B.3	−0.52	−0.651	−1.391	−1.376
C.1	1.028	0.469	0.484	1.213
C.2	0.098	0.527	−0.919	0.712
C.3	−1.288	−0.951	0.203	−1.624
D.1	−0.079	−0.351	−1.231	0.52
D.2	1.486	1.462	2.285	0.695
D.3	0.285	1.079	1.045	−0.232
E.1	1.08	0.257	0.203	−1.189
E.2	−0.167	0.298	−0.358	−0.917
E.3	0.753	−0.374	0.531	0.133

* A.1. Cereal harvested land; A.2. Cereal production volume; A.3. Cereal economic output; B.1. Self-sufficiency ratio; B.2. Self-sufficiency trade offset; B.3. Import dependency ratio; C.1. Strategic trade specialization ratio; C.2. Value chain utilization ratio; C.3. Value-added trade ratio; D.1. Land productivity in physical terms; D.2. Land productivity in monetary terms; D.3. Revenue per unit output; E.1. N_2O emissions from crop residues per total cropland; E.2. N_2O emissions from crop residues per cereal output; E.3. N_2O emissions from crop residues per economic output.

The weight matrix results (Table 5) further complement these insights by providing a precise measurement of the conditional dependencies between the competitiveness drivers. Their associated absolute weight values indicate the strength of the conditional dependencies. Higher values reveal strong relationships, characterized by the fact that changes in one driver have a great influence on the other, though not necessarily in a strictly proportional manner. In contrast, lower weight values reveal weaker, less influential relationships with marginal impact within the competitiveness network. By reorienting the analysis from magnitude assessment to the study of the relationship direction, this shift calls for greater attention regarding the weight's sign. Positive values are indicative of synergistic relationships, in which the combined effect of two drivers strengthens overall systemic competitiveness rather than operating in isolation, reinforcing mutually beneficial dynamics. Conversely, negative weight values signal a trade-off or decoupling, meaning that an increase in one factor corresponds to an unfavorable reaction in another competitiveness driver, revealing systemic misalignments in the EU cereal value chain, since gains in one competitiveness direction may come at the expense of another. In this research, the observed negative weight (−0.37) between C.1 (strategic trade specialization) and B.2 (self-sufficiency trade offset) confirms drivers' decoupling, further detailed in Section 3.3.1. As expected, competitiveness drivers within the same category displayed strong positive weights, indicating internal category coherence.

Table 5. Weights matrix of the competitiveness drivers.

Variable *	Network														
	A.1	**A.2**	**A.3**	**B.1**	**B.2**	**B.3**	**C.1**	**C.2**	**C.3**	**D.1**	**D.2**	**D.3**	**E.1**	**E.2**	**E.3**
A.1	0.000	0.185	0.424	0.094	−0.164	0.036	0.000	0.000	0.000	−0.029	−0.033	0.000	0.079	−0.003	0.012
A.2	0.185	0.000	0.776	−0.035	0.233	0.023	0.000	0.000	−0.052	0.036	0.010	−0.002	−0.046	0.000	0.000
A.3	0.424	0.776	0.000	0.000	0.000	0.000	0.016	0.000	0.000	0.000	0.013	0.000	−0.052	0.000	0.041
B.1	0.094	−0.035	0.000	0.000	0.294	0.363	0.000	−0.228	0.075	−0.007	0.000	−0.130	0.318	0.076	0.011
B.2	−0.164	0.233	0.000	0.294	0.000	0.130	−0.376	−0.124	0.237	0.000	0.000	−0.020	−0.063	−0.072	−0.048
B.3	0.036	0.023	0.000	0.363	0.130	0.000	0.019	0.130	0.015	−0.115	0.126	−0.081	0.147	0.095	0.000
C.1	0.000	0.000	0.016	0.000	−0.376	0.019	0.000	−0.168	0.695	−0.010	0.083	0.000	−0.081	0.062	−0.034
C.2	0.000	0.000	0.000	−0.228	−0.124	0.130	−0.168	0.000	0.209	0.123	0.000	−0.036	0.073	0.040	0.000
C.3	0.000	−0.052	0.000	0.075	0.237	0.015	0.695	0.209	0.000	−0.155	0.225	0.033	−0.085	−0.139	0.000
D.1	−0.029	0.036	0.000	−0.007	0.000	−0.115	−0.010	0.123	−0.155	0.000	0.496	−0.128	−0.184	0.498	0.000
D.2	−0.033	0.010	0.013	0.000	0.000	0.126	0.083	0.000	0.225	0.496	0.000	0.016	−0.455	0.301	0.376
D.3	0.000	−0.002	0.000	−0.130	−0.020	−0.081	0.000	−0.036	0.033	−0.128	0.016	0.000	0.082	−0.194	0.842
E.1	0.079	−0.046	−0.052	0.318	−0.063	0.147	−0.081	0.073	−0.085	−0.184	−0.455	0.082	0.000	0.428	0.321
E.2	−0.003	0.000	0.000	0.076	−0.072	0.095	0.062	0.040	−0.139	0.498	0.301	−0.194	0.428	0.000	0.000
E.3	0.012	0.000	0.041	0.011	−0.048	0.000	−0.034	0.000	0.000	0.000	0.376	0.842	0.321	0.000	0.000

* A.1. Cereal harvested land; A.2. Cereal production volume; A.3. Cereal economic output; B.1. Self-sufficiency ratio; B.2. Self-sufficiency trade offset; B.3. Import dependency ratio; C.1. Strategic trade specialization ratio; C.2. Value chain utilization ratio; C.3. Value-added trade ratio; D.1. Land productivity in physical terms; D.2. Land productivity in monetary terms; D.3. Revenue per unit output; E.1. N_2O emissions from crop residues per total cropland; E.2. N_2O emissions from crop residues per cereal output; E.3. N_2O emissions from crop residues per economic output.

The network analysis highlighted localized synergies, cross-category misalignments, and critical competitiveness decouplings, notably: the decoupling of self-sufficiency trade offers from strategic trade specialization; the misalignment between trade strategy, in general, and factor endowments; and three other categories (A, D, and E) situated between asymmetry and synergy. To further detail research findings, Section 3.3 was dedicated to the analysis of these three critical relationships, exposing the vulnerabilities of the EU cereal value chain based on the competitiveness drivers' systemic misalignments.

3.3. Revealing Decoupled Competitiveness Drivers Through Asymmetry Analysis

3.3.1. Strategic Trade Specialization (C.1)—Asymmetric with Self-Sufficiency Balance (B.2)

Countries like France, Romania, Hungary, and Bulgaria, despite achieving high self-sufficiency trade surpluses, register minimal strategic trade specialization. Conversely, Ireland, Italy, the Netherlands, Sweden, and Belgium successfully capitalize on strategic trade patterns driven by exports with added-value cereal-based products, with the trade-off of the countries' dependence on raw cereal imports. Figure 4 graphically depicts these dynamics. It illustrates the decoupling of the self-sufficiency trade offset from the patterns of strategic trade in global markets. Future CAP reforms should focus on mitigating the negative effects of these asymmetries by ensuring proper financing instruments for underdeveloped EU cereal value chains to foster technological innovation, knowledge transfer, and efficient marketing strategies for sustainable value chain integration, including but not limited to digitalization and cutting-edge artificial intelligence optimization.

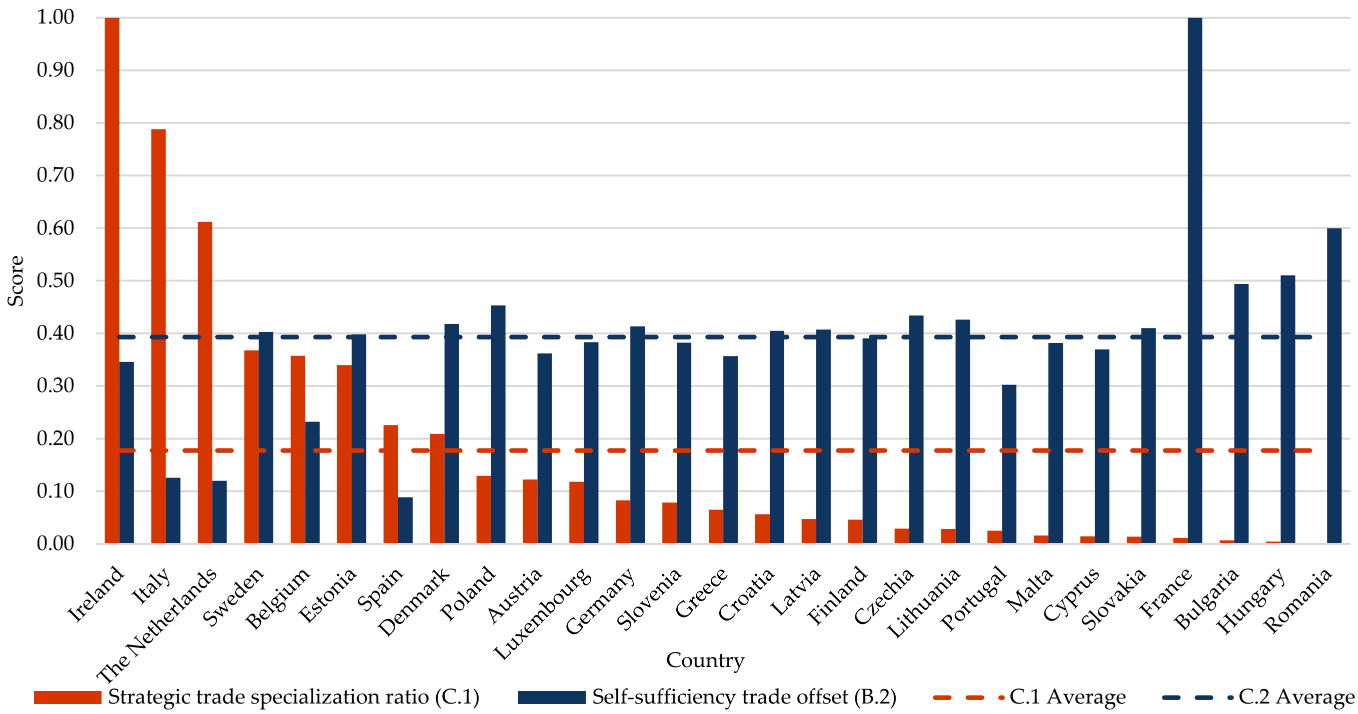


Figure 4. The decoupled relationship between strategic trade specialization and self-sufficiency trade offset.

Regarding the distribution of competitiveness, Gini coefficients were computed. The strategic trade specialization ratio (C.1) registered a higher Gini coefficient (0.62) than the self-sufficiency trade offset (B.2: 0.21), indicating that a small group of countries dominate the EU competitiveness landscape in terms of high-end cereal-based exported products, while the vast majority is inefficient in this regard. While B.2 might suggest a more even distribution of trade offsets, this apparent uniformity masks subtle systemic inefficiencies.

The negative correlation (−0.376) between B.2 and C.1, coupled with the Gini coefficients, shows that significant trade offsets do not automatically translate to high-value exports of cereal-based products, hence the emergence of the decoupling of surplus generation and strategic value-added trade pathways. The inability to synchronize production volumes with strategic trade practices driven by efficient processing capacities represents a major systemic vulnerability identified by the network-based analysis.

3.3.2. Trade Strategy (C)—Misaligned with Factor Endowments (A)

Graphically represented in Figure 5, the relationship between trade strategy (C) and factor endowments (A) reveals a critical structural asymmetry within the EU cereal sector, similar to the one described in Section 3.3.1. Category A follows the same patterns as B.2. Although the Gini coefficients for A (0.59) and C (0.57) suggest comparable levels of internal (EU) competitiveness disparities, they further highlight an aggravating inverse relationship: production potential is not systematically leveraged for strategic trade gains.

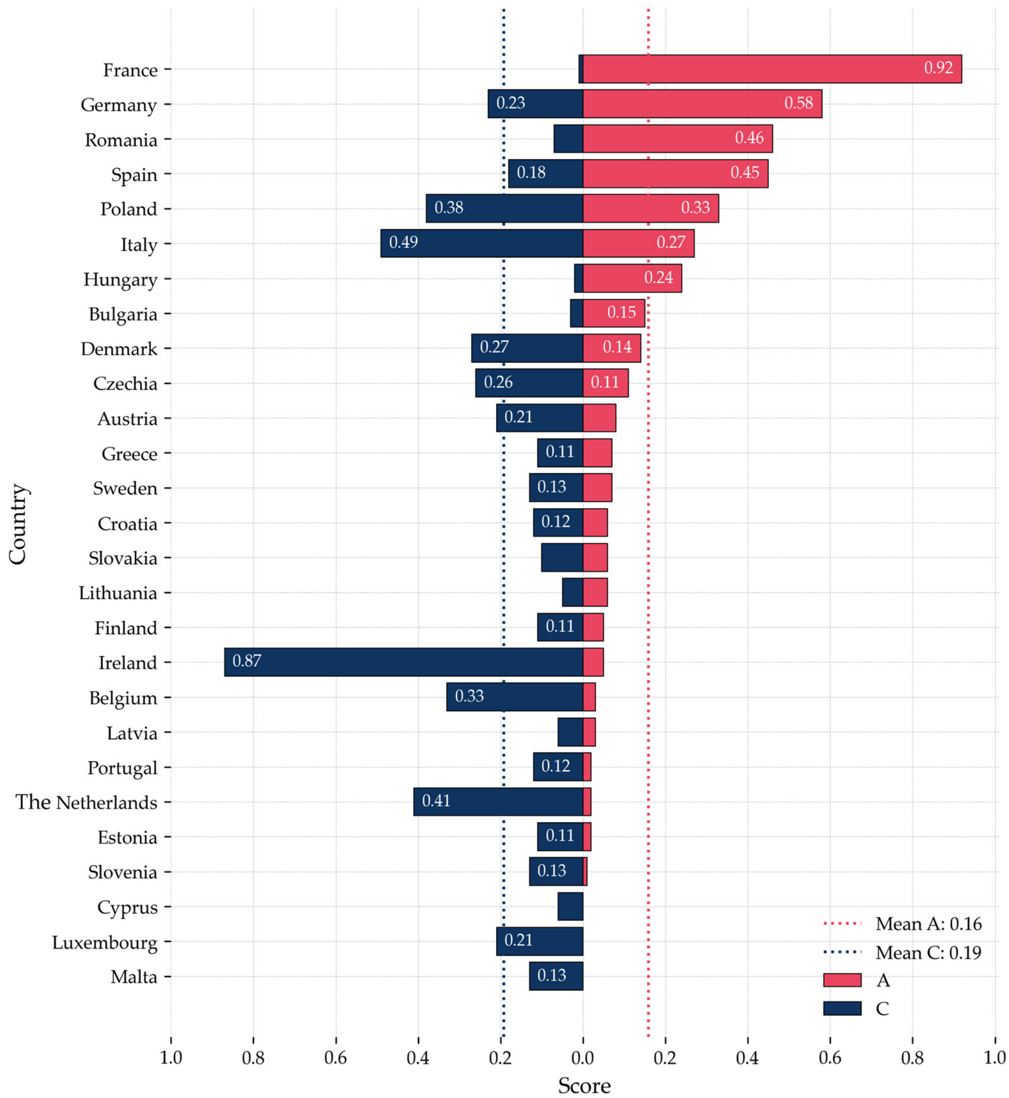
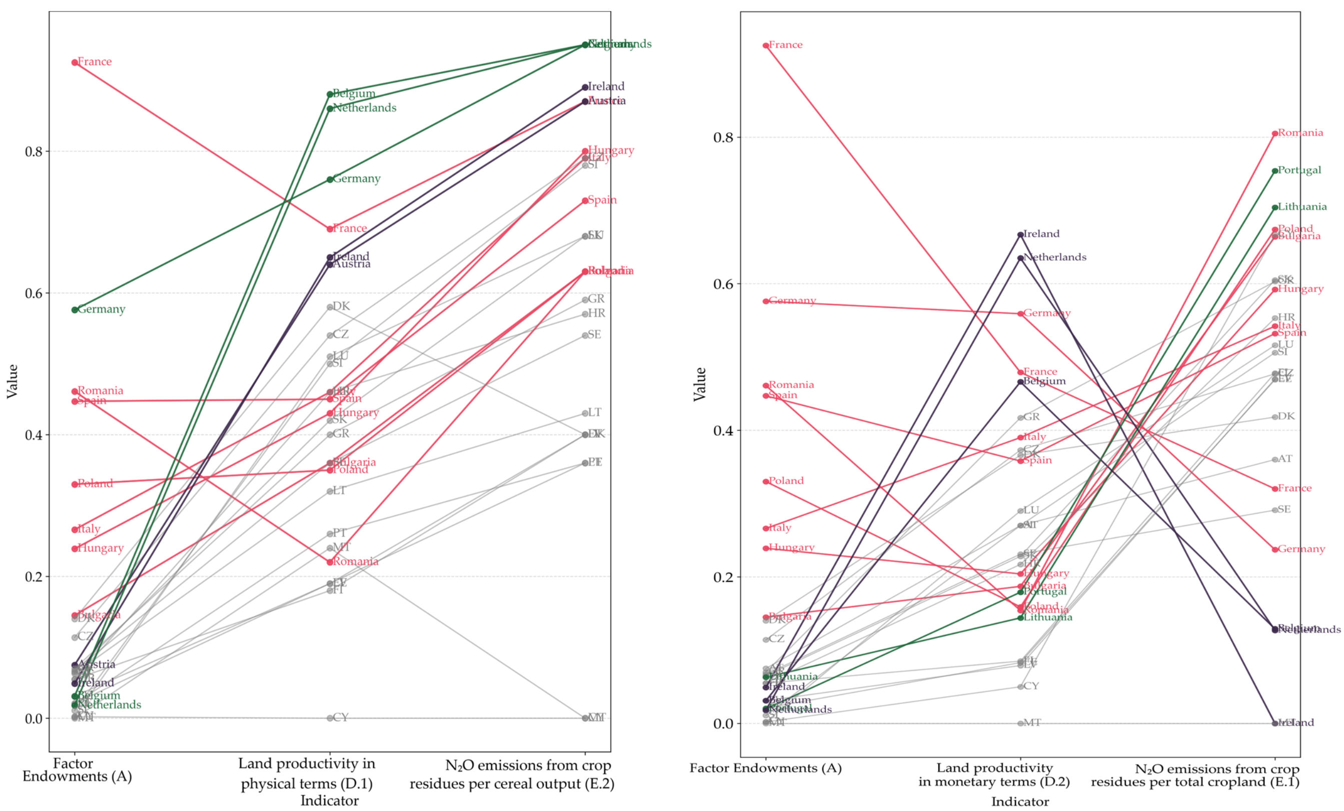


Figure 5. Decoupled competitiveness drivers—Factor endowments (A) and Strategic trade (C).

The policy-driven implications of this decoupling are profound. In line with the EU's objective of structural cohesion, synergistic coordinated strategies should be designed and implemented with the purpose of aligning domestic cereal production capacities with strategic trade. A competitiveness model of dual-speed risks to be perpetuated within the Union, with only a few countries dominating high-margin exports. Without action, the competitiveness fragmentation of the EU cereal market will intensify. Stopping the export of low-value raw cereal will become even more challenging than it already is. Such asymmetries weaken the EU global market positioning, as resource-endowed states are trapped in vicious circles of underutilized potential and value leakage. Expanding upon the CAP recommendations formulated thus far, future policy augmentation should be done by revisiting the criteria governing cereal subsidies, aiming to couple production incentives with performance and strategic trade conditionalities. By doing so, domestic cereal value chains can be developed in harmony with systemic dependencies.

3.3.3. Between Asymmetry and Synergy: Structural Complexity in Factor Endowments (A), Resource Productivity (D), and Environmental Impact (E)

The strong positive weight (0.49) between D.1 (land productivity in physical terms) and E.2 (N_2O emissions per cereal output) signifies systemic congruencies in terms of land use optimization, which translates to producing more cereal output per hectare while achieving lower N_2O emissions per ton of cereal produced, as graphically represented in Figure 6. On the other hand, land productivity in economic terms (D.2) is misaligned with environmentally efficient management of the land harvested with cereals.



(**a**) Decoupled Factor Endowments from the Synergistic Relationship Between Land Productivity in Physical Terms and Environmental Efficiency

(**b**) Decoupled Land Productivity from the Synergistic Relationship Between Factor Endowments and Environmental Impact

Figure 6. Between Asymmetry and Synergy in the case of Factor Endowments, Resource Productivity, and Environmental Impact.

The D.2–E.1 misalignment shows that the economic valorization of the land harvested with cereals is not congruent with land management evaluated based on N_2O emission efficiency. To add more layers to the D.2E.1 relationship, characterized by the highest negative weight (-0.45) within the competitiveness model, factor endowments category A is aligned with environmental performance (E.1), but not with economic productivity (D.2). These results are coherent with the findings presented thus far, suggesting that raw cereal endowments are environmentally compliant yet economically underutilized. Conversely, factor endowments are decoupled from the synergistic relationship between D.1–E.2. This indicates that productivity techniques optimizing cereal output based on the management of land and minimizing N_2O emissions per output unit are employed through knowledge and technology, rather than being simply a function of available land resources. To link these findings with key policy implications, future CAP measures should empower the modernization of agricultural processing infrastructure in resource-rich but economically underperforming regions to mitigate disparities in terms of productivity and ecological efficiency. Precision farming technologies should be expanded to increase yield/hectare while minimizing N_2O emissions per output.

3.4. Robustness Checks

To perform the first type of robustness check, the network's tuning parameter (γ) was changed two times, and the resulting topology changes were examined. In an effort to balance interpretability and sparsity, the original network was estimated using $\gamma = 0.1$. However, for the robustness checks, the tuning parameter was tested at 0.05 and 0.2, reevaluating key structural properties of the network and facilitating sensitivity analysis.

A denser set of retained connections was indicated by the network's lower sparsity (0.2) at $\gamma = 0.05$, with B.2 (self-sufficiency trade offset) becoming more central (0.602). However, the most central nodes were still E.1 (N_2O emissions from crop residues per total cropland) and D.2 (Land productivity in monetary terms), strength: 1.845 and 1.633, respectively, reaffirming their dominant positions within the network. On the other hand, at $\gamma = 0.2$, the network became sparser (0.467), with the most structurally significant drivers not changing despite the network's density reduction: E.1 and D.2 dominated the strength centrality ranking. These findings support robustness by confirming that the fundamental topological characteristics of the network are essentially constant across different sparsity levels. Although lower sparsity settings highlight additional central competitiveness drivers (B.2 and C.3), the most influential nodes—particularly E.1 and D.2—persist at different parameter settings, indicating that the identified synergies, asymmetries, and decouplings are not merely artifacts but rather actual key vectors that reveal various systemic interdependencies within the EU cereal competitiveness network.

The second type of robustness check was performed by changing the estimator from EBICglasso to correlation. While D.2 (Land productivity in monetary terms) retained the highest strength (1.76) within the network and added to the robustness findings, E.1 (N_2O emissions from crop residues per total cropland) declined in centrality, suggesting that its influence is more pronounced when conditional dependencies are explicitly modeled. Conversely, competitiveness drivers specific to the factor endowments category (A.1, A.2, A.3) gained prominence under the correlation-based estimator, with strength values of 0.860, 0.905, and 0.877, respectively. These results reinforce the added value of the sparse Gaussian graphical modeling, as it captures structural interdependencies beyond simple correlations, hence revealing competitiveness synergies and decouplings within the EU cereal sector in a more holistic manner. Other studies that employed different modeling techniques, predominantly econometric models, have reached similar conclusions: land productivity plays a central role in mediating agricultural competitiveness [110–114]. Yet, the network model proposed in this paper expands the scope of econometric modeling by capturing systemic interdependencies that econometric models—whether linear or non-linear—often fail to account for.

4. Discussion

While most results converge with existing literature, others expose inflection points. On a convergence level, factor endowments are reaffirmed as non-substitutable and foundational conditions to attain and maintain sustainable competitiveness [32,115–117]. By integrating efficiency into the competitiveness equation, Western EU member states demonstrated higher productivity than their Eastern EU counterparts, reflecting efficient farming practices and technological advancement, while Eastern EU states are lacking in this regard, largely due to infrastructure gaps, as also identified in the literature [118–121]. The implication is that different historical accession timelines have impacted CAP funding disparities and it continues to perpetuate structural asymmetries within the Union. The different accessibility timelines for funding opportunities are also reflected in trade performances, another key driver of competitiveness. By resorting to modern agricultural infrastructure, Western EU countries strategically outperform in terms of exporting high-added-value cereal-based products, while Eastern EU states are in a vicious circle of exporting raw cereal commodities for immediate economic benefits, lacking efficient processing techniques to fully leverage their potential findings, which are aligned with the literature [122–125]. Moreover, the literature is also convergent with the results of this research regarding the ecological dimension of competitiveness. More precisely, the symmetry of environmental impact scores across EU member states aligns with the CAP role of standardizing environmental regulations [126–128] in a model that ties economic competitiveness with environmental sustainability.

However, findings also challenge existing paradigms. Traditional literature links self-sufficiency as a positive competitiveness indicator [129], referring to reduced dependency on global markets. Results showed that self-sufficiency does not automatically translate to strategic competitive advantages, if not coupled with high-value trade integration. They can, however, both synergically lead to sustainable competitiveness. To further articulate the decoupling of self-sufficiency from strategic competitive advantages, findings showed that strategic trade conditionalities are necessary to mitigate the negative effects that emerged from the nexus of subsidy allocation–cereal production volumes–bulk commodity export, which was shown leading to competitiveness leaks. Moreover, another similar inflection can be identified if comparing the findings with the resource-based view of competitiveness (RBV) [130–132]. Contrary to the RBV rationale, this study uncovered systemic decoupling between factor endowments and strategic trade performance, which, metaphorically, can be described as an "agricultural resource curse", where resource-rich countries are trapped in low-value export cycles and inefficient trade strategies. This resonates with established theories in development economics, where resource abundance can paradoxically hinder strategic growth [133,134]. The empirical results of this research showed that countries like Romania, Hungary, and Bulgaria are endowed with raw agricultural resources, but fail to leverage this advantage into strategic trade gains, conversely to countries like Ireland, with limited agricultural resources and high-yield productivity.

By operationalizing a sparse Gaussian graphical model, this research adds new layers to the literature by revealing how certain competitiveness drivers function synergistically while others operate asymmetrically, reinforcing the need for integrative policy to resolve the vulnerabilities within the EU cereal market. This paper brings its contribution to the theory of systemic competitiveness [135,136] with a strategic departure from traditional linear econometric models to a network model that captures the nonlinear, conditional dependencies among competitiveness drivers. The employed model demonstrates that competitiveness is not a function of isolated performance metrics but an outcome of dynamic interrelations among multiple dimensions of influence. While Zhang and Yang's [137] global agricultural trade network considered endowment, economic, geographical, and institutional factors that influence competitiveness, it did not explore the decoupled nature of factors. This paper advances their approach by revealing subtle yet impactful structural decouplings that affect competitiveness outcomes, which is essential for designing systemic targeted policy interventions.

Zhou and Wen [138] were focused on assessing the competitiveness drivers through the lens of green agricultural development. For this, a spatial association network was constructed to study complex dependencies and interactions among variables. While their work spotlights the value of network-based research methods in capturing systemic relationships, by design, it remains overly focused on sector-specific sustainability. In a similarly narrow scope, Wang et al. [139] operationalized a spatial correlation network to assess competitiveness in 30 Chinese provinces, but their analysis is primarily confined to the impact of agricultural science and technology innovation. Boafowaa Oppong and Tweneboah [140] overcome the shortcoming of Wang et al. [139] by examining the causal effect of global competitiveness and its pillars on the various indicators of the global value chain while also recognizing the complexity of the system. However, research applying network-based modeling to assess systemic competitiveness in agricultural value chains remains scarce, with most studies favoring traditional econometric or trade specialization approaches that overlook structural interdependencies.

Building on these perspectives, this paper advances the field by addressing the lack of systemic, network-based analyses of agricultural competitiveness. Competitiveness drivers are included in a unified network structure that reveals the critical role of decoupled relationships—an area overlooked in existing research. This network-based approach provides a novel systemic lens that captures hidden structural misalignments, offering recommendations to mitigate the systemic vulnerabilities of the EU cereal market.

Lastly, the discussion should address the interplay between policy implementation challenges, market volatility risks, and competitiveness strategy scalability. Although performance-oriented CAP subsidy frameworks could lead to strategic trade patterns for enhanced competitiveness, their implementation is limited by administrative complexity, farmers' resistance, food security concerns, and regional disparities in policy adoption. The misalignment of CAP subsidy distribution with performance outcomes reinforces competitiveness asymmetries across the EU, as subsidies disproportionately benefit certain countries while leaving others at a structural disadvantage. These barriers have broader negative implications—they can exacerbate volatility risks by limiting the adaptability of the EU cereal sector to shocks. Price swings, trade disruptions, and geopolitical unforeseen events can further destabilize competitiveness in the absence of a flexible and well-aligned policy framework, especially for EU countries that heavily rely on CAP subsidies. Additionally, the scalability of competitiveness strategies remains complicated, as policies intended for short-term market stability are not flexible enough to accommodate structural changes in international trade, technological breakthroughs, or sustainability-driven regulatory changes. Consequently, this paper argues for a long-term, systemic approach that integrates dynamic policy adjustments, investment in value-added processing, and diversification of trade networks to enhance both resilience and scalability in the EU cereal sector.

5. Conclusions

This research investigated the systemic nature of competitiveness within the EU cereal sector and focused on the structural interdependencies of the competitiveness drivers. A sparse Gaussian graphical model was designed and operationalized to study synergies, trade-offs, and decouplings across five key categories of influence: factor endowments, self-sufficiency, trade strategy, resource productivity, and environmental impact. Results were utilized to formulate policy recommendations aimed at fostering systemic coherence and enhancing the general level of competitiveness across the EU cereal value chain.

This research advances the theoretical discourse on competitiveness by introducing a systemic network-based assessment framework that captures nonlinear, conditional dependencies among multiple competitiveness drivers. Unlike conventional studies that employ sector-limited frameworks or assume linearity among variables, this research adopted a broader approach, revealing subtle synergies and asymmetries that shape competitiveness. Thus, the conceptual understanding of competitiveness was enriched by treating competitiveness as an outcome of the systemic efficiency and interdependencies among its influencing factors. This research also advances the argument that sustainable competitiveness emerges not from singular strengths but from the coherent alignment and interaction of multiple dimensions. To add more, the study provides a foundation for the CAP to address decoupled relationships by leveraging systemic-driven empirical insights and fostering synergies to enhance the overall competitiveness of the EU cereal sector.

Empirical findings revealed systemic vulnerabilities. High self-sufficiency levels in Eastern European countries are decoupled from strategic trade, causing competitiveness leaks through premature raw commodity exports without value-added processing. This asymmetry stems from a broader misalignment between factor endowments and trade strategies, trapping resource-rich nations in low-value export cycles—an agricultural resource curse. A pronounced East–West productivity divide weakens competitiveness even further, as the vicious circle described is entertained by current CAP reforms that prioritize environmental performance over addressing agricultural infrastructure gaps between high-yielding productive Western EU countries and the lower-yielding Eastern EU counterparts. The empirical findings showed environmental performance symmetry across member states, which is attributed to the CAP's standardizing influence. Although synergies emerged for land use optimization through pathways that maximize the output of cereals while simultaneously minimizing environmental impact, a misalignment was noticed: the economic valorization of the land harvested with cereals is decoupled from ecological land management, evaluated through the lens of N_2O emission efficiency.

The policy implications derived from the empirical findings of this research involve refining the CAP to align cereal production surpluses with high-value trade pathways. This can be achieved through systemic measures, including incentivizing the domestic cereal processing infrastructure and ensuring the economic sustainability of cereal value chains. Moreover, incentives linked with strategic trade conditionalities could prevent value leakage. Thus, raw commodity export dependencies are mitigated through export intensification of high-added-value cereal-based products. Policy implications also refer to the EU East–West productivity divide, which can be ameliorated through targeted CAP financing for technological modernization in Eastern EU states, promoting precision farming and smart agriculture to enhance yield. Regarding environmental-specific policy implications, green productivity synergies can be empowered through incentives that reward economic efficiency aligned with ecological performances that can transform environmental compliance into a competitive advantage.

The conclusions of this study call for pragmatic systemic reforms. Thus, three more interconnected policy prescriptions are proposed in this paper: (1) implementing a cereal trade competitiveness index (CTCI) to link structural deficiencies with access to funding, (2) complementing flat-rate CAP subsidies with universally accessible but scaled cereal innovation bonds to support productivity-enhancing investments on all farms, and (3) establishing a strategic decentralized EU grain buffer stock system with dynamic pricing mechanisms to counteract trade volatility and global supply shocks. CTCI would assess raw vs. high-value cereal exports, aligning CAP investment incentives with structural deficiencies. To achieve cohesion within the Union and to lessen dependency on low-margin trade, EU countries that export more unprocessed cereals than a certain set threshold should receive CAP-backed investment credits, co-financed with private-sector funding, to develop processing infrastructure rather than facing market distortions. The second policy prescription could reform CAP funding instruments while accounting for accessibility across different farm structures. Thus, small farms could receive higher co-financing rates for automation and AI adoption in agricultural activities with lower risk exposure, large agribusinesses could benefit from incentives for technology-sharing, based on their output performance, and cooperative networks could qualify for collective bonds, strengthening shared cereal processing infrastructure and ensuring equitable market access. The third policy prescription could ensure market stability: a decentralized EU grain buffer stock system linked to a dynamic price adjustment fund. Such a system would allow industry actors to be protected from global market trade shocks, with minimal public intervention. These prescriptions would lead to structural shifts across the EU cereal value chain. Small and mid-sized farmers would gain better access to capital for modernizing operations and reducing the risks associated with price volatility. Moreover, agribusinesses would scale up and cooperatives would have new financing pathways to strengthen local processing infrastructure. For traders, these measures would enhance cereal supply predictability by reducing reliance on volatile bulk commodity markets, enabling more stable contract pricing, and mitigating exposure to global price shocks. These policy prescriptions are actionable, but success is highly dependent on effective public-private collaboration and regulatory adaptability integrated into CAP instruments that align incentives with systemic competitiveness objectives. A phased rollout, supported by pilot programs and incremental CAP adjustments, would facilitate a smooth transition from policy prescription to industry adaptation.

While valuable theoretical and empirical findings were drawn from this research, along with detailed policy implications, limitations must be acknowledged, presenting avenues for future research. Firstly, although the analysis incorporated yearly averages from 2012 to 2023, it did not explicitly model temporal dynamics. As a result, year-to-year dynamics, policy impacts, and market shocks were not accounted for, although they do influence competitiveness trajectories. With reference to future research, longitudinal models could address this limitation. Secondly, despite the fact that a robust set of fifteen indicators across five categories of influence were integrated into the sparse Gaussian graphical model, the inclusion of additional variables could further refine the systemic analysis of competitiveness. Factors such as technological innovation rates, soil quality, irrigation system performance, climate change adaptation policies, logistics infrastructure performance, and policy compliance indices could provide an even more comprehensive understanding of the systemic relationships influencing competitiveness outcomes. Moreover, stakeholder perspectives on agricultural policy design and implementation, perceptions of farmers' adaptability, subjective assessments of the efficiency of institutional governance, and the integration of other qualitative-based data into the framework were beyond the scope of this research. Lastly, by design, this research was exclusively focused on the internal competitiveness landscape of the EU cereal value chain. Future studies could expand this framework through comparative analyses with other major cereal-producing regions, contextualizing the EU's performance within the global cereal value chain.

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