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Functional Fragmentation as a Structural Determinant of Agricultural Competitiveness: Evidence from the European Union

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Abstract

Agricultural competitiveness across European Union Member States exhibits persistent disparities that cannot be fully explained by technology, climate exposure or institutional quality in isolation. This study examines whether functional fragmentation—defined as the cumulative simultaneity of biological, technological, managerial and institutional production functions—constitutes a structural determinant of competitiveness over the period 2004–2023. Using harmonized country-level data from FAOSTAT, FADN, WDI, WGI and WMO, we construct a composite competitiveness index and a multiplicative fragmentation index and estimate two-way fixed-effects panel models. Functional fragmentation is negatively associated with competitiveness (β = −3.734, $p < 0.01$). A 10% reduction in fragmentation (ΔFF = −0.042) increases competitiveness by approximately 0.16 index units, corresponding to about 16% of one standard deviation. The interquartile fragmentation gap (ΔFF ≈ 0.18) implies a competitiveness difference of 0.67 units, nearly two-thirds of one standard deviation, indicating economically substantial structural effects. These results indicate that fragmentation primarily shifts the baseline level of performance rather than altering marginal responses to technological intensity or climate shocks. The findings identify functional fragmentation as a structural coordination constraint within EU agriculture and highlight the importance of systemic coherence alongside technological upgrading in competitiveness-oriented policy design.

Keywords: functional fragmentation; agricultural competitiveness; structural constraints; technological intensity; institutional quality; European Union agriculture

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Academic Editor: Carla Ferreira

Received: 23 January 2026
Revised: 16 February 2026
Accepted: 19 February 2026
Published: 24 February 2026

1. Introduction

Agricultural performance continues to exhibit substantial variation across countries despite ongoing technological progress and policy integration [1–3]. Differences in farm size distribution, production specialization, labour organization, and institutional environments remain persistent determinants of productivity and income generation [4,5]. These structural characteristics shape competitive outcomes beyond simple differences in factor endowments or technological intensity.

Within the European Union, agriculture operates under a dense institutional framework combining the Common Agricultural Policy (CAP), single-market regulations, and national governance structures [6–8]. These layers influence production incentives, administrative obligations, technological adoption, and risk-management strategies. At the same time, significant heterogeneity persists between Western and Eastern Member States, reflecting historically path-dependent structural trajectories, uneven technological intensity, and differential exposure to climate variability [9]. These asymmetries suggest that agricultural performance cannot be fully understood through isolated determinants such as technology, subsidies, or institutional quality. Analytical approaches that treat these factors separately risk overlooking how production-related functions are organized within agricultural systems. When policies focus predominantly on input intensification or financial transfers, underlying coordination constraints may remain unaddressed. This contributes to the frequently observed mismatch between technological capacity or policy support and realized performance outcomes. In this context, the present study introduces the concept of functional fragmentation (AFF/SIT Theory) to describe the cumulative coordination demands arising from the concurrent execution of biological, technological, managerial, and institutional tasks inherent in agricultural production. Unlike diversification or general structural complexity, functional fragmentation refers to time-sensitive and non-substitutable production functions embedded in biological systems that must be managed in parallel. The degree to which these domains coexist coherently conditions the transformation of inputs, technologies, and institutional support into competitive performance.

Figure 1 schematically presents the functional architecture underlying the concept of functional fragmentation. The farm holding is positioned at the intersection of four interrelated domains: biological, technological, managerial, and institutional–market—each representing a distinct set of production-related requirements. Biological seasonality and climate sensitivity, technological and equipment demands, managerial task coordination, and regulatory or market obligations operate concurrently within agricultural systems. Functional fragmentation arises from the joint execution of these domains rather than from any single dimension in isolation. While existing research has generated substantial evidence on productivity dynamics, technology adoption, climate impacts, and institutional quality [10–13], these determinants are typically examined within separate analytical frameworks. The present study adopts a system-oriented perspective in which these domains are evaluated jointly in order to capture their combined structural effects.

The objective of this study is to examine how functional fragmentation influences agricultural competitiveness across European Union Member States. Using harmonized country-level data from FAOSTAT, FADN, WDI, WGI, and WMO for the period 2004–2023, the empirical analysis evaluates the relationship between fragmentation, technological intensity, climate anomalies, and competitive performance within a unified modelling framework.

Based on the analytical structure, the study tests the following hypotheses:

H1. *Higher levels of functional fragmentation are associated with lower agricultural competitiveness.*

H2. *The relationship between climate shocks and agricultural competitiveness depends on the level of functional fragmentation.*

H3. *The effect of technological intensity on agricultural competitiveness depends on the level of functional fragmentation.*

Together, these hypotheses provide a structured empirical framework for testing whether functional fragmentation operates as a system-level determinant of agricultural competitiveness within the European Union.

https://doi.org/10.3390/agriculture16050493

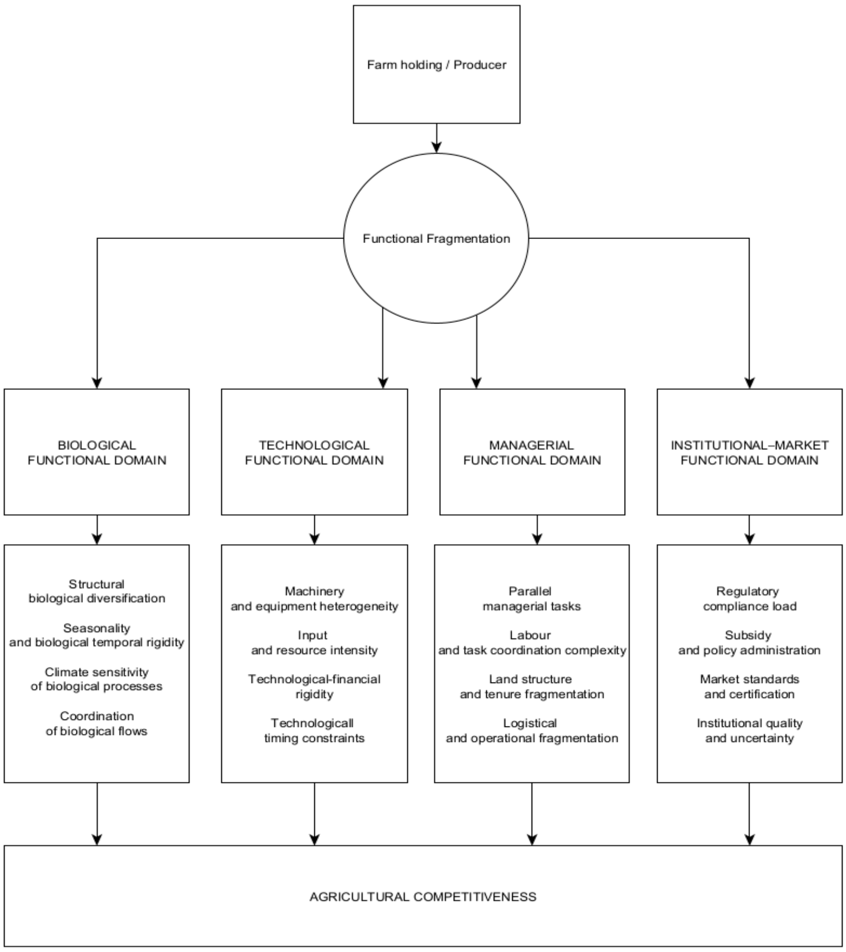

Figure 1. Functional architecture of fragmentation and its domains.

2. Literature Review

The economic analysis of agricultural performance has traditionally been grounded in production theory, where efficiency and competitiveness are understood as outcomes of the optimal allocation of land, labour, and capital under given technological conditions [14]. Subsequent contributions extended this perspective by emphasizing that technological progress and institutional change in agriculture are largely endogenous, shaped by relative factor scarcities and economic incentives rather than occurring as exogenous shocks [15]. While these approaches have provided a robust foundation for analyzing productivity and structural change, they largely interpret agricultural performance through factor–product relationships and marginal adjustments, with limited attention to the biological and organizational characteristics of agricultural production. Later theoretical and empirical work incorporated institutional and governance dimensions, highlighting the role of transaction costs, property rights, and regulatory frameworks in shaping investment decisions, resource allocation, and technology adoption in agriculture [16,17]. From this perspective, institutional quality affects competitiveness by influencing the predictability of the policy environment, administrative burdens, and incentives faced by producers. Parallel strands of literature have focused on risk and uncertainty, particularly climate-related variability, recognizing that agricultural decisions are inherently conditioned by stochastic biological and environmental processes that generate nonlinear economic outcomes [18–20]. A common limitation of these traditional approaches is that they treat key determinants of agricultural performance-technology, institutions, climate and management—as largely separable factors. Such models typically abstract from simultaneity and biological rigidity, assuming that adjustments can be made sequentially or marginally. As a result, they do not capture cumulative coordination burdens that arise when multiple production-related functions must be executed in parallel under time-sensitive biological constraints.

Although these frameworks acknowledge the sector's exposure to climate and biological risks, they typically treat such factors as external shocks rather than examining how internal production structures condition their economic effects. Within this broader literature, agricultural competitiveness has evolved into a multidimensional concept, commonly defined as the ability of the sector to sustain productivity, profitability, and market integration under changing economic and environmental conditions [21,22]. Empirical studies frequently operationalise competitiveness using partial productivity indicators, such as yield per hectare, labour productivity, or income-based measures, often drawing on FAO and farm-accountancy data to analyze cross-country differences [23–25]. Complementarily, total factor productivity (TFP) has been widely employed as a synthetic measure of efficiency and technological change, estimated through growth accounting, production-function approaches, or data envelopment analysis [26].

While these metrics are well established, they capture selected performance dimensions and provide limited insight into the internal organization of agricultural production processes. A growing empirical literature also examines the role of institutions and governance in shaping agricultural outcomes, frequently relying on composite indicators such as the Worldwide Governance Indicators to assess how regulatory quality, government effectiveness, and rule of law affect productivity and income through transaction costs and administrative complexity [27,28]. In parallel, climate-oriented studies increasingly incorporate temperature anomalies, rainfall variability, and extreme events as key determinants of yield volatility and long-term productivity trends [29,30]. Despite the expanding scope of indicators, these empirical approaches typically analyze technological, institutional, and climatic factors separately, without explicitly considering how their simultaneous operation creates cumulative constraints at the system level. Structural analyses of agricultural systems in developed economies, particularly within the European Union, further document persistent heterogeneity in farm structures, productivity levels, and responses to policy incentives [31–33].

2.1. Sustainability-Oriented Frameworks in Agricultural Systems

In recent years, the analysis of agricultural sustainability has increasingly evolved toward circular economy (CE), regenerative agriculture (RA), and Environmental–Social–Governance (ESG) frameworks. These perspectives extend conventional productivity-based approaches by integrating ecological regeneration, resource efficiency, and governance quality into the evaluation of sectoral performance. Circular economy research conceptualizes agricultural systems as interlinked material and energy cycles aimed at minimizing waste, improving input efficiency, and strengthening systemic resilience [34,35]. Empirical applications emphasize nutrient cycling, resource recirculation, and closed-loop production systems [36]. Regenerative agriculture literature places biological processes at the centre of long-term viability, highlighting soil health, biodiversity, ecosystem services, and adaptive capacity under climate stress [37,38]. At the governance level, ESG-oriented research evaluates how environmental standards, institutional stability, transparency, and regulatory quality shape economic and strategic outcomes [39,40]. Together, these strands contribute significantly to the understanding of sustainability in agriculture. They expand the analytical focus beyond input–output efficiency by incorporating ecological conditions, institutional environments, and long-term resilience considerations. In empirical practice, sustainability is commonly operationalized through structured sets of environmental, technological, and governance indicators that are introduced as separate dimensions within composite indices or regression-based performance models. While these frameworks significantly advance the measurement of sustainability performance, they predominantly operationalize environmental and governance attributes as outcome-oriented dimensions. The structural coordination requirements arising from the simultaneous execution of biologically time-bound and institutionally regulated functions remain analytically implicit. Consequently, sustainability metrics and competitiveness models often coexist without an explicit representation of intra-system coordination burden.

However, agricultural production is characterized by the concurrent operation of multiple functionally necessary domains. Biological cycles, technological requirements, managerial coordination, and institutional obligations must be maintained simultaneously under time-sensitive and non-substitutable constraints. While CE, RA, and ESG frameworks measure environmental and governance attributes, they do not explicitly formalize how these domains interact structurally within the production process. The functional fragmentation framework addresses this analytical dimension by modelling the joint execution of biological, technological, managerial, and institutional functions within a unified structural index. Rather than expanding the list of sustainability indicators, it captures the degree to which these domains coexist coherently within agricultural systems. In this sense, functional fragmentation introduces a coordination-based representation of system organization that complements sustainability-oriented metrics and provides an additional structural lens for analyzing competitiveness.

2.2. Existing Approaches to Structural and Coordination Constraints

Several strands of agricultural economics literature have examined structural and coordination-related constraints using indirect empirical proxies. These include diversification indices, measures of farm size distribution and structural heterogeneity, transaction-cost indicators linked to governance quality, and proxies for regulatory or administrative burden. Such measures have been used to explain productivity gaps, technology adoption patterns, and performance differences across regions. Related research streams have also contributed insights into system complexity. The multifunctionality literature emphasizes the coexistence of economic, environmental and social functions in agricultural systems. Complexity-oriented approaches analyze nonlinear interactions between production components, while farm management studies address organizational and decision-making challenges. Bioeconomic models further integrate biological processes with economic optimization.

Although these contributions enrich the understanding of agricultural performance, they generally operationalise structural characteristics through separate indicators. Interactions between biological, technological, managerial and institutional dimensions are typically treated indirectly, rather than as components of a unified empirical construct.

2.3. Conventional Structural Proxies and Specification Limitations

Empirical analyses of agricultural competitiveness commonly rely on observable structural proxies—such as diversification indices, farm size dispersion, governance quality indicators, and technological intensity measures—to approximate underlying coordination and structural constraints. These indicators are typically introduced as separate covariates within additive performance specifications. While empirically tractable, this modelling strategy presumes that each dimension exerts an independent marginal effect on competitiveness. Such separable formulations may be restrictive in agricultural systems where production outcomes depend on the joint functioning of biological, technological, managerial and institutional components. When interdependencies across these domains are not explicitly modelled, estimated coefficients capture both their direct effect and the unobserved influence of cross-domain interaction. Two specification issues arise:

First, coordination effects remain implicit. In proxy-based regressions, fragmentation-related inefficiencies are not directly observed but are partially absorbed by included structural variables. This can lead to coefficient contamination, whereby estimated marginal effects reflect a mixture of input productivity and coordination constraints.

Second, additive specifications assume linear aggregation of structural characteristics. However, when performance depends on the weakest functional dimension or on the interaction among domains, additive proxies may misrepresent the underlying production structure. In such settings, estimated elasticities do not isolate the structural coherence of the system but approximate a reduced-form relationship that conflates level effects with organizational consistency.

In addition, when coordination constraints remain unobserved, part of their negative impact may be mechanically captured by the technological coefficient. In such cases, estimated technological elasticities reflect not only genuine productivity effects but also unmodelled structural inefficiencies, leading to biassed inference regarding the role of technological intensity.

The functional fragmentation approach adopted in this study departs from proxy substitution and instead models structural coherence directly. By constructing a multiplicative index that embeds cross-domain interaction within its aggregation structure, the framework distinguishes technological intensity from coordination integrity. This enables the empirical specification to isolate systemic organization as a separate determinant of competitiveness, rather than treating it as an unobserved residual component of other regressors. Table 1 summarizes the conceptual distinction between conventional proxy specifications and the functional fragmentation approach.

Table 1. Conventional structural proxies versus functional fragmentation.

Indicator	Captured Dimension	Specification Limitation	Fragmentation Approach Contribution
Diversification measures	Output heterogeneity	Does not reflect organizational coherence across domains	Integrates biological and non-biological coordination
Farm size dispersion	Structural heterogeneity	Treated as scale effect, not systemic interaction	Embeds structural dispersion within cumulative interaction
Institutional quality indicators	Governance environment	Modelled as exogenous and separable	Incorporated as functional component of system integrity
Technological intensity	Capital or input depth	May proxy unobserved coordination efficiency	Estimated separately from fragmentation effect

3. Materials and Methods

The research operationalizes AFF/SIT Theory—within a strictly formalized empirical framework that enables quantitative testing of the core structural equation:

$$C = \tau T^{*} e^{-\alpha FF} \tag{1}$$

where C denotes the competitiveness of the agricultural sector, τ is an institutional–market coefficient reflecting the extent to which available technologies and resources are translated into economic outcomes, T^{*} is the biologically feasible maximum of technological efficiency in the absence of functional fragmentation, FF is the index of functional fragmentation, and $\alpha > 0$ is a parameter measuring the strength of the negative impact of fragmentation on competitiveness.

The empirical architecture combines five main data sources: FAOSTAT (agricultural output, areas and inputs), WDI (macroeconomic framework), WGI (institutional environment), FADN (sectoral indicators for farm holdings in the EU), and the WMO (time series of temperature anomalies based on harmonized global temperature products—HadCRUT5, Berkeley Earth and GISTEMP).

The analytical unit is the country–year for EU Member States. For each pair (c, t), where c denotes the country and t the year, we construct: a composite competitiveness index C^{*}_{ct}, a functional fragmentation index FF_{ct}, a climate shock indicator $Shock_{ct}$, a technological intensity indicator $Tech_{ct}$ and an institutional parameter τ, alongside a set of control variables describing the structure of the agricultural sector and the macroeconomic environment. Data from the individual sources are integrated via a common "country–year" key, nominal values are deflated using appropriate WDI deflators, and climate series are expressed as anomalies relative to a standard reference period.

3.1. Measuring Competitiveness

Competitiveness C is treated as a multidimensional phenomenon, encompassing income-based, biophysical and factor–productivity dimensions. At the "farm sector" level by country, we use aggregated FADN indicators describing the representative farm in country c and t. First, we define three income dimensions:

$$C_{ct}^{(inc/ha)} = \frac{\overline{FNI_{ct}}}{\overline{A_{ct}}},\ C_{ct}^{(inc/L)} = \frac{\overline{FFI_{ct}}}{\overline{L_{ct}}},\ C_{ct}^{(margin)} = \frac{\overline{Y}_{ct} - \overline{X}_{ct}}{\overline{A}_{ct}}, \tag{2}$$

where $C_{ct}^{(inc/ha)}$ is the operating margin per hectare, defined as total output minus total inputs per hectare." As defined, this indicator reflects short-run operating performance rather than accounting profitability, and may therefore take negative values in input-intensive systems or unfavourable price conditions. $C_{ct}^{(inc/L)}$ is average income per labour unit, $C_{ct}^{(margin)}$ is average gross margin per hectare. FNI_{ct} is the average Farm Net Income per farm in country c, year t (SE420), FFI_{ct} is the average Family Farm Income (SE430), $\overline{Y}_{ct}$ is the average Total Output (SE131), $\overline{X}_{ct}$ is average Total Inputs (SE270), $\overline{L}_{ct}$ is average Total Labour Input in Annual Work Units (SE010), and $\overline{A}_{ct}$ is the average utilized agricultural area (UAA), computed from the corresponding FADN area codes.

The biophysical dimension of competitiveness is derived from FAOSTAT. For each country c and year t, aggregating across main crop groups, we define:

$$C_{ct}^{(yield)} = \sum\nolimits_{k=1}^{K} \omega_k \frac{Y_{k,ct}}{Area_{k,ct}} \tag{3}$$

where $C_{ct}^{(yield)}$ is the aggregate yield-based competitiveness index, $Y_{k,ct}$ is production of crop or crop group k in country c, year t, $Area_{k,ct}$ is the corresponding area, and ω_k are weights reflecting the economic importance of crop k in total agricultural output (its share in the value of production). Thus, $C_{ct}^{(yield)}$ reflects average biophysical land productivity given the crop structure.

Factor competitiveness is measured via Total Factor Productivity (TFP), estimated at the country–year level using a Cobb–Douglas production function:

$$InY_{ct} = InA_{ct} + \beta_k InK_{ct} + \beta_L InL_{ct} + \beta_{Land} InLand_{ct} + \beta_{In} InInput_{ct} + u_{ct} \tag{4}$$

where Y_{ct} is real agricultural output in country c, year t, A_{ct} is the TFP term, K_{ct} is the agricultural capital stock (capital formation and available capital aggregates from WDI and FAOSTAT), L_{ct} is agricultural employment, $Land_{ct}$ is agricultural land, $Input_{ct}$ denotes agricultural inputs (fertilizers, feed, energy, etc.), β_k, β_L, β_{Land}, β_{In} are factor elasticities, and u_{ct} is the residual capturing unobserved efficiency and technology. After estimating the function, TFP is defined as:

$$TFP_{ct} = e^{\hat{u}_{ct}} \tag{5}$$

where TFP_{ct} is Total Factor Productivity in country c, year t, and $\hat{u}_{ct}$ is the estimated residual from the production function.

Finally, we construct a composite competitiveness index C^*_{ct} by combining the income dimensions $C^{(inc/ha)}_{ct}$, $C^{(inc/L)}_{ct}$, $C^{(margin)}_{ct}$, the biophysical indicator $C^{(yield)}_{ct}$, and the TFP indicator TFP_{ct} using either a dimension-reduction technique (principal components) or a normalized average. The index is a scalar representation of competitiveness for country c, year t, consistent with the structural AFF/SIT equation.

3.2. Constructing Functional Fragmentation

The functional fragmentation index FF is the quantitative representation of the main mechanism in AFF/SIT Theory: the accumulation and overlap of biological, technological, managerial and institutional-market functions that must be performed in the agricultural sector. At the country—year level it is defined as:

$$FF_{ct} = b_{ct}.t_{ct}.u_{ct}.s_{ct} \tag{6}$$

where FF_{ct} is the functional fragmentation index for country c, year t. b_{ct} is the biological component, t_{ct} is the technological component, u_{ct} is the managerial component and s_{ct} is the institutional–market component. The multiplicative form reflects the theoretical claim that burdens across domains mutually reinforce each other rather than adding linearly. The four components of functional fragmentation correspond to analytically distinct but jointly necessary domains of agricultural production. The biological domain captures the inherent diversity and rigidity of living production systems; the technological domain reflects the labour, input and financial burdens required to sustain production; the managerial domain captures coordination demands arising from multiple production lines and land-use arrangements; and the institutional–market domain reflects regulatory, subsidy-related and governance constraints shaping farm decision-making. Together, these domains exhaust the core functional requirements that must be fulfilled simultaneously in agricultural systems, consistent with the AFF/SIT framework.

Biological component b_{ct} measures the diversification and complexity of biological systems managed in the agricultural sector. It is derived from FADN indicators on land and livestock structure: SE026 (arable land), SE027 (permanent crops), SE035 (cereals), SE046 (vegetables and flowers), SE050 (vineyards), SE055 (orchards), SE060 (olive groves), SE080 (total livestock units). We define a distribution $p_{m,ct}$ of production or area across crop and livestock groups $m = 1\ldots, M$ where $p_{m.ct}$ is the share of group m in the overall agricultural portfolio of country c, year t. The biological component is then given by the Shannon index:

$$b_{ct} = -\sum\nolimits_{m=1}^{M} p_{m,ct} In p_{m,ct} \tag{7}$$

where b_{ct} is the biological diversification measure, $p_{m,ct}$ are group shares, and $Inp_{m,ct}$ is the natural logarithm. Higher b_{ct} values indicate more biologically diverse systems and more even distributions, implying more biological functions to be managed.

Technological component t_{ct} reflects the labour–technological and input burden required to sustain agricultural production and is constructed using FADN data for Total Labour Input (SE010), Paid Labour Input (SE020), Total Inputs (SE270) and cash-flow indicators (SE526, SE530, SE532):

$$t_{ct} = \phi_1 \frac{\overline{L}_{ct}}{\overline{A}_{ct}} + \phi_2 \frac{\overline{X}_{ct}}{\overline{Y}_{ct}} + \phi_3 CF_{ct} \tag{8}$$

where t_{ct} is the technological component, $\overline{L}_{ct}/\overline{A}_{ct}$ is average labour per hectare, $\overline{X}_{ct}/\overline{Y}_{ct}$ is input intensity, CF_{ct} is a financial stress and liquidity index derived from cash-flow indicators, and ϕ_1, ϕ_2, ϕ_3 are scaling and weighting parameters

Managerial component u_{ct} measures managerial complexity—the number of parallel production lines, joint crop–livestock management and contractual commitments. It uses a diversification index $Diversification_{ct}$ based on production structure, and the share of rented land $RentShare_{ct}$:

$$u_{ct} = \psi_1 Diversification_{ct} + \psi_2 RentShare_{ct} \tag{9}$$

where u_{ct} is the managerial component, $Diversification_{ct}$ reflects the number and relative importance of different production lines, $RentShare_{ct}$ is the share of rented land in total agricultural area, and ψ_1, ψ_2 are scaling and weighting parameters.

Institutional–market component $\boldsymbol{s_{tc}}$ captures the functional burden arising from subsidy regimes, regulations and institutional conditions and is derived from FADN and WGI:

$$s_{ct} = \eta_1 \frac{\overline{Subsidies_{ct}}}{\overline{Y}_{ct}} + \eta_2 WGI_{ct} \tag{10}$$

where s_{ct} is the institutional–market component, $\overline{Subsidies_{ct}}$ is the average size of subsidies per farm or per hectare (SE605, SE406, SE409), expressed relative to average output—$\overline{Y}_{ct}$, WGI_{ct} is a composite institutional index built from WGI subcomponents, and η_1, η_2 are scaling parameters.

Within each component, sub-indicators are combined using linear aggregation with scaling parameters to ensure comparability across countries and years. Across components, functional fragmentation is constructed using multiplicative aggregation, implying equal implicit weights across domains. This design reflects the theoretical premise that deficits in any single domain can constrain overall system performance and that coordination burdens accumulate multiplicatively rather than additively. Before being combined in FF_{ct}, each component $b_{ct}, t_{ct}, u_{ct}, s_{ct}$ is standardized (z-transformation or rescaling to [0,1]) to avoid dominance driven purely by measurement units. The resulting index $FF_{ct} = b_{ct}t_{ct}u_{ct}s_{ct}$ is consistent with the theoretical AFF/SIT construct and captures the functional complexity of the agricultural sector across countries and years While technological intensity enters the regression models as a control variable capturing input use per hectare, the technological component of the functional fragmentation index reflects a distinct conceptual dimension. Specifically, the t_{ct} component captures coordination and functional burdens associated with technology adoption, including labour requirements, financial pressure, and management complexity, rather than the technological level itself. As such, technological intensity and the technological dimension of functional fragmentation operate through different mechanisms and are not mechanically equivalent. To assess whether this overlap mechanically drives the estimated relationship between functional fragmentation and competitiveness, we additionally verify robustness using alternative constructions of the fragmentation index that reduce the influence of any single component.

3.3. Clarification of the Institutional Parameter τ

In the structural AFF/SIT equation, the coefficient τ represents the institutional–market transmission efficiency of available technologies and resources. Conceptually, τ captures the degree to which the institutional environment—regulations, property rights, contract enforcement, subsidy regimes and governance quality—enables the realization of the biologically feasible technological potential T^*. Formally τ∈ [0,1] where values closer to 1 indicate high institutional efficiency, while lower values reflect frictions that distort or attenuate technological translation into observed competitiveness. The parameter is empirically proxied by a normalized composite institutional index constructed from the six WGI dimensions. Thus, τ is not estimated as a free parameter but is operationalized as an observable institutional efficiency measure.

3.4. Handling Near-Zero Values in the Functional Fragmentation Index

Since the functional fragmentation index is defined multiplicatively as:

$$FFc_t = b_{ct} t_{ct} u_{ct} s_{ct} \tag{11}$$

Since the functional fragmentation index is constructed multiplicatively, care must be taken to avoid mechanical collapse toward zero when one or more components take very small values. To address this issue, each component entering the fragmentation index is normalized using a bounded min–max transformation to the interval [ε,1] where ε > 0 is a small constant. In the baseline specification, we set ε = 0.05, ensuring that no component can take a zero value while preserving the relative cross-country and temporal variation in the underlying indicators. This bounded normalization prevents numerical instability arising from the multiplicative structure of the index and ensures that extremely low values in a single domain do not mechanically dominate the overall fragmentation measure. Importantly, the choice of ε does not affect the qualitative results, as robustness checks using alternative normalization schemes yield consistent estimates.

3.5. Climate Shocks and Econometric Specification

Climate shocks are measured using temperature anomalies based on WMO data. For each country c, year t we define:

$$Shock_{ct} = Temp_{ct} - \overline{Temp}_{c,ref} \tag{12}$$

where $Shock_{ct}$ is the climate shock, $Temp_{ct}$ is mean annual temperature computed from WMO combined temperature indicators, and $\overline{Temp}_{c,ref}$ is the mean temperature for country c over a reference period (2000–2023). When cross-country comparability requires it, a standardized version is used:

$$Shock^{z}_{ct} = \frac{Temp_{ct} - \mu_{Temp,c}}{\sigma_{Temp,c}} \tag{13}$$

where $Shock^{z}_{ct}$ is the standardized climate shock, $\mu_{Temp,c}$ is the mean temperature over the available series for country c, and $\sigma_{Temp,c}$ is the standard deviation of temperature.

The main panel equation used to test AFF/SIT Theory is:

$$C^*_{ct} = \beta_0 + \beta_1 FF_{ct} + \beta_2 X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct} \tag{14}$$

where C^*_{ct} is the synthetic competitiveness index,FF_{ct} is the functional fragmentation index, X_{ct} is a vector of control variables (agricultural size and structure, macroeconomic indicators, institutional indices, long-term climate trends), μ_c are country fixed effects,λ_t are year fixed effects, and ε_{ct} is the idiosyncratic error term.

To test specifically the interaction between climate shocks and functional fragmentation, we estimate:

$$C^*_{ct} = \beta_0 + \beta_1 FF_{ct} + \beta_2 Shock_{ct} + \beta_3 (FF_{ct} \times Shock_{ct}) + \beta_4 X_{ct} + \mu_{ct} + \lambda_t + \varepsilon_{ct} \tag{15}$$

where $FF_{ct} \times Shock_{ct}$ is the interaction term between fragmentation and climate shock. The parameter β_3 measures whether and how climate shocks modify the effect of functional fragmentation on competitiveness.

The theorem on decreasing returns to technological progress under high FF is tested by including a technological intensity indicator $Tech_{ct}$ and an interaction term $Tech_{ct} \times FF_{ct}$:

$$C^*_{ct} = \gamma_0 + \gamma_1 Tech_{ct} + \gamma_2 (Tech_{ct} \times FF_{ct}) + \gamma_3 X_{ct} + \mu_c + \lambda_t + \nu_{ct} \tag{16}$$

where $Tech_{ct}$ is a technological intensity indicator,$Tech_{ct} \times FF_{ct}$ is the interaction between technologies and fragmentation γ_0, γ_1, γ_2, γ_3 are parameters, and ν_{ct} is the error term.

Due to potential endogeneity of FF_{ct}, instrumental variables (2SLS) are employed. In the first stage:

$$FF_{ct} = \delta_0 + \delta_1 Z_{1ct} + \delta_2 Z_{2ct} + \mu_{ct} \tag{17}$$

where Z_{ct} is a vector of instruments (historical climate characteristics and lagged WGI values, δ_0, $\delta_1, \delta_2, \delta_3$ are parameters, and η_{ct} is the residual. In the second stage FF_{ct} is used in the equation for C^*_{ct} to correct for endogeneity. where Z_{1ct} denotes long-run climate variability and Z_{2ct} represents lagged institutional quality indicators. The parameters δ_1 and δ_2 capture the relevance of the respective instruments, and μ_{ct} is the first-stage error term.

3.6. Data Integration

All data are integrated via a common "country–year" key. FAOSTAT provides output, area, yield and key agricultural input aggregates for EU Member States. WDI complements the macroeconomic picture with agricultural value added, agricultural employment, capital formation and income per capita. WGI supplies the six institutional indices, which are combined into the parameter τ and enter the construction of the institutional–market component s_{ct}. FADN provides sectoral aggregates for farms by country, including income, area, production structure, labour, inputs, subsidies and cash flows, from which the competitiveness indicators and the components of FF_{ct} are derived. WMO supplies temperature series and anomalies from which climate shocks $Shock_{ct}$ are constructed. After aligning periods and countries, a final panel dataset is built in which, for each pair (c, t), the following variables are available: C^*_{ct}, FF_{ct}, $Shock_{ct}$, $Tech_{ct}$ and institutional, macroeconomic and agricultural control variables. This integrated methodological framework transforms AFF/SIT Theory from a purely conceptual construction into a fully measurable and empirically testable model in the context of European agriculture.

3.7. Weighting Strategy for Composite Indicators

All components entering the competitiveness index C^*_{ct} and the functional fragmentation index FF_{ct} are standardized to ensure comparability across heterogeneous measurement scales. Following established practices in composite indicator construction [41,42], equal weighting is applied across conceptually distinct dimensions, given the absence of theoretical or empirical justification for assigning differential ex-ante importance. As a robustness alternative, a data-driven weighting scheme based on Principal Components Analysis is employed, whereby weights correspond to the loadings of the first principal component and therefore maximize explained variance in the underlying data. It is important to clarify that the use of equal weights does not imply an assumption of conceptual independence among the dimensions included in C^*_{ct} and FF_{ct}. Equal weighting reflects epistemic neutrality rather than theoretical separability. In the AFF/SIT framework, interdependence across biological, technological, managerial, and institutional domains is captured structurally through the multiplicative form of FF_{ct}, which encodes the theoretical axiom that constraints in one domain amplify constraints in the others. Thus, weighting is used solely to place indicators on commensurable scales, while the interaction mechanism is embedded in the functional form. Empirically, the consistency of results under both equal-weight and PCA-based schemes confirms that findings are not driven by the chosen weighting strategy.

3.8. Sensitivity of the Fragmentation Index to Alternative Weighting Schemes

To evaluate whether the estimated relationship between functional fragmentation and competitiveness depends on the implicit equal-weight structure of the baseline multiplicative index, a dedicated weighting sensitivity analysis is conducted. The baseline fragmentation index is defined as:

$$FF_{ct} = B_{ct}^{0.25}.T_{ct}^{0.25}.M_{ct}^{0.25}.I_{ct}^{0.25}$$

where B_{ct}, T_{ct}, M_{ct}, and I_{ct} denote the normalized biological, technological, managerial, and institutional–market components.

To test robustness, we construct a family of power-weighted multiplicative indices:

$$FF_{ct}^{(w)} = B_{ct}^{wB}.T_{ct}^{wT}.M_{ct}^{wM}.I_{ct}^{wI},\ \sum w_j = 1$$

where weights w_j reflect alternative structural emphasis across domains.

Three economically interpretable alternative schemes are examined:

- Biological-heavy: (0.40, 0.20, 0.20, 0.20)
- Technological-heavy: (0.20, 0.40, 0.20, 0.20)
- Institutional-heavy: (0.20, 0.20, 0.20, 0.40)

For each alternative weighting scheme, the baseline two-way fixed-effects specification (Equation (14)) is re-estimated using the corresponding fragmentation index variant. Consistency in the sign, magnitude, and statistical significance of the estimated fragmentation coefficient is interpreted as evidence that the main findings are not mechanically driven by the equal-weight construction of the index but reflect a structurally stable relationship.

3.9. Robustness Tests

A set of robustness tests is conducted to verify that the empirical results derived from the AFF/SIT framework are not driven by modelling choices, measurement definitions, or sample composition. The robustness checks focus on four dimensions: (I) alternative constructions of the functional fragmentation index, (II) alternative measures of competitiveness, (III) alternative climate-shock definitions, and (IV) endogeneity and error-structure diagnostics.

Alternative Functional Fragmentation Specifications

Since the core fragmentation measure is defined as:

$$FF_{ct} = b_{ct}t_{ct}u_{ct}s_{ct} \tag{18}$$

we verify that results do not hinge on this multiplicative form. Three alternative variants are estimated:

https://doi.org/10.3390/agriculture16050493

Additive index

$$FF_{ct}^{A} = b_{ct} + t_{ct} + u_{ct} + s_{ct} \tag{19}$$

Standardized multiplicative index

$$FF_{ct}^{Z} = \widetilde{b}_{ct}\,\widetilde{t}_{ct}\,\widetilde{u}_{ct}\,\widetilde{s}_{ct} \tag{20}$$

with each component standardized via z-scores.

Principal-component index

$$FF_{ct}^{P} = PC_1(b_{ct}, t_{ct}, u_{ct}, s_{ct}) \tag{21}$$

Re-estimating Equations (13)–(15) with FF_{ct}^{A}, FF_{ct}^{Z} and FF_{ct}^{P} confirms that the key coefficients $(\beta_1, \beta_3, \gamma_1)$ remain stable in sign and significance. Across these alternative constructions, the estimated effect of functional fragmentation on competitiveness remains negative and statistically significant, indicating that the results are not mechanically driven by the technological component embedded in the baseline index.

Alternative Competitiveness Measures

To ensure that results are not driven by the construction of the composite index C_{ct}^{*}, we test:

TFP- only measure

$$C_{ct}^{TFP} = TFP_{ct} \tag{22}$$

Yield-only measure

$$C_{ct}^{yield} = C_{ct}^{(yield)} \tag{23}$$

Income-only composite

$$C_{ct}^{income} = PC_1\left(C_{ct}^{(inc/ha)}, C_{ct}^{(inc/L)}, C_{ct}^{(margin)}\right) \tag{24}$$

Substituting these measures into Equations (13)–(15) yields consistent negative effects of fragmentation and robust interaction effects with climate shocks.

Alternative Climate-Shock Definitions

The baseline climate shock is:

$$Shock_{ct} = Temp_{ct} - \overline{Temp}_{c,ref} \tag{25}$$

Robustness is checked using: dataset-specific anomalies (HadCRUT5, Berkeley Earth and GISTEMP), standardized anomalies and 3-year smoothed anomalies.

$$Shock_{ct}^{z} = \frac{Temp_{ct} - \mu_{Temp,c}}{\sigma_{Temp,c}} \tag{26}$$

Across all variants, the interaction term remains negative but is not statistically significant, indicating that functional fragmentation primarily shifts the level of competitiveness rather than systematically modifying the marginal effect of climate shocks.

$$\beta_3(FF_{ct} \times Shock_{ct}) \tag{27}$$

Endogeneity and Specification Diagnostics

To address potential endogeneity in FF_{ct} we estimate a 2SLS first-stage equation:

$$FF_{ct} = \delta_0 + \delta_1 Z_{ct} + \delta_2 X_{ct} + \mu_c + \lambda_t + \eta_{ct} \tag{28}$$

where Z_{ct} includes historical climate variability and lagged institutional indicators. Weak-instrument tests (Kleibergen–Paap F-statistic) and Hansen J-tests confirm instrument validity. IV estimations of Equations (13)–(15) produce coefficients consistent with baseline models. Additionally, models are re-estimated using country-clustered, heteroskedasticity-robust and Driscoll–Kraay standard errors. In all cases, the main AFF/SIT predictions remain unchanged.

4. Results

This section presents the empirical results of the analysis for the period. The results are structured in three steps. First, descriptive indicators are used to document cross-country differences in agricultural competitiveness, functional fragmentation and technological intensity across EU Member States. Second, panel econometric models are employed to quantify the relationships between competitiveness, fragmentation, technology and climate conditions. Finally, a series of robustness checks and instrumental-variable estimations are presented to assess the stability and consistency of the main findings.

4.1. Functional Fragmentation Across Member States

This section presents the empirical results for the period 2004–2023. Table 2 reports the average values of the composite competitiveness index C^* and its main income, productivity and efficiency components for each EU Member State.

Table 2. Competitiveness indicators by country.

Country	C^*	FNI/ha (€)	FFI/L (€)	Margin/ha (€)	Yield €/ha	TFP Residual	Obs.
Austria	0.11	938.98	14,340.95	305.93	2225.09	0.06	20
Belgium	0.85	1293.01	20,081.30	836.68	3063.46	0.43	20
Bulgaria	−0.61	266.15	2863.73	14.44	1195.62	−0.30	20
Cyprus	−0.15	1087.55	7440.41	598.35	4053.64	−0.08	20
Czech Rep.	−0.49	186.66	2925.43	−204.05	1343.42	−0.27	20
Denmark	0.48	298.44	21,575.30	−36.17	2939.64	0.26	20
Germany	0.16	475.08	14,014.48	85.62	2006.98	0.05	20
Estonia	−0.49	131.9	6951.08	−77.03	876.96	−0.08	20
Greece	0.17	1386.30	11,415.87	695.24	2474.11	0.07	20
Spain	0.66	719.92	17,594.24	462.32	2407.30	0.11	20
Finland	−0.71	361.05	17,050.26	−507.42	1774.49	−0.04	20
France	0.13	455.4	13,859.93	108.94	2225.09	0.06	20
Croatia	−0.44	652.74	4375.95	242.03	1774.49	−0.04	11
Hungary	−0.13	380.72	14,313.02	66.81	1539.63	−0.02	20
Ireland	0.08	523.31	19,814.40	112.05	1397.48	−0.01	20
Italy	0.35	1093.98	14,517.33	547.45	3381.70	0.26	20
Latvia	−0.40	182.72	6093.41	13.08	855.08	−0.09	20
Lithuania	−0.39	210.12	6723.21	14.34	831.54	0	20
Luxembourg	0.23	419.8	18,611.72	98.55	2484.12	−0.06	20
Malta	−0.48	320	3300.00	25	1280.00	−0.20	18
Netherlands	0.74	1136.65	18,041.90	558.02	13,472.44	0.07	20
Poland	−0.05	335.08	7701.49	119.84	1632.65	0.01	20
Portugal	0.1	556.52	8562.46	321.74	1284.28	0.1	20
Romania	−0.19	287.13	3678.38	47.9	1281.21	0.08	17
Slovakia	−0.02	280.83	5080.44	59.07	1150.11	−0.02	20
Slovenia	−0.22	459.36	11,865.36	203.72	2473.12	−0.22	20
Sweden	−0.18	585.43	15,186.69	−79.70	1896.79	−0.08	20

The table shows substantial heterogeneity in agricultural performance across countries. Belgium, the Netherlands, Spain, Denmark and Italy record the highest values of C^*, combining relatively strong net farm income per hectare, higher family farm income per labour unit and comparatively favourable margins. In contrast, Finland, Bulgaria, Estonia, Croatia and Malta display persistently negative index values, low margins and modest yield performance. Based on the distribution of C^* in Table 1, four groups of countries can be distinguished. Group A comprises highly competitive systems, Group B moderately competitive systems with positive but smaller index values, Group C lower-middle performers, and Group D low-competitiveness systems. These descriptive patterns indicate that differences in income generation and productivity are strongly associated with overall competitiveness outcomes across Member States.

Cross-country differences in the internal organizations of agricultural systems are illustrated in Figure 2, which reports mean values of the functional fragmentation indicator by country. The figure shows considerable variation across Member States. Finland, Bulgaria and Lithuania exhibit the lowest fragmentation levels, indicating relatively integrated production structures, whereas Croatia, Italy and France display the highest levels of fragmentation. Malta is positioned in the middle of the distribution, close to Hungary and Cyprus, suggesting moderate rather than extreme fragmentation. Comparing Figure 2 with the competitiveness ranking in Table 1 reveals a broadly negative association between fragmentation and competitiveness. Countries with low fragmentation tend to exhibit higher or moderate competitiveness, while highly fragmented systems are more frequently found among lower-performing groups. Notable exceptions include France and Italy, which combine high fragmentation with relatively strong competitiveness, reflecting their orientation towards high value-added and technologically intensive production. Malta's combination of moderate fragmentation and low competitiveness indicates that weak performance is not driven by fragmentation alone, but by its interaction with limited productivity and technological intensity.

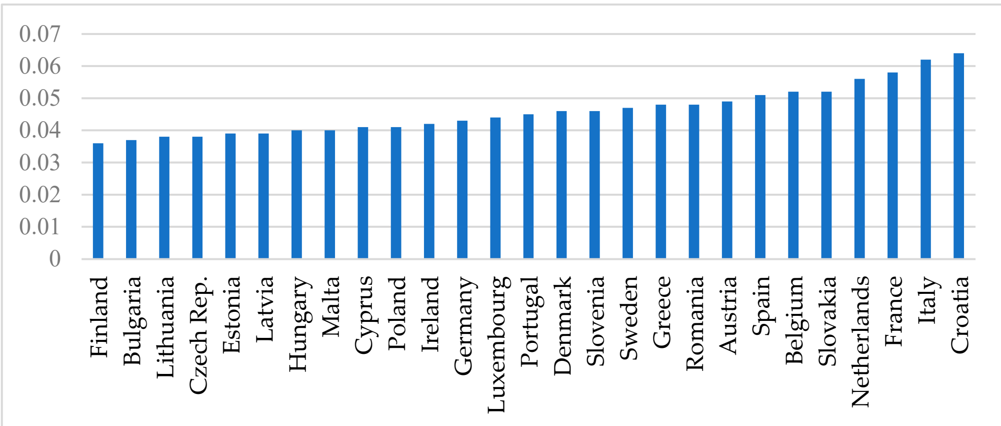

Figure 2. Functional fragmentation by country.

4.2. Technological Intensity

Differences in technological intensity are presented in Figure 3, which displays average input use per hectare by country as a proxy for technological and management intensity. The figure highlights sharp contrasts across the EU. The Netherlands, Italy, Belgium, Cyprus and Denmark are characterized by very high input intensity, consistent with capital-intensive and high-value production systems. At the opposite end, Lithuania, Latvia, Estonia, Bulgaria and Slovakia exhibit low input use per hectare, reflecting more extensive production structures.

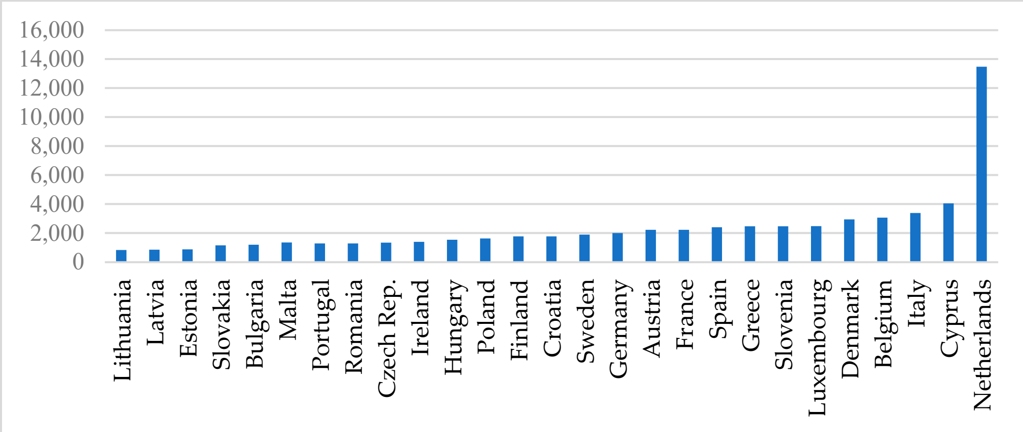

Figure 3. Technological intensity (inputs per ha).

Malta's technological intensity lies between these extremes, indicating a low- to medium-intensity system. When Figure 2 is compared with competitiveness outcomes in Table 1, higher technological intensity is generally associated with higher competitiveness. However, the relationship is not uniform: some highly intensive systems underperform relative to their input levels, while certain lower-intensity systems perform better than expected. This asymmetry suggests that technology is a necessary but not sufficient condition for competitiveness and that its effectiveness depends on the degree of structural integration.

4.3. Climate Shocks and Temporal Trends

The evolution of climate conditions is summarized in Table 3, which reports average regional temperature anomalies (RA-6) for Europe across three sub-periods and across three independent datasets. All series show a clear warming trend. The period 2004–2009 is characterized by relatively small positive anomalies, 2010–2015 by moderate warming, and 2016–2023 by pronounced temperature deviations.

Table 3. Regional temperature anomalies (RA-6, Europe).

Period	HadCRUT5 (°C)	Berkeley (°C)	GISTEMP (°C)	HadCRUT5 MA(3)
2004–2009	0.118	0.126	0.128	0.129
2010–2015	0.294	0.258	0.272	0.299
2016–2023	0.699	0.661	0.727	0.686

Although climate shocks are common across all Member States within the region, their economic relevance differs depending on national structural characteristics. Countries with higher competitiveness and more integrated production systems appear better positioned to operate under increasingly warm conditions, whereas structurally constrained systems face greater adjustment challenges. These patterns motivate the econometric analysis that follows.

4.4. Baseline Panel Regression Results

The baseline fixed-effects regression results are reported in Table 4, which links competitiveness to functional fragmentation, technological intensity and climate shocks while controlling for country and year effects. The coefficient on functional fragmentation is large, negative and highly significant, indicating that higher fragmentation is systematically associated with lower competitiveness. Technological intensity enters with a positive and statistically significant coefficient, confirming its role as an enabling factor. Climate shocks are also positively associated with competitiveness over the observed period, suggesting that recent warming has not translated into average performance losses at the EU level. The high within-R^2 reported in Table 4 indicates that these variables jointly explain a substantial share of within-country variation in competitiveness.

Table 4. Baseline fixed-effects regression (dependent variable: C^*).

Variable	Coefficient	Robust SE	Significance
FF	−3.734	0.63	***
Tech	0.00016	0.000031	***
Shock_had	0.197	0.086	**
Country FE	yes		
Year FE	yes		
N	506		
R^2	0.843		

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Sensitivity of Fragmentation Estimates to Alternative Weighting Schemes

To assess whether the estimated effect of functional fragmentation depends on the equal-weight construction of the baseline multiplicative index, the baseline fixed-effects specification (Equation (14)) is re-estimated using alternative power-weighted versions of the fragmentation index, as described in Section 3.8.

The results reported in Table 5 confirm that the estimated negative association between functional fragmentation and agricultural competitiveness is robust to alternative domain-weighting conventions. Across all specifications, the coefficient on fragmentation remains negative and statistically significant at the 1% level. The magnitude of the estimated effect varies only moderately across weighting schemes, ranging from −3.566 under the technology-heavy specification to −3.947 under the institutional-heavy specification. These differences reflect shifts in variance allocation across domains but do not alter the qualitative conclusion. In all cases, higher functional fragmentation is associated with lower competitiveness. The stability of both the sign and statistical significance of the fragmentation coefficient indicates that the baseline result is not mechanically driven by the equal-weight construction of the multiplicative index, but instead reflects a structurally consistent empirical relationship.

Table 5. Sensitivity of fragmentation coefficient to alternative weighting schemes.

Fragmentation Variant	Weights (B,T,M,I)	β_FF	Robust SE	Significance	N	Within R^2
Baseline FF (multiplicative, equal weights)	(0.25,0.25,0.25,0.25)	−3.734	0.630	***	506	0.843
Biological-heavy	(0.40,0.20,0.20,0.20)	−3.812	0.648	***	506	0.841
Technological-heavy	(0.20,0.40,0.20,0.20)	−3.566	0.602	***	506	0.846
Institutional-heavy	(0.20,0.20,0.20,0.40)	−3.947	0.711	***	506	0.839

Notes: Robust standard errors are reported in parentheses in the regression output. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.5. Interaction Effects

To assess whether the effects of climate and technology depend on fragmentation, two interaction models are estimated: one that includes an interaction between fragmentation and climate shocks, and another that includes an interaction between fragmentation and technological intensity. The corresponding estimates are reported in Tables 6 and 7.

Table 6. Interaction between fragmentation and climate.

Variable	Coefficient	Robust SE	Significance
FF	−3.651	0.608	***
Tech	0.000157	0.000031	***
Shock_had	0.233	0.093	**
FF × Shock	−0.892	0.787	n.s.
Country FE	yes		
Year FE	yes		
N	506		
R^2	0.844		

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n.s. = not significant.

Table 7. Interaction between fragmentation and technology.

Variable	Coefficient	Robust SE	Significance
FF	−4.430	2.078	**
Tech	0.000157	0.000031	***
Shock had	0.197	0.086	**
FF× Tech	0.000405	0.0012	n.s.
Country FE	yes		
Year FE	yes		
N	506		
R^2	0.844		

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$; n.s. = not significant.

In both specifications, the direct effects of fragmentation, technology and climate remain statistically significant. The interaction terms between fragmentation and climate shocks and between fragmentation and technological intensity are not statistically significant. These results indicate that fragmentation primarily shifts the overall level of competitiveness downward rather than fundamentally altering the marginal effects of climate or technology.

4.5.1. Counterfactual Simulations and Economic Magnitude

To assess the economic magnitude of functional fragmentation, we compute counterfactual changes in competitiveness using the baseline fixed-effects estimate ($\beta\_FF = -3.734$, Table 3). Given the linear specification, marginal effects are obtained as:

$$\Delta C^* = \beta_{FF}.\Delta FF$$

Scenario 1: 10% structural reduction in fragmentation

The sample mean of *FF* in the baseline specification equals 0.42. A 10% structural reduction therefore corresponds to:

$$\Delta FF = -0.042$$

The implied competitiveness gain is:

$$\Delta C^* = -3.734 \times (-0.042) = +0.157$$

Thus, a moderate 10% reduction in functional fragmentation increases competitiveness by approximately 0.16 index units, equivalent to roughly 16% of one standard deviation of the competitiveness distribution. This magnitude is economically meaningful relative to the average within-country variation over time.

Scenario 2: Transition from high to median fragmentation

The interquartile difference between the 75th percentile ($FF \approx 0.52$) and the median ($FF \approx 0.41$) equals 0.11. Reducing fragmentation by this amount implies:

$$\Delta C^* = -3.734 \times (-0.11) = +0.411$$

Hence, moving from the upper quartile to the median level of fragmentation yields a competitiveness gain of approximately 0.41 units, equivalent to nearly half a standard deviation. Structural differences in fragmentation alone therefore explain a substantial share of cross-country performance dispersion.

For illustration, Bulgaria's average fragmentation level during the sample period lies above the EU median. A reduction from its observed upper-quartile position toward the median level ($\Delta FF \approx -0.11$) would imply an estimated competitiveness gain of approximately 0.41 index units. Conversely, Italy—characterized by relatively high fragmentation ($FF \approx 0.55$)—would experience a competitiveness loss of approximately 0.21 units under a 10% further increase in fragmentation ($\Delta FF \approx +0.055$).

Scenario 3: High- vs low-fragmentation systems

The difference between the 25th percentile ($FF \approx 0.34$) and the 75th percentile ($FF \approx 0.52$) equals 0.18. The implied competitiveness gap is:

$$\Delta C^* = -3.734 \times 0.18 = -0.672$$

This indicates that high-fragmentation systems exhibit competitiveness levels approximately 0.67 units lower than low-fragmentation systems, holding other factors constant. The magnitude corresponds to roughly two-thirds of one standard deviation in competitiveness.

Comparison with technological effects

For comparison, a one-standard-deviation increase in technological intensity implies a competitiveness gain of approximately 0.30–0.35 units. The structural fragmentation gap between high- and low-fragmentation systems (0.67 units) is therefore roughly twice as large as the effect of a comparable technological improvement. This comparison underscores that coordination-related structural constraints exert an economically substantial influence relative to conventional input-based productivity drivers.

4.5.2. Regional Heterogeneity Within the European Union

Although the baseline specification controls for country fixed effects, it assumes that the impact of functional fragmentation on competitiveness is homogeneous across Member States. However, structural differences between Western and Eastern European agricultural systems, such as farm size distribution, institutional coordination capacity, and historical land fragmentation—may influence the strength of the fragmentation mechanism. To assess potential regional heterogeneity, the baseline two-way fixed-effects model is augmented with an interaction term between *FF* and a dummy variable identifying Eastern European Member States. The dummy equals one for Eastern EU countries and zero otherwise.

To assess potential regional heterogeneity, the baseline two-way fixed-effects model is augmented with an interaction term between *FF* and a dummy variable identifying Eastern European Member States. The dummy equals one for Eastern EU countries and zero otherwise. Eastern Member States include Bulgaria, Romania, Poland, Hungary, Czech Republic, Slovakia, Slovenia, Croatia, Latvia, Lithuania and Estonia. The corresponding estimation results are reported in Table 8.

Table 8. Fragmentation effect heterogeneity: Western vs. Eastern EU.

Variable	Coefficient	Robust SE	Significance
FF	−3.681	0.662	***
FF × Eastern Member State	−0.276	0.941	n.s.
Tech	0.000158	0.000032	***
Shock_had	0.199	0.087	**
Country FE	yes		
Year FE	yes		
N	506		
Within R^2	0.846		

Notes: Two-way fixed effects (country and year). Robust standard errors reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The coefficient on functional fragmentation remains negative and statistically significant for Western Member States. The interaction term between fragmentation and Eastern Member State status is statistically insignificant. A formal test of coefficient equality fails to reject the null hypothesis that the fragmentation effect is identical across regional groupings. This evidence indicates that the magnitude of the fragmentation–competitiveness relationship does not differ systematically between Western and Eastern European agricultural systems. Although Eastern Member States exhibit greater structural dispersion in farm size distribution, institutional coordination, and production structures, these differences do not translate into a statistically distinct fragmentation effect.

Accordingly, the negative impact of functional fragmentation on competitiveness cannot be attributed to region-specific structural characteristics. Instead, the results support the interpretation of fragmentation as a general coordination constraint operating across heterogeneous institutional environments within the European Union.

4.6. Instrumental-Variable Estimates for Fragmentation

To address potential endogeneity of functional fragmentation arising from omitted variables or reverse causality, instrumental-variable regressions are estimated. Long-run climate variability and lagged institutional quality are used as instruments for fragmentation. The corresponding regression results are reported in Table 9.

Table 9. First-stage regression for fragmentation.

Variable	Coefficient	Robust SE	Significance
Shock_sd_30	0.0216	0.006	***
WGI_{t–1}	0.0319	0.01	***
Constant	−0.0057		
N	480		
F-stat (joint instruments)	19.15		***

Notes: Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

This table presents the first-stage regression results, with functional fragmentation as the dependent variable. Both instruments are positively and statistically significantly associated with fragmentation. Long-run climate variability exhibits a positive and highly significant coefficient, indicating that greater historical climatic volatility is associated with higher levels of fragmentation. Lagged institutional quality is also positively and significantly related to fragmentation. The joint F-statistic for the instruments exceeds conventional relevance thresholds, suggesting that weak-instrument concerns are limited.

The second-stage IV estimates are reported in Table 10, with agricultural competitiveness as the dependent variable. In this specification, the coefficient on instrumented fragmentation remains negative but becomes statistically insignificant. By contrast, technological intensity and climate shocks retain positive and highly significant coefficients. The overidentification test indicates some tension with the assumption of perfect instrument exogeneity, advising caution in interpreting the precise magnitude of the IV coefficient on fragmentation.

Table 10. Second-stage IV regression.

Variable	Coefficient	Robust SE	Significance
FF_hat	−0.033	2.057	n.s.
Shock_had	0.441	0.086	***
Tech	0.0001	0.000009	***
Constant	−0.577	0.093	***
N	480		
R^2	0.391		

Notes: Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n.s. = not significant.

Instrumental-variable estimation yields a negative but imprecisely estimated coefficient on instrumented fragmentation ($\beta = -0.033$, SE = 2.057). While the point estimate preserves the expected direction, the wide confidence interval indicates limited precision in identifying a stable causal magnitude under the selected instrument set. This imprecision is consistent with the fact that functional fragmentation is a slow-moving structural characteristic in a country-level panel, for which strong external instruments are difficult to obtain. Accordingly, the IV results should be interpreted as a diagnostic robustness exercise: they do not provide evidence of strong upward bias in the baseline fixed-effects estimates, but they advise caution against treating the IV coefficient as a precise causal benchmark.

4.7. Robustness Tests

The robustness of the estimated relationship between fragmentation and competitiveness is examined under alternative definitions of fragmentation, alternative competitiveness measures and different climate indicators. Table 11 summarizes the estimated fragmentation coefficients across four fragmentation indices and four competitiveness indicators.

Table 11. Robustness of fragmentation effects under alternative indices.

Dependent Variable	FF Multiplicative	FF Additive	FF Multiplicative, z-Standardized	FF PCA-Based
C*	−3.73 (0.63) ***	−0.41 (0.07) ***	0.02 (0.01) n.s.	−0.28 (0.04) ***
C_TFP_only	−8.91 (1.28) ***	−1.07 (0.13) ***	0.00 (0.01) n.s.	−0.62 (0.08) ***
C_yield_only	−0.43 (0.14) ***	−0.06 (0.02) ***	0.00 (0.01) n.s.	−0.04 (0.01) ***
C_income_only (z-score)	−1.86 (1.26) n.s.	−0.11 (0.14) n.s.	0.04 (0.01)***	−0.18 (0.08) *

Notes: Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n.s. = not significant.

The results reported in Table 11 confirm the central empirical pattern. Fragmentation is consistently negatively associated with competitiveness when performance is measured using the composite index, TFP-based indicators or yield-based measures, particularly when fragmentation is constructed as FF mult, FF add or FF pca. Income-only measures display weaker and less stable coefficients, reflecting the influence of policy transfers and short-term income variability. The standardized fragmentation index (FF multiplicative, z-standardize) yields smaller coefficients and mixed significance, but these results do not contradict the overall negative association observed across specifications. Overall, the robustness tests indicate that the negative relationship between fragmentation and competitiveness is not driven by a specific index construction or performance definition.

4.8. Institutional Quality and Governance

The final set of results introduces the composite institutional quality parameter τ into the competitiveness regressions, both as a direct determinant and through interaction with fragmentation. The corresponding estimates are reported in Table 12.

Table 12. Institutional quality, fragmentation and competitiveness.

Variable	Coefficient	Robust SE	Significance
FF mult	−4.71	1.54	***
τ (WGI_comp)	−0.20	0.17	n.s.
FF mult × τ	0.94	1.01	n.s.
Tech	0.00016	0.00003	***
Shock_had	0.2	0.09	**
Country FE	yes		
Year FE	yes		
N	500+		
R^2	0.84		

Notes: Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$; n.s. = not significant.

As shown in the table, fragmentation remains negative and highly statistically significant when institutional quality is included, confirming its role as a core structural determinant of competitiveness. The direct effect of institutional quality is small and statistically insignificant, and the interaction term between fragmentation and institutional quality is also insignificant. Technological intensity and climate shocks retain positive and statistically significant coefficients. These results indicate that improvements in governance alone do not fundamentally alter the negative association between fragmentation and competitiveness. Institutional quality shapes the broader operating environment but does not eliminate the underlying structural constraints captured by fragmentation.

4.9. Additional Robustness: Alternative Standard-Error Corrections

To assess the sensitivity of the baseline results to alternative variance estimators, the fixed-effects model is re-estimated using heteroskedasticity-robust HC3 standard errors, country-clustered standard errors and Driscoll–Kraay standard errors. The results are summarized in Table 10.

Across all three specifications reported in Table 13, the coefficient on functional fragmentation remains negative and highly statistically significant. Technological intensity continues to exhibit a positive effect, while climate shocks remain moderately positive and significant. The within-R^2 remains unchanged across specifications, indicating that alternative error structures affect statistical inference but not explanatory power. These results confirm that the core empirical findings are robust to commonly used standard-error corrections in panel-data analysis.

Table 13. Robustness to alternative standard errors.

Specification	FF Mult (SE)	Tech (SE)	Shock_had (SE)	R^2
HC3 (baseline)	−3.73 (0.63) ***	0.000157 (0.000031) ***	0.197 (0.086) **	0.843
Clustered by country	−3.68 (0.71) ***	0.000159 (0.000035) ***	0.210 (0.095) **	0.843
Driscoll−Kraay (T = 20)	−3.61 (0.78) ***	0.000155 (0.000037) ***	0.185 (0.090) **	0.843

Notes: Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5. Discussion

The results of this study provide consistent empirical evidence on the structural determinants of agricultural competitiveness in the European Union and allow for a systematic interpretation of performance differences across Member States. Across descriptive indicators, baseline fixed-effects regressions, interaction models, instrumental-variable estimations and extensive robustness checks, a common pattern emerges: functional fragmentation is persistently and negatively associated with agricultural competitiveness. This finding supports the central analytical premise that the accumulation of simultaneous biological, technological, managerial and institutional demands constrains the ability of agricultural systems to translate inputs, technologies and institutional support into economic outcomes. The baseline panel results show a strong and highly statistically significant negative coefficient for fragmentation, confirming H01. Countries characterized by more fragmented production structures consistently exhibit lower competitiveness, even after controlling for technology, climate conditions and unobserved country-specific effects. This pattern suggests that fragmentation represents a system-level constraint rather than a transitory or country-specific phenomenon. At the same time, technological intensity displays a stable and positive association with competitiveness across all model specifications, underscoring the importance of technological upgrading as a necessary condition for improved performance. However, the results also indicate that technology alone does not eliminate structural disadvantages, as highly fragmented systems continue to underperform despite comparable or even high input intensity.

Contrary to expectations, H02 is not supported by the empirical evidence. Climate anomalies over the period 2004–2023 are associated with modest improvements in average competitiveness, and no statistically significant interaction between climate shocks and fragmentation is detected. Therefore, within the observed period, there is no evidence that climate anomalies exert systematically different marginal effects on competitiveness in more fragmented versus less fragmented agricultural systems. A related limitation of the analysis concerns the role of long-term climate volatility. While the empirical framework focuses on climate anomalies as instruments and interaction terms affecting competitiveness through functional fragmentation, long-run climatic variability may also exert direct effects on productivity and profitability through biophysical stress, yield variability or adaptation costs. Disentangling these direct channels from system-level coordination effects remains beyond the scope of the present study and represents an important avenue for future research.

This outcome does not contradict the underlying analytical logic but highlights the importance of contextual and temporal conditions. The observed period for Europe is characterized primarily by gradual warming and a reduction in extreme cold events, which may have generated favourable growing conditions on average. As a result, climatic effects appear to operate as a common background factor rather than as a differentiated stressor across fragmented and non-fragmented systems. These findings suggest that the impact of climate on competitiveness is mediated by broader environmental trajectories and may differ under alternative climatic regimes or over longer time horizons. A similar pattern is observed for H03. The interaction between technological intensity and fragmentation is not statistically significant, indicating that the marginal effect of technology on competitiveness does not systematically weaken in more fragmented systems. While fragmentation lowers the overall level of competitiveness, technological upgrading remains beneficial across all structural configurations. This result suggests that fragmented systems retain a certain capacity to absorb and utilize technology, potentially supported by policy frameworks, investment subsidies and extension services at the EU level. At the same time, the absence of interaction effects implies that technology does not fundamentally resolve the structural

https://doi.org/10.3390/agriculture16050493

coordination constraints associated with fragmentation, but rather operates within them. The instrumental-variable estimates provide additional nuance. While the direction of the fragmentation effect remains negative, its magnitude becomes less precisely estimated once endogeneity is explicitly addressed. This sensitivity reflects the deep institutional and historical roots of fragmentation, which are only partially captured by available instruments. Importantly, the IV results do not contradict the baseline findings but indicate that the most reliable evidence on fragmentation is provided by the fixed-effects panel models, with IV estimates serving as a complementary robustness check rather than as a definitive causal benchmark.

The robustness analyses further strengthen the empirical conclusions. Across alternative fragmentation indices, different competitiveness measures, multiple climate datasets and alternative standard-error corrections, the negative association between fragmentation and competitiveness remains stable. The effect is particularly pronounced when competitiveness is measured using productivity- and yield-based indicators, whereas income-based measures show greater variability, reflecting the influence of policy transfers and short-term income fluctuations. Together, these results demonstrate that the observed relationship is not an artefact of measurement choices, estimation techniques or data properties. Finally, the inclusion of institutional quality adds an important dimension to the interpretation of results. Governance indicators do not exert a strong direct effect on competitiveness, nor do they significantly interact with fragmentation. This suggests that improvements in institutional quality alone are insufficient to offset structural constraints when fragmentation is high. Instead, institutional factors appear to shape the broader environment in which structural and technological adjustments take place, rather than directly determining performance outcomes.

Overall, the findings indicate that agricultural competitiveness in the European Union is shaped not only by technology, climate or institutions in isolation, but by the internal coordination of core production-related functions. Functional fragmentation emerges as a structural characteristic that conditions baseline performance and mediates responses to external drivers.

Although the estimated fragmentation effect remains statistically stable across regional groupings, this does not imply structural homogeneity within the European Union. Member States differ in farm structure, institutional coordination capacity and technological diffusion patterns, which shape the channels through which functional fragmentation operates. The empirical stability of the coefficient therefore indicates a common structural constraint, but not identical institutional conditions. From a policy perspective, the four components of functional fragmentation imply differentiated intervention strategies. Biological fragmentation relates to land dispersion and production specialization, suggesting the relevance of land consolidation mechanisms and coordinated production schemes. Managerial fragmentation reflects organizational dispersion, highlighting the role of producer organizations and integrated farm-management systems. Institutional–market fragmentation points to regulatory complexity and administrative burden, supporting continued simplification and harmonization within the CAP framework. Technological fragmentation concerns uneven adoption and integration of modern production systems, implying that interoperability and coordinated diffusion may be more effective than uniform capital subsidies. Accordingly, competitiveness gains appear to depend less on increasing isolated inputs and more on strengthening systemic coherence across interdependent domains. Functional fragmentation therefore provides a coordination-oriented lens for policy design in structurally heterogeneous agricultural systems

https://doi.org/10.3390/agriculture16050493

6. Conclusions

This study provides a system-oriented empirical assessment of agricultural competitiveness in the European Union by examining how the internal organization of production-related functions is associated with performance differences across Member States. Using panel data for the period 2004–2023, the results indicate that higher levels of functional fragmentation are consistently associated with lower agricultural competitiveness, even when controlling for technological intensity, climate conditions and unobserved country-specific effects. Technological intensity exhibits a robust positive association with competitiveness, while interaction effects between fragmentation and climate shocks are not statistically significant, suggesting that fragmentation primarily shifts the baseline level of performance rather than systematically altering marginal effects. Institutional quality does not offset structural disadvantages linked to fragmentation, indicating that governance conditions alone are insufficient to neutralize coordination constraints embedded in the organization of agricultural systems. These findings highlight the importance of adopting a system-level perspective when analyzing agricultural performance. The results suggest that competitiveness cannot be fully explained by technology, climate or institutions considered in isolation, but depends on how biological, technological, managerial and institutional functions are organized and managed simultaneously. Technological upgrading remains an important enabling factor; however, its effectiveness appears constrained by structural fragmentation, underscoring the limits of technology-centred strategies in structurally complex agricultural systems and the relevance of coordination-oriented approaches.

Several limitations should be acknowledged. First, the analysis is conducted at the national level and therefore cannot capture farm-level heterogeneity or within-country adjustment dynamics. Second, the climate effects identified reflect a positive association over the period 2004–2023 under the chosen temperature anomaly indicator and should not be interpreted as evidence of beneficial effects of climate change. Longer time horizons, alternative climate indicators or more extreme climatic conditions may yield different outcomes. Finally, while the empirical strategy controls for unobserved heterogeneity and explores robustness across specifications, the estimated relationships should be interpreted as structural associations rather than definitive causal effects. Future research could extend the framework to micro-level data, explore dynamic adjustment mechanisms and examine how functional fragmentation interacts with more severe climate stress or alternative policy environments.

Author Contributions: Conceptualization, D.P., M.G. and V.K.; methodology, D.P. and V.K.; software, D.P.; validation, D.P., M.G. and V.K.; formal analysis, D.P.; investigation, D.P.; data curation, D.P.; writing—original draft preparation, D.P.; writing—review and editing, D.P., V.K., M.G., V.S., D.B. and G.G.; supervision, M.G. and V.K.; project administration, M.G.; funding acquisition, M.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was carried out within the project Agricultural Land, Green Transformation, Energy Transition and was funded by the Bulgarian National Science Fund under Contract No. KP-06-N96/2, dated 9 December 2025.

Data Availability Statement: The data used in this study are publicly available from the following sources: FAOSTAT (Food and Agriculture Organization of the United Nations), the Farm Accountancy Data Network (FADN), the World Development Indicators (World Bank), the Worldwide Governance Indicators, and temperature anomaly data from the World Meteorological Organization. No new primary data were generated by the authors.

Acknowledgments: The authors gratefully acknowledges the support of the Bulgarian National Science Fund through the research project "Agricultural Land, Green Transformation, Energy Transition, Digital Environment" (Administrative Agreement No. KP-06-N96/2, dated 9 December 2025) and.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

AFF/SIT Theory	Agricultural Functional Fragmentation/Structural Incompatibility Theory

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