

Article

Convergence of the Agricultural Share in GDP in Central and Eastern Europe: A Statistical and Econometric Analysis

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Abstract

The study examines the evolution and convergence of the agricultural share in GDP across seven Central and Eastern European countries (Bulgaria, Croatia, the Czech Republic, Poland, Romania, Slovakia, and Hungary) over the period 1995–2024. The main objective is to assess the structural transformation of the agricultural sector and to test the existence of regional convergence. The methodological framework combines descriptive statistics, the Shapiro–Wilk normality test, Spearman correlation analysis, cluster analysis using the Ward method, σ -convergence, β -convergence and ARIMA models for medium-term forecasting. The results reveal a clear downward trend in the agricultural share of GDP across all analysed economies, confirming ongoing processes of modernization and structural reorientation. At the beginning of the period, Romania and Bulgaria exhibited relatively high levels and pronounced volatility, whereas the Czech Republic and Slovakia recorded lower and more stable shares. Over the long term, a significant convergence process becomes evident, as cross-country differences gradually narrow, with most economies recently falling within the range of 1.5–3.5% of GDP. Spearman correlations indicate strong regional synchronization, with the exception of Slovakia, which emerges as an atypical case. Augmented Dickey–Fuller tests confirm that the series are integrated of order one, while the selected ARIMA specifications demonstrate satisfactory predictive performance. Forecasts for 2025–2028 suggest a continued decline or stabilization of the agricultural share in GDP. Overall, the findings confirm the existence of a robust process of structural convergence in the region and provide empirical support for the design of agricultural and economic policy frameworks.

Keywords: convergence; agricultural share in GDP; regional convergence; Central and Eastern Europe; ARIMA forecasting



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1. Introduction

Building directly on this conclusion, the present study proposes to examine whether the cross-country differences in CEE contribute to gross domestic product (GDP), employment, and food security. In the post-communist period, however, the sector underwent a profound transformation, as these economies shifted from centrally planned to market-oriented systems and progressively integrated into the European and global economy. This transformation is reflected in a pronounced decline of agriculture's relative weight: in 1995, agriculture, forestry and fishing accounted for 18.2% of GDP in Romania and 9.2% in Bulgaria, compared with only 2.1% in Slovakia and 4.0% in the Czech Republic ([World Bank](https://www.worldbank.org/), n.d.). By 2024, cross-country dispersion had narrowed markedly, with all

seven economies falling within a band of 1.6–2.9% of GDP and the cross-sectional standard deviation of the agricultural share declining from approximately 5.36 in 1995 to 0.45 in 2024 (World Bank, n.d.). Consistent with structural transformation theory, this decline reflects productivity growth and the reallocation of activity towards industry and services rather than an absolute contraction of agricultural output (Chenery, 1960; Kuznets, 1967; Herrendorf et al., 2013).

These divergent starting points—high and volatile agricultural shares in Romania and Bulgaria versus low and stable shares in the Czech Republic and Slovakia—gave rise to distinct adjustment trajectories, shaped by institutional reforms, agricultural policy frameworks, technological investment, climatic conditions, and, not least, the process of European Union accession.

European integration has played a pivotal role in accelerating structural transformation through the adoption of the *Acquis Communautaire*, access to structural and cohesion funds, and the implementation of the Common Agricultural Policy. These mechanisms have contributed to the modernization of the agricultural sector, improvements in efficiency and a reduction in its relative share in GDP, without necessarily implying a decline in agricultural output in absolute terms.

However, differences exist regarding the timing of the analyzed countries' accession to the European Union. While the Czech Republic, Hungary, Poland, and Slovakia became EU Member States in 2004, followed by Bulgaria and Romania in 2007, Croatia acceded only in 2013. This asymmetry in the duration of EU membership implies differing levels of exposure to EU policies, funding mechanisms, and the European institutional framework, including the instruments of the Common Agricultural Policy. Consequently, the dynamics and pace of convergence in agriculture's share of GDP cannot be attributed solely to domestic economic developments or broader regional trends but should also be interpreted in light of the countries' effective period of European integration.

At the same time, the economies under analysis have been exposed to major external shocks, such as the global financial crisis of 2008–2009 and the COVID-19 pandemic, which generated temporary fluctuations in the agricultural share of GDP as a result of rapid changes in overall economic activity.

The existing literature (Chenery, 1960; Kuznets, 1967; Herrendorf et al., 2013) highlights that the declining share of agriculture in GDP represents a typical feature of the economic development process; however, the magnitude and pace of this transformation vary considerably across countries. In the case of Central and Eastern Europe, the analysis of this phenomenon is particularly relevant, as it reflects the combined effects of post-communist transition and economic convergence towards European Union standards. Nevertheless, while comparative studies of real convergence across EU and Central and Eastern European economies over extended horizons exist for aggregate income (Miron & Holobiuc, 2020), comparative empirical studies that focus on sectoral convergence—and that integrate descriptive statistical approaches with advanced econometric modelling—remain relatively limited.

The main objective of this study is to analyze the evolution of the agricultural share in GDP across seven Central and Eastern European countries—namely Bulgaria, Croatia, the Czech Republic, Poland, Romania, Slovakia, and Hungary—over the period 1995–2024. The research aims to identify initial structural differences, assess temporal dynamics, and test the existence of an economic convergence process among these economies. These questions are addressed empirically through a combination of complementary techniques—descriptive statistics, normality tests, non-parametric correlation coefficients, cluster analysis, and ARIMA time-series modelling—which jointly serve to

test for convergence, synchronization, and the medium-term trajectory of the agricultural share rather than constituting the contribution in their own right.

While the long-run decline of agriculture's share in GDP is a well-established feature of economic development, and the convergence of income levels across European regions has been extensively documented, far less is known about the structural convergence of the agricultural sector itself, that is, whether cross-country differences in agriculture's share of GDP narrow over time. The present study addresses this gap in four respects. First, it shifts the focus from income convergence to sectoral structural convergence, analysing the agricultural GDP share across seven Central and Eastern European economies over a three-decade horizon. Second, it moves beyond documenting a common downward trend by testing whether the economies form distinct groups of similar trajectories, using cluster analysis to identify convergence "clubs" within the region. Third, it operationalizes the synchronization of structural change explicitly, through non-parametric rank-based co-movement measures rather than informal comparison. Fourth, it links the persistence properties of the series to a forward-looking assessment, connecting unit-root diagnostics to ARIMA-based forecasts in order to evaluate whether the observed convergence is likely to continue. Together, these elements provide an integrated account of structural change in the region's agriculture that distinguishes genuine sectoral convergence from a merely shared directional trend, and that offers a robust basis for medium-term economic and agricultural policy design.

Building on the main objective of the study, four research hypotheses are formulated, each encompassing two complementary dimensions. Three of these—H1, H2, and H4—concern the substantive dynamics of the agricultural share in GDP, whereas H3 concerns the distributional and integration properties of the series and functions as a *methodological precondition*, establishing the admissibility of the techniques applied in the analysis rather than making a substantive claim about the sector's dynamics.

H1. *Over the period 1995–2024, the agricultural share in GDP has followed a significant downward trend across Central and Eastern European countries, starting from significantly different initial structural levels.*

H2. *The agricultural share in GDP exhibits a long-term convergence process across the analyzed economies, accompanied by a strong cross-country synchronization of dynamics that reflects the influence of common regional factors.*

H3. *The time series of the agricultural share in GDP deviates from the normality assumption for the majority of the countries considered and are integrated of order one (I(1)), thereby justifying the use of non-parametric dependence measures and differenced (ARIMA) modelling.*

H4. *Adequately specified ARIMA models capture the dynamics of the agricultural share in GDP and indicate a continued decline or stabilization of this share across the analyzed economies over the medium term.*

2. Literature Review

2.1. Agricultural Share in GDP

A thematic reading of the literature indicates that the agricultural share in GDP should not be treated as a singular, homogeneous indicator, but rather as a multidimensional construct that can be examined along five analytical dimensions, which structure the remainder of this section. The first concerns the process of structural transformation, whereby the declining share of agriculture is interpreted as a natural outcome of economic development and sectoral reallocation (Section 2.1.1). The second concerns measurement

boundaries, in particular the distinction between primary agricultural production and the broader agribusiness system, which incorporates upstream and downstream value chains (Section 2.1.2). The third concerns the coexistence of a declining relative share with the persistent strategic role of agriculture in transition economies (Section 2.1.3). The fourth concerns value-chain dynamics and the composition of agricultural output (Section 2.1.4). The fifth concerns the macro-institutional and spatial factors that condition the pace of this decline (Section 2.1.5).

2.1.1. Structural Transformation and the Relative Decline of Agriculture

The literature consistently interprets the declining share of agriculture in GDP as a fundamental feature of socio-economic development, whereby higher-income economies tend to exhibit a lower relative contribution of agriculture to aggregate output (Chenery, 1960; Herrendorf et al., 2013; Kuznets, 1967). Crucially, this decline should be understood in relative rather than absolute terms. It does not imply a deterioration of the agricultural sector itself, but rather reflects broader structural dynamics, including productivity growth, economic diversification and the expansion of industrial and service activities, which collectively reduce agriculture's share in total value added even when its absolute output increases.

This distinction has important implications for empirical analysis, as it highlights that a declining agricultural share may signal either successful structural transformation, driven by productivity gains and sectoral reallocation, or, alternatively, persistent structural imbalances, where the relatively high weight of agriculture reflects underperformance in other sectors. Consequently, the interpretation of agricultural GDP shares requires careful consideration of the broader economic context, as similar quantitative trends may correspond to markedly different development trajectories.

Empirical evidence from transition and neighboring economies consistently confirms the downward trajectory of agriculture's share in GDP, while also revealing substantial heterogeneity in initial conditions and adjustment dynamics. Across these contexts, the decline in the relative importance of agriculture reflects broader processes of structural transformation, yet the speed and implications of this adjustment vary considerably. In Serbia, for instance, the agricultural share in GDP decreased significantly over the period 2000–2015, although the sector has continued to maintain strategic relevance through its contribution to exports, agro-industrial linkages and rural employment (Mitrovic et al., 2017).

A similar pattern can be observed in the Republic of Moldova, where agriculture's share in GDP declined markedly between 2001 and 2013, despite the persistence of high rural labor dependence. This suggests that macroeconomic restructuring may coexist with slower adjustments in the rural economy, reflecting structural rigidities and limited labor mobility (Rotaru, 2015). In the Romanian case, the evolution of sectoral contributions to GDP indicates a gradual transition towards a service-oriented economic structure, with agriculture's share declining from double-digit levels in the early 2000s to mid-single-digit values in more recent years. Nevertheless, the continued positioning of Romania above the EU average in terms of agricultural share highlights the persistence of productivity gaps and uneven modernization processes across sectors (Mănescu et al., 2024).

Taken together, these findings are consistent with the predictions of structural transformation theory, while also indicating that cross-country differences in agricultural shares should not be interpreted solely as sector-specific outcomes. Rather, they reflect broader developmental asymmetries, encompassing variations in productivity, structural diversification and the pace of economic modernization.

2.1.2. Measurement Boundaries: Primary Agriculture Versus the Agribusiness System

A second, analytically distinct strand of the literature emphasizes that the economic role of agriculture may be substantially misrepresented when it is measured exclusively through primary agricultural value added. In such cases, the indicator captures only a limited segment of the agri-food system, neglecting the broader network of upstream and downstream activities that contribute to overall value creation. Input–output analyses demonstrate that a more comprehensive measure—encompassing agribusiness linkages—can reveal a significantly larger contribution, often several times exceeding the direct share of agriculture in GDP.

Empirical evidence supports this broader perspective. In the case of Iran, agribusiness is estimated to account for approximately one-fifth of GDP, far surpassing the contribution of primary agricultural production. Although its relative share declines over time, this trend is attributed to structural constraints, such as limited integration into value chains and low productivity, rather than to a simple contraction of agriculture’s economic relevance (Permeš & Gilanpour, 2024). Similarly, evidence from China indicates that the declining weight of agribusiness is largely driven by the reduced importance of primary agriculture, while upstream input sectors and downstream food industries gain prominence. This pattern reflects an internal restructuring of the agri-food system, consistent with broader processes of economic transformation, rather than a uniform decline in sectoral significance (Mrówczyńska-Kamińska & Bajan, 2019).

These findings have important implications for empirical research based on agriculture’s share in GDP. This indicator should be interpreted as reflecting the structural position of primary agriculture within the economy, rather than as a comprehensive measure of the entire agri-food sector. The distinction is particularly relevant in cross-country analyses, where differences in value-chain organization, technological development and processing intensity may lead to divergent representations of agriculture’s economic role despite similar aggregate shares.

2.1.3. The Persistent Strategic Role of Agriculture in Transition Economies

A recurrent theme in the literature on transition economies is the coexistence of a declining agricultural share in GDP with the continued strategic importance of the sector. This apparent paradox reflects the fact that, although structural transformation reduces agriculture’s relative contribution to aggregate output, it does not eliminate its broader economic and social functions. In particular, agriculture often retains a central role through its contribution to exports, its integration with agro-industrial activities and its importance for rural employment and social cohesion (Mitrović et al., 2017).

At the same time, more recent evidence points to a stabilization of agriculture’s share at moderate levels in certain contexts, while also highlighting structural constraints that limit the sector’s capacity to fully benefit from modernization processes. Insufficient public support at the local level, underinvestment and institutional weaknesses may hinder productivity growth and competitiveness, even when agriculture continues to play a significant role in regional development and labor absorption (Grujić-Vučkovski et al., 2022).

Taken together, these findings suggest that the decline in agriculture’s share of GDP should be interpreted not as a process of sectoral marginalization, but rather as a structural rebalancing within the economy. The developmental significance of agriculture depends less on its relative size and more on its capacity for technological upgrading, organizational transformation and integration into higher value-added segments of the agri-food system.

2.1.4. Value-Chain Dynamics and the Composition of Agricultural Output

A complementary perspective emerging from the literature emphasizes the importance of value-chain dynamics, shifting the analytical focus from the relative size of agriculture to the composition and sophistication of its outputs. From this viewpoint, the developmental impact of agriculture depends not only on its share in GDP, but also on the extent to which production is integrated into higher value-added segments of the agri-food system. Evidence from Uzbekistan suggests that a continued reliance on primary agricultural commodities constrains broader economic benefits, whereas increasing the share of processed agricultural goods in exports can enhance income generation, support rural infrastructure development and improve economic resilience, even in the context of a declining agricultural share in GDP (Horska et al., 2017).

A similar argument is supported by evidence from Romania, where the relationship between agricultural production and macroeconomic performance is mediated by structural and organizational factors. While higher levels of domestic output—particularly in fruit production—are associated with increased agricultural GDP and reduced dependence on imports, persistent structural weaknesses, including declining orchard areas, technological limitations and fragmented producer organization, constrain the sector's competitiveness in external markets (Niculae & Costache, 2016).

These findings suggest that the interpretation of agriculture's share in GDP should be complemented by qualitative indicators of structural transformation, such as processing intensity, supply chain integration and productivity performance. Without such contextualization, similar patterns of decline in agricultural shares may obscure fundamentally different development trajectories across countries and regions.

2.1.5. Macro-Institutional and Spatial Determinants of Agricultural Decline

The literature further highlights the role of macro-institutional and spatial factors in shaping the pace at which agriculture's share in GDP declines. At the macroeconomic level, cross-country evidence indicates that institutional transformation—particularly the transition towards democratic governance—is associated with a statistically significant reduction in the relative importance of agriculture. This effect is reinforced by higher income levels and increased trade openness, which facilitate structural reallocation towards more productive sectors and accelerate integration into global markets (Güvercin & Gök, 2020).

At the regional level, structural characteristics also play a critical role in determining the contribution of agriculture to economic performance. Empirical evidence suggests that regions with a higher intensity of agricultural activity tend to exhibit a lower contribution to national GDP, reflecting structural constraints such as production fragmentation, lower capital intensity and persistent productivity gaps (Dimitrijević et al., 2020). These factors limit the capacity of agriculture to act as a driver of regional growth, particularly in comparison with more diversified and capital-intensive sectors.

Taken together, these findings indicate that the evolution of agriculture's share in GDP cannot be understood solely as a sector-specific process. Rather, it is shaped by the interaction between institutional frameworks, the degree of economic integration and the structural characteristics of regional economies. Consequently, cross-country convergence in agricultural shares reflects not only sectoral transformation but also broader governance dynamics and spatial patterns of economic development.

Building directly on this conclusion, the present study proposes to examine whether the cross-country differences in agriculture's share of GDP across Central and Eastern Europe—understood as expressions of broader developmental asymmetries rather than purely sectoral outcomes—have narrowed over the period 1995–2024. If these asymmetries reflect an uneven but ongoing process of structural modernization, they would be expected

to diminish over time as the less advanced economies catch up, giving rise to a measurable process of convergence. This expectation motivates the convergence-oriented framework developed in the remainder of the paper, in which the dispersion, co-movement, and dynamic properties of agricultural GDP shares are analysed jointly to determine whether the region is evolving as an integrated structural system.

2.2. Economic Convergence Theory

The literature on economic convergence can be organized along four dimensions, which structure this section: the theoretical foundations of the concept (Section 2.2.1); the potential divergence between its two principal empirical measures, β - and σ -convergence (Section 2.2.2); the differences in convergence dynamics observed between the national and regional levels (Section 2.2.3); and the domain-specific character of convergence across economic sectors (Section 2.2.4).

2.2.1. Theoretical Foundations of Convergence

The theoretical foundations of convergence are rooted in the neoclassical growth model, which posits that diminishing returns to capital lead poorer economies, characterized by lower capital intensity, to grow faster than richer ones, thereby converging towards a steady-state equilibrium (Dornbusch et al., 2008; Solow, 1956; Solow & Swan, 1956). Within the empirical literature, convergence is typically operationalized through two complementary concepts: β -convergence, which captures the inverse relationship between initial income levels and subsequent growth rates, and σ -convergence, which refers to a reduction in the dispersion of income levels over time. A further distinction is made between absolute convergence, where all economies converge towards a common steady state, and conditional convergence, where long-run equilibrium levels differ according to structural characteristics such as savings rates, demographic dynamics or institutional conditions (Barro & Sala-i-Martin, 1992, 1997).

These conceptual frameworks can be extended to the analysis of sectoral structures, including agriculture's share in GDP, by treating the sectoral share as a structural state variable. In this context, convergence would imply that economies with initially higher agricultural shares experience more rapid declines, accompanied by a gradual reduction in cross-country dispersion. However, the notion of conditional convergence is particularly relevant in the case of sectoral variables, as the long-term position of agriculture within the economic structure is likely to depend on persistent factors such as resource endowments, value-chain configurations, demographic patterns and policy regimes. As a result, the assumption of convergence towards a single common steady state becomes less plausible, and sectoral convergence is more appropriately understood as a process shaped by heterogeneous structural conditions across economies.

2.2.2. Divergence Between β - and σ -Convergence

A key empirical insight emerging from the literature is that β -convergence and σ -convergence may evolve in different directions, and such divergence should be interpreted as an inherent feature of the convergence process rather than an inconsistency. Evidence from regional analyses in Slovakia indicates the presence of conditional β -convergence in GDP per capita and labour productivity, accompanied by σ -divergence in income levels. This pattern is interpreted as convergence towards region-specific steady states, shaped by persistent structural asymmetries such as differences in infrastructure, human capital and investment dynamics (Banerjee & Jarmuzek, 2010). Similarly, broader evidence at the European Union level identifies absolute β -convergence without corresponding σ -convergence, as poorer regions tend to grow faster while overall dispersion increases. This outcome reflects uneven technological diffusion, institutional heterogeneity and dif-

ferentiated regional development trajectories, suggesting that economic integration alone does not ensure balanced convergence (Qinetti et al., 2011).

These findings have important implications for the analysis of structural convergence in agriculture. In particular, they indicate that a common directional trend—such as the widespread decline in agriculture’s share of GDP—does not necessarily imply a reduction in cross-country disparities. Conversely, a narrowing of dispersion may occur even in the absence of strong catch-up dynamics, especially over shorter time horizons or in the presence of non-linear adjustment processes. As such, a comprehensive assessment of convergence requires the simultaneous consideration of both β - and σ -dimensions in order to capture the complexity of structural transformation across economies.

2.2.3. Convergence at the National Versus Regional Level

A second recurring theme in the convergence-focused literature is that its dynamics may differ significantly between the national and regional levels. Comparative evidence for EU Member States highlights particularly strong catching-up processes among Central and Eastern European economies during the period 2000–2017, with both β - and σ -convergence observed within the CEE group, while other European clusters display weaker or absent convergence patterns (Miron & Holobiuc, 2020). However, this tendency is not uniformly replicated at lower spatial scales. Analyses conducted at the NUTS-2 regional level indicate that, although convergence is evident at the country level, it becomes substantially weaker within countries, as capital regions maintain persistent growth advantages that contribute to widening intra-national disparities (Miron & Holobiuc, 2020).

These findings can be reconciled through a broader interpretative framework that emphasizes the coexistence of convergence and divergence processes. In particular, it has been argued that cumulative causation and agglomeration effects may dominate during certain stages of development, leading to increased regional polarization even in the presence of overall convergence trends. Moreover, convergence dynamics may follow non-linear trajectories and remain conditional on national development levels and structural characteristics (Monastiriotis, 2014).

For studies focusing on sectoral convergence, including the evolution of agriculture’s share in GDP, these insights carry important implications. On the one hand, macro-level convergence in sectoral structures appears plausible in the context of European integration and post-transition restructuring. On the other hand, such convergence should not be interpreted as indicative of uniform territorial development, as it may coexist with significant internal disparities in terms of rural–urban dynamics, regional productivity and economic specialization.

2.2.4. The Domain-Specific Nature of Convergence

A further important theme in the literature is that convergence is inherently domain-specific, with outcomes varying significantly across sectors depending on investment patterns, structural conditions and institutional contexts. Sectoral analyses demonstrate that the conventional “catch-up” mechanism may not hold uniformly, as initial endowments and sector-specific dynamics can alter convergence trajectories. For instance, evidence from the tourism sector in Romania reveals the presence of β -divergence alongside partial σ -convergence, indicating that less developed regions do not systematically grow faster, even though overall disparities tend to decline gradually. This pattern is consistent with uneven spatial diffusion processes and the concentration of investment in more developed areas (Butnaru & Niță, 2016).

Similar complexities are observed in the agricultural sector. Empirical evidence from rural Poland shows only partial and cyclical σ -convergence in labour productiv-

ity, with alternating phases of convergence and divergence, while no evidence of absolute β -convergence is identified. These dynamics are closely linked to structural characteristics such as farm size distribution, natural conditions and the effectiveness of institutional support mechanisms (Adamowicz & Szepeluk, 2022). At a broader level, institutional convergence studies suggest that improvements in economic indicators do not necessarily coincide with convergence in governance quality. In particular, σ -convergence in macroeconomic outcomes may coexist with divergence in government effectiveness, indicating that structural performance and institutional capacity may evolve independently (Andres & Franco, 2025).

Additional evidence from the Czech Republic's convergence towards the Eurozone, analyzed within the framework of the Optimum Currency Area theory, points to the existence of partial and fragile convergence processes, which are sensitive to external shocks and methodological specifications. In this context, convergence appears uneven and subject to disruption, while standard β -convergence results may weaken when more refined empirical approaches are employed (Jan et al., 2016).

Taken together, these findings underline the need for an analytical framework capable of capturing heterogeneous adjustment paths, non-linear dynamics and structural breaks. In the context of agriculture's share in GDP, this implies that convergence should not be assessed through a single methodological lens, but rather through a combination of complementary approaches that can account for the complexity and variability of sectoral transformation processes.

2.2.5. Empirical Evidence on Convergence in the Agricultural Sector

A smaller but directly relevant body of work narrows the focus from aggregate convergence to convergence within the agricultural sector itself. Kijek et al. (2019) examine the convergence of agricultural productivity across new and old European Union member states and find that catch-up is neither uniform nor unconditional: productivity convergence proceeds unevenly and is better described by the formation of distinct convergence "clubs" than by a single common trajectory, with the newer member states converging among themselves at a different pace from the established ones. This finding is particularly pertinent to the present study, as it indicates that, even within an integrated policy framework, agricultural convergence may be group-specific, an expectation our clustering approach is designed to test. Complementing this productivity-based perspective, Calegari et al. (2016) analyse convergence in the agricultural sector across European regions and highlight the role of the interaction between agricultural and regional policy in shaping convergence outcomes, showing that sectoral convergence cannot be dissociated from the broader spatial and policy context in which it occurs.

Taken together, these studies establish that convergence in agriculture is empirically documented but partial, conditional and spatially differentiated. They also delimit the object of that convergence in specific ways: Kijek et al. (2019) address agricultural productivity, while Calegari et al. (2016) address regional agricultural performance and its policy determinants. The convergence of the agricultural share in GDP—a structural indicator capturing the relative weight of the sector within the national economy—across a defined group of Central and Eastern European countries, and over a three-decade horizon spanning transition and EU accession, remains comparatively underexplored. It is this specific intersection that the present study addresses.

2.3. Research Gaps

Drawing together the shortcomings identified in the preceding review, this section states the specific research gaps that the present study addresses and links each of them to the corresponding element of the empirical strategy developed below.

For research that examines agricultural GDP shares across multiple Central and Eastern European countries over 1995–2024, these themes imply a coherent interpretive strategy. The decline in agriculture's share should be framed as an expected structural transformation, but differences in levels and volatility across countries likely reflect heterogeneous starting points, speed of diversification, and the extent of upgrading and value-chain integration (Mănescu et al., 2024; Mitrovic et al., 2017; Mrówczyńska-Kamińska & Bajan, 2019). At the same time, input–output evidence cautions against interpreting a small agricultural share as “low relevance”: agribusiness linkages can remain macroeconomically substantial even when primary agriculture is small. This reinforces the need for careful language: the paper's dependent variable captures primary agriculture's structural weight, which is analytically suited for studying structural convergence but should not be overstated as the full agri-food economy's contribution.

The existing literature on the agricultural share in GDP provides strong empirical support for the long-run decline in agriculture's share of GDP and identifies a range of underlying mechanisms, including value-chain upgrading, institutional transformation, trade openness and spatial economic structures. However, several limitations remain that are directly relevant to the present study, which focuses on the evolution and convergence of agricultural shares across Central and Eastern European countries over the period 1995–2024.

First, a substantial part of the empirical evidence is based on single-country analyses or on case studies outside the CEE region, which restricts the ability to draw robust conclusions regarding long-term cross-country structural convergence in primary agriculture's GDP share within this specific group of economies (Mănescu et al., 2024; Mitrovic et al., 2017; Rotaru, 2015). Second, although the literature emphasizes the importance of distinguishing between primary agriculture and the broader agribusiness system, comparative studies rarely incorporate this distinction when analyzing sectoral convergence, resulting in conceptual ambiguity regarding the object of convergence itself (Mrówczyńska-Kamińska & Bajan, 2019; Permeheh & Gilanpour, 2024).

Third, while several contributions acknowledge that agriculture retains strategic relevance despite its declining share—particularly through exports and rural labor markets—this perspective is seldom integrated with systematic analyses of cross-country dispersion, limiting the understanding of how structural transformation relates to convergence dynamics over time. Finally, although the determinants of agricultural decline, such as institutional change, openness and regional structural characteristics, are widely discussed, there is limited empirical evidence on whether these processes lead to synchronized adjustment patterns or the emergence of distinct convergence clubs. Addressing this gap requires a more integrated analytical framework capable of combining dispersion measures with correlation and clustering techniques in order to capture both convergence trends and underlying structural heterogeneity.

On the other hand, while the convergence literature offers a robust conceptual framework and extensive empirical evidence on income convergence within the EU and CEE contexts, several limitations remain with respect to the analysis of sectoral structural convergence, particularly in the case of agriculture's share in GDP. First, the majority of empirical contributions focus on GDP per capita at national or regional levels, with comparatively limited attention devoted to sectoral indicators. As a result, the mechanisms underlying convergence in economic structure—especially in terms of agriculture's rela-

tive weight—remain less clearly specified than those associated with income convergence (Butnaru & Niță, 2016; Miron & Holobiuc, 2020; Qineti et al., 2011).

Second, although the literature frequently documents divergences between β - and σ -convergence and emphasizes the importance of conditional convergence, relatively few studies provide empirical tools capable of capturing heterogeneity in a structured manner, such as the identification of convergence “clubs” based on similar adjustment trajectories. This leaves scope for methodological approaches that explicitly account for group-specific dynamics, in line with the conditional convergence framework (Banerjee & Jarmuzek, 2010; Figueras et al., 2014).

Third, while several studies highlight the role of crisis episodes and asymmetric shocks in shaping convergence patterns, the notion of synchronization is rarely operationalized using robust non-parametric measures. In this regard, rank-based correlation techniques, such as Spearman coefficients, can offer valuable insights into the extent to which economies exhibit similar structural dynamics over time, beyond linear relationships (Jan et al., 2016).

Finally, although unit-root and stochastic convergence approaches are increasingly employed in the literature, these are seldom integrated with forecasting techniques. Linking persistence diagnostics, such as Augmented Dickey–Fuller tests, with time-series forecasting models (e.g., ARIMA) would allow for a forward-looking assessment of convergence processes, providing insight into whether observed patterns in agricultural GDP shares are likely to persist. This dimension remains largely underexplored in the existing literature (Akkay, 2022).

3. Research Methodology

3.1. Data

The empirical analysis is based on annual data on agriculture, forestry and fishing value added, expressed as a percentage of GDP, obtained from the World Bank’s World Development Indicators database (indicator NV.AGR.TOTL.ZS) (World Bank, n.d.). This indicator provides a harmonized, internationally comparable measure of the relative structural weight of primary agriculture within the national economy and is available on a consistent basis for all countries in the sample. The dataset covers seven Central and Eastern European economies—Bulgaria, Croatia, the Czech Republic, Poland, Romania, Slovakia, and Hungary—selected on the basis of their shared experience of post-socialist transition and subsequent accession to the European Union, which makes them a coherent group for the study of structural convergence in agriculture.

The baseline observation period is 1995–2024, providing 30 annual observations per country. This horizon spans the consolidation of the post-transition period, the successive waves of EU accession (2004, 2007, and 2013), and the major external shocks of the global financial crisis and the COVID-19 pandemic, and is used in full for the descriptive statistics, the Spearman correlation and cluster analyses, and the σ - and β -convergence tests.

One country-specific adjustment is applied for the time-series modelling. For Bulgaria, the ARIMA model is estimated over the sub-period 1998–2024 rather than the full sample. During the Bulgarian financial crisis of 1996–1997, the agricultural share in GDP rose to approximately 20.5% (1997); this value reflects the abrupt contraction of aggregate GDP during the crisis rather than an increase in agricultural output, and it constitutes a pronounced structural break at the start of the series. Estimating ARIMA specifications on the full 1995–2024 series produced unstable models with forecast errors exceeding 30% (MAPE), indicating that the crisis-affected observations could not be adequately accommodated within a single linear specification. Restricting the estimation sample to 1998–2024 removes this break and yields a stable, diagnostically valid model (Section 4.2.2). The earlier obser-

vations are nonetheless retained in the descriptive and convergence analyses, where they are informative about Bulgaria's structural starting point and its subsequent adjustment.

3.2. Methods

The combined use of descriptive and inferential statistical methods enables a thorough analysis of economic and financial datasets, making it possible to generate meaningful insights that can guide well-founded decision-making. At the same time, sound empirical research necessitates careful attention to the specific contextual factors involved, as well as the adoption of analytical approaches that are appropriately aligned with the structural features and distributional characteristics of the data under investigation.

The distributional properties of the analyzed time series are assessed using the Shapiro–Wilk test, a procedure especially suited to small samples, generally those comprising fewer than 50 observations. Under the conventional 5% significance threshold, a p -value greater than 0.05 suggests that the null hypothesis of normality cannot be rejected. For a time series Y_t , where $t = 1, \dots, n$, the Shapiro–Wilk statistic, originally proposed by [Shapiro and Wilk \(1965\)](#), offers a formal framework for determining whether the empirical distribution departs from the assumption of normality:

$$W = \frac{\sum_{t=1}^n (p_t y_t)^2}{\sum_{t=1}^n (y_t - \bar{y})^2}, \quad (1)$$

where y_t denotes the ordered observations of the original series Y_t , arranged in ascending order $y_1 \leq y_2 \leq \dots \leq y_n$, $\bar{y}$ represents the sample mean, and p_t are the corresponding weighting coefficients. The null hypothesis of normality is rejected when the calculated test statistic is less than or equal to the critical value W_α as reported by Shapiro and Wilk ([Shapiro & Wilk, 1965](#)) for the chosen significance level. Furthermore, the procedure yields an associated p -value, computed using IBM SPSS Statistics 31.0; a probability value exceeding 0.05 implies that the null hypothesis of normality cannot be rejected at the conventional 5% significance threshold.

Spearman's rank correlation coefficient is a non-parametric measure used to assess the strength and direction of the monotonic relationship between two variables. Unlike Pearson's correlation coefficient, Spearman's correlation is based on ranked data and does not require the assumptions of normality or linearity. The coefficient ranges from -1 to $+1$, where values close to $+1$ indicate a strong positive monotonic association, values close to -1 indicate a strong negative monotonic association, and values around zero suggest the absence of a monotonic relationship. Owing to its robustness to non-normal distributions and outliers, Spearman's correlation is particularly suitable for economic and agricultural data, where variables often violate the assumptions required for parametric correlation analysis.

Spearman's rank correlation is used in preference to Pearson's coefficient because the Shapiro–Wilk results reject normality for six of the seven series and the data contain pronounced early-period extreme values. Being based on ranks, Spearman's coefficient is robust to non-normality and outliers and captures the monotonic co-movement of the series, making it the appropriate measure of the cross-country synchronization of structural change examined in this study.

The σ -convergence test evaluates whether disparities among a group of countries or regions decrease over time by examining the evolution of the cross-sectional dispersion of a given indicator. σ -convergence is considered to occur when the dispersion, commonly measured by the standard deviation, declines throughout the study period. A reduction in dispersion indicates that the analyzed units are becoming more similar in terms of the selected variable, whereas an increase suggests divergence. In this study, the σ -convergence

test is employed to assess whether differences in agriculture's share of GDP among the selected countries have diminished over time, thereby providing evidence of convergence or divergence.

The β -convergence test examines whether countries or regions with lower initial levels of a given indicator tend to experience faster growth than those with higher initial levels. The test is typically implemented by estimating a regression in which the average growth rate of the variable is explained by its initial value. A statistically significant negative coefficient of the initial level indicates the presence of β -convergence, implying that economies with lower starting values catch up over time. In this study, β -convergence is used to assess whether countries with a higher initial share of agriculture in GDP experienced a faster decline in this indicator, thereby converging toward the levels observed in the rest of the sample.

The parameters of the ARIMA forecasting models were estimated using the least squares method. The statistical relevance of individual coefficients was examined through Student's *t*-test, whereas the overall adequacy of each model specification was assessed using the F-test. Under the null hypothesis (H_0), the estimated coefficients are assumed to be statistically indistinguishable from zero, while the alternative hypothesis (H_1) implies that the parameters are statistically significant. When the probability values associated with the *t*- and F-statistics are lower than the conventional 0.05 threshold, the null hypothesis is rejected in favor of H_1 at the 5% level of significance.

Subsequently, several diagnostic procedures are conducted to assess the adequacy of the estimated models. First-order serial correlation and the independence of the residuals are evaluated using the Durbin–Watson test, while higher-order autocorrelation is examined through the Breusch–Godfrey test. In addition, the ARCH test is applied to determine whether the variance of the error terms remains constant over time or displays conditional heteroskedasticity. Autocorrelation occurs when residuals are correlated across successive periods, potentially leading to underestimated standard errors and, consequently, unreliable inferences regarding parameter significance. The Durbin–Watson statistic (DW) is calculated on the basis of the differences between residuals observed in consecutive time intervals (Durbin & Watson, 1950).

$$DW = \frac{\sum_{i=2}^n (e_i - e_{i-1})^2}{\sum_{i=1}^n (e_i)^2} \quad (2)$$

where *n* represents the total number of observations included in the sample. The Durbin–Watson statistic ranges between 0 and 4, with values approaching 2 indicating the absence of first-order autocorrelation in the residuals. In empirical applications, the computed DW value is typically compared with the lower *dl* and upper *du* critical bounds reported in the Durbin–Watson reference tables for the selected significance level. When the statistic falls within the interval (*du*, 4 − *du*), the null hypothesis (H_0) of no residual autocorrelation is not rejected.

The Breusch–Godfrey test (Breusch, 1978; Godfrey, 1978) is employed to detect the presence of higher-order serial correlation in the residuals of the estimated model and provides an associated probability value. When this probability exceeds the conventional 0.05 threshold, the null hypothesis (H_0) cannot be rejected, indicating that higher-order autocorrelation is not statistically significant at the 5% level of significance.

The Dickey–Fuller test (Dickey & Fuller, 1979) is commonly used to determine whether a time series is stationary, which represents a fundamental requirement in time-series modelling. Stationarity implies that essential statistical characteristics of the series, such as its mean and variance, remain stable over time. The test investigates the presence of a unit root within an autoregressive specification, as the existence of such a root signals

non-stationarity. In this situation, the series tends to display persistent fluctuations and does not converge toward a constant long-run mean.

To increase the reliability of the analysis, the Augmented Dickey–Fuller test is applied because establishing the order of integration of each series is a prerequisite both for correctly specifying the differencing order in the ARIMA models and for interpreting the persistence of shocks to the agricultural share.

ARIMA modelling is adopted because the Augmented Dickey–Fuller results (Section 4.2) establish that the agricultural-share series are integrated of order one for all countries—non-stationary in levels but stationary after first differencing—which is precisely the setting for which ARIMA(p,1,q) specifications are designed. As a parsimonious and transparent univariate approach, ARIMA is well suited to generating medium-term forecasts for a single, slowly evolving structural indicator, and it serves as a widely used benchmark in applied time-series forecasting (Box et al., 2015). Residual diagnostics (Durbin–Watson, Breusch–Godfrey and ARCH tests) are applied to confirm that the selected specifications are free of serial correlation and conditional heteroskedasticity, ensuring the reliability of the resulting forecasts.

Ward’s hierarchical method is applied to a distance matrix defined as $d_{ij} = 1 - \rho_{ij}$, where ρ_{ij} is the Spearman correlation between the agricultural-share series of countries i and j , so that economies with similar temporal dynamics are separated by smaller distances. This approach is used because it translates the pairwise correlation structure into interpretable groups of countries with similar structural trajectories, directly addressing the study’s aim of identifying convergence “clubs” within the region.

In the context of this study, Ward’s method was applied to a distance matrix defined by the relationship $d_{ij} = 1 - \rho_{ij}$, where ρ_{ij} denotes the Spearman correlation coefficient between the time series of the agricultural share in GDP for countries i and j . This specification ensures that countries exhibiting similar temporal dynamics (i.e., high correlations) are characterized by smaller distances and, consequently, a higher likelihood of being grouped within the same cluster.

The algorithm starts from an initial configuration in which each country constitutes a separate cluster. At each iteration, the two clusters whose merger results in the smallest increase in total within-cluster variance are combined. Formally, Ward’s criterion seeks to minimize internal variability following aggregation, ensuring that the resulting clusters are as compact and statistically homogeneous as possible.

4. Results

4.1. Statistical Analysis

The analysis of the descriptive statistics presented in Table 1, complemented by the examination of temporal dynamics over the period 1995–2024, illustrated in Figure 1, provides a coherent overview of the evolution of the agricultural share in GDP across the seven countries under study. The results highlight significant initial structural differences among the economies, followed by a clearly observable process of long-term economic convergence.

From the perspective of average levels and relative positioning, Romania and Bulgaria stand out as recording the highest shares of agriculture in GDP, particularly during the 1990s, reflecting a lower degree of industrialization and a stronger dependence on the agricultural sector at the onset of the transition period. The relatively high mean values (8.04% in Romania and 6.66% in Bulgaria), together with the exceptionally high peaks observed in the early years of the analyzed period (exceeding 18% in Romania and 20% in Bulgaria), confirm this initial economic structure. By contrast, Poland, Hungary, and Croatia consistently occupy an intermediate position, while the Czech Republic and Slovakia

display the lowest agricultural shares in GDP, indicating economies that were already more strongly oriented towards industry and services.

Table 1. Descriptive statistics (% of GDP).

Country	Mean	Standard Deviation	Coefficient of Variation	Kurtosis	Skewness	Minimum	Maximum
Croatia	3.8948	0.9351	24.0108	−0.9659	0.6053	2.6839	5.6515
Czechia	2.4263	0.6563	27.0502	0.2237	1.1004	1.5225	4.0052
Hungary	4.1750	1.2434	29.7823	1.3318	1.4332	2.7111	7.3921
Poland	3.1178	0.8132	26.0827	4.1520	2.0522	2.2455	5.7358
Romania	8.0392	4.7016	58.4832	−0.4215	0.9354	2.8114	18.1628
Bulgaria	6.6647	4.0817	61.2440	3.1271	1.6242	2.3510	20.4768
Slovakia	1.8855	0.2705	14.3466	0.3788	0.4648	1.4712	2.61492

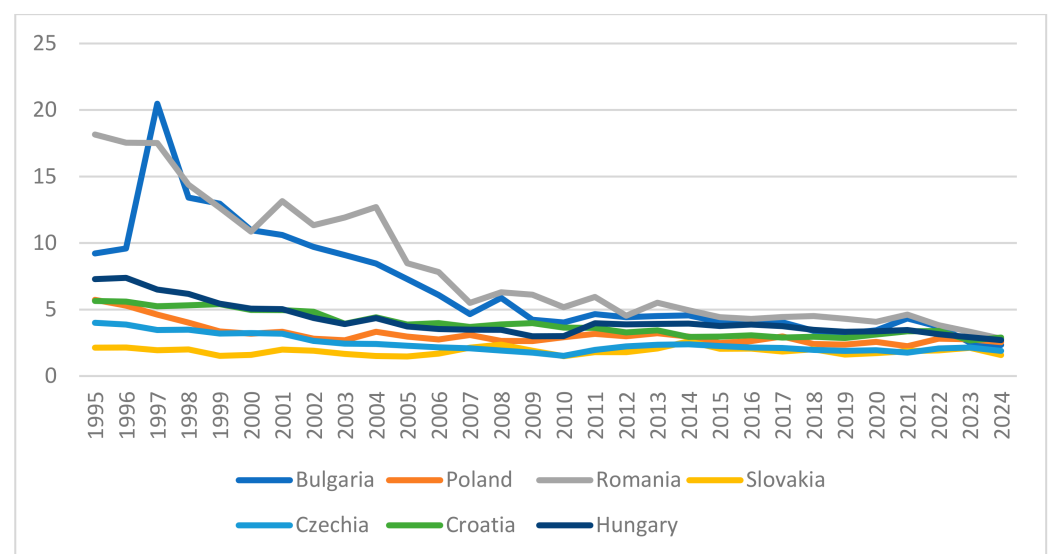


Figure 1. Agriculture, forestry and fishing, value added (% of GDP), authors' contribution based on data from (World Bank, n.d.).

The analysis of variability further supports these structural differences. Romania and Bulgaria exhibit the highest levels of volatility, with coefficients of variation exceeding 50%, indicating substantial fluctuations between minimum and maximum values, particularly in the early years of the analyzed period. This instability points to a high sensitivity of the agricultural sector to economic, institutional, and climatic changes. In contrast, the Czech Republic and Slovakia are characterized by relatively stable time series, with limited variation and coefficients of variation below 30%, while Poland and Hungary display moderate fluctuations.

From the perspective of statistical distributions, the positive skewness values observed for Romania and Bulgaria indicate a concentration of higher values in the early part of the period, particularly during the 1990s, when agriculture played a dominant economic role. Croatia and Slovakia display nearly symmetrical distributions, reflecting a more uniform evolution over time. The analysis of kurtosis reveals more “peaked” distributions in the case of Poland and Bulgaria, suggesting a stronger concentration of observations around the mean alongside the presence of extreme values, whereas Croatia and Romania exhibit flatter distributions, indicating a wider dispersion of values.

The examination of temporal dynamics reveals a clear downward trend in the agricultural share of GDP across all seven countries over the period 1995–2024. This general

tendency can be explained by post-communist economic restructuring, the expansion of the services sector, the modernization of agriculture—which increased productivity while reducing its relative contribution to GDP—and the process of European Union integration. At the national level, Romania and Bulgaria record the most pronounced declines, characterized by a rapid reduction in the agricultural share alongside cyclical fluctuations influenced by climatic and structural factors. In Bulgaria, a relative stabilization can be observed after 2007, associated with EU accession. Poland displays one of the smoothest and most consistent downward trajectories, indicating a balanced process of structural transition, while Hungary and Croatia register moderate declines, with a slight stabilization after 2010 in the case of Croatia, partly linked to the expansion of the tourism sector. The Czech Republic and Slovakia maintain comparatively low levels throughout the entire period, with gradual decreases and only minor variations.

The analysis of extreme values further confirms these trends: the absolute maxima are observed in Romania and Bulgaria during the 1990s, whereas the absolute minima are recorded after 2020, particularly in the Czech Republic and Slovakia, at levels of approximately 1.5–2%. Notably, Romania reaches, for the first time, values comparable to those observed in Central European economies, signaling the emergence of a process of structural convergence.

An important statistical result is the process of structural convergence observed among the analyzed countries. While in 1995 the dispersion of the agricultural share in GDP was very high, during the period 2015–2024 it declined substantially, with all economies falling within a relatively narrow range of approximately 1.5–3.5% of GDP. This trend suggests a gradual structural harmonization of the economies in Central and Eastern Europe.

Overall, the results confirm a substantial decline in the relative importance of agriculture across all analyzed economies, with the most pronounced structural adjustments occurring in countries where agriculture played a dominant role at the beginning of the period, notably Romania and Bulgaria. At the same time, a clear convergence process among the states can be observed, although volatility remains comparatively higher in economies characterized by traditional agricultural structures and stronger climatic dependence.

The Shapiro–Wilk normality test (Table 2) was applied to the time series of the agricultural share in GDP for the seven countries under analysis over the period 1995–2024, with the aim of assessing the normality assumption of the distributions. The test is based on two hypotheses: the null hypothesis (H_0), which states that the data are drawn from a normally distributed population, and the alternative hypothesis (H_1), which assumes deviations from normality.

Table 2. Test Shapiro–Wilk.

Test Shapiro–Wilk	Bulgaria	Poland	Romania	Slovakia	Czechia	Croatia	Hungary
<i>p</i> -value	0.000	0.000	0.000	0.271	0.001	0.008	0.000

The obtained results indicate the rejection of the normality assumption for the majority of the countries analyzed. The very low *p*-values ($p < 0.01$) reported for Bulgaria, Poland, Romania, the Czech Republic, Croatia, and Hungary suggest that the distributions of the agricultural share in GDP differ significantly from a normal distribution. These deviations can be explained by the presence of pronounced downward trends, extreme values recorded particularly during the 1990s, as well as cyclical fluctuations driven by economic and climatic factors.

In contrast, for Slovakia, the *p*-value ($p = 0.271$) does not allow the rejection of the null hypothesis, suggesting that the distribution of the agricultural share in GDP can be

regarded as compatible with normality. This result is consistent with the earlier descriptive analysis, which highlighted the relatively low and stable contribution of agriculture to Slovakia's GDP, as well as its limited variability over time.

From a methodological perspective, the rejection of the normality assumption for most of the series justifies the use of non-parametric statistical methods in subsequent analyses, such as the Spearman correlation coefficient. At the same time, the result obtained for Slovakia reinforces its status as a structural outlier, displaying a development trajectory distinct from that of the other economies under consideration.

Overall, the Shapiro–Wilk test highlights the asymmetric and non-normal nature of the distributions of the agricultural share in GDP for most Central and Eastern European countries, reflecting the structural adjustment processes and economic convergence dynamics characteristic of the post-transition period.

The analysis of the Spearman correlation coefficients (Table 3), considered in conjunction with the Shapiro–Wilk normality test results, enhances the robustness of the conclusions regarding the regional dynamics of the agricultural share in GDP over the period 1995–2024. The normality tests indicate that, for most of the countries analyzed, the assumption of normality is rejected ($p < 0.01$), whereas only Slovakia exhibits a distribution compatible with normality. In this context, the use of the Spearman correlation coefficient—which does not require the normality assumption and is robust to asymmetry and extreme values—is methodologically well justified.

Table 3. Spearman Coefficients and p -value Matrix.

	Bulgaria	Poland	Romania	Slovakia	Czechia	Croatia	Hungary
Bulgaria	1.000						
Poland	$\rho = 0.730$ $p = 4.61 \times 10^{-6}$	1.000					
Romania	$\rho = 0.927$ $p = 1.74 \times 10^{-13}$	$\rho = 0.732$ $p = 4.33 \times 10^{-6}$	1.000				
Slovakia	$\rho = 0.018$ $p = 0.927$	$\rho = 0.116$ $p = 0.541$	$\rho = 0.019$ $p = 0.925$	1.000			
Czechia	$\rho = 0.799$ $p = 1.18 \times 10^{-7}$	$\rho = 0.752$ $p = 2.08 \times 10^{-6}$	$\rho = 0.726$ $p = 5.15 \times 10^{-6}$	$\rho = 0.188$ $p = 0.319$	1.000		
Croatia	$\rho = 0.886$ $p = 7.46 \times 10^{-11}$	$\rho = 0.692$ $p = 1.10 \times 10^{-5}$	$\rho = 0.926$ $p = 2.13 \times 10^{-13}$	$\rho = -0.028$ $p = 0.882$	$\rho = 0.654$ $p = 4.09 \times 10^{-5}$	1.000	
Hungary	$\rho = 0.862$ $p = 2.03 \times 10^{-10}$	$\rho = 0.793$ $p = 1.44 \times 10^{-7}$	$\rho = 0.798$ $p = 1.19 \times 10^{-7}$	$\rho = 0.171$ $p = 0.366$	$\rho = 0.899$ $p = 4.98 \times 10^{-12}$	$\rho = 0.704$ $p = 7.21 \times 10^{-6}$	1.000

The Spearman correlation results reveal the existence of strong to very strong positive monotonic associations among the majority of the non-normal time series. The highest coefficient values are observed between Romania and Bulgaria ($\rho = 0.93$), Romania and Croatia ($\rho = 0.93$), as well as between the Czech Republic and Hungary ($\rho = 0.90$), with all relationships confirmed as statistically significant at the 1% level. These correlations reflect similar structural trajectories in the process of reducing the agricultural share of GDP, despite initial differences in levels and the asymmetric distribution patterns of the series.

The strong correlations identified between Poland and the other economies, as well as between Romania and Hungary or the Czech Republic, indicate a pronounced regional synchronization of structural transformation processes. This finding suggests the presence of common influencing factors—such as European integration, institutional convergence, and the implementation of similar agricultural and economic policy frameworks—which

have contributed to a coherent evolution of the agricultural share in GDP, even in the context of non-normal data distributions.

In contrast, Slovakia—the only country for which the Shapiro–Wilk test does not reject the normality assumption—exhibits very weak and statistically insignificant Spearman correlations with all the other states ($\rho \approx 0$). This lack of association underscores the distinct trajectory of Slovakia's development, characterized by a relatively low and stable agricultural share in GDP and the absence of major structural adjustments. The result is consistent both with the near-normal distribution of the series and with the trend analysis, which indicated only minor variations over time.

To synthesize these relationships, a cluster analysis based on Spearman correlation coefficients was conducted using the distance measure defined as $d_{ij} = 1 - \rho_{ij}$ and Ward's aggregation method. The application of Ward's method leads to the construction of a dendrogram, which illustrates the sequence of aggregation stages and the levels at which cluster mergers occur. Cutting the dendrogram at an optimal threshold—determined on the basis of significant increases in aggregation distance—enabled the identification of a finite number of clusters that are economically meaningful. The application of Ward's method in combination with the distance measure $d_{ij} = 1 - \rho_{ij}$ revealed the existence of three distinct clusters, characterized by a high degree of internal homogeneity and a clear separation between groups.

The initial mergers occurred between the countries exhibiting the highest Spearman correlation coefficients, namely Romania–Bulgaria and Romania–Croatia, indicating nearly identical trajectories in the reduction in the agricultural share of GDP. These early linkages confirm that Ward's method prioritizes a high degree of structural similarity in the aggregation process.

Subsequently, Poland, the Czech Republic, and Hungary were grouped into a separate cluster, characterized by strong, albeit more moderate correlations than those observed in the first cluster. The mergers among these economies occurred at higher levels of the dendrogram, reflecting smaller differences in the dynamics of the time series and a more stable evolution of the agricultural share in GDP.

In contrast, Slovakia was incorporated only at a very late stage in the hierarchical aggregation process, at a relatively high level of aggregation distance, indicating a pronounced structural dissimilarity compared with the other countries. This positioning confirms its status as a structural outlier, characterized by a distinct dynamic and weak correlation with the general regional pattern.

From an economic perspective, the results obtained through Ward's method reflect different stages of structural transformation in Central and Eastern Europe. The identified clusters clearly distinguish between economies with initially dominant agricultural sectors and rapid adjustment processes (Romania, Bulgaria, and Croatia) and those with more diversified economic structures and more gradual transition paths (Poland, the Czech Republic, and Hungary). At the same time, Slovakia emerges as an atypical case, characterized by relative stability and a consistently low agricultural share in GDP throughout the entire analyzed period.

Overall, Ward's aggregation method, applied based on Spearman correlations, proved to be appropriate for capturing both structural similarities and differences in the dynamic patterns of the analyzed economies. The results are consistent with the findings derived from descriptive analysis, normality tests and the econometric models estimated subsequently, thereby reinforcing the conclusion that a regional process of structural convergence is underway, albeit with varying degrees of intensity across different groups of countries.

σ -Convergence and β -Convergence

σ -convergence checks whether the dispersion between countries decreases over time. The standard indicator used is the standard deviation calculated annually for the group of countries analyzed (Figure 2).

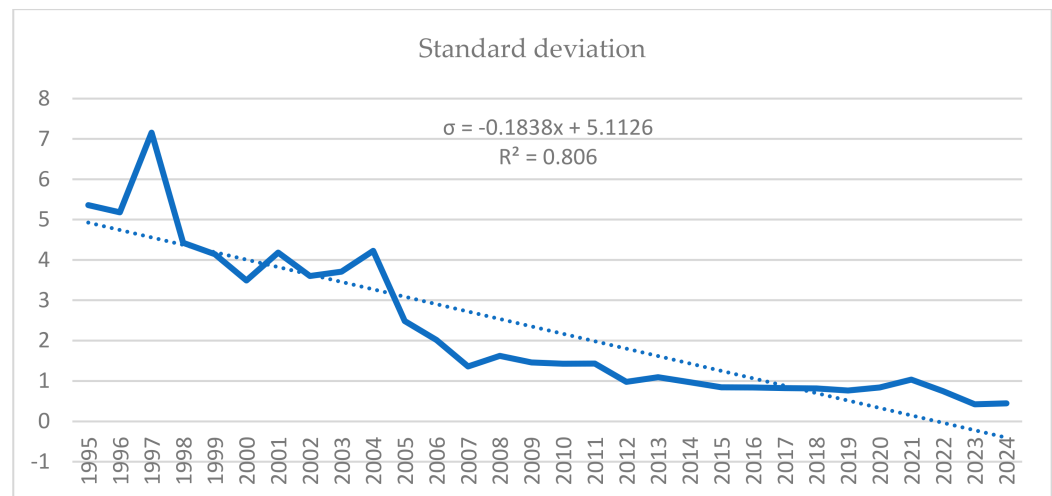


Figure 2. Cross-country standard deviation in the period 1994–2024, authors’ contribution based on data from (World Bank, n.d.).

One can formally test the trend $\sigma_i = \alpha + \delta x_i + \varepsilon_i$, where $i = 1995, \dots, 2024$. The hypotheses are $H_0 : \delta = 0$, $H_1 : \delta < 0$. It results $\sigma = -0.1838x + 5.1126$, with the graph given in Figure 2 (blue dashed line).

From the resulting series, the slope is negative, which indicates the systematic reduction in dispersion and confirms the existence of σ -convergence. To assess σ -convergence, the cross-country standard deviation of agriculture value added (% of GDP) was computed for each year. The results indicate a marked decline in dispersion, from approximately 5.36 in 1995 to only 0.45 in 2024, despite a temporary increase around 1997. This substantial reduction demonstrates that the agricultural share of GDP has become increasingly similar across the seven Central and Eastern European countries, providing strong evidence of σ -convergence.

The β -convergence test (Table 4) is a standard test used in the literature (Barro & Sala-i-Martin, 1992). It is estimated $\Delta y_i = \alpha + \beta y_{i,1995} + \varepsilon_i$, where $\Delta y_i = y_{i,2024} - y_{i,1995}$.

Table 4. β -convergence test.

Country	$y_{i,1995}$	$y_{i,2024}$	Δy_i
Bulgaria	9.22	2.35	−6.87
Poland	5.74	2.54	−3.20
Romania	18.16	2.81	−15.35
Slovakia	2.13	1.58	−0.55
Czechia	4.01	1.90	−2.11
Croatia	5.65	2.90	−2.76
Hungary	7.28	2.71	−4.57

It results $\Delta y_i = -0.9439y_{i,1995} + 1.9788 + \varepsilon_i$.

Absolute β -convergence was tested by regressing the long-run change in the agricultural share of GDP on its initial (1995) level. The estimated slope is negative, indicating that countries with initially higher agricultural shares experienced faster declines over the sample period. Romania and Bulgaria, which started with the highest agricultural shares,

recorded the largest reductions, whereas Slovakia and Czechia, which initially exhibited relatively low agricultural shares, experienced much smaller changes. These results provide evidence of absolute β -convergence across the seven countries.

In conclusion, the two tests are complementary:

- σ -convergence shows that the dispersion between countries has reduced over the period analyzed (1995–2024), with the standard deviation decreasing from approximately 5.36 to 0.45.
- β -convergence shows that countries with higher initial agricultural shares have experienced faster reductions, which is consistent with the process of structural convergence.

4.2. ARIMA Forecasting

The stationarity of the time series was examined using the Augmented Dickey–Fuller (ADF) test, specified with both a constant and a linear trend, over the period 1998–2004 for Bulgaria and 1995–2024 for the remaining countries (Table 5). The test was applied to the variable AGRI, which measures the share of agriculture in gross domestic product. The null hypothesis of the ADF test assumes the presence of a unit root, implying the non-stationary nature of the series, whereas the alternative hypothesis indicates stationarity. The statistical decision is based on the p -values associated with the t -statistic, with a significance threshold of 5% employed in the analysis.

Table 5. Augmented Dickey–Fuller test (Exogenous: Constant, Linear Trend), based on data from (World Bank, n.d.).

	Bulgaria 1998–2024	Poland	Romania	Slovakia	Czechia	Croatia	Hungary
AGRI	t -Statistic = −2.069793	t -Statistic = 3.555152	t -Statistic = −2.136998	t -Statistic = −3.427255	t -Statistic = −1.887602	t -Statistic = −1.560613	t -Statistic = −2.196844
	p -value = 0.5377	p -value = 0.0520	p -value = 0.5048	p -value = 0.0673	p -value = 0.6350	p -value = 0.7828	p -value = 0.4736
D(AGRI)	t -Statistic = −5.996374	t -Statistic = −4.914706	t -Statistic = −4.198011	t -Statistic = −5.233651	t -Statistic = −4.716467	t -Statistic = −8.839550	t -Statistic = −5.780197
	p -value = 0.0003	p -value = 0.0027	p -value = 0.0146	p -value = 0.0012	p -value = 0.0040	p -value = 0.0000	p -value = 0.0003

Note: For Bulgaria, the ADF test is estimated over 1998–2024; the observations for 1995–1997 are excluded because the elevated agricultural share during the 1996–1997 Bulgarian financial crisis reflects the sharp contraction of aggregate GDP rather than developments in the agricultural sector, and it introduces a structural break that distorts the time-series properties of the series. For all other countries, the test uses the full 1995–2024 period. See Section 3.1 for details.

The results of the ADF test applied to the series in levels indicate that the null hypothesis cannot be rejected for any of the countries under analysis. The p -values exceed the 5% critical significance level, ranging from 0.0520 in the case of Poland to 0.7828 for Croatia. Even for Poland and Slovakia, where the t -statistics are relatively close to the critical values, the decision criterion does not allow for the rejection of the null hypothesis.

These results suggest that the AGRI series is non-stationary in levels, exhibiting a dynamic largely driven by long-term trends. From an economic perspective, this pattern reflects the structural transformation processes experienced by the analyzed economies, characterized by the gradual decline in the contribution of the agricultural sector to GDP formation.

To determine the order of integration of the variable, the ADF test was subsequently reapplied to the first difference in the series, D(AGRI). In this case, the null hypothesis was rejected for all countries included in the sample, as the p -values were significantly below the 5% significance threshold.

The obtained *t*-statistics are substantially lower than the corresponding critical values, confirming the stationary nature of the differenced series. This finding indicates that the trend component is effectively removed through differencing, leading to the stabilization of fluctuations around a constant mean.

Based on the results of the Augmented Dickey–Fuller test, it can be concluded that the variable AGRI is integrated of order one, $I(1)$, for all the countries under analysis. The series is non-stationary in levels but becomes stationary after first differencing. This finding has important methodological implications for the subsequent econometric analysis.

4.2.1. Romania

Following the correlogram (Table A1), the estimation of several ARIMA(*p*,1,*q*) specifications for the AGRI series corresponding to Romania, the selection of the optimal model was carried out on the basis of a set of standard criteria widely used in the econometric literature. These included information criteria (AIC and Schwarz Criterion), residual diagnostics (the Durbin–Watson statistic, the Breusch–Godfrey test for autocorrelation, and the ARCH test for heteroskedasticity), as well as forecast performance indicators (RMSE and MAPE).

The comparative results reveal a gradual improvement in model performance as the autoregressive (AR) and moving average (MA) orders increase (Table 6). The ARIMA(2,1,2) and ARIMA(3,1,3) specifications display relatively high AIC values and substantial forecast errors, indicating limited explanatory and predictive capacity. Although these models satisfy stability conditions and do not exhibit major residual-related issues, their overall performance remains inferior to that of higher-order specifications.

Table 6. AIC, SC, diagnostic tests and prediction errors for Romania.

Model	AIC	SC	DW	B-G Test <i>p</i> -Value	ARCH Test <i>p</i> -Value	RMSE	MAPE
ARIMA(2,1,2)	3.1835	3.3275	2.53	0.3610	0.9171	3.6873	53.74
ARIMA(3,1,3)	3.0088	3.1540	2.83	0.1045	0.3034	2.6232	36.84
ARIMA(4,1,3)	3.0049	3.1511	2.50	0.2992	0.8957	1.8380	29.83
ARIMA(4,1,5)	2.4880	2.6343	1.91	0.7298	0.1143	1.8427	30.26
ARIMA(5,1,7)	1.7229	1.8702	2.79	0.1059	0.3922	1.3262	12.29

The ARIMA(4,1,3) and ARIMA(4,1,5) models record lower values of the information criteria and a substantial reduction in forecast errors, suggesting an improved capacity to capture the dynamics of the series. However, the differences between these two specifications are marginal, and the accuracy indicators (RMSE and MAPE) remain higher than those obtained for the higher-order model.

The most performant specification among the estimated models is ARIMA(5,1,7) (Table A2). This model records the lowest values of the AIC and Schwarz information criteria, as well as the smallest RMSE and MAPE values, indicating superior forecasting capability. Moreover, diagnostic tests confirm the correct specification of the model: the Breusch–Godfrey and ARCH statistics do not indicate the presence of residual autocorrelation or heteroskedasticity, while the value of the Durbin–Watson statistic is close to 2, suggesting the absence of first-order autocorrelation.

Based on the information criteria, diagnostic tests and forecast performance, the ARIMA(5,1,7) specification is selected as the optimal model for analyzing the evolution of the AGRI series in the case of Romania. This model provides an appropriate balance between statistical accuracy and predictive capability and is therefore employed for generating medium-term forecasts. The inclusion of a higher number of lags allows for the capture of persistent effects and delayed shocks that are characteristic of the agricultural sector, such as climatic variability, policy changes, and fluctuations in production inputs.

We acknowledge that ARIMA(5,1,7) is relatively parameter-rich given the sample size. However, both the comparison with more parsimonious alternatives and the out-of-sample validation indicate that this specification provides the best empirical performance for the available dataset.

The forecast results indicate a moderately declining trend in the analyzed indicator, with the estimated values for 2025 ranging between 2.51 and 1.58, depending on the forecasting horizon (Table 7).

Table 7. Forecast for Romania.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(5,1,7)	2.5110	2.3959	1.7921	1.5841

This evolution suggests a gradual slowdown in the dynamics of the agricultural sector, which may be interpreted as an adjustment process following periods characterized by pronounced fluctuations or temporary favorable shocks. From an econometric perspective, the progressive decline in the forecasted values reflects the persistence of the autoregressive components and moving-average effects identified by the model, indicating the gradual dissipation over time of past shocks affecting the AGRI series.

From an economic standpoint, the anticipated downward trend may be associated with structural factors specific to the agricultural sector, such as productivity constraints, the volatility of climatic conditions, a gradual shift towards higher value-added processed products, or changes in agricultural policy frameworks. In this context, the obtained forecasts do not point to an abrupt deterioration in sectoral performance but rather to a normalization in the evolution of the AGRI indicator, consistent with a medium-term stabilization scenario.

Overall, the forecast results highlight the usefulness of the ARIMA(5,1,7) model as an appropriate tool for anticipating the evolution of the agricultural sector in Romania, providing relevant insights for economic analysis and for the formulation of agricultural policy decisions. However, it should be noted that the reliability of these estimates remains contingent upon the absence of major exogenous shocks, such as extreme weather events, significant changes in agricultural policy, or adverse developments in the international economic environment.

Figure 3 graphically illustrates the historical evolution of the indicator together with the forecast and its associated confidence interval for the period 2025–2028.

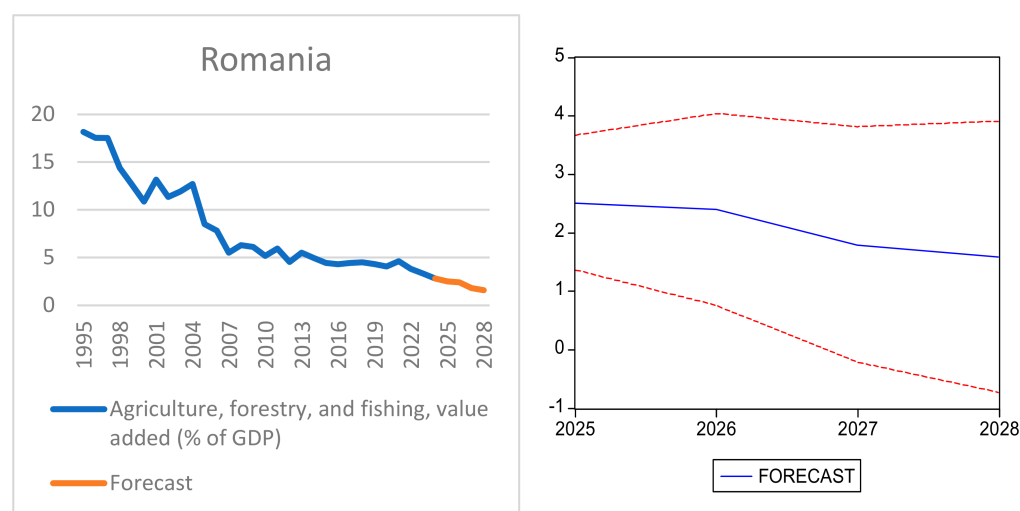


Figure 3. Agriculture, forestry and fishing (%GDP) and forecast in Romania with confidence interval (red dash line), authors' own contribution based on data from (World Bank, n.d.).

4.2.2. Bulgaria

The stationarity of the AGRI series for Bulgaria was assessed using the Augmented Dickey–Fuller (ADF) test, specified with both a constant and a linear trend (Table 5). For the full sample period 1995–2024, the ADF test results indicate the rejection of the null hypothesis of a unit root at the 5% significance level (p -value = 0.0422), suggesting an apparent stationarity of the series in levels. However, the analysis of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) reveals a high degree of persistence and statistically significant autocorrelations across several lags, pointing to a complex dynamic structure and potential model specification issues.

The estimation of several ARMA models for the series in levels over the full sample period resulted in high forecast errors, with all tested specifications recording MAPE values above the 30% threshold. These findings suggest that, despite the conclusions of the ADF test, the series is affected by structural instability and cannot be adequately modelled in levels across the entire analyzed interval. The value recorded in 1997 (approximately 20.48%) is accurate, although unusually high; it reflects a sharp contraction in total GDP rather than an absolute increase in agricultural output. The AGRI series for Bulgaria exhibits a major structural shock in the late 1990s, associated with the economic transition process and structural reforms. The presence of this shock distorts ARIMA model estimates based on the full sample, affecting both the stability of the coefficients and the accuracy of the resulting forecasts.

Consequently, the analysis was restricted to the sub-sample period 1998–2024, considered to be more structurally homogeneous. For this sub-sample, the ADF test indicates that the null hypothesis of a unit root cannot be rejected for the series in levels (p -value = 0.5377), while the first-differenced series is clearly stationary (p -value = 0.0003). Therefore, the series is integrated of order one, and the subsequent modelling is conducted within the class of ARIMA($p,1,q$) specifications, using also the correlogram (Table A3).

Table 8 highlights significant differences among the candidate models. Although the ARIMA(1,1,1) specification exhibits relatively close values of the information criteria, its forecasting performance is extremely weak, as reflected by a very high MAPE value (approximately 100%) and by a dominant bias component in the total forecast error. These findings indicate an inadequate specification of the series dynamics.

Table 8. AIC, SC, diagnostic tests and prediction errors for Bulgaria.

Model	AIC	SC	DW	B-G Test p -Value	ARCH Test p -Value	RMSE	MAPE
ARIMA(1,1,1)	2.0847	2.2310	2.27	0.4027	0.0873	4.3981	99.80
ARIMA(2,1,2)	2.1008	2.2481	2.30	0.6032	0.3314	0.8913	16.05

In contrast, the ARIMA(2,1,2) specification delivers markedly superior performance, recording the lowest forecast error (RMSE $\approx$ 0.89) and a substantially lower MAPE value (approximately 16%). Diagnostic tests confirm the correct specification of the model, as no evidence of residual autocorrelation (Breusch–Godfrey test) or conditional heteroskedasticity (ARCH test) is detected, while the value of the Durbin–Watson statistic is close to 2.

Based on these results, the ARIMA(2,1,2) specification is selected as the optimal model for Bulgaria and is subsequently employed to generate medium-term forecasts (Table A4).

The estimated values for the forthcoming period (Table 9) indicate a gradual downward trajectory of the series, with the forecasted level declining from approximately 2.15 in the initial forecasting horizons to around 1.46 in the more distant ones.

Table 9. Forecast for Bulgaria.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(2,1,2)	2.1544	1.8888	1.6954	1.4580

This dynamic reflects the gradual dissipation of the effects of previous shocks and a slow adjustment of the agricultural sector towards a more stable regime. From an econometric perspective, the downward trend results from the autoregressive structure and the moving-average components embedded in the model, which suggest a moderate persistence of past fluctuations but without long-term amplification mechanisms. The integration of the series of order one indicates that changes in AGRI are primarily driven by transitory factors, the effects of which tend to fade over time.

From an economic perspective, the results suggest a normalization in the relative weight and performance of the agricultural sector in Bulgaria, consistent with the maturation of the economic transition process and its gradual integration into the European market framework. The projected evolution does not indicate an abrupt deterioration of the sector but rather a structural adjustment towards a more stable level, potentially influenced by factors such as productivity convergence, technological change, and the implementation of common agricultural policies.

Overall, the forecast generated by the ARIMA(2,1,2) model highlights a moderation in the dynamics of the AGRI indicator in Bulgaria over the medium term, confirming the usefulness of differenced ARIMA models as appropriate tools for anticipating sectoral developments in economies that have previously experienced episodes of structural instability. The results should be interpreted subject to the assumption of the absence of major exogenous shocks, particularly those of a climatic or institutional nature. Figure 4 presents the graphical representation of both the historical evolution of the indicator and the corresponding forecast, together with the associated confidence interval.

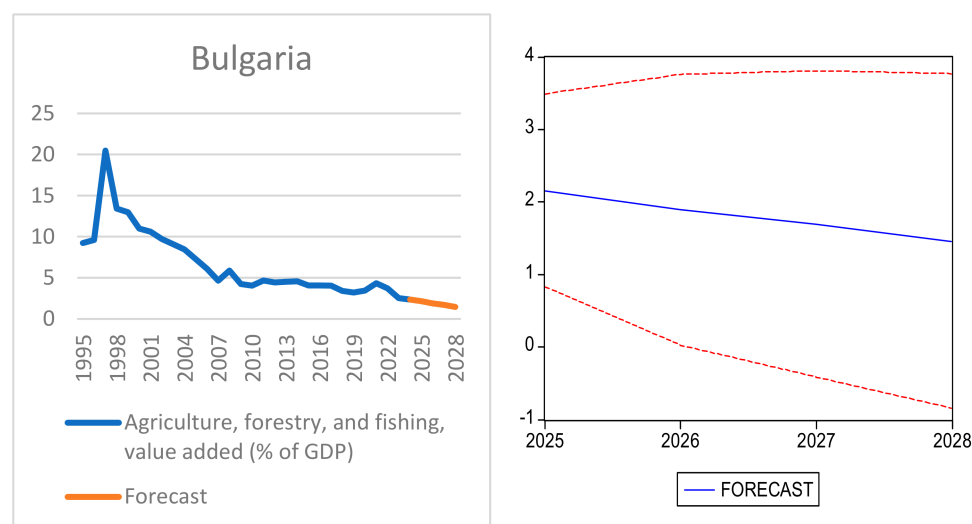


Figure 4. Agriculture, forestry and fishing (%GDP) and forecast in Bulgaria with confidence interval (red dash line), authors' contribution based on data from (World Bank, n.d.).

4.2.3. Hungary

Augmented Dickey–Fuller (ADF) unit root tests indicate that the AGRI series is non-stationary in levels but becomes stationary after first-order differencing (Table 5). This finding confirms that the series is integrated of order one and supports the use of ARIMA(p,1,q) models in analysing its dynamic behaviour (Table A5).

Table 10 reports the information criteria, diagnostic test results, and forecast errors for four alternative ARIMA specifications. From the perspective of the information criteria, the ARIMA(2,1,2) model records the lowest AIC and Schwarz Criterion values, suggesting a good in-sample fit. However, its forecasting performance is weak, as reflected in relatively high RMSE and MAPE values, as well as a dominant bias component in the total forecast error structure. This contrast indicates that, although the model is statistically well fitted, it fails to adequately capture the dynamics that are most relevant for forecasting purposes.

Table 10. AIC, SC, diagnostic tests and prediction errors for Hungary.

Model	AIC	SC	DW	B-G Test <i>p</i> -Value	ARCH Test <i>p</i> -Value	RMSE	MAPE
ARIMA(1,1,1)	0.7196	0.8623	2.14	0.7347	0.3838	1.2035	25.00
ARIMA(2,1,2)	0.3651	0.5091	2.18	0.7068	0.3863	1.4805	39.56
ARIMA(4,1,4)	0.4371	0.5833	2.18	0.5550	0.7721	0.4479	10.28
ARIMA(5,1,5)	0.4271	0.5743	1.87	0.4031	0.6333	0.4216	10.67

Higher-order specifications, namely ARIMA(4,1,4) and ARIMA(5,1,5), lead to a substantial improvement in predictive performance. In particular, the ARIMA(5,1,5) model stands out by recording the lowest RMSE value (approximately 0.42) and a relatively low MAPE (around 10.7%), comparable to that obtained for the ARIMA(4,1,4) specification. Furthermore, the forecast error decomposition shows that, in the case of ARIMA(5,1,5), the bias component is nearly zero, with the total error being predominantly explained by covariance. This finding suggests a high degree of alignment between forecasted and observed values and indicates the superior forecasting capability of this specification.

From a diagnostic perspective, the residuals of the ARIMA(5,1,5) model do not exhibit serial autocorrelation or conditional heteroskedasticity, as confirmed by the high *p*-values of the Breusch–Godfrey and ARCH tests. Moreover, the Durbin–Watson statistic, which is close to the reference value of 2, provides additional support for the hypothesis of residual independence (Table A6).

Overall, the results highlight the existence of a trade-off between information criteria and forecasting accuracy. Although the ARIMA(2,1,2) specification is preferable from the perspective of parsimony, its modest predictive performance limits its practical usefulness. By contrast, the ARIMA(5,1,5) model provides the best overall performance, combining an adequate residual specification with superior forecasting accuracy. Therefore, it is selected as the optimal model for Hungary and is subsequently employed for medium-term forecasting purposes.

Forecasts generated using the ARIMA(5,1,5) model, presented in Table 11, indicate a relatively stable evolution of the analyzed variable over the period 2025–2028. Following a moderate decline in 2026, the projected values suggest a slight recovery and subsequent stabilization in the following years. This dynamic is consistent with the structure of the historical series and reflects the model’s capacity to capture both medium-term trends and short-term cyclical adjustments. Historical data and forecasted values are illustrated in Figure 5, together with the associated forecast confidence interval.

Table 11. Forecast for Hungary.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(5,1,5)	2.7031	2.5324	2.5678	2.6286

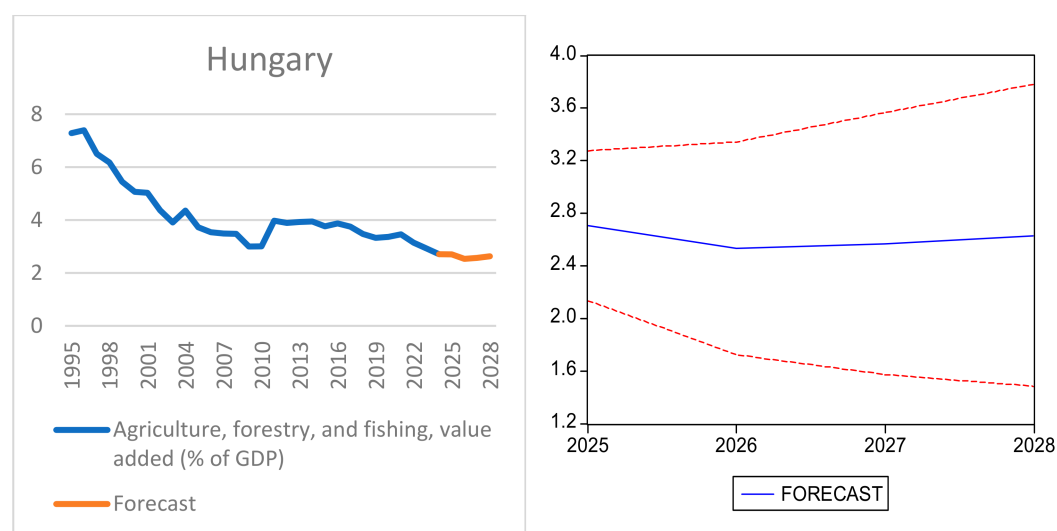


Figure 5. Agriculture, forestry and fishing (%GDP) and forecast in Hungary with confidence interval (red dash line), authors' contribution based on data from (World Bank, n.d.).

4.2.4. Poland

The Augmented Dickey–Fuller tests (Table 5) indicate that the AGRI series for Poland is non-stationary in levels, with the p -value being very close to the conventional 5% significance threshold ($p \approx 0.052$). However, after applying first-order differencing, the series becomes clearly stationary. This result confirms that the variable is integrated of order one, thereby providing empirical support for the specification and estimation of ARIMA($p,1,q$) models, using also the correlogram (Table A7).

The comparative results of the candidate models are presented in Table 12. The analysis reveals significant differences between in-sample performance, assessed using the information criteria AIC and SC, and forecasting accuracy, measured through RMSE and MAPE indicators. The ARIMA(5,1,7) specification records the lowest values of the information criteria, suggesting a very good fit to the historical data. However, its predictive performance proves to be weak, as reflected by the very high values of RMSE and MAPE, as well as by the predominance of bias within the total forecast error structure. These findings point to model over-parameterization and reduced stability outside the estimation sample.

Table 12. AIC, SC, diagnostic tests and prediction errors for Poland.

Model	AIC	SC	DW	B-G Test p -Value	ARCH Test p -Value	RMSE	MAPE
ARIMA(3,1,2)	0.4593	0.6045	2.62	0.1215	0.2557	0.3991	12.61
ARIMA(3,1,7)	0.3826	0.5277	2.17	0.2104	0.2149	0.3081	9.80
ARIMA(5,1,7)	0.1960	0.3433	2.55	0.1051	0.3124	0.9706	34.15

The ARIMA(3,1,2) model provides a more parsimonious alternative and exhibits properly specified residuals; however, its forecasting accuracy is comparatively lower than that of other specifications, as indicated by the higher values of RMSE and MAPE. By contrast, the ARIMA(3,1,7) specification achieves the most balanced trade-off between structural complexity and predictive performance.

More specifically, the ARIMA(3,1,7) specification stands out by recording the lowest RMSE value (approximately 0.31) and the smallest MAPE (around 9.8%), indicating superior forecasting accuracy. The error decomposition analysis shows that the total forecast error is predominantly explained by the covariance component, while the bias component

is negligible. From a diagnostic perspective, the residuals do not exhibit serial autocorrelation or conditional heteroskedasticity, as confirmed by the p -values associated with the Breusch–Godfrey and ARCH tests, all of which exceed the conventional 5% significance threshold. Furthermore, the Durbin–Watson statistics, being close to the value of 2, provide additional support for the assumption of residual independence.

Overall, the results obtained for Poland confirm that model selection based exclusively on information criteria may lead to specifications that are unstable from a predictive standpoint. Although the ARIMA(5,1,7) model minimizes the AIC and SC values, its weak forecasting performance limits its practical relevance. By contrast, the ARIMA(3,1,7) specification provides the best overall performance, combining adequately specified residuals with superior forecasting accuracy. Consequently, the ARIMA(3,1,7) model (Table A8) is selected as the optimal specification for Poland and is subsequently employed for medium-term forecasting purposes.

The forecasts generated by the ARIMA(3,1,7) model, presented in Table 13 and Figure 6, indicate a slightly downward trend in the analysed variable over the period 2025–2027, followed by a moderate recovery in 2028. This evolution suggests a gradual adjustment of the series without excessive fluctuations and reflects the ability of the selected model to capture both medium-term dynamics and short-term corrective movements.

Table 13. Forecast for Poland.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(3,1,7)	2.5101	2.4731	2.3666	2.4823

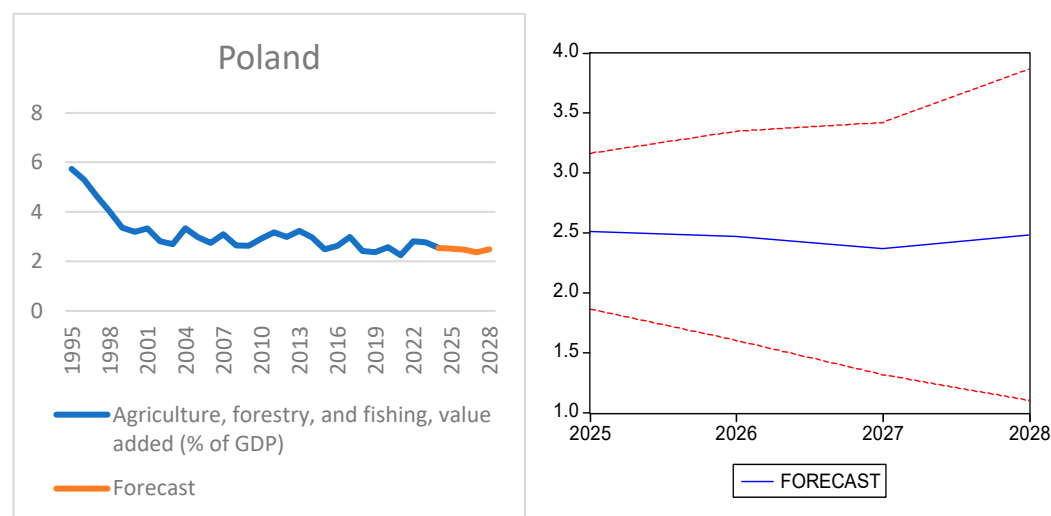


Figure 6. Agriculture, forestry and fishing (%GDP) and forecast in Poland with confidence interval (red dash line), authors' contribution based on data from (World Bank, n.d.).

4.2.5. The Czech Republic

The Augmented Dickey–Fuller stationarity tests (Table 5) indicate that the AGRI series for the Czech Republic is non-stationary in levels but becomes stationary after first-order differencing. During the identification stage, several ARIMA specifications were estimated, using the correlogram (Table A9) and evaluated based on information criteria (AIC, SC), diagnostic tests, and forecasting accuracy indicators.

The results (Table 14) show that the ARIMA(3,1,4) model minimizes the information criteria (AIC = -0.7373 ; SC = -0.5921), yet it exhibits significant residual autocorrelation according to the Breusch–Godfrey test ($p = 0.0451 < 0.05$), as well as the highest forecast errors

(RMSE $\approx$ 1.02; MAPE $\approx$ 46.82%). Consequently, although optimal from the perspective of information criteria, this specification is considered unsuitable for predictive purposes.

Table 14. AIC, SC, diagnostic tests and prediction errors for Czech Republic.

Model	AIC	SC	DW	B-G Test <i>p</i> -Value	ARCH Test <i>p</i> -Value	RMSE	MAPE
ARIMA(1,1,1)	−0.3812	−0.2385	1.73	0.7367	0.2355	0.9650	43.46
ARIMA(1,1,6)	−0.5473	−0.4046	1.92	0.6827	0.6724	0.8098	34.76
ARIMA(2,1,2)	−0.4767	−0.3327	1.74	0.9323	0.8200	0.4003	16.30
ARIMA(3,1,3)	−0.3239	−0.1787	1.53	0.7817	0.3630	0.6645	27.09
ARIMA(3,1,4)	−0.7373	−0.5921	2.04	0.0451	0.9964	1.0197	46.82

The ARIMA(1,1,1) and ARIMA(1,1,6) models provide slight improvements in model fit and do not raise major diagnostic concerns; however, their forecasting performance remains modest (MAPE values of 43.46% and 34.76%, respectively), suggesting an incomplete capture of the series dynamics. The ARIMA(3,1,3) specification displays acceptable residual properties, but its forecasting accuracy is inferior to that of the optimal model (MAPE $\approx$ 27.09%), while the Durbin–Watson statistic (1.53) points to possible residual positive autocorrelation.

By contrast, the ARIMA(2,1,2) model emerges as the most appropriate specification, as it records the best predictive performance (RMSE $\approx$ 0.40; MAPE $\approx$ 16.30%), shows no evidence of residual autocorrelation (Breusch–Godfrey *p*-value = 0.9323), does not indicate conditional heteroskedasticity (ARCH *p*-value = 0.8200), and maintains a satisfactory balance between parsimony and goodness of fit. Accordingly, the ARIMA(2,1,2) model is selected as the optimal specification for the agricultural share of GDP series in the Czech Republic (Table A10).

The medium-term forecast, presented in Table 15 and Figure 7 and generated using the ARIMA(2,1,2) model, indicates a slightly downward trend in the share of agriculture in the Czech Republic's GDP, from 1.8721% in 2025 to 1.7704% in 2028. The projected dynamics suggest a continued gradual decline in the relative importance of the agricultural sector within the national economy, in line with the structural trends typically observed in developed economies.

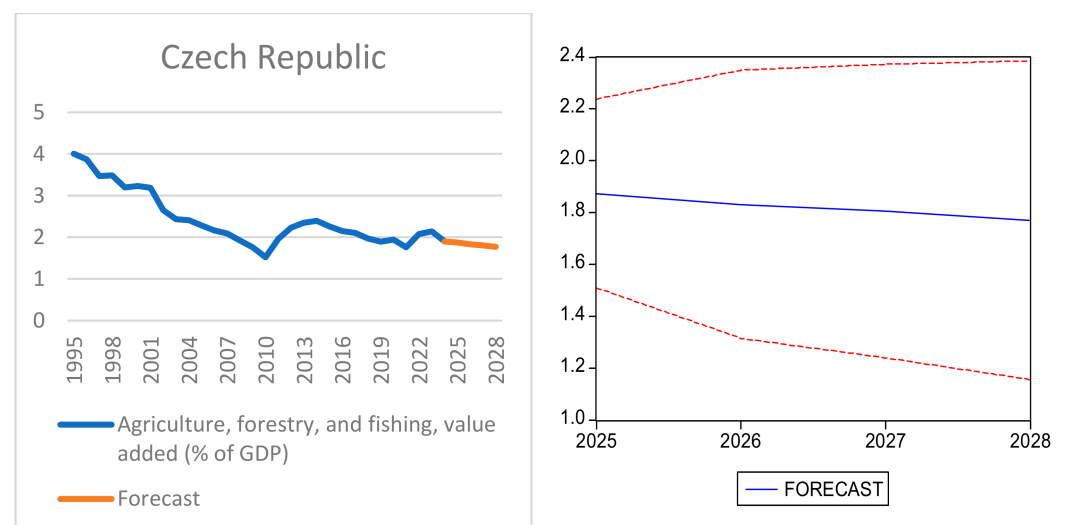


Figure 7. Agriculture, forestry and fishing (%GDP) and forecast in the Czech Republic with confidence interval (red dash line), authors' contribution based on data from (World Bank, n.d.).

Table 15. Forecast for the Czech Republic.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(2,1,2)	1.8721	1.8305	1.8045	1.7704

4.2.6. Slovakia

The Augmented Dickey–Fuller stationarity tests (Table 5) indicate that the AGRI series for Slovakia is non-stationary in levels but becomes stationary after first-order differencing. Using the correlogram (Table A11), the candidate models were evaluated using information criteria, residual diagnostic tests, and forecasting accuracy indicators. The results (Table 16) show that all estimated specifications satisfy the conditions of stationarity and invertibility; however, differences emerge in terms of predictive performance and error structure.

Table 16. AIC, SC, diagnostic tests and prediction errors for Slovakia.

Model	AIC	SC	DW	B-G Test <i>p</i> -Value	ARCH Test <i>p</i> -Value	RMSE	MAPE
ARIMA(1,1,2)	0.2690	0.4117	1.86	0.9201	0.4598	0.4326	22.23
ARIMA(1,1,6)	0.2579	0.4006	1.83	0.4853	0.2981	0.3330	14.41
ARIMA(3,1,1)	0.2855	0.4306	1.43	0.4403	0.3188	0.3905	19.89
ARIMA(5,1,5)	0.3873	0.5345	2.37	0.4552	0.2591	0.8745	40.91

The ARIMA(1,1,2) model exhibits well-behaved residuals ($DW \approx 1.86$; Breusch–Godfrey $p = 0.9201$; ARCH $p = 0.4598$), yet its forecasting accuracy is relatively modest ($RMSE \approx 0.4326$; $MAPE \approx 22.23\%$), suggesting an incomplete capture of the series dynamics. The ARIMA(3,1,1) specification provides a slight improvement compared with ARIMA(1,1,2), but the Durbin–Watson statistic (1.43) indicates possible residual positive autocorrelation, while its predictive performance remains inferior ($MAPE \approx 19.89\%$). The ARIMA(5,1,5) model is characterized by over-parameterization, recording the highest forecast errors ($RMSE \approx 0.8745$; $MAPE \approx 40.91\%$) despite acceptable residual diagnostics, and is therefore rejected.

By contrast, the ARIMA(1,1,6) specification emerges as the most appropriate model, as it achieves the lowest forecast errors ($RMSE \approx 0.3330$; $MAPE \approx 14.41\%$), shows no evidence of residual autocorrelation (Breusch–Godfrey $p = 0.4853$), does not indicate conditional heteroskedasticity (ARCH $p = 0.2981$), and offers a satisfactory balance between model complexity and predictive accuracy. Accordingly, the ARIMA(1,1,6) model is selected as the optimal specification for Slovakia (Table A12).

The medium-term forecast generated by the ARIMA(1,1,6) model and presented in Table 17 and Figure 8 indicates a fluctuating evolution of the agricultural share in Slovakia's GDP: 1.6048% in 2025, followed by a decline to 1.3240% in 2026, then a recovery to 1.6586% in 2027, and a moderation to 1.5291% in 2028. The projected dynamics suggest higher volatility compared with other economies in the region, without the emergence of a clear downward or upward trend in the medium term.

Table 17. Forecast for Slovakia.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(1,1,6)	1.6048	1.3240	1.6586	1.5291

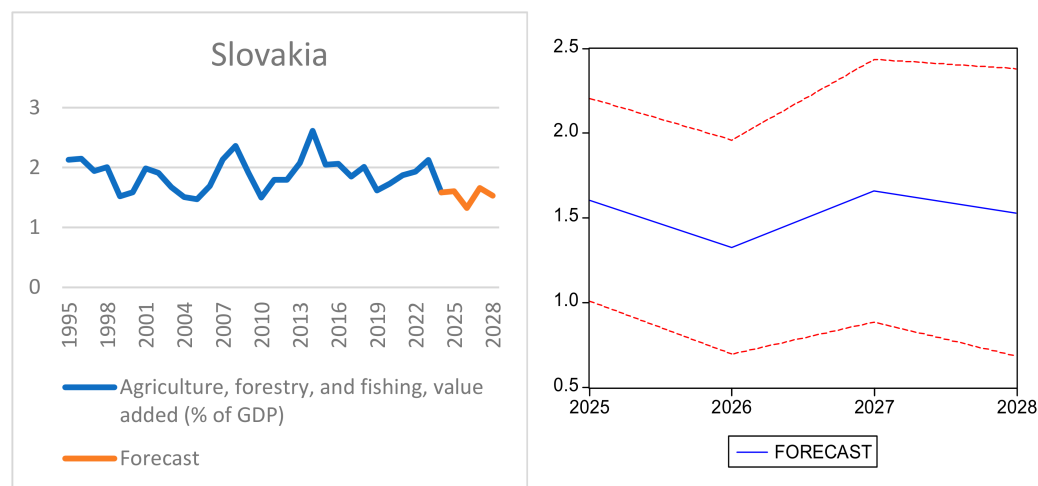


Figure 8. Agriculture, forestry and fishing (%GDP) and forecast in Slovakia with confidence interval (red dash line), authors' contribution based on data from (World Bank, n.d.).

4.2.7. Croatia

The Augmented Dickey–Fuller stationarity test (Table 5) indicates that the AGRI series for Croatia is non-stationary in levels but becomes stationary after first-order differencing, thereby justifying the use of ARIMA(p,1,q) models. Using the correlogram (Table A13), some ARIMA models were selected.

The results (Table 18) show that the ARIMA(3,1,3) specification performs poorly from a predictive standpoint, recording the highest forecast errors (RMSE ≈ 0.7225 ; MAPE $\approx 19.45\%$). In addition, the Durbin–Watson statistic (2.80) suggests possible negative residual autocorrelation, while the Breusch–Godfrey test approaches the conventional significance threshold ($p = 0.0813$). Consequently, this model is excluded from the final selection.

Table 18. AIC, SC, diagnostic tests and prediction errors for Croatia.

Model	AIC	SC	DW	B-G Test <i>p</i> -Value	ARCH Test <i>p</i> -Value	RMSE	MAPE
ARIMA(1,1,5)	0.2786	0.4213	2.04	1.0000	0.1663	0.5475	13.61
ARIMA(1,1,6)	0.2122	0.3549	2.00	1.0000	0.7587	0.5086	12.59
ARIMA(3,1,3)	0.5318	0.6770	2.80	0.0813	0.5476	0.7225	19.45

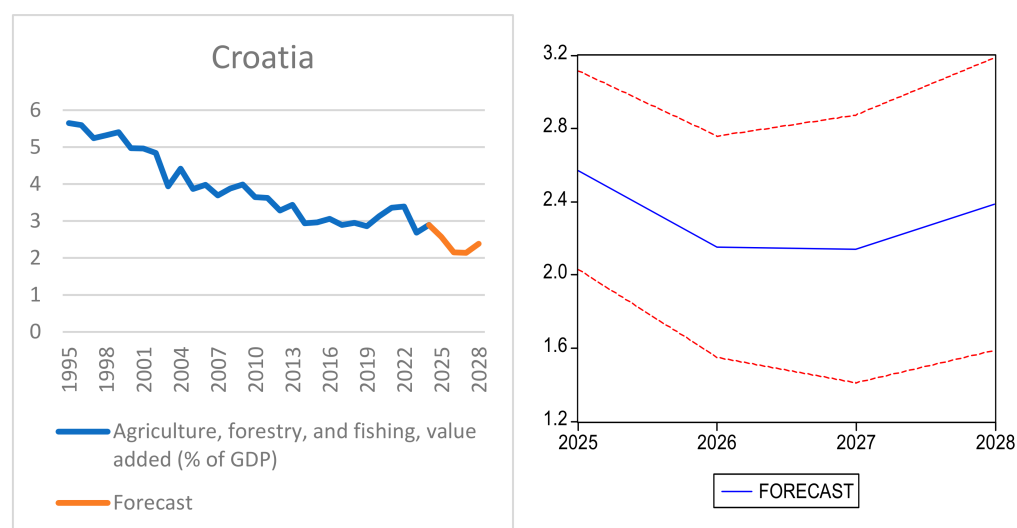
The ARIMA(1,1,5) model exhibits well-behaved residuals (DW ≈ 2.04 ; Breusch–Godfrey $p = 1.0000$; ARCH $p = 0.1663$), confirming an adequate specification. However, its forecasting performance is inferior to that obtained with the higher-order MA specification (RMSE ≈ 0.5475 ; MAPE $\approx 13.61\%$).

By contrast, the ARIMA(1,1,6) model emerges as the most robust specification, as it records the lowest AIC value (0.2122), achieves the smallest forecast errors (RMSE ≈ 0.5086 ; MAPE $\approx 12.59\%$), shows no evidence of residual autocorrelation (Breusch–Godfrey $p = 1.0000$), does not indicate conditional heteroskedasticity (ARCH $p = 0.7587$), and maintains a balanced error structure. Accordingly, the ARIMA(1,1,6) model is selected as the optimal specification for Croatia (Table A14).

With regard to the medium-term forecast generated by the ARIMA(1,1,6) model and presented in Table 19 and Figure 9, the results indicate an initially declining trajectory of the agricultural share in Croatia's GDP, from 2.5715% in 2025 to approximately 2.14% during the period 2026–2027, followed by a slight recovery to 2.3862% in 2028. The projected dynamics suggest a moderate adjustment in the role of the agricultural sector within the economy, characterized by medium-term fluctuations rather than a clearly defined linear trend.

Table 19. Forecast for Croatia.

	Forecast 2025	Forecast 2026	Forecast 2027	Forecast 2028
ARIMA(1,1,6)	2.5715	2.1532	2.1411	2.3862

**Figure 9.** Agriculture, forestry and fishing (%GDP) and forecast in Croatia with confidence interval (red dash line), authors' contribution based on data from (World Bank, n.d.).

5. Discussion

In order to achieve the research objective, the formulated hypotheses were assessed using descriptive statistical analysis, normality tests, nonparametric correlation measures, cluster analysis, and ARIMA modelling techniques. The results obtained are discussed in the following section and summarized in Table 20.

Table 20. Summary of hypothesis testing results.

Hypothesis	Testing Approach	Key Empirical Evidence	Decision
H1 Over the period 1995–2024, the agricultural share in GDP has followed a significant downward trend across Central and Eastern European countries, starting from significantly different initial structural levels (Downward trend dimension)	Descriptive statistics and time-series trend analysis, β -convergence	All seven countries exhibit a clear declining trajectory; highest values concentrated in the 1990s, followed by sustained decreases, especially in Romania and Bulgaria.	Accepted
H1 Over the period 1995–2024, the agricultural share in GDP has followed a significant downward trend across Central and Eastern European countries, starting from significantly different initial structural levels (Structural heterogeneity dimension)	Comparative descriptive analysis (mean, min–max, coefficient of variation), β -convergence	Romania ($\approx 8.04\%$) and Bulgaria ($\approx 6.66\%$) start from much higher levels than Czechia and Slovakia; very high coefficients of variation ($>50\%$) confirm heterogeneity.	Accepted
H2 The agricultural share in GDP exhibits a long-term convergence process across the analyzed economies, accompanied by a strong cross-country synchronization of dynamics that reflects the influence of common regional factors. (Convergence dimension)	Dispersion analysis, Spearman correlations, Ward cluster analysis, σ -convergence	Post-2015 values cluster within ~ 1.5 – 3.5% of GDP; strong positive correlations and clear grouping patterns indicate structural convergence.	Accepted

Table 20. Cont.

Hypothesis	Testing Approach	Key Empirical Evidence	Decision
H2 The agricultural share in GDP exhibits a long-term convergence process across the analyzed economies, accompanied by a strong cross-country synchronization of dynamics that reflects the influence of common regional factors. (Synchronization dimension).	Spearman correlation matrix and hierarchical clustering, σ -convergence,	Strong and very strong correlations among most countries; however, Slovakia shows near-zero correlations and late clustering, indicating atypical behavior.	Partially accepted
H3 (methodological precondition) The time series of the agricultural share in GDP deviates from the normality assumption for the majority of the countries considered and are integrated of order one (I(1)), thereby justifying the use of non-parametric dependence measures and differenced (ARIMA) modelling (Non-normality dimension)	Shapiro–Wilk normality test	p -values < 0.01 for six countries lead to rejection of normality; only Slovakia ($p = 0.271$) is compatible with normal distribution.	Accepted
H3 (methodological precondition) The time series of the agricultural share in GDP deviates from the normality assumption for the majority of the countries considered and are integrated of order one (I(1)), thereby justifying the use of non-parametric dependence measures and differenced (ARIMA) modelling. (integration dimension).	Augmented Dickey–Fuller (ADF) unit root tests	Series are non-stationary in level but stationary after first differencing for all countries ($p < 0.05$ for D(AGRI)).	Accepted
H4 Adequately specified ARIMA models capture the dynamics of the agricultural share in GDP and indicate a continued decline or stabilization of this share across the analyzed economies over the medium term (Modelling adequacy dimension)	Information criteria (AIC, SC), residual diagnostics (B–G, ARCH, DW), forecast accuracy (RMSE, MAPE)	Optimal models pass diagnostic tests and display lower forecast errors compared with alternatives.	Accepted
H4 Adequately specified ARIMA models capture the dynamics of the agricultural share in GDP and indicate a continued decline or stabilization of this share across the analyzed economies over the medium term (Forecasting trajectory dimension).	ARIMA forecasts (2025–2028)	Most countries show gradual decline (Romania, Bulgaria, Czechia) or low-level stabilization (Hungary, Poland, Croatia); Slovakia remains low but more volatile.	Accepted

Our analysis broadly confirms the validity of the formulated hypotheses and highlights the existence of profound structural transformations in the agricultural sector over the period 1995–2024.

First, the descriptive results and the dynamics of the time series clearly indicate a downward trend in the share of agriculture in GDP across all analyzed economies, thereby confirming the downward trend dimension of H1. The decline is more pronounced in economies with initially high agricultural dependence, particularly Romania and Bulgaria. This differential rate of decline is formally confirmed by the β -convergence test (Section σ -Convergence and β -Convergence): regressing the long-run change in the agricultural share on its initial 1995 level yields a negative slope (-0.9439), indicating that economies that began the period with higher agricultural shares reduced them faster. The observed downward shift is theoretically aligned with structural transformation models in which rising aggregate productivity and changing demand patterns reduce agriculture's relative contri-

bution to GDP, even where absolute agricultural output can grow (Herrendorf et al., 2013). Within the CESEE/EU context, sectoral-share evidence based on value-added proportions identifies a broadly declining agricultural share across the post-socialist period, supporting the interpretation that the region's development path includes sustained de-agrarianisation (Novák, 2020).

The policy-relevant interpretation of the downward trend dimension of H1 is that agriculture will increasingly matter through channels not fully captured by GDP share—food security, trade balances, ecosystem services, and rural livelihoods—while its relative GDP weight continues to fall. Because our results show this decline to be sustained and common to all seven economies, the policy objective shifts from maintaining sectoral GDP share to supporting productivity-led competitiveness and managing the associated labour reallocation; the specific instruments this implies are set out in relation to the forecast results below.

Second, the statistical analysis reveals significant initial structural differences between countries, thus supporting the structural-heterogeneity dimension of H1. At the beginning of the period, Romania and Bulgaria recorded substantially higher agricultural shares in GDP compared with the Czech Republic and Slovakia, whose economies were already more diversified. This initial heterogeneity is precisely what the β -convergence test exploits: because the countries with the highest starting shares (Romania and Bulgaria) subsequently recorded the largest reductions (−15.35 and −6.87 percentage points, respectively), the negative slope reported in Section σ -Convergence and β -Convergence indicates that these initial differences have been progressively eroded through a catch-up process, linking the structural heterogeneity documented here to the convergence established under H2. The early-period heterogeneity (high agriculture shares and volatility in Romania and Bulgaria versus lower, more stable shares in Czechia and Slovakia) is theoretically consistent with path dependence in transition economies: initial conditions in farm structure, industrial legacy, and the sequencing of reforms shape sectoral starting points (Swinnen, 2010). The literature on EU enlargement and agricultural transition emphasizes that policy reforms (price liberalization, subsidy removal, privatization, restructuring) and transition shocks produced differentiated agricultural outcomes across Central and Eastern Europe, making cross-country dispersion an expected feature in the 1990s and early 2000s (Swinnen, 2010). This heterogeneity has two theoretical implications. First, convergence in sectoral shares (as later identified under H2) should be interpreted as conditional on diverse starting points, meaning that “catch-up” can reflect both genuine sector modernization and mechanical denominator effects from accelerated growth in non-agricultural sectors. Second, volatility at high initial shares is compatible with the idea that agriculture functions as a macroeconomic “buffer” during transition—absorbing labor or stabilizing incomes when industrial employment contracts—before gradually shrinking in relative terms as services expand (Landesmann, 2000).

Initial heterogeneity implies that policy benchmarks should avoid “one-size-fits-all” expectations for agricultural restructuring. For high-initial-share economies, sequencing matters: land consolidation, irrigation and water governance, and extension services become priorities to convert structural adjustment into productivity growth and to reduce volatility. For lower-initial-share economies, a principal challenge is maintaining competitiveness and environmental compliance in a comparatively small sector, where marginal gains may come from precision agriculture, quality upgrading, and targeted support for multifunctional rural development. Importantly, the finding also supports differentiated CAP implementation across national strategic plans: countries entering the period with higher agricultural dependence plausibly require more intensive rural diversification strategies to avoid welfare losses from rapid de-agrarianisation.

However, the findings regarding dispersion and temporal evolution point to a consistent reduction in cross-country differences, confirming the existence of a process of structural convergence (convergence dimension of H2). After 2015, all economies fell within a relatively narrow range (approximately 1.5–3.5% of GDP), suggesting a gradual harmonization of regional economic structures. This descriptive impression is confirmed by the formal σ -convergence test (Section σ -Convergence and β -Convergence): the cross-country standard deviation of the agricultural share declined markedly, from approximately 5.36 in 1995 to 0.45 in 2024, and the estimated trend in dispersion is negative, providing formal evidence of σ -convergence. The σ -convergence result (declining dispersion) and the Spearman correlations (strong co-movement) are complementary; the former establishes that the economies have become more similar in the level of their agricultural shares, while the latter establishes that they move together over time. The narrowing dispersion of agricultural GDP shares is consistent with both neoclassical convergence intuition (integration and technology diffusion reduce structural gaps) and “institutional convergence” associated with EU accession, shared market regulations, and common policy frameworks (Jambor & Gorton, 2025). A CESEE structural-change assessment explicitly states that the region experienced “apparent structural convergence” towards OECD/EU economies over the past two decades, which—given the stylised shift away from agriculture—supports the expectation that agricultural GDP shares would compress towards a low band (Novák, 2020). A distinctive theoretical implication is that convergence in agriculture’s GDP share can occur even when convergence in agricultural productivity is incomplete, because the GDP-share measure is a relative indicator influenced by non-agricultural growth. Accordingly, “structural convergence” in this paper should be read as convergence in macro-structure, not necessarily convergence in micro-level efficiency or rural income outcomes. This is important given EU evidence that productivity convergence often proceeds unevenly and in “clubs,” even where macro shares align (Kijek et al., 2019).

Evidence of convergence strengthens the case for regional policy coordination, because a shrinking dispersion implies that countries are increasingly subject to similar structural constraints: a small agricultural GDP share, tighter environmental conditionality, and greater exposure to common shocks (energy costs, climate extremes, EU regulatory changes). However, the “club-like” caution from the literature implies that convergence in GDP shares should not trigger premature policy harmonisation that ignores persistent differences in farm structure (e.g., fragmentation vs concentration), rural poverty exposure, or agri-food value-chain sophistication. Practically, ministries should treat convergence as an opportunity for joint benchmarking (best practices in digital farming, water policy, agri-environment schemes), while maintaining targeted instruments for lagging rural regions and for countries whose convergence largely reflects denominator effects rather than agricultural upgrading.

It should be emphasized that, while the cluster analysis groups the economies into sets with similar trajectories, these groupings are suggestive of—but do not formally establish—convergence clubs, which were not tested econometrically in this study. A formal test of club convergence (e.g., via the Phillips–Sul procedure) is left to future research.

Spearman correlation coefficients indicate strong regional synchronization among most countries, thereby validating the synchronization dimension of H2. The highest correlations are observed between Romania, Bulgaria and Croatia, as well as between Poland, the Czech Republic and Hungary, reflecting the influence of common factors such as European integration and similar agricultural policy frameworks. Slovakia emerges as a structural outlier, displaying weaker correlations and a more stable trajectory. The strong positive Spearman correlations (and the clustering structure) indicate that agricultural GDP shares co-move across most of the region, suggesting that common drivers—EU market integra-

tion, policy timing, and region-wide structural change—produce synchronised declines. This can be interpreted through an integration lens: increasing trade and institutional alignment tend to raise cross-country co-movement in macro variables, especially where economies share exposure to common shocks and policy cycles (Benčík, n.d.). The critical theoretical nuance is the identification of Slovakia as an atypical case. The weak association between Slovakia's agricultural GDP share and the regional pattern indicates that, even under shared EU institutions, sectoral dynamics can remain idiosyncratic due to national production structures, farm-size distributions, and the relative role of industry/services in GDP. This is consistent with evidence that Slovakia's agricultural structure is unusual within the EU context, including very large farm sizes relative to many member states, which can translate into different adjustment speeds and volatility regimes (Rovný, 2016).

Where synchronisation is strong, coordinated regional policy has higher expected returns: joint risk management (e.g., climate adaptation strategies, water governance, and early-warning systems), coordinated positions in CAP negotiations, and aligned rural development investments can reduce duplication and strengthen resilience. Conversely, the Slovak atypical case implies that national policy must remain adaptive: relying on regional “average” dynamics may mis-specify Slovakia's agricultural transition path. A practical implication is that policy evaluation and forecasting exercises should include country-specific diagnostics (structural breaks, distinct variance patterns) before generalising region-level strategies. Finally, partial synchronisation suggests that CEE coordination is most effective when structured around “clusters” (as the dendrogram implies), enabling policy learning among structurally similar economies rather than uniformly across the entire region).

The Shapiro–Wilk test shows that most series do not follow a normal distribution, confirming the non-normality dimension of H3 and justifying the use of nonparametric methods. From a theoretical standpoint, non-normality in macro time series is consistent with underlying structural breaks, asymmetric adjustment, and occasional extreme observations induced by weather shocks, policy regime changes, and transition-related discontinuities. The empirical finding that normality is rejected for most countries, but not for Slovakia, is coherent with a volatility-based narrative: trending series with early-period extremes and non-constant variance are unlikely to be Gaussian. Theoretical implications are methodological but not trivial. First, non-normality supports the choice of rank-based (Spearman) dependence measures in this study, strengthening inference validity where Pearson-type assumptions would be fragile. Second, the finding underscores that model-based policy conclusions should be robust to non-Gaussian error structures, in particular, where agriculture is exposed to fat-tailed shock distributions (e.g., drought losses). This is consistent with evidence that macroeconomic forecast errors can be leptokurtic and skewed, making normality-based inference inappropriate (Harvey & Newbold, 2003).

The practical implication is that agricultural GDP-share dynamics embed asymmetry and “tail risk,” which matters for resilience planning. Policy design should therefore incorporate contingency buffers (e.g., disaster risk financing, flexible income stabilisation tools) rather than relying exclusively on average-path planning. For empirical policy evaluation, the non-normality dimension of H3 strengthens the case for robust statistical toolkits: non-parametric correlation, bootstrap-based inference for small samples, and (where feasible) regime-switching or structural-break-aware models for stress periods. The Slovakia exception also suggests that where sector shares are stable and low, Gaussian approximations may be less problematic, enabling simpler statistical monitoring; however, reliance on that convenience should remain conditional on diagnostics.

In addition, the Augmented Dickey–Fuller tests demonstrate that the series are first-order integrated, becoming stationary after first differencing, thus confirming the inte-

gration dimension of H3. The integration finding implies that shocks to the level of the agricultural GDP share behave as persistent, with differencing required to achieve stationarity. Econometrically, this is consistent with the broader macro time-series literature in which many aggregate variables are difficult to distinguish from unit-root processes. (Dickey & Fuller, 1979) Substantively, for a structural-share variable, $I(1)$ behaviour is interpretable as reflecting long-run compositional change rather than short-lived cyclical deviations, consistent with the idea that structural transformation is not a mean-reverting phenomenon over the sample horizon (Herrendorf et al., 2013). A theoretical implication for convergence analysis is that persistence complicates “quick convergence” narratives: even if cross-sectional dispersion narrows, the underlying processes may carry permanent components, and convergence may be driven by long-run structural drift rather than rapid adjustment to a stable steady state. This also implies that policy interventions may have long-lived effects—beneficial or adverse—thus raising the stakes for CAP design, land-market regulation, and rural investment choices.

If the agricultural GDP share contains a persistent component, then policy planning should assume that structural changes are durable. This supports medium-term strategies (multi-annual investment in irrigation, advisory systems, and rural infrastructure) over short-term, reactive measures. For monitoring and evaluation, evidence of $I(1)$ suggests that policies should be assessed using appropriately differenced or cointegration-aware frameworks; otherwise, spurious inference can arise. Additionally, persistence strengthens the rationale for policy stability: frequent regime shifts can amplify non-stationary behaviour by creating repeated structural breaks, reducing predictability and undermining investment incentives in the agri-food sector.

Finally, the ARIMA modelling results support H4 (both dimensions), as an adequately specified model with satisfactory diagnostic and predictive performance was identified for each country. Regarding the ARIMA adequacy dimension of H4, the study’s ARIMA modelling strategy—ADF-guided differencing, model selection using information criteria, residual diagnostics, and forecast-error evaluation—is consistent with established best practice in applied univariate forecasting. More broadly, ARIMA methods remain a benchmark in automatic time-series forecasting systems and are widely used for large-scale production of medium-term forecasts (Hyndman & Khandakar, 2008). The key theoretical implication is that, for slowly evolving structural-share variables, parsimonious linear stochastic models can capture substantial predictive content, at least over medium horizons, provided the main non-stationary component is handled appropriately (here, via first differencing). Importantly, “adequate” should be interpreted in the econometric sense (diagnostically well-behaved residuals and comparatively lower forecast errors among candidate models), not as proof of structural causality.

For policy institutions, the principal implication is operational: the ARIMA framework can be used as a transparent baseline tool for monitoring structural change and informing medium-term planning (e.g., anticipating the fiscal salience of the sector, or calibrating rural development programmes). However, H7 also implies a governance requirement: forecasts should be embedded in a model-risk framework. Given known sensitivity to breaks and crises, ministries and analysts should complement baseline ARIMA projections with (i) stress scenarios (drought years, commodity price spikes, recessions) and (ii) models that incorporate exogenous drivers (ARIMAX, state-space models, or threshold/regime-switching variants) for decision-critical contexts.

On the other hand, regarding the forecast trajectory dimension of H4, the forecast trajectory—continued decline or low-level stabilisation—fits the structural transformation expectation that agriculture’s value-added share typically falls as economies converge towards service-dominant structures, while agriculture increasingly operates through

productivity gains rather than expansion of GDP share (Herrendorf et al., 2013). For the CESEE context, empirical structural-change evidence supports the persistence of declining agricultural shares over long horizons, making the forecast direction theoretically coherent (Novák, 2020). The theoretical implication is that, once agricultural GDP shares reach a low band (as in the post-2015 range highlighted in the study), marginal changes may reflect stabilisation dynamics rather than continued steep declines, especially where productivity gains and value-chain upgrading offset denominator growth. This is consistent with the notion that the “late stage” of de-agrarianisation is characterised by smaller absolute movements in shares, even as structural vulnerabilities (climate risk, income volatility) remain (Calegari et al., 2016).

Forecasted decline/stabilisation should shift the policy focus from “sector size” to “sector function.” A small GDP share does not reduce agriculture’s strategic importance for food security, trade, climate mitigation/adaptation, and rural cohesion. Policymakers should therefore prioritise: (i) productivity-enhancing investments that raise value added per unit of labour and land; (ii) risk management and climate adaptation to reduce volatility and protect rural incomes; (iii) value-chain upgrading (processing capacity, quality standards, logistics) to retain more value added domestically; and (iv) rural diversification to ensure inclusive growth as agriculture’s GDP weight stabilises at low levels. For the atypical (more weakly synchronised) case, forecasts should be interpreted more cautiously and updated frequently with diagnostics that detect breaks and variance shifts.

Overall, the hypothesis-based evidence supports a coherent narrative of structural convergence in Central and Eastern Europe: agriculture’s GDP share exhibits a sustained long-run decline (H1), large initial heterogeneity (H2), and substantial cross-country convergence towards a low band in recent years (H3), accompanied by strong regional synchronization except for a persistent outlier pattern in Slovakia (H4). Methodologically, the rejection of normality for most series (H5) and confirmation of I(1) behavior (H6) justify the use of non-parametric dependence measures and differenced ARIMA modelling. The selected ARIMA specifications display adequate diagnostic properties and forecasting performance (H7), yielding medium-term projections consistent with continued decline or stabilization in agricultural GDP shares (H8).

6. Conclusions

This study investigates how the agricultural share in GDP evolved in seven Central and Eastern European economies—Bulgaria, Croatia, the Czech Republic, Poland, Romania, Slovakia, and Hungary—from 1995 to 2024, testing for structural convergence and producing medium-term forecasts. The empirical results are consistent with the canonical “structural transformation” stylized facts: as economies develop, activity reallocates away from agriculture towards industry and, ultimately, services (Herrendorf et al., 2013). In the Central and South Eastern European EU member context, a dedicated sectoral-share analysis (Novák, 2020) reports that the agriculture share in value added and employment “uniformly delineate a declining trend” over time, which directly corroborates the direction of change observed in the present study.

Conceptually, this paper’s contribution is twofold. First, it documents long-horizon “de-agrarianisation” in GDP structure using a harmonized indicator (agriculture, forestry and fishing value added as a percentage of GDP), highlighting early-transition heterogeneity—particularly in Romania and Bulgaria—and subsequent narrowing of cross-country differences. Second, it triangulates convergence using complementary tools: non-parametric dependence (Spearman), similarity-based clustering (Ward on correlation-derived distances), and time-series modelling (ADF-informed differencing and ARIMA selection) to generate a policy-relevant outlook for 2025–2028.

Taken together, the results portray a region completing a major phase of post-socialist structural transformation: agriculture's GDP share declines (H1), initial disparities fade (H3), and most countries' paths are strongly co-moving (H4), while the data exhibit non-Gaussian and persistent time-series properties that require robust methods (H5–H6). From a policy design standpoint, this combination implies that “agricultural modernisation” can no longer be assessed by sectoral GDP weight alone; instead, the relevant metrics are productivity, resilience, value-chain depth, and rural inclusion rather than sectoral GDP weight alone (Calegari et al., 2016).

The cluster structure emerging from correlation-based Ward grouping suggests that policy learning and coordination may be most effective when organised around structurally similar sub-groups rather than uniform region-wide templates. This is particularly important in the presence of country-specific atypicalities (Slovakia), which the broader synchronisation literature also treats as potentially idiosyncratic depending on the indicator and period (Benčík, n.d.). Finally, the forecasting results support the use of transparent baseline models for planning, while reinforcing the necessity of scenario-based governance given the known sensitivity of agriculture and macro structures to breaks, crises, and climate shocks (Guerron-Quintana & Zhong, 2017).

Taken as a whole, the analysis shows that the agricultural sectors of the seven Central and Eastern European economies have moved from marked structural heterogeneity at the outset of transition towards a low and narrow common band, and that this movement is not merely a shared downward trend but a formally measurable process of convergence, supported by the σ - and β -convergence tests and reflected in the co-movement and grouping of the series. The central qualification that unifies these findings is one of interpretation: because the indicator analysed is the agricultural share in GDP—a relative, macro-structural measure—the convergence documented here is convergence in economic structure, and does not by itself establish convergence in agricultural productivity, rural incomes, or welfare. This distinction is what gives the results their broader significance and, at the same time, defines the direction of future work: establishing whether the region's structural convergence is accompanied by genuine convergence in the efficiency and inclusiveness of its agricultural sectors. It is in answering that question that the transparent, reproducible framework applied here—combining dispersion and catch-up tests, rank-based synchronization measures, similarity-based clustering, and time-series forecasting—can be most usefully extended.

Several limitations qualify interpretation. First, the analysis relies on a single relative indicator (agriculture, forestry and fishing value added as % of GDP), which is sensitive to changes in the GDP denominator; therefore, a falling share can reflect faster growth in non-agricultural sectors even if agricultural value-added rises in absolute terms. Second, the period includes multiple regime changes and potential structural breaks (transition consolidation, EU accession episodes, crises, and climate shocks), and while the paper uses robust non-parametric tools and differenced ARIMA models, it does not explicitly estimate break dates or regime-switching dynamics. Third, univariate ARIMA forecasts omit exogenous determinants (CAP reforms, commodity prices, input costs, drought indices), so predictive adequacy is conditional on the absence of major shocks and on stable policy environments. Fourth, inference from normality and unit-root tests is subject to small-sample power and size issues common in macro time series, especially under heteroscedasticity.

Future research could extend this contribution in four complementary ways. First, expanding the indicator set—adding agricultural employment shares, rural poverty measures, value added per worker, and agri-food export indicators—would enable distinguishing “denominator-driven” share convergence from genuine sectoral upgrading and welfare

improvement. Second, panel convergence methods (β/σ convergence, stochastic convergence tests, and club-convergence procedures) could formally test whether the observed narrowing reflects a single convergence path or multiple steady states consistent with the convergence-club literature. Third, incorporating explicit structural-break testing (endogenous break unit-root tests, segmented trends) would strengthen the econometric characterization of agricultural share dynamics in economies exposed to policy discontinuities and crises. (Guerron-Quintana & Zhong, 2017) Fourth, the forecasting framework could be broadened via ARIMAX/state-space models using policy and climate covariates, and benchmarked against machine learning approaches, given evidence that non-linear models can outperform ARIMA in some macro forecasting contexts.

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Appendix A

Table A1. Correlogram D(AGRI) for Romania.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. ** .	. ** .	1	−0.249	−0.249	1.9867	0.159
. * .	. * .	2	0.151	0.095	2.7464	0.253
. * .	. .	3	−0.077	−0.021	2.9537	0.399
. ** .	. ** .	4	−0.235	−0.292	4.9408	0.293
. * .	. * .	5	0.187	0.097	6.2514	0.283
. ** .	. * .	6	−0.244	−0.142	8.5780	0.199
. ***	. ***	7	0.433	0.339	16.231	0.023
. .	. * .	8	−0.054	0.104	16.353	0.038
. .	. .	9	0.010	−0.036	16.358	0.060
. * .	. .	10	0.069	0.028	16.585	0.084
. * .	. .	11	−0.175	0.057	18.116	0.079
. .	. * .	12	0.066	−0.081	18.343	0.106

*, **, *** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$; ***—significant at $\approx 1\%$).

Table A2. ARIMA(5,1,7) model for Romania.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.212289	0.300808	−0.705729	0.4881
AR(5)	0.327408	0.116259	2.816185	0.0103
MA(7)	0.957846	0.029826	32.11464	0.0000
R-squared	0.837284	Mean dependent var		−0.335103
Adjusted R-squared	0.821787	S.D. dependent var		1.279771
S.E. of regression	0.540259	Akaike info criterion		1.722933
Sum squared resid	6.129477	Schwarz criterion		1.870189

Table A2. *Cont.*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Log likelihood	−17.67519	F-statistic		54.02945
Durbin-Watson stat	2.793782	Prob(F-statistic)		0.000000
Inverted AR Roots	0.80	0.25 − 0.76i	0.25 + 0.76i	−0.65 − 0.47i
		−0.65 + 0.47i		
Inverted MA Roots	0.90 + 0.43i	0.90 − 0.43i	0.22 − 0.97i	0.22 + 0.97i
	−0.62 − 0.78i	−0.62 + 0.78i	−0.99	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	2.197390	Probability		0.138525
ARCH Test:				
F-statistic	0.690308	Probability		0.415406

Table A3. Correlogram D(AGRI) for Bulgaria.

Sample: 1998–2024 Included Observations: 26						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. * .	. * .	1	−0.064	−0.064	0.1198	0.729
. .	. .	2	0.052	0.048	0.2018	0.904
. **	. **	3	0.204	0.212	1.5215	0.677
. .	. *	4	0.065	0.095	1.6616	0.798
. *	. *	5	0.128	0.125	2.2315	0.816
. .	. .	6	0.024	−0.006	2.2522	0.895
. *	. .	7	0.073	0.032	2.4587	0.930
. * .	. ** .	8	−0.169	−0.236	3.6104	0.890
. *	. *	9	0.139	0.083	4.4415	0.880
. .	. * .	10	−0.044	−0.062	4.5302	0.920
. ** .	. * .	11	−0.194	−0.152	6.3486	0.849
. * .	. ** .	12	−0.162	−0.254	7.7150	0.807

*, ** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$).

Table A4. ARIMA(2,1,2) model for Bulgaria.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.187645	0.112840	−1.662924	0.1112
AR(2)	0.639488	0.131603	4.859230	0.0001
MA(2)	−0.930384	0.037211	−25.00297	0.0000
R-squared	0.223218	Mean dependent var		−0.359143
Adjusted R-squared	0.149239	S.D. dependent var		0.707547
S.E. of regression	0.652618	Akaike info criterion		2.100818
Sum squared resid	8.944110	Schwarz criterion		2.248075
Log likelihood	−22.20982	F-statistic		3.017313
Durbin-Watson stat	2.298349	Prob(F-statistic)		0.070492
Inverted AR Roots	0.80	−0.80		
Inverted MA Roots	0.96	−0.96		
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.571836	Probability		0.573908
ARCH Test:				
F-statistic	0.898219	Probability		0.354039

Table A5. Correlogram D(AGRI) for Hungary.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. .	. .	1	0.000	0.000	3×10^{-6}	0.999
. .	. .	2	0.001	0.001	2×10^{-5}	1.000
. **.	. **.	3	0.291	0.291	2.9263	0.403
. *.	. *.	4	0.076	0.083	3.1326	0.536
. .	. .	5	0.031	0.035	3.1675	0.674
. .	. * .	6	0.000	−0.091	3.1675	0.788
. .	. .	7	0.050	0.002	3.2692	0.859
. .	. .	8	−0.016	−0.044	3.2799	0.916
. * .	. * .	9	−0.108	−0.097	3.8005	0.924
. *.	. *.	10	0.124	0.122	4.5290	0.920
. ** .	. ** .	11	−0.238	−0.248	7.3589	0.769
. * .	. * .	12	−0.128	−0.078	8.2211	0.768

*, ** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$).

Table A6. ARIMA(5,1,5) model for Hungary.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.011719	0.075746	−0.154714	0.8785
AR(5)	0.456668	0.172944	2.640553	0.0153
MA(5)	−0.880006	0.058159	−15.13109	0.0000
R-squared	0.353659	Mean dependent var		−0.098110
Adjusted R-squared	0.292102	S.D. dependent var		0.335908
S.E. of regression	0.282621	Akaike info criterion		0.427051
Sum squared resid	1.677372	Schwarz criterion		0.574308
Log likelihood	−2.124616	F-statistic		5.745286
Durbin-Watson stat	1.867423	Prob(F-statistic)		0.010229
Inverted AR Roots	0.85	0.26 − 0.81i	0.26 + 0.81i	−0.69 + 0.50i
		−0.69 − 0.50i		
Inverted MA Roots	0.97	0.30 + 0.93i	0.30 − 0.93i	−0.79 − 0.57i
		−0.79 + 0.57i		
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.839786	Probability		0.447213
ARCH Test:				
F-statistic	0.209949	Probability		0.651514

Table A7. Correlogram D(AGRI) for Poland.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. .	. .	1	0.003	0.003	0.0002	0.988
. * .	. * .	2	−0.129	−0.129	0.5557	0.757
. ***	. ***	3	0.447	0.455	7.4582	0.059
. * .	. ** .	4	−0.115	−0.206	7.9337	0.094
. ** .	. * .	5	−0.221	−0.096	9.7638	0.082
. **.	. *.	6	0.302	0.125	13.327	0.038
. .	. .	7	−0.046	−0.001	13.414	0.063
. ** .	. * .	8	−0.303	−0.186	17.352	0.027
. *.	. .	9	0.188	0.031	18.947	0.026
. *.	. *.	10	0.094	0.130	19.362	0.036
. ** .	. .	11	−0.230	−0.027	22.005	0.024
. .	. * .	12	0.035	−0.163	22.069	0.037

*, **, *** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$; ***—significant at $\approx 1\%$).

Table A8. ARIMA(3,1,7) model for Poland.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009617	0.172381	0.055787	0.9560
AR(3)	0.442952	0.200200	2.212550	0.0371
MA(7)	0.775005	0.097180	7.974923	0.0000
R-squared	0.434297	Mean dependent var		−0.056848
Adjusted R-squared	0.385106	S.D. dependent var		0.353956
S.E. of regression	0.277555	Akaike info criterion		0.382575
Sum squared resid	1.771851	Schwarz criterion		0.527740
Log likelihood	−1.973470	F-statistic		8.828692
Durbin-Watson stat	2.169371	Prob(F-statistic)		0.001428
Inverted AR Roots	0.76	−0.38 + 0.66i	−0.38 − 0.66i	
Inverted MA Roots	0.87 − 0.42i	0.87 + 0.42i	0.21 + 0.94i	0.21 − 0.94i
	−0.60 + 0.75i	−0.60 − 0.75i	−0.96	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	1.431462	Probability		0.261339
ARCH Test:				
F-statistic	1.507655	Probability		0.231916

Table A9. Correlogram D(AGRI) for Czech Republic.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. * .	. * .	1	0.142	0.142	0.6440	0.422
. .	. .	2	−0.003	−0.023	0.6443	0.725
. * .	. * .	3	0.075	0.081	0.8406	0.840
* .	* .	4	−0.146	−0.173	1.6077	0.807
. * .	. * .	5	0.067	0.125	1.7756	0.879
. * .	. .	6	0.095	0.052	2.1317	0.907
. .	. .	7	0.003	0.013	2.1322	0.952
. * .	. .	8	0.068	0.028	2.3300	0.969
* .	* .	9	−0.113	−0.123	2.9087	0.968
* .	. .	10	−0.085	−0.027	3.2490	0.975
. ** .	. ** .	11	0.210	0.220	5.4546	0.907
* .	* .	12	−0.131	−0.200	6.3557	0.897

*, ** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$).

Table A10. ARIMA(2,1,2) model for Czech Republic.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.024546	0.021587	−1.137075	0.2667
AR(2)	0.567940	0.144782	3.922732	0.0006
MA(2)	−0.940992	0.042317	−22.23670	0.0000
R-squared	0.230129	Mean dependent var		−0.058053
Adjusted R-squared	0.165973	S.D. dependent var		0.198145
S.E. of regression	0.180956	Akaike info criterion		−0.476687
Sum squared resid	0.785881	Schwarz criterion		−0.332705
Log likelihood	9.435275	F-statistic		3.587029
Durbin-Watson stat	1.739738	Prob(F-statistic)		0.043353
Inverted AR Roots	0.75	−0.75		
Inverted MA Roots	0.97	−0.97		
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.058745	Probability		0.943094

Table A10. Cont.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARCH Test:				
F-statistic	0.047914	Probability		0.828584

Table A11. Correlogram D(AGRI) for Slovakia.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. * .	. * .	1	−0.097	−0.097	0.3042	0.581
. ** .	. ** .	2	−0.191	−0.202	1.5172	0.468
. ** .	. ** .	3	−0.247	−0.304	3.6256	0.305
. ** .	. *** .	4	−0.201	−0.372	5.0834	0.279
. *	. * .	5	0.116	−0.175	5.5878	0.348
. **	. .	6	0.220	−0.029	7.4800	0.279
. **	. *	7	0.239	0.183	9.8197	0.199
. ** .	. * .	8	−0.260	−0.180	12.714	0.122
. .	. *	9	−0.006	0.135	12.716	0.176
. .	. *	10	−0.001	0.186	12.716	0.240
. * .	. .	11	−0.082	0.002	13.049	0.290
. .	. * .	12	−0.007	−0.149	13.051	0.365

*, **, *** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$; ***—significant at $\approx 1\%$).

Table A12. ARIMA(1,1,6) model for Slovakia.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.019781	0.060216	−0.328504	0.7453
AR(1)	−0.495115	0.205340	−2.411199	0.0236
MA(6)	0.834853	0.056644	14.73866	0.0000
R-squared	0.333588	Mean dependent var		−0.020117
Adjusted R-squared	0.280275	S.D. dependent var		0.308502
S.E. of regression	0.261722	Akaike info criterion		0.257892
Sum squared resid	1.712465	Schwarz criterion		0.400628
Log likelihood	−0.610490	F-statistic		6.257163
Durbin-Watson stat	1.830016	Prob(F-statistic)		0.006263
Inverted AR Roots		−0.50		
Inverted MA Roots	0.84 − 0.49i −0.84 − 0.49i	0.84 + 0.49i	0.00 + 0.97i −0.84 + 0.49i	−0.00 − 0.97i
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.627058	Probability		0.543047
ARCH Test:				
F-statistic	1.044490	Probability		0.316568

Table A13. Correlogram D(AGRI) for Croatia.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *** .	. *** .	1	−0.484	−0.484	7.5340	0.006
. *	. * .	2	0.169	−0.085	8.4900	0.014
. .	. .	3	−0.011	0.049	8.4940	0.037
. .	. .	4	−0.045	−0.022	8.5666	0.073
. *	. .	5	0.087	0.061	8.8528	0.115
. * .	. * .	6	−0.171	−0.133	10.001	0.125
. *	. .	7	0.103	−0.054	10.437	0.165

Table A13. Cont.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. * .	. * .	8	−0.154	−0.154	11.448	0.178
. **	. *	9	0.230	0.154	13.818	0.129
. * .	. .	10	−0.187	−0.015	15.477	0.116
. *	. .	11	0.125	0.047	16.252	0.132
. .	. *	12	0.051	0.118	16.387	0.174

*, **, *** indicate the level of statistical significance of autocorrelations (*—significant at $\approx 10\%$; **—significant at $\approx 5\%$; ***—significant at $\approx 1\%$).

Table A14. ARIMA(1,1,6) model for Croatia.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.098460	0.022534	−4.369452	0.0002
AR(1)	−0.505619	0.195322	−2.588651	0.0158
MA(6)	−0.820703	0.069342	−11.83564	0.0000
R-squared	0.418323	Mean dependent var		−0.096296
Adjusted R-squared	0.371789	S.D. dependent var		0.322744
S.E. of regression	0.255806	Akaike info criterion		0.212162
Sum squared resid	1.635918	Schwarz criterion		0.354899
Log likelihood	0.029725	F-statistic		8.989592
Durbin-Watson stat	2.001758	Prob(F-statistic)		0.001144
Inverted AR Roots		−0.51		
Inverted MA Roots	0.97	0.48 + 0.84i	0.48 − 0.84i	−0.48 + 0.84i
	−0.48 − 0.84i		−0.97	
Breusch-Godfrey Serial Correlation LM Test:				
F-statistic	0.083949	Probability		0.919758
ARCH Test:				
F-statistic	0.087687	Probability		0.769584

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