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COMPARISON OF LOGISTICS PERFORMANCE INDEX DEVELOPMENT AMONG EU MEMBER STATES

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Abstract:

This paper deals with a performance analysis and classification of EU member states based on their Logistics Performance Index (LPI) published by the World Bank. Our study covers 2010 to 2023 with 117 countries evaluated. The goal is to analyse, classify and compare countries based on their LPI scores using cluster analysis with parametric and non-parametric measures. Parametric measures include the mean LPI score, average growth, and linear trend slope. The focus is especially on the differences between EU member countries. For non-parametric measures, we used the Malmquist Productivity Index (MPI). This novel approach uses clustering based on the' long-term development of LPI scores and MPI. The classification highlights three distinct clusters: "Struggling Performers," "Improvers with Moderate Performance," and "Rapid Advancers." The paper confirms that older EU members have mostly stable logistics, but are less influenced by recent growth. It also shows that sustained improvement over time is a key driver of better logistics performance in the newer EU members. In addition, it was found that countries still in the catch-up phase tend to have lower current performance.

Key words: *Logistics Performance Index, Malmquist Productivity Index, cluster analysis, European Union*

1. Introduction

The logistics performance of a country or group of countries is crucial for international trade (Martí, Puertas & García, 2014) and economic prosperity (Ojala & Çelebi, 2015). Since 2007, the World Bank has evaluated this performance using the Logistics Performance Index (LPI), which helps countries identify challenges and opportunities in trade logistics (The World Bank, 2023). The latest edition, published in 2023 after the WHO declared the pandemic over, compares 139 countries; the previous evaluation was in 2018, near the onset of Covid-19, which significantly disrupted supply chains (Lukoszová, 2021).

Previous studies have examined logistics performance using LPI, but most analyses focus on single-year snapshots (Ittmann, 2018) or short-term comparisons (Ioan et al., 2010; Anuşlu & Firat, 2019; Loucanova et al., 2022; Ulkhaq, 2023). Hadžikadunic et al. (2023) performed a recent comparative analysis of EU countries based on the continuous evolution of the LPI ranking from 2007 to 2023, but their work was limited to comparing data sets rather than analysing the dynamics of development. This approach overlooks the evolving nature of logistics systems. Few studies integrate time-series analysis with productivity measures such as the Malmquist Productivity Index (MPI) to capture both efficiency changes and technological progress (Martí, Martín & Puertas, 2017; Hong & Kim, 2023). Moreover, clustering based on long-term development remains underexplored, particularly for EU member states (Ulkhaq, 2023; Pehlivan et al., 2024). Recent research increasingly combines MPI with LPI to evaluate productivity changes within the logistics sector. The MPI, which measures productivity changes over time, enables a complete analysis by accounting for input and output efficiencies. These studies cover longer periods and investigate country developments using data envelopment analysis (Bayraktar et al., 2024; Stević et al., 2024; Hasan et al., 2025), but classification often focuses on a single aspect of development. Our study employs both parametric and nonparametric approaches to examine the dynamics of LPI between the investigated countries. Cluster analyses based on LPI have gained attention in recent research for evaluating and comparing logistics capabilities between regions (Sergi et al., 2021; Loucanova et al., 2022; Yıldırım, 2023; Ulkhaq, 2023; Pehlivan et al., 2024). Those studies classify countries based on LPI scores, providing insight into logistics performance, but most focus on data from a specific period.

Our research addresses this gap by combining long-term analysis of LPI development with clustering. We classify countries based on performance trends from 2010 to 2023 using time-series analysis and MPI. The main contributions are derived from a clear methodological approach that integrates parametric and nonparametric techniques and introduces unique clustering characteristics to capture dynamic changes. We also benchmark EU member countries globally, ensuring numerous decision-making units for reliable comparisons.

The paper is structured as follows. The second section reviews the literature on cluster analysis and LPI, along with the application of MPI, and outlines hypotheses. The third section details our methodology, including the variables used in the cluster analysis. The fourth section is focused on presentation of our results including uncovered clusters of

countries This is followed by a discussion, and in the conclusion, we will explain our contribution and limitations of the study.

2. Literature

In this paper, we aim to perform cluster analysis by combining results of previous research that used LPI and similar indices from a stationary perspective. To address this, we used time series analysis and Malmquist Productivity Index to assess performance changes between countries using the LPI.

2.1 Recent research on Logistics Performance Index

The Logistics Performance Index (LPI), developed by the World Bank, is derived from a global survey of freight forwarding companies and logistics carriers. It measures productivity across supply chains within a country (Arvis et al., 2018). The LPI ranges from 1 to 5, where 5 indicates maximum performance. Countries aim to improve their scores and rankings while shaping logistics strategies (Senir, 2021). The empirical model applies gravity theory and includes six subcomponents: “Customs,” “Infrastructure,” “Ease of arranging shipments,” “Quality of logistics services,” “Tracking and tracing,” and “Timeliness” (Górecka et al., 2021). These indicators are combined into a single measure.

The LPI serves as a critical benchmarking tool for assessing logistics systems, particularly within the European Union (EU). Studies highlight logistics performance as a key driver of international trade, with higher LPI scores linked to favourable trade outcomes and economic integration (Zaninović & Bugarčić, 2023; Bugarčić et al., 2020). For example, Zaninović et al. (2020) compare the EU15 and CEMS countries, showing differences in trade facilitation related to logistics capabilities. LPI components such as infrastructure quality, border clearance efficiency, and service quality positively influence trade in consumption goods across EU states (Górecka et al., 2021). These findings confirm that a well-developed logistics sector strengthens bilateral trade and economic growth (Górecka et al., 2021). Modern assessments must also account for technological advancements that shape logistics operations (Bajor et al., 2024). Future LPI calculations should meet the completeness, reliability, and relevance requirements for digital technology development and be updated semi-annually (Janno et al., 2021).

The 2023 LPI edition integrates key performance indicators into overall country scores (The World Bank, 2023). Historically, LPI analyses have focused on individual years (Ittmann, 2018). Some studies examine longer periods using data envelopment analysis (Bayraktar et al., 2024), while others apply cluster analysis to LPI scores (Ioan et al., 2010; Anuşlu & Firat, 2019; Loucanova et al., 2022; Ulkhaq, 2023).

In the following subsection, we will concentrate on state-of-the-art MPI and clustering approaches based on the LPI scores.

2.2 Evaluation of the’ logistics performance of countries using the Malmquist Productivity Index

Several studies have combined the Malmquist Productivity Index (MPI) with the LPI to assess productivity changes in logistics. The MPI, which measures productivity over

time, enables a thorough analysis by considering both input and output efficiencies. The research by Hong and Kim (2023) highlights the application of the LPI in conjunction with the MPI to analyse the logistics efficiency in member countries of the OECD. Their study utilised the LPI as an output factor while employing the MPI to assess changes in logistics performance, specifically focussing on "Logistics quality and competence" and "Infrastructure" as input factors. Additionally, the work of Amiri et al. (2024) emphasises the importance of employing both indices in logistics and transportation contexts, arguing that these indices together provide a holistic view of productivity in complex systems. Mariano et al. (2017) used LPI components as outputs in their DEA model with C02 emissions as inputs, creating a novel composite index. Martí, Martín and Puertas (2017) divided the LPI components into inputs and outputs, allowing the use of MPI for a longitudinal study. Integrating MPI with LPI provides a robust framework for assessing changes in logistics efficiency and productivity.

2.3 Clustering of countries based on LPI

Cluster analysis employs similarity or dissimilarity measures to assign points in space to clusters based on proximity. Its goal is to group objects within clusters that differ from those in other clusters. Greater homogeneity within clusters increases inter-cluster differences and provides finer granularity (King, 2015).

In a broader context, Rezaei et al. emphasised the importance of the LPI in international logistics, noting its widespread application among policymakers and researchers (Rezaei et al., 2018). Ioan et al. (2010) performed a cluster analysis from a Romanian perspective using LPI data from 2007 and 2010, revealing three clusters. Sergi et al. (2021) clustered countries using descriptive statistics and assessed the relationship between LPI and the Global Competitiveness Index (GCI). Similarly, Loucanova, Olisakova and Palus (2022) applied cluster analysis with LPI and GCI from 2018, identifying three clusters of high, medium and low performance. Anuşlu and Firat (2019) combined global indices such as LPI, Global Innovation Index, and Sustainable Development Goals Index, classifying countries into three groups based on 2018 LPI scores. Yıldırım (2023) evaluated logistics performance using LPI.integrated supply chain indicators incorporating LPI. Ulkhaq (2023) focused on clustering countries by LPI data from 2018. Pehlivan et al. (2024) ranked G20 countries and conducted cluster analysis, comparing the results with World Bank LPI scores, identifying three main clusters. A recent comparative analysis of EU countries based on continuous LPI ranking development from 2007 to 2023 was performed by Hadžikadunic et al. (2023), but their work was limited to dataset comparison rather than analysing development dynamics.

2.4 Research gap and research hypotheses

The existing literature emphasises the role of logistics performance in trade facilitation and economic growth (Martí et al., 2014; Bayraktar, 2024). However, most studies adopt static approaches, neglecting longitudinal patterns and productivity shifts. Recent works (Loucanova et al., 2022; Ulkhaq, 2023) suggest clustering as a useful tool but do not incorporate MPI-based efficiency measures. Despite progress in measuring logistics performance, several gaps remain. Research disproportionately focusses on

regions such as the EU, the OECD and the G20, while Africa, Latin America, and smaller developing nations receive less attention. Many studies analyse European countries or top global performers, but few explore long-term logistics trends in emerging economies.

Integration of time-series dynamics is limited. Most analyses rely on single-year LPI snapshots or simple rankings. Few combine LPI with productivity indices over extended periods, leaving gaps in understanding logistics evolution, especially in developing countries or post-crisis contexts. Big data and real-time logistics information remain underutilised. The LPI's 2023 inclusion of shipping data is a start, but research has yet to leverage IoT devices, GPS tracking, and port sensors for continuous, high-frequency monitoring. Similarly, advanced analytical techniques such as network analysis, machine learning, and multi-criteria decision frameworks are rare. Current models rarely incorporate resilience, sustainability, or policy effectiveness.

Finally, a discrepancy persists between measured performance and policy interventions. Although LPI and MPI studies identify areas for improvement, they rarely link reforms - such as customs modernisation or infrastructure projects - to frontier shifts or catch-up effects. The hypotheses that arise from these gaps are as follows:

- H1: Newer EU member states exhibit higher LPI growth rates than older members.
- H2: Technological progress (MPI frontier shift) exerts stronger influence in newer EU countries.
- H3: Countries with higher catch-up effects started from lower levels of logistics performance.

To investigate these hypotheses, we combined a time-series analysis of LPI development, productivity changes, and overall LPI scores to classify and compare countries from a more comprehensive perspective.

3. Methodology

To fulfil the objective of this paper, secondary research was conducted. The LPI was published every two years from 2010 to 2018, including 139 countries in its last edition in 2023 (The World Bank, 2023). The LPI methodology changed from 2018 to 2023, incorporating new big data-based KPIs alongside the traditional survey-based index. These KPIs offer deeper insight into supply chain bottlenecks. Although earlier indices relied on perceptions of logistics professionals', the 2023 index uses real-time shipping and port efficiency data for a more objective assessment. The 2023 LPI, using both original survey-based methods and new big data sources, offers a realistic reflection of logistics performance levels (The World Bank, 2023).

3.1 Research methodology

The research focus is designed to analyse the development of LPI of EU countries that were subject to benchmarking with other world countries, for which we have a continual set of data for our studied period. Our research approach is divided into 6 steps:

- Data collection – we collected data from the World Bank LPI database for the period 2010 to 2023 (The World Bank, 2023). In total, 117 countries were continuously covered by LIP issues from 2010 until 2023.

- Horizontal analysis of trends and differences – we performed analysis of trends among selected countries using the calculation of linear trend slopes and their differences when comparing the development of the LPI index with and without the COVID-19 pandemic interrupted years. Thus, two main changes have been observed between 2018 and 2023: the discontinuation of index determination due to COVID-19 and the difference in the LPI evaluation methodology.

- Correlation analysis – we performed a correlation analysis of LPI and its sub-indices among selected countries to uncover similarities of the LPI development in the covered period 2010 to 2023.

- Calculation of the MPI – we calculated the Malmquist Performance Index using the sub-indices of the LPI, where the inputs were identified as customs, infrastructure, and interna-tional shipments scores. The results were identified as logistics competence and quality, tracking and tracing, and timeliness scores based on (Martí, Martín and Puertas, 2017). Calculation of the MPI was based on a full LPI dataset (e.g. including all participating countries). The applied model was input orientated and based on constant returns to scale.

- Cluster analysis – we focused on four main characteristics that were used for analysis of the LPI developments during the period 2010 to 2023: LPI average growth, LPI linear trend slope, efficiency change (Catch-up) and technology change (Frontier shift). We used Ward's method of initial clustering and k-means clustering method to confirm our results.

- Aggregation of results and interpretation – we tried to explain the results via additional changes and characteristics that can show how the LPI indices are progressing with relation to EU member countries.

3.2 Correlation analysis

The correlation analysis measures the strength and direction of the relationship between two variables, revealing how changes in one variable are associated with changes in another. This method helps identify patterns, dependencies, and redundant variables, improving the accuracy and simplicity of the model. Correlation coefficients can be tested for statistical significance to determine whether observed relationships in a sample reflect those in the larger population (Field, 2018).

The most common measure of correlation is the Pearson correlation coefficient (r), which ranges from -1 to 1. r = 1 indicates a perfect positive linear relationship, meaning that as one variable increases, the other increases proportionally. r = -1 indicates a perfect negative linear relationship, meaning that as one variable increases, the other decreases proportionally, whereas r = 0 means no linear relationship exists between the variables.

Other types of correlation indices that might be used are Spearman's Rank Correlation for ordinal data or Kendall's Tau, often used when dealing with small sample sizes or tied ranks. Main assumptions related to correlation are linearity, continuous data, and normality. As noted by Field (2018), understanding these assumptions and choosing the appropriate correlation index is crucial for ac-curate data interpretation and analysis.

3.3 Malmquist productivity index

The Malmquist Productivity Index (MPI), used in Data Envelopment Analysis (DEA), measures productivity changes over time, distinguishing performance improvements from regressions. Developed by Sten Malmquist in 1953, MPI decomposes changes into two components: catch-up effect and frontier shift, isolating operational improvements from technological progress. Coelli et al. (2005) and Fare et al. (1994) emphasised the importance of MPI, including its application in seventeen OECD countries during 1979-1988. MPI evaluates input usage and output production through distance functions, comparing performance across periods to identify best practices and improvement areas—particularly useful in sectors with rapid technological advancements. Distance functions (D) are calculated using DEA models. MPI components:

- Efficiency Change (Catch-up): Indicates whether a DMU moves closer to or further from the efficient frontier, reflecting operational efficiency changes.

- Technical Change (Frontier Shift): Captures shifts in the efficient frontier, representing technological progress or regression.

MPI applications span healthcare, agriculture, banking, and logistics. Zhou et al. (2023) analysed Chinese healthcare efficiency; Singh et al. (2021) benchmarked ASEAN systems; Aydin (2022) applied MPI to OECD countries. In banking, Shah et al. (2019) linked sustainability to productivity; Yu and Huang (2023) examined Polish banks. Nguyen (2023) integrated MPI with LPI to assess Asian logistics competitiveness. In general, MPI is a robust tool for evaluating logistics performance, especially when combined with LPI. The model applied here is input-oriented with constant returns to scale.

3.4 Cluster analysis

Cluster Analysis is a technique for classifying large data sets into clusters or groups to identify relationships within the data (Everit et al., 2011). The purpose of this project is to find subsets (clusters) that are internally similar and distinct from other clusters.

Cluster analysis methods are divided into hierarchical and non-hierarchical. Hierarchical methods create clusters with different levels, either agglomerative (merging smaller clusters) or divisional (dividing a full set). These are represented by dendrograms that visually show the clustering process (Kaufman & Rousseeuw, 2010). Ward's method merges clusters by minimising the sum of squared deviations from cluster means (Everitt et al., 2011).

Non-hierarchical methods, like the k-means method, do not create hierarchical structures. Instead, they divide objects into a set number of clusters by iteratively assigning and reassigning objects based on proximity to cluster centres (Xu & Wunsch, 2010). This paper used hierarchical cluster analysis to explore the data's structure, followed by k-means to confirm the exploratory results, employing IBM SPSS Software.

Ward’s method minimizes within-cluster variance at each step, producing highly homogeneous clusters. This suits our standardised continuous variables (LPI growth, trend, MPI components), where the Euclidean distance accurately reflects differences without scale distortions. Euclidean distance is widely used in logistics performance

studies because it captures absolute differences in standardized indicators, ensuring interpretability and comparability.

After identifying the preliminary cluster structure with Ward's method, we applied k-means clustering to validate and refine the groupings. K-means optimizes cluster centroids and reduces residual variance, improving stability in assignments.

This hybrid approach leverages both methods: Ward's method provides a hierarchical view and helps to determine the optimal number of clusters, while the k-means ensure precision in the final formation. This methodology aligns with best practices in logistics and performance benchmarking research (Ioan et al., 2010; Loucanova et al., 2022; Ulkhaq, 2023).

4. Results/findings

In this section, we are going to present results according to our research approach. Firstly, we will focus on the analysis of time series using linear slopes of LPI and its sub-indices. Next, we will focus on the differences that may have occurred due to COVID-19 closures and how this period of measures against spreading of this virus influenced LPI development. Then we will analyse the development of LPI among all selected countries using correlation. This will be followed by calculation and analysis of the Malmquist Performance Index based on the LPI sub-indices. To envelope the previous findings, we will apply clustering that can help to identify some similarities and groups of countries that share similar characteristics.

4.1 Comparison of logistic performance index components of EU member countries

Table 1 presents linear trend slopes of partial logistics performance indexes for EU countries, comparing ten member states that joined in 2004 and 2007 based on LPI values from 2010 to 2023. Changes in score levels are omitted due to the impacts of COVID-19 and the revised LPI evaluation method in 2023. The length of those green bars indicates the positive slope magnitude—the higher the bar, the stronger the growth. Negative values show declining trends. Components C1–C3 are inputs; C4–C6 are outputs. Greece shows the most significant growth, driven by international shipments (C3) and logistics competence (C4). Estonia also records notable improvement in infrastructure and tracking. Croatia exhibits positive trends in five sub-criteria, except delivery time, which declines slightly. Conversely, Luxembourg and Ireland show overall decreases: Luxembourg falls in all sub-criteria except logistics competence, while Ireland declines across all except international shipments, which remains stable.

Table 1. Slopes of linear trend functions based on total LPI values and its components for the period 2010-2023

	LPI	Customs	Infrastructure	International Shipments	Logistics Competence and Quality	Tracking and Tracing	Timeliness Score
		C1	C2	C3	C4	C5	C6
Greece	0,060	0,051	0,059	0,081	0,077	0,054	0,039
Estonia	**0,042**	**0,027**	**0,053**	**0,027**	**0,046**	**0,062**	**0,050**
Croatia	0,030	0,018	0,023	0,044	0,058	0,030	0,005
Lithuania	**0,024**	**0,032**	**0,057**	**0,015**	**0,054**	**0,006**	**-0,016**
Finland	0,022	0,005	0,013	0,037	0,014	0,022	0,024
Austria	0,022	0,012	0,017	0,014	0,021	0,028	0,031
Romania	**0,021**	**0,016**	**0,048**	**0,016**	**0,041**	**0,037**	**-0,005**
Slovenia	**0,021**	**0,055**	**0,054**	**0,029**	**0,013**	**-0,014**	**0,003**
Latvia	**0,021**	**0,026**	**0,043**	**-0,006**	**0,054**	**0,004**	**0,016**
Spain	0,021	0,013	0,014	0,036	0,019	0,022	0,008
Malta	0,019	0,044	0,048	-0,011	0,028	0,043	-0,012
Denmark	0,016	0,031	0,006	0,002	0,015	0,033	-0,015
Hungary	**0,014**	**0,002**	**0,004**	**0,041**	**0,010**	**0,024**	**0,010**
Bulgaria	**0,013**	**0,033**	**0,028**	**-0,011**	**0,023**	**0,019**	**0,002**
Poland	**0,013**	**0,016**	**0,037**	**0,006**	**0,028**	**0,029**	**-0,039**
Slovak Republic	**0,006**	**0,027**	**0,019**	**0,003**	**0,019**	**-0,001**	**-0,037**
Italy	0,005	0,005	0,008	0,007	0,007	0,009	-0,010
Belgium	0,004	0,001	0,001	0,033	0,010	-0,012	-0,001
Germany	0,004	-0,002	0,002	0,007	0,011	0,007	-0,022
France	0,004	0,004	-0,012	0,016	-0,002	0,002	-0,010
Sweden	0,004	0,021	0,014	-0,012	0,007	0,001	-0,006
Portugal	0,003	-0,006	0,021	0,006	0,017	-0,015	-0,012
Netherlands	0,003	-0,002	-0,001	0,001	0,006	0,004	-0,022
Cyprus	0,003	0,000	-0,017	-0,004	0,018	-0,009	0,009
Czech Republic	**0,002**	**-0,009**	**-0,003**	**0,018**	**0,030**	**-0,010**	**-0,003**
Ireland	-0,017	-0,016	-0,017	0,000	-0,013	-0,021	-0,045
Luxembourg	-0,028	-0,024	-0,030	-0,012	0,013	-0,032	-0,079

Table 2 shows changes in LPI trends and components when comparing slopes before and after the COVID-19 pandemic and the revised LPI methodology. Green bars indicate a positive change; red bars, negative. The average Stringency Index (Hale et al., 2021) for 2020–2022 (Github, 2024), based on COVID-19 restrictions and sea access, illustrates how openness during the pandemic was influenced by these factors. The slope difference reflects whether trends changed with or without the 2023 LPI edition, capturing pandemic and methodological impacts.

Countries with increasing trends include Bulgaria, Cyprus, Denmark, Estonia, Finland, France, Greece, Ireland, Latvia, Lithuania, Malta, Poland, and Slovakia. The Netherlands shows no change. Austria and Germany exhibit negative differences, possibly due to strong trading ties. Czech Republic, Hungary, and Austria may be affected by lack of sea access. The 2023 methodology change likely boosted scores for better-performing countries, while lowering others. The development of new members' from 2018 to 2023 resembles the development of older EU states, although sea access appears to be a differentiating factor. Germany's slump may explain the downward trend of the Czech Republic given their trade linkage.

Table 2. Differences in the slopes of the linear trend functions of EU member states when comparing the development until 2018 and until 2023

	LPI	Customs	Infrastructure	International Shipments	Logistics Competence and Quality	Tracking and Tracing	Timeliness	Stringency Index_Average	Direct Sea Access
Latvia	**0,037**	**0,020**	**-0,003**	**0,029**	**0,048**	**0,059**	**0,073**	**35,49**	**1**
Malta	0,025	0,041	0,054	0,015	0,045	0,015	-0,001	39,90	1
Finland	0,020	0,008	0,026	0,038	0,030	0,004	0,001	32,52	1
Greece	0,014	-0,008	0,014	0,022	0,033	0,037	-0,004	52,54	1
Bulgaria	**0,013**	**0,018**	**0,025**	**-0,011**	**0,022**	**0,035**	**0,001**	**36,17**	**1**
Cyprus	0,013	-0,018	-0,004	0,015	0,021	0,069	-0,022	45,10	1
Slovak Republic	**0,012**	**0,006**	**0,007**	**-0,031**	**0,018**	**0,040**	**0,030**	**38,98**	**0**
Denmark	0,012	0,003	0,025	-0,003	0,003	0,027	-0,004	35,38	1
Ireland	0,007	0,004	0,009	0,007	-0,003	0,002	0,018	42,54	1
Poland	**0,003**	**0,004**	**0,011**	**-0,038**	**-0,009**	**0,016**	**0,030**	**39,79**	**1**
Estonia	**0,002**	**-0,037**	**-0,001**	**0,005**	**0,031**	**0,023**	**-0,004**	**32,02**	**1**
France	0,001	0,004	-0,015	-0,004	0,001	0,001	0,000	42,27	1
Lithuania	**0,001**	**-0,009**	**0,006**	**0,029**	**0,014**	**-0,028**	**-0,011**	**36,02**	**1**
Netherlands	0,000	-0,009	-0,004	-0,011	0,004	0,011	-0,020	42,90	1
Spain	-0,001	-0,006	-0,011	-0,033	-0,001	0,026	0,014	44,96	1
Croatia	-0,003	-0,019	-0,025	0,040	-0,014	0,013	-0,034	33,40	1
Romania	**-0,006**	**-0,024**	**-0,037**	**0,019**	**0,002**	**0,009**	**0,002**	**44,32**	**1**
Italy	-0,009	-0,009	-0,008	-0,029	0,010	0,000	-0,014	52,28	1
Belgium	-0,012	0,018	0,007	-0,051	0,005	-0,004	-0,025	39,05	1
Sweden	-0,012	-0,008	-0,014	-0,051	0,014	0,007	-0,012	36,69	1
Luxembourg	-0,013	0,009	-0,010	-0,009	-0,005	-0,012	-0,042	37,26	0
Germany	-0,014	-0,023	-0,011	-0,023	-0,016	-0,009	-0,020	44,04	1
Austria	-0,015	-0,012	-0,034	-0,003	-0,021	-0,017	-0,015	49,14	0
Slovenia	**-0,018**	**-0,020**	**-0,005**	**0,006**	**0,000**	**-0,029**	**-0,050**	**40,58**	**1**
Portugal	-0,023	-0,001	0,029	-0,065	-0,006	-0,051	-0,043	43,70	1
Czech Republic	**-0,042**	**-0,037**	**-0,044**	**-0,046**	**-0,031**	**-0,054**	**-0,028**	**39,49**	**0**
Hungary	**-0,042**	**-0,060**	**-0,032**	**-0,025**	**-0,033**	**-0,051**	**-0,041**	**36,54**	**0**

Based on the values presented in Table 2, it cannot be clearly demonstrated that there is a direct link between the increasing strength of the anti-COVID measures and the downward trend in the country's logistics performance, as this relationship does not hold in the case of Greece, which has the highest stringency index, and the correlation is not significant for LPI or its subindices. This phenomenon can be explained by the more objective LPI evaluations performed by the World Bank in their 2023 edition.

4.2 Correlation analysis of LPI index and its components

In the next phase of the analysis, we focused on the correlation between selected countries with their overall LPI scores from 2010 to 2023. We focused only on EU countries where the data were the most consistent throughout the analysed period. Table 3 shows the correlation coefficients between the LPI (Logistics Performance Index) scores from 2010 through 2023. The correlation values range from -1 to 1, where values closer to 1 indicate a strong positive relationship, and values closer to -1 indicate a strong negative relationship.

Notably, the high average correlation among most developed EU countries (Germany, Netherlands, France, Italy, Spain, Sweden, Belgium) suggests similar LPI development, with improvements or declines largely aligned. In contrast, countries that joined the EU later (since 2004)—such as the Czech Republic, Poland, Hungary, Slovakia, and the Baltic states—exhibit a lower correlation with older members but a higher correlation among themselves, indicating that regional factors may influence logistics performance similarly.

Table 3. The average correlation coefficients between the LPI (Logistics Performance Index) scores of different countries from 2010 to 2023

Average Correlation	AUT	BEL	BGR	HRV	CYP	CZE	DNK	EST	FIN	FRA	DEU	GRC	HUN	IRL	ITA	LVA	LIT	LUX	MLT	NED	POL	PRT	ROU	SVK	SVN	ESP	SWE
AUT																											
BEL	0,725																										
BGR	0,495	0,567																									
HRV	0,553	0,598	0,735																								
CYP	0,517	0,534	0,812	0,776																							
CZE	0,604	0,675	0,710	0,742	0,741																						
DNK	0,550	0,676	0,452	0,453	0,481	0,416																					
EST	0,587	0,538	0,789	0,694	0,880	0,658	0,615																				
FIN	0,609	0,684	0,177	0,245	0,389	0,333	0,764	0,582																			
FRA	0,837	0,845	0,531	0,545	0,650	0,513	0,768	0,685	0,754																		
DEU	0,660	0,828	0,149	0,334	0,296	0,221	0,806	0,385	0,768	0,855																	
GRC	0,701	0,721	0,622	0,658	0,771	0,685	0,528	0,780	0,640	0,770	0,543																
HUN	0,645	0,677	0,554	0,673	0,743	0,708	0,558	0,675	0,536	0,773	0,477	0,727															
IRL	0,787	0,719	0,562	0,626	0,703	0,767	0,508	0,626	0,446	0,688	0,520	0,780	0,803														
ITA	0,798	0,900	0,624	0,602	0,651	0,602	0,736	0,665	0,665	0,939	0,803	0,826	0,798	0,752													
LVA	0,664	0,695	0,812	0,750	0,817	0,703	0,415	0,678	0,346	0,641	0,346	0,658	0,679	0,660	0,690												
LIT	0,569	0,689	0,728	0,788	0,778	0,803	0,490	0,764	0,369	0,652	0,423	0,720	0,709	0,709	0,701	0,771											
LUX	0,414	0,686	0,546	0,672	0,690	0,610	0,689	0,734	0,432	0,681	0,624	0,724	0,726	0,589	0,753	0,579	0,795										
MLT	0,389	0,550	0,634	0,455	0,431	0,442	0,418	0,530	0,096	0,556	0,464	0,464	0,534	0,321	0,713	0,559	0,684	0,697									
NED	0,658	0,823	0,205	0,382	0,379	0,259	0,790	0,468	0,758	0,885	0,976	0,581	0,549	0,526	0,821	0,390	0,429	0,670	0,508								
POL	0,640	0,676	0,867	0,791	0,822	0,884	0,516	0,790	0,319	0,673	0,320	0,671	0,694	0,772	0,689	0,827	0,857	0,611	0,618	0,348							
PRT	0,511	0,821	0,674	0,585	0,738	0,851	0,477	0,787	0,436	0,653	0,509	0,735	0,692	0,731	0,764	0,594	0,764	0,765	0,592	0,552	0,860						
ROU	0,527	0,553	0,804	0,804	0,870	0,867	0,266	0,739	0,225	0,505	0,117	0,743	0,753	0,787	0,574	0,783	0,788	0,570	0,554	0,174	0,887	0,762					
SVK	0,596	0,776	0,816	0,562	0,758	0,733	0,610	0,684	0,364	0,635	0,498	0,680	0,519	0,649	0,711	0,674	0,778	0,721	0,606	0,483	0,823	0,758	0,762				
SVN	0,494	0,752	0,667	0,581	0,545	0,486	0,327	0,538	0,177	0,530	0,413	0,626	0,609	0,590	0,797	0,636	0,775	0,598	0,619	0,464	0,552	0,661	0,485	0,539			
ESP	0,911	0,897	0,747	0,604	0,723	0,689	0,673	0,798	0,657	0,885	0,670	0,886	0,715	0,770	0,928	0,714	0,702	0,714	0,566	0,710	0,793	0,766	0,684	0,751	0,786		
SWE	0,739	0,893	0,464	0,466	0,401	0,394	0,745	0,469	0,532	0,828	0,881	0,595	0,500	0,565	0,877	0,618	0,552	0,565	0,543	0,827	0,497	0,599	0,255	0,676	0,715	0,787	

Overall, while some correlations are moderate, many are strong, reflecting varied LPI dynamics across regions, yet the distinction between older and newer member states remains evident.

4.3 Analysis of efficiency of logistic performance based on LPI components using the Malmquist Productivity Index

The Malmquist Productivity Index measures changes in relative efficiency of countries over time, based on an input-output principle. In this analysis, we used the LPI component scores from 2010 to 2023 to assess the progress of logistics performance. The “Catch-up” index in Table 4 reflects whether a country moves closer to or farther from the efficiency frontier. For example, Latvia’s average catch-up value of 1.030 indicates improved efficiency, suggesting that it has generally approached the frontier of best-practices. In contrast, Slovenia’s average of 0.977 suggests a slight decline, indicating that it has not kept up with best practices as effectively as Latvia.

Overall, looking at the slopes (linear trend) of all analysed countries, we can see that the highest improvement of efficiency over time was experienced by Sweden, Slovak Republic, Latvia, Slovenia, Spain and Belgium. Conversely, the negative development can be seen in the Catch-up index of Austria, Croatia, Finland, Ireland, and Slovenia. In general, the Catch-up index of all countries analysed in the dataset was stagnating.

The "Frontier shift index” in Table 5 captures the technological changes, reflecting shifts in the efficiency frontier itself. A value above 1 indicates technological progress, while values below 1 suggest technological regression.

The average “value of the "Frontier”" of Croatia of 1.004 implies a stable technological environment with minimal progress. Greece’s 0.976 suggests a slight technological decline, indicating challenges in adopting newer logistics practices. This difference shows that Croatia’s advantage stems not only from efficiency gains but also from less technological regression compared to Greece.

Table 4. The "Catch-up" index of the LPI components for the period 2010 to 2023

Catch-up	2010=>2012	2012=>2014	2014=>2016	2016=>2018	2018=>2023	Average	Slope
Latvia	1,056	0,974	1,026	0,927	1,169	1,030	0,018
Czech Republic	1,160	0,870	1,084	0,994	1,028	1,027	-0,014
Luxembourg	1,133	0,941	0,984	1,039	1,035	1,026	-0,010
Sweden	1,071	0,923	1,053	0,870	1,206	1,025	0,022
Cyprus	1,042	0,945	1,060	0,983	1,089	1,024	0,013
Hungary	1,164	0,917	0,978	1,066	0,984	1,022	-0,021
Estonia	1,043	0,892	1,133	0,910	1,131	1,022	0,019
Austria	1,117	1,009	1,004	0,925	1,031	1,017	-0,025
Malta	1,036	0,923	1,048	1,018	1,051	1,015	0,012
Denmark	1,046	0,917	1,118	0,973	1,013	1,014	-0,001
Croatia	1,097	0,963	1,074	0,953	0,973	1,012	-0,026
Poland	0,949	1,056	1,012	1,016	1,028	1,012	0,012
Portugal	1,029	1,007	0,972	1,068	0,983	1,012	-0,003
Lithuania	1,032	0,947	1,065	1,068	0,937	1,010	-0,007
Germany	1,056	0,966	1,057	0,925	1,031	1,007	-0,009
Bulgaria	0,929	1,038	1,115	0,838	1,111	1,006	0,017
Netherlands	1,014	1,025	1,001	0,945	1,044	1,006	-0,002
Romania	0,958	1,059	0,888	1,149	0,969	1,005	0,011
Slovak Republic	1,010	0,929	0,964	1,075	1,040	1,004	0,021
Ireland	1,029	1,072	0,921	1,014	0,968	1,001	-0,018
Italy	0,983	0,964	1,032	0,999	1,021	1,000	0,011
Greece	1,020	0,945	0,996	0,985	1,037	0,996	0,007
Spain	0,960	1,005	1,003	0,931	1,082	0,996	0,017
Finland	1,013	0,964	1,091	1,012	0,889	0,994	-0,020
France	0,965	0,966	1,063	1,008	0,962	0,993	0,004
Belgium	0,938	0,996	0,989	0,993	1,022	0,987	0,016
Slovenia	0,966	1,089	0,953	0,920	0,957	0,977	-0,019
Max	1,164	1,089	1,133	1,149	1,206	1,030	
Min	0,929	0,870	0,888	0,838	0,889	0,977	
SD	0,064	0,056	0,060	0,069	0,070		

In general, technological improvement was most evident in Croatia, Czech Republic, and Austria (index> 1), while Belgium, Lithuania, Greece, and Romania recorded declines. Romania's index below 1 reflects a decrease, largely due to 2014–2016. Linear trends show that Finland and Romania are improving, suggesting a positive outlook similar to that of the top-performing countries.

Table 5. Frontier shift index of the LPI components for the period 2010 to 2023

Frontier Shift	2010=>2012	2012=>2014	2014=>2016	2016=>2018	2018=>2023	Average	Slope
Croatia	0,963	1,023	0,949	1,052	1,032	1,004	0,017
Czech Republic	0,959	1,048	0,948	1,014	1,041	1,002	0,013
Austria	0,952	1,031	0,978	1,029	1,010	1,000	0,012
Estonia	0,985	1,035	0,958	1,030	0,986	0,999	0,000
Netherlands	0,937	1,023	0,953	1,087	0,987	0,997	0,016
Germany	0,933	1,024	0,954	1,084	0,991	0,997	0,017
Hungary	0,946	1,062	0,981	0,976	1,007	0,995	0,003
Bulgaria	0,983	1,030	0,999	0,972	0,986	0,994	-0,005
Ireland	0,968	1,023	0,966	1,018	0,994	0,994	0,005
Italy	0,939	1,034	0,971	1,012	1,010	0,993	0,012
Spain	0,922	1,039	0,960	1,033	1,001	0,991	0,015
Slovenia	0,966	1,042	0,962	1,016	0,969	0,991	-0,002
Slovak Republic	0,947	1,023	0,980	1,016	0,988	0,991	0,007
Cyprus	0,941	1,031	0,990	1,002	0,990	0,991	0,007
Denmark	0,943	1,014	0,950	1,070	0,977	0,990	0,012
France	0,936	1,025	0,966	1,018	1,008	0,990	0,014
Sweden	0,942	1,025	0,962	1,055	0,965	0,990	0,008
Poland	0,972	0,993	0,948	1,010	1,024	0,989	0,012
Luxembourg	0,935	1,017	0,975	1,043	0,973	0,989	0,010
Portugal	0,952	1,044	0,970	0,964	1,011	0,988	0,004
Latvia	0,942	1,002	0,973	1,026	0,985	0,985	0,011
Malta	0,943	1,028	0,971	0,996	0,986	0,985	0,005
Romania	0,995	0,929	0,986	0,982	1,031	0,985	0,013
Finland	0,928	1,013	0,954	1,029	0,997	0,984	0,015
Belgium	0,929	1,026	0,960	1,022	0,981	0,984	0,010
Lithuania	0,970	0,980	0,971	0,999	0,987	0,981	0,005
Greece	0,936	1,026	0,998	0,913	1,010	0,976	0,004
Max	0,995	1,062	0,999	1,087	1,041	1,004	
Min	0,922	0,929	0,948	0,913	0,965	0,976	
SD	0,019	0,025	0,015	0,037	0,020		

The Malmquist Productivity Index (MPI) in Table 6 combines catch-up and frontier effects, offering a comprehensive measure of productivity change. The average MPI of the Czech Republic of 1.026 indicates 3% growth, driven by efficiency gains and stable technology. Romania's 0.988 signals slight decline, while Estonia, Latvia, Hungary, Croatia, and Bulgaria average above 1, showing notable improvements despite volatility compared to Germany's steadier trajectory.

The global development of MPI among EU countries is generally positive, increasing for many countries in this set. The greatest improvement from 2010 to 2023 occurred in Latvia and Sweden (average MPI above 1 and positive linear trend, represented by slope value). In contrast, some countries show declining productivity based on LPI components (negative slope), such as Austria, Finland, Ireland, and Slovenia.

Table 6. The Malmquist productivity scores of the LPI components for the period 2010 to 2023

MPI	2010=>2012	2012=>2014	2014=>2016	2016=>2018	2018=>2023	Average	Slope
Czech Republic	1,112	0,912	1,028	1,009	1,070	1,026	0,001
Estonia	1,027	0,923	1,086	0,937	1,115	1,018	0,019
Austria	1,063	1,040	0,982	0,952	1,042	1,016	-0,013
Latvia	0,994	0,977	0,998	0,951	1,151	1,014	0,029
Hungary	1,102	0,974	0,960	1,041	0,991	1,014	-0,015
Luxembourg	1,060	0,958	0,959	1,083	1,007	1,013	0,002
Croatia	1,056	0,985	1,019	1,002	1,004	1,013	-0,009
Cyprus	0,980	0,974	1,050	0,985	1,077	1,013	0,021
Sweden	1,009	0,946	1,013	0,918	1,164	1,010	0,028
Netherlands	0,950	1,049	0,954	1,027	1,031	1,002	0,014
Denmark	0,986	0,930	1,062	1,041	0,989	1,002	0,012
Poland	0,922	1,048	0,959	1,026	1,053	1,001	0,024
Bulgaria	0,913	1,069	1,114	0,815	1,096	1,001	0,011
Germany	0,986	0,989	1,008	1,002	1,021	1,001	0,008
Portugal	0,980	1,051	0,943	1,029	0,993	1,000	0,000
Malta	0,977	0,948	1,018	1,014	1,036	0,999	0,018
Ireland	0,996	1,097	0,890	1,032	0,962	0,996	-0,013
Slovak Republic	0,957	0,951	0,945	1,092	1,028	0,994	0,028
Italy	0,923	0,997	1,001	1,011	1,031	0,993	0,023
Lithuania	1,002	0,928	1,034	1,067	0,925	0,991	-0,002
Romania	0,953	0,984	0,876	1,128	1,000	0,988	0,024
Spain	0,885	1,043	0,964	0,962	1,084	0,988	0,031
France	0,903	0,990	1,026	1,026	0,970	0,983	0,017
Finland	0,940	0,977	1,041	1,042	0,886	0,977	-0,004
Greece	0,954	0,970	0,993	0,900	1,047	0,973	0,012
Belgium	0,872	1,022	0,949	1,015	1,003	0,972	0,026
Slovenia	0,933	1,135	0,916	0,935	0,927	0,969	-0,021
Max	1,112	1,135	1,114	1,128	1,164	1,026	
Min	0,872	0,912	0,876	0,815	0,886	0,969	
SD	0,062	0,056	0,056	0,066	0,065		

In general, the results highlight varied experiences in efficiency gains and technological adaptation. This analysis offers insights into how countries adapted to changes in logistics over time, enabling targeted policy recommendations to enhance future productivity. The average scores were low, but they gradually improved.

4.4 Cluster analysis of countries based on their LPI development from 2010 to 2023

The goal of this analysis is to find groups of countries that have experienced some common developments regarding their LPI growth, trend, and average value, as well as the MPI catch-up and frontier shift indices. This can help us to understand the different developments and identify the strengths and weaknesses of these countries.

First, the hierarchical Ward clustering method was applied, using the squared Euclidean distance. Clustering was performed using IBM SPSS 29, which allows the creation of multiple variants, generates individual outputs, and records results. The data for

the cluster analysis were imported into SPSS and standardised using the z-score method. Subsequently, a multicollinearity analysis was performed using SPSS. Variance Inflation Factor (VIF) was chosen as the measure of multicollinearity.

Table 7 shows that none of the variables exceeded the desired criterion. The highest VIF is 4.8, which meets the more stringent criterion of VIF < 5. Based on the results, it was not necessary to proceed with the removal of variables from the data set, and it is possible to proceed with the cluster analysis. A dendrogram was created using the hierarchical Ward method of clustering with a squared Euclidean distance, shown in Figure 1.

Table 7. Multicollinearity statistics with Variance Inflation Factor

	Dependent variable: LPI_Average		**Dependent variable: LPI_Growth**		**Dependent variable: *LPI_Trend***			**Dependent variable: MPI_Catchup**		**Dependent variable: MPI_Frontier**
	VIF		**VIF**		**VIF**			**VIF**		**VIF**
MPI_Catchup	1.020	MPI_Catchup	1,020	MPI_Catchup	1,020	MPI_Frontier		1,127	LPI_Average	1,183
MPI_Frontier	1.012	MPI_Frontier	1,130	MPI_Frontier	1,123	LPI_Average		1,052	LPI_Growth	4,595
LPI_Growth	4.458	LPI_Average	1,159	LPI_Average	1,130	LPI_Growth		4,545	LPI_Trend	4,764
LPI_Trend	4.461	LPI_Trend	1,054	LPI_Growth	1,027	LPI_Trend		4,674	MPI_Catchup	1,010

The division into clusters defines countries with similar characteristics of MPI and LPI values. There might be 3 to 5 clusters. The number of clusters was determined through iterative testing using the Ward method in hierarchical order and validated by clustering k-means. We evaluated solutions ranging from three to five clusters and selected three based on the cophenetic correlation coefficient (0.238) and the interpretability of the results. This combination of hierarchical and non-hierarchical methods ensures robustness and consistency in cluster formation.

Our results align with previous studies that applied cluster analysis using LPI metric (Ioan et al., 2010; Anuşlu and Firat, 2019; Loucanova, Olisakova and Palus, 2022; Ulkhaq, 2023).

Figure 1. Dendrogram for hierarchical clustering by Ward's method

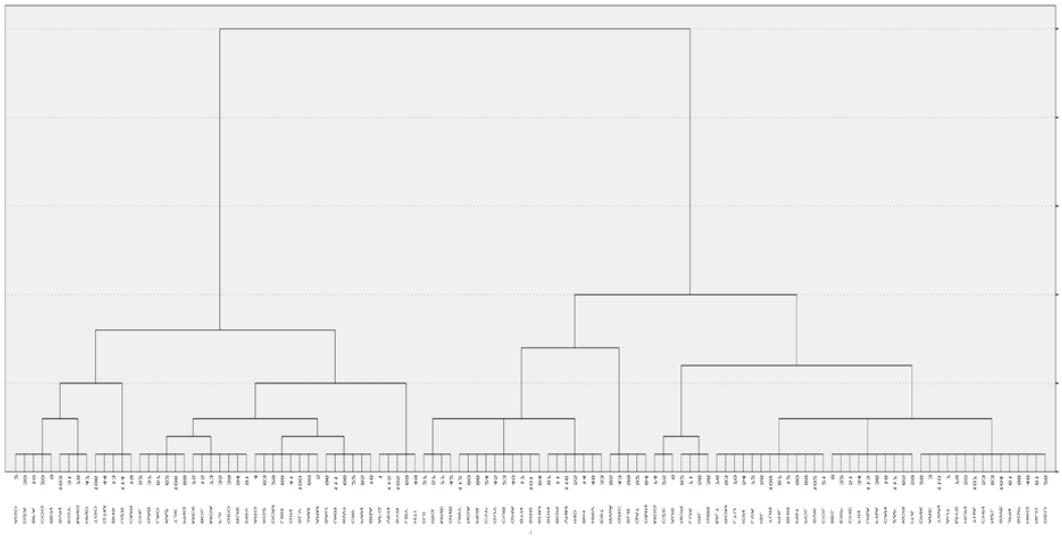


Table 8 lists individual countries with their cluster membership. MPI_Average represents the average Malmquist Productivity Index from 2010 to 2023.

Table 8. Cluster membership and individual characteristics of the investigated countries

Country	Code	MPI_Average	MPI_Catchup	MPI_Frontier	LPI_Average	LPI_Growth	LPI_Trend	Cluster
Ireland	IRL	0,996	1,000	0,993	3,698	0,984	-0,017	1
Luxembourg	LUX	1,013	1,024	0,988	3,866	0,980	-0,028	1
Austria	AUT	1,016	1,015	1,000	3,904	1,012	0,022	2
Belgium	BEL	0,972	0,987	0,983	4,019	1,003	0,004	2
Bulgaria	BGR	1,001	1,000	0,994	3,040	1,025	0,013	2
Cyprus	CYP	1,013	1,022	0,990	3,120	1,004	0,003	2
Czech Republic	CZE	1,026	1,023	1,001	3,466	0,988	0,002	2
Germany	DEU	1,001	1,006	0,996	4,133	0,999	0,004	2
Denmark	DNK	1,002	1,011	0,989	3,926	1,013	0,016	2
Spain	ESP	0,988	0,995	0,990	3,750	1,015	0,021	2
Estonia	EST	1,018	1,016	0,998	3,273	1,027	0,042	2
Finland	FIN	0,977	0,992	0,984	3,941	1,016	0,022	2
France	FRA	0,983	0,992	0,990	3,865	1,003	0,004	2
Croatia	HRV	1,013	1,010	1,003	3,092	1,036	0,030	2
Hungary	HUN	1,014	1,018	0,994	3,278	1,014	0,014	2
Italy	ITA	0,993	0,999	0,993	3,700	1,003	0,005	2
Lithuania	LTU	0,991	1,008	0,981	3,218	1,016	0,024	2
Latvia	LVA	1,014	1,027	0,985	3,178	1,015	0,021	2
Malta	MLT	0,999	1,014	0,985	3,045	1,032	0,019	2
Netherlands	NLD	1,002	1,005	0,996	4,074	1,002	0,003	2
Poland	POL	1,001	1,011	0,989	3,488	1,009	0,013	2
Portugal	PRT	1,000	1,011	0,988	3,475	1,004	0,003	2
Romania	ROM	0,988	1,001	0,984	3,068	1,024	0,021	2
Slovak Republic	SVK	0,994	1,002	0,991	3,198	1,004	0,006	2
Sweden	SWE	1,010	1,018	0,989	4,024	0,996	0,004	2
Greece	GRC	0,973	0,996	0,975	3,189	1,046	0,060	3
Slovenia	SVN	0,969	0,975	0,990	3,224	1,028	0,021	3

The MPI_Catchup measure shows whether a country moves closer to or further from the efficiency frontier, reflecting its ability to achieve best practice in logistics performance. MPI_Frontier captures technological changes, indicating shifts in the efficiency frontier; values above 1 signal progress, while those below 1 suggest regression relative to a frontier based on all countries' performance.

The following measures were used: MPI_Total: Overall score of the Malmquist Productivity Index; MPI_Catchup: Reflects productivity improvements relative to others; MPI_Frontier: Indicates changes in the frontier or best practice performance; LPI_Average: Average score of the Logistics Performance Index; LPI_Growth: Growth in logistics performance over time; LPI_Trend: Trend of changes in logistics performance.

LPI_Average covers 2010–2023; LPI_Growth is the geometric mean of LPI growth; LPI_Trend represents the linear trend slope. A deeper cluster analysis will follow, confronting the results of previous studies on clustering or MPI using LPI scores.

4.5 Characteristics of individual clusters identified based on the results of the cluster analysis

In this section, we will focus on individual clusters, and we will explain reasons behind the membership of individual countries. We also developed names or labels for each cluster to better characterise their common features.

The map in Figure 2 shows the global outlook of the membership of the cluster based on the characteristics mentioned above.

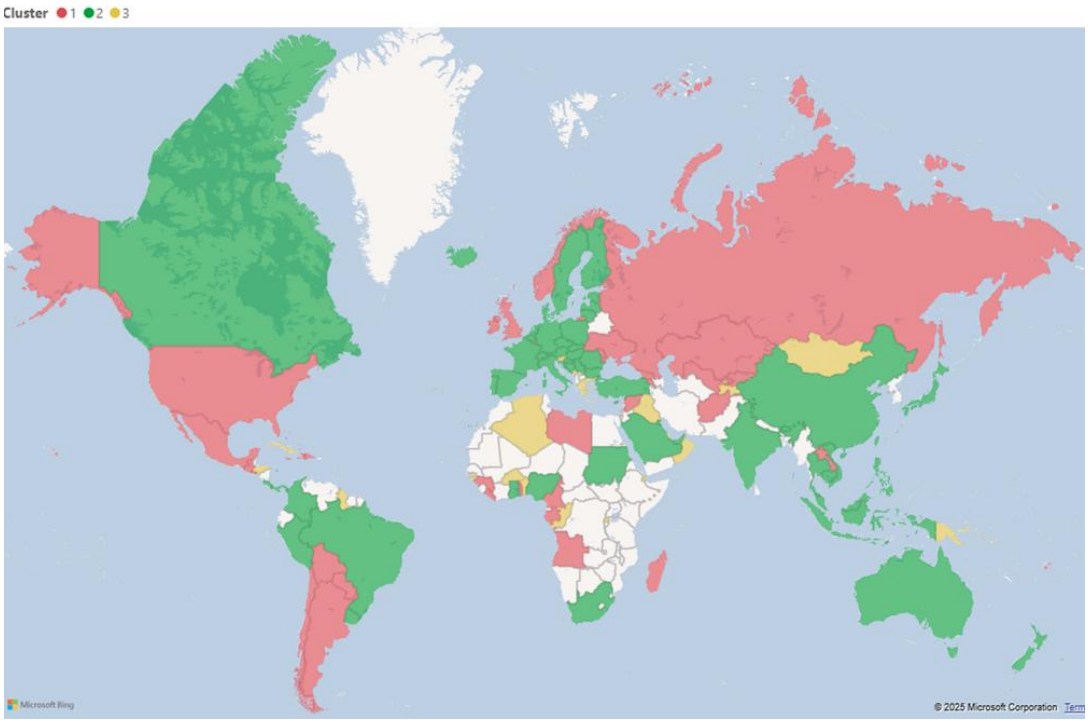
Cluster 1: "Struggling Performers"

The first cluster, "Struggling Performers," includes 37 countries: AFG, AGO, ARG, ARM, BHS, BOL, CMR, DOM, FJI, GAB, GBR, GEO, GIN, GTM, HTI, CHL, IRL, JAM, KAZ, KGZ, LAO, LBR, LBY, LUX, MDA, MDG, MEX, NOR, PRY, RUS, SLV, SYR, TGO, UKR, USA, UZB, and VEN. These countries struggle with logistics infrastructure and efficiency, showing limited improvements over time. They have slightly negative overall growth and trend, relatively low LPI, slow recovery (Catch-up index just over 1), and low innovation levels. Some, like USA, UK, Ireland, Norway, and Luxembourg, have relatively high LPI scores but steadily declining values.

Results show moderate logistics performance (LPI_Average ~2.706), indicating underperformance. Productivity decreases (MPI_Average ~0.988) with minimal catch-up (MPI_Catchup ~1.002) and slightly negative frontier shift (MPI_Frontier ~0.986). Negative logistics growth (LPI_Growth ~0.988) and downward trend (LPI_Trend ~-0.013) suggest efforts to improve but lagging behind global leaders. Cluster 1 countries typically exhibit lower productivity and deteriorating logistics performance over time.

Investigated countries include Angola, Luxembourg, and Ireland. This cluster generally comprises nations with lower logistics performance and declining productivity trends, despite stable logistics growth. These less developed or economically challenged countries face stagnant logistics systems and struggling productivity.

Figure 2. Cluster membership of countries



Cluster 2: "Improvers with Moderate Performance"

The second cluster includes highly developed countries—Belgium, Finland, France, Italy, Malta, Slovakia, Slovenia, and Spain—where Slovakia and Slovenia are “new members” (joined 1 May 2004). These fast-growing countries rapidly expand logistics capacity, though not yet productivity leaders. Often middle-income, they focus on improving logistics despite minor productivity issues. This cluster has 59 members: ARE, AUS, AUT, BEL, BGR, BHR, BIH, BRA, BTN, CAN, COL, CRI, CYP, CZE, DEU, DNK, ESP, EST, FIN, FRA, GHA, HKG, HRV, HUN, CHE, CHN, IDN, IND, ISL, ITA, JPN, KHM, KOR, KWT, LTU, LVA, MLT, MYS, NGA, NLD, NZL, PAN, PER, PHL, POL, PRT, ROM, SAU, SDN, SGP, SRB, SVK, SWE, THA, TUR, TWN, URY, VNM, ZAF. These countries improve logistics through investments and modernization, most achieving above-average LPI scores with steady gains.

Results show moderate logistics performance (LPI_Average ~3.35), indicating good but not superior capabilities. Productivity progress is slow (MPI_Average ~1.002) with steady catch-up (MPI_Catchup ~1.01) and slightly negative frontier shift (MPI_Frontier ~0.992). Positive logistics growth (LPI_Growth ~1.01) and upward trend (LPI_Trend ~0.011) suggest ongoing improvements. Cluster 2 countries typically have balanced but slightly lower productivity with noticeable logistics gains. Some below-average LPI scorers include Bhutan, Cambodia, Sudan, Nigeria, and Ghana.

Cluster 3: "Rapid Advancers"

The last cluster, “Rapid Advancers,” includes countries historically weaker in logistics infrastructure but showing the most significant improvements: BEN, BFA, COG, CUB, DJI, DZA, EGY, GNB, GRC, GUY, HND, IRQ, MNE, MNG, OMN, PNG, QAT, RWA, SLB, SVN, TJK. These nations exhibit moderate recovery and lower innovation, still achieving below-average LPI scores but recording the fastest improvement over the investigated period.

Analysis shows these countries have the lowest logistics performance (LPI_Average ~2.62), indicating less efficient systems than other clusters. They face productivity decline (MPI_Total ~0.984), minimal catch-up (MPI_Catchup ~1.005), and the largest negative frontier shift (MPI_Frontier ~0.979), signaling lag in best practices. Although underdeveloped, logistics growth remains stable (LPI_Growth ~1.025) with a positive trend (LPI_Trend ~0.024). Foreign investment, education, and training in logistics could further improve solutions. Cluster 3 generally includes countries with lower performance and declining productivity trends, despite maintaining stable logistics growth.

5. Discussions

Based on the empirical results, we can now address the three hypotheses formulated in Section 2.4:

- H1: Newer EU member states exhibit higher growth rates in LPI compared to older members.

This hypothesis was supported. The analysis of LPI growth and trend slopes indicates that newer EU members (post-2004 entrants) generally exhibit higher growth rates. Countries such as Croatia, Estonia, and Latvia show significant positive trends, while older members such as Luxembourg and Ireland show stagnation or decline. This suggests that newer members are actively catching up, likely due to targeted investments and EU cohesion policies.

- H2: Technological progress (MPI frontier shift) has a stronger influence on performance in newer EU countries.

This hypothesis was supported. The MPI frontier shift component was more pronounced in newer EU members such as the Czech Republic and Croatia, indicating that technological advances and modernisation efforts contribute significantly to their logistics performance. In contrast, older members showed limited frontier movement, suggesting a plateau in technological innovation or adoption.

- H3: Countries with higher catch-up effects started from lower logistics performance levels.

This hypothesis was supported. The catch-up index (MPI_Catchup) was higher in countries with initially lower LPI scores, such as Latvia and Bulgaria. This confirms that countries with lower baseline performance have more room for efficiency improvements and are actively closing the gap with the top performers. The negative association between catch-up and current performance further supports this hypothesis.

The findings of our study provide a deeper understanding of the development of logistics performance among EU member states in the period 2010–2023. By integrating parametric (trend analysis, average growth) and non-parametric approaches (Malmquist Productivity Index – MPI), we have gained a multidimensional view of how logistics systems have developed within the EU.

The results of the classification analysis confirmed the existence of three distinct groups: "Lagging performance," "Improving with moderate performance," and "Fast progressing." These clusters reflect not only the current state of logistics performance, but also the dynamics of change, whether driven by increased efficiency (catch-up effect) or technological progress (frontier shift). Similar clusters have been identified in previous studies, e.g., Anuşlu and Fırat (2019), Loucanova, Olsiakova, and Palus (2022), and Pehlivan et al. (2024), but without taking into account long-term developments.

The findings confirm that older EU member states, especially the so-called EU15, maintain higher average LPI values, which correspond to their more advanced logistics systems (Zaninović et al., 2020; Bugarčić et al., 2020). However, their growth is limited, which may be due to market saturation or less urgency for reform (Martí et al., 2014; Ojala & Çelebi, 2015). In contrast, newer member states that joined the EU after 2004 show higher growth rates and a more pronounced shift in the technological frontier, indicating active modernisation and adaptation to single market standards (Bayraktar et al., 2024; Hong & Kim, 2023).).

The correlation analysis further supports the hypothesis of regional convergence. Although older and newer member states show different performance patterns, the correlation within groups is stronger than between them. This suggests that regional factors, shared infrastructure, and policy harmonisation affect logistics performance in a similar way (Sergi et al., 2021; Górecka et al., 2022).

The impacts of the COVID-19 pandemic and a methodological change in the LPI 2023 edition have added another layer of complexity. Although some countries have seen a decline in performance, others—particularly those with more agile or digitised logistics systems—have maintained or even improved their scores (Janno et al., 2021; Hasan et al., 2025). This underscores the importance of the resilience and adaptability of logistics systems in times of global upheaval.

The MPI analysis showed that countries such as Latvia, Sweden, and the Czech Republic achieved significant productivity gains, thanks to both efficiency improvements and technological advances. In contrast, Ireland, Austria, and Finland show stagnation or regression, pointing to the need for a renewed focus on policy and investment (Amiri et al., 2024; Martí, Martín & Puertas, 2017).

Our study thus contributes to the literature not only with a methodological framework combining the LPI and MPI, but also with practical implications for policymakers. Identifying clusters enables for targeted benchmarking, sharing of best practices, and formulation of strategies tailored to the specific development trajectories of individual countries.

6. Conclusions

The Logistics Performance Index (LPI) is a measure developed by the World Bank to evaluate countries' logistics and trade facilitation performance. It provides an overview of the logistical competitiveness of countries based on six key dimensions: customs performance, infrastructure quality, international shipments, logistics quality and competence, tracking and tracing, and timeliness. The LPI reflects the efficiency of the supply chain, affecting a country's economic development and international trade competitiveness. High LPI scores indicate robust logistics systems that handle trade flows efficiently, reducing costs and enhancing reliability for businesses. Lower scores highlight areas for improvement, helping policy makers improve logistics capabilities.

Using hierarchical Ward clustering and k-means methods, three clusters were identified: "Struggling Performers," "Improvers with Moderate Performance," and "Rapid Advancers." These clusters highlight the diversity in logistics performance between countries. "Struggling Performers" show limited growth and efficiency in logistics. " Improvers with Moderate Performance" advance through investments and modernization. "Rapid Advancers" demonstrate significant improvements over time despite weaker initial logistics infrastructure. Clustering based on LPI development monitors changes and helps to understand these developments to pinpoint strengths and improvement opportunities in global logistics. Policymakers can tailor strategies to improve logistics performance, fostering economic growth and global trade connectivity. The paper confirms that older EU members have mostly stable logistics but are less influenced by recent growth. Their continuous relationship with newer countries has helped them achieve higher growth with positive long-term trends. It also shows that sustained improvement over time is a key driver of better logistics performance. Also, it was found that countries still in the catch-up phase tend to have lower current performance.

Further research on LPI could explore additional metrics, technological advancements, or case studies of countries with significant improvements or decreases in LPI scores. The forthcoming LPI report from 2025 might show whether the trends uncovered by the analysis are sustainable.

Limitations of our study are stemming from the fact that it relies on LPI data, which combines survey-based and big-data metrics, introducing potential inconsistencies across editions (for example, introducing subjective biases). The LPI focuses primarily on logistics performance, potentially overlooking factors like political stability, governance quality, and economic conditions. The LPI does not account for rapid changes and disruptions in global trade and logistics. Monitoring the LPI using a time series remains essential despite these limitations. The index identifies countries' logistical assumptions and tendencies, ensuring quality international trade relations. Methodological changes between 2018 and 2023 may affect comparability. Additionally, the analysis focusses on EU countries that limit generalisability to other regions. Future research should incorporate broader datasets and explore additional factors such as governance quality and geopolitical risks.

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