JEL Classification: C32; E32; F44 **DOI**: https://doi.org/10.31521/modecon.V39(2023)-06

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Ukraine within the system of European business cycles: a cluster analysis

Abstract. Introduction*. Categorizing data into related clusters is used in many areas of research, including economics and business statistics. Cluster analysis allows quality data segmentation and visualisation of relatedness between different observations, which is particularly useful when there is a large number of heterogeneous observations. In economic literature, many issues of relevance have been effectively addressed by employing cluster analysis. At the same time, many studies have highlighted important deficiencies, such as some level of subjectivity in choosing the most appropriate methods of cluster analysis and a lack of comprehensive commercially available software that implements new methods, which, in turn, necessitates custom programming and makes it difficult to access and replicate the results obtained by other researchers.*

Purpose. *The purpose of this study was to investigate the position of Ukraine among the clusters of European business cycles by extracting the cyclical component of the real GDP series of Ukraine and then comparing it to similarly extracted and analyzed data for 34 other European countries using both hierarchical and non-hierarchical clustering algorithms as implemented in the OriginPro software.*

Results. *Changes in detrended GDP values of 35 European countries over the period of time from the 2nd quarter of 2006 to the 4th quarter of 2021 (2006Q2-2021Q4) fall into 4 clusters for variables and 5 clusters for observations (countries). Similarities in the common components of detrended GDP series found using Origin Cluster Analysis were such that the nearest neighbors of Ukraine were Lithuania, Finland and Estonia, with the same order of similarity. Lithuania and Finland clustering with Ukraine was also confirmed by K-means cluster analysis. Hierarchical cluster analysis of country-specific components of the detrended GDP series of 35 European countries followed by K-means cluster analysis showed that for most European countries, the time series of their ln(GDP) values fall into two major clusters, which, with few exceptions, represented Western and Eastern European countries.*

Conclusions. *It was shown that the common component of detrended GDP series of Ukraine clearly clustered with those of two Baltic and one Scandinavian EU member state – Lithuania, Finland and Estonia – in the order indicated. The country-specific component of the detrended GDP series of Ukraine, both qualitatively as revealed by our hierarchical cluster analysis, and quantitatively as revealed by K-means cluster analysis, clustered with the majority of countries comprising Eastern Europe during the entire period of time under investigation. We conclude that these observations are of both theoretical and practical significance in the framework of the Ukraine-EU integration policy.*

Keywords: *business cycles; cluster analysis; hierarchical clustering; K-means clustering; external compound shocks; global risks; European integration.*

УДК 339.9

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Місце України серед європейських ділових циклів: кластерний аналіз

Класифікація даних у кластери використовується в багатьох галузях досліджень, зокрема в економіці та бізнесовій статистиці. Кластерний аналіз дозволяє якісно сегментувати дані та візуалізувати зв'язок між різними спостереженнями, що особливо корисно, коли існує велика кількість різнорідних спостережень. В економічній літературі за допомогою кластерного аналізу ефективно вирішувалися значна кількість важливих проблем. Водночас багато досліджень підкреслюють важливі недоліки цього методу аналізу, такі як певний рівень суб'єктивності у виборі найбільш адекватних методів кластерного аналізу й відсутність комплексного комерційно доступного програмного забезпечення, яке реалізує нові методи, що, своєю чергою, вимагає спеціального програмування, а це ускладнює доступ і можливість відтворення результатів отриманих іншими дослідниками.

Таким чином, мета цього дослідження полягала в аналізі кластеризації ділового циклу України шляхом виділення циклічного компонента часового ряду реального ВВП України та порівняння його з подібним чином

[1]**Стаття надійшла до редакції**: 06.04.2023
Received: 06 April 2023

отриманими та проаналізованими даними для 34 інших європейських країн з використанням як ієрархічної, так і неієрархічної кластеризації даних, алгоритми яких реалізовані у програмному пакеті OriginPro.

Флуктуації значень циклічного компонента ВВП для різних європейських країн за період часу з 2-го кварталу 2006 року до 4-го кварталу 2021 року включно (2006Q2-2021Q4) поділяються на 4 кластери для змінних і 5 кластерів для спостережень (країни). Подібності у спільних компонентах циклічного ВВП, що виявились з використанням кластерного аналізу в Origin, вказують на те, що найближчими сусідами України у зазначеному порядку є Литва, Фінляндія та Естонія. Кластеризація України з Литвою та Фінляндією була також підтверджена кластеризацією К-середніх.

Аналіз специфічних компонентів циклічного ВВП кожної країни за допомогою ієрархічного кластерного аналізу з подальшою кількісною оцінкою результатів методом кластеризації К-середніх показав, що для більшості європейських країн часові ряди циклічного ВВП поділяються на два основні кластери, які, за кількома винятками, представляють країни Західної та Східної Європи.

Таким чином, було показано, що часовий ряд спільного компоненту циклічного ВВП України чітко утворює кластер з даними для двох балтійських і однієї скандинавської країни ЄС, які були розташовані у тому самому порядку їх подібності до України – це Литва, Фінляндія й Естонія. Специфічний компонент циклічного ВВП України, як якісно, як було виявлено ієрархічною кластеризацією, так і кількісно, як було виявлено методом К-середніх, протягом усього аналізованого періоду часу кластеризувалися з більшістю країн Східної Європи. Отримані результати мають як теоретичне, так і практичне значення в рамках політики інтеграції Україна-ЄС.

Ключові слова: *ділові цикли; кластерний аналіз; ієрархічна кластеризація; метод кластеризації К-середніх; зовнішні комплексні шоки; глобальні ризики; Євроінтеграція.*

JEL Classification: *C32; E32; F44*

Formulation of the problem. Categorising data into related clusters is used in many areas of research, including economics and business statistics. The classical example is World Bank country classification for analytical purposes by income level, whereby the world's economies are assigned to one of the four income groups, namely low, lower-middle, upper-middle, and high income countries, as based on the gross national income (GNI) per capita [1]. This classification is based on the World Bank Atlas method for data smoothing by applying a three year moving average and price-adjusted conversion factor, which allows the cross-country comparison of GNI [2]. In general, clustering is about rational and scientifically justified grouping of diverse data/characteristics (which are often large in volume) into several most closely related categories. This analytical procedure is based on sophisticated statistical algorithms, which necessitates the use of specialised software packages, and it can address various questions, reveal patterns, make forecasts and help policymakers with informed decision making.

Using appropriate data analysis tools is essential for quality data segmentation, in particular when there is a large number of observations. Clustering can be performed according to two main approaches. In hierarchical clustering, each data point initially represents a separate cluster, which is then merged iteratively with other data points based on certain parameters of their relatedness, thus producing a tree-like structure called a dendrogram. In other words, the initially formed lower-level groups are joined to form higher-level groups during the subsequent steps of data analysis. The dendrogram thus obtained reveals the relation between different objects within each cluster, as well as the overall hierarchy at different levels. This is a highly useful tool in exploratory data analysis, which identifies grouping of the data, their patterns and, if these exist, any outliers in the dataset.

Non-hierarchical cluster analysis, in contrast, requires some initial data partitioning; these elements can subsequently be moved between groups, while the algorithm aims to define such clustering of elements that certain parameters are maximized or minimized. One such widely used method is K-means clustering. Its initialization requires a user defined number of clusters (K); the algorithm execution then iteratively maximizes their separation while, at the same time minimizing the distances of within-cluster objects from the cluster mean (centroid) [3].

In economic literature, as outlined below, many different problems have been effectively addressed by employing cluster analysis. However, given the growing complexity of clustering algorithms and a lack of pre-programmed solutions for their implementation, which necessitates writing custom computer code, large scale data clustering remains challenging. Here we took advantage of Multivariate Analysis tools available in the OriginPro software (OriginLab Corporation, Northampton, MA, USA), including Hierarchical Cluster Analysis and K-Means Cluster Analysis, complimented with the available custom Apps, such as Optimal Cluster Number, with the aim of revealing the patterns of business cycle co-movement in Europe over 15 years (2006-2021). Particular attention was paid to the co-movement of the business cycle of Ukraine vis-à-vis the EU, which is of both theoretical and practical importance within the context of Ukraine's European integration policy.

Analysis of recent research and publications. Application of cluster analysis in economics studies spans more than 50 years of research. Some of the initial studies addressed the clusterization of global markets for use in international marketing (Sethi, 1971) [4], international comparisons of macroeconomic structures (Szilágyi, 1991) [5], and the perceptions of the economic environment by entrepreneurs using both hierarchical and non-hierarchical clustering algorithms (Barr, Waters & Fairbairn, 1980) [6]. Cluster analysis was shown to be useful for revealing linkages between economic sectors, which are important for economic growth, for analysing both the connectivity between sectors in different countries and the development of clusters in time (Hoen, 2002) [7]. The versatility of this analytical approach can be illustrated by studies that addressed very diverse problems, ranging from the role of corruption in different countries with implications for global companies (Grein, Sethi & Tatum, 2010) [8] to the identification of important factors that determine socio-economic status (Balasankar, Penumatsa & Vital, 2021) [9], for example comparative analysis of socio-economic development of different municipalities in Latvia was done this way (Brauksa, 2013) [10]. Zhang and Gao (2015) used cluster and taxonomy analysis to examine growth patterns in emerging market economies to better understand their convergence during the past five decades, including growth dynamics before and after the 2008 global financial crisis [11]. Scutariu et al. (2022), with the help of cluster analysis, addressed changes in behavioral patterns of enterprises with e-commerce activity in 31 European countries in response to the COVID-19 pandemic [12].

Cluster analysis is not only of theoretical interest, but also of important practical value; e.g., it has implications in determining which countries can receive concessional loans from the IMF Fund for PRGT (Poverty Reduction and Growth Trust), the recent example being IMF Concessional Financing Support for Low-income Countries during the COVID-19 pandemic [13].

There are different approaches for cluster identification. Their applicability to economic data has been addressed by Řezanková (2014), who argues that "probably the most applied method in economy is agglomerative hierarchical cluster analysis", while noting that commercial software implements new methods rather slowly and hence "the analysts need to use several software products to perform modern analyses" [14]. Indeed, new algorithms are being constantly proposed. For instance, a two-layer Distributed Clustering Algorithm based on K-means clustering and affinity propagation clustering algorithms have recently been used to develop strategy for new energy consumption in power systems [15]. Such deficiency can be offset by custom programming, e.g. in the recent study by Wang and Lu (2021), the authors resorted to programming in R for their analysis of panel data clustering in economic and social research [16].

We therefore reasoned that cluster analysis tools implemented in the category Statistics>Multivariate Analysis>Hierarchical Cluster Analysis & K-Means Cluster Analysis in the OriginPro software can be explored for our analysis of 35 European economies over a long (2006-2021) and structurally heterogeneous period that included two major external compound shocks — the global financial crisis of 2008-2009 and the COVID-19 pandemic.

Formulation of research goals. The purpose of this study was to investigate the position of Ukraine among the clusters of European business cycles by extracting the cyclical component of the real GDP series of Ukraine and then comparing it to similarly extracted and analyzed data for other 34 European countries.

Outline of the main research material. The data used in this study were the real GDP series of Ukraine and 34 other European countries, sourced from the World Bank's Global Economic Monitor database [17]. Before further analysis, a natural logarithmic transformation was applied to the level series, which were then detrended using the machine-learning-boosted Hodrick-Prescott filter of Phillips and Shi (2021) [18]. The series thus transformed are conventionally considered to be representative of business cycles and are hereinafter denoted as ln(GDP). Since the Great Recession and the COVID-19 pandemic period may have an outsized impact on the output of clustering algorithms, the detrended ln(GDP) series were decomposed using a Bayesian dynamic factor model as follows:

$$ln(GDP)_{i,t} = B_{i,t}F_t + e_{i,t}, \quad (1)$$

where the product of the factor loadings $B_{i,t}$ and the factor F_t are the common components that capture that part of ln(GDP) which may be explained by common shocks, e.g. the Great Recession and the COVID-19 pandemic, and $e_{i,t}$ are the residual country-specific components. The final series are quarterly and cover the period of 2006Q2-2021Q4.

For data cluster analysis we used the latest licensed OriginPro 2023 (version 10.0.0.154) software. The clustering algorithms were first applied to the common components of ln(GDP) and then the country-specific components. Several algorithms for hierarchical cluster analysis are implemented in Origin, as described in detail on the OriginLab website [19]. Methods for calculating distance for clustering are different for clustering observations (in our case countries) and clustering variables (in our case ln(GDP) values). For observations, these include Euclidean, Squared Euclidean, Absolute (City block metrics), Cosine, Pearson correlation and Jaccard metrics. For variables, these are Correlation and Absolute correlation metrics. For merging the nearest clusters one can also use several different methods, including Single link or Nearest neighbor, Complete link or Furthest neighbor, Group average, Centroid, Median and Minimum variance or Ward. In our analysis, we used the latter cluster method (Ward), while distance type was absolute (City block) with clustroid identification by the sum of distances. The Ward method tends to produce clusters of smaller size, i.e., it is somewhat more discriminative as it calculates the squared Euclidean distance to the cluster means; these distances are then summed for all cases and the cluster that is selected for merging is the one which will minimally increase this sum. The City block and Euclidean distances are special cases of the Minkowski metric. As a distance measure, it refers to the sum of distances along each dimension [20]. It is the preferred measure when the data are standardized.

Fig. 1A illustrates changes in the values of the common components of ln(GDP) for different European countries over the period of time from the 2nd quarter of 2006 to the 4th quarter of 2021 (2006Q2-2021Q4). Their variability was minimal for Norway and maximal for the UK (with SD values of 0.009 and 0.031, respectively).

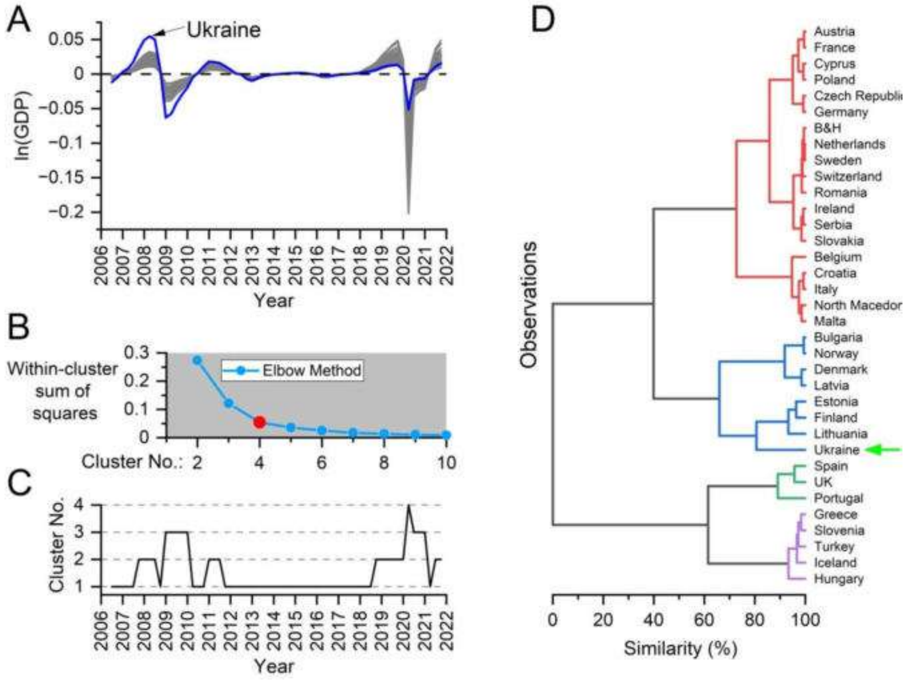

Figure 1 – **Cluster analysis of common components of detrended real GDP time series of 35 European Countries**

Source: compiled by the authors

There is no general method for determining the number of clusters, which is thus an arbitrary value. For this purpose, we used OriginLab App «Optimal Cluster Number» [21]. Its application, by the Elbow Method, suggested 4 clusters for the common components of ln(GDP) (Fig. 1B). Clustering of variables is shown in Fig.1C, revealing a dominant number of 2-4 clusters during financial crisis of 2008-2009 and the COVID-19 pandemic. According to the clustering of countries (observations) shown in Fig 1D, Ukraine forms a cluster with 7 other predominantly Northern European countries: Lithuania, Finland, Estonia, Latvia, Denmark, Norway and Bulgaria as based on their similarity measure.

Having established the appropriate methodology, we moved on to perform cluster analysis of country-specific components of ln(GDP). The time series of the country-specific components of ln(GDP) values for different countries over the same period of time are superimposed in Fig. 2A.

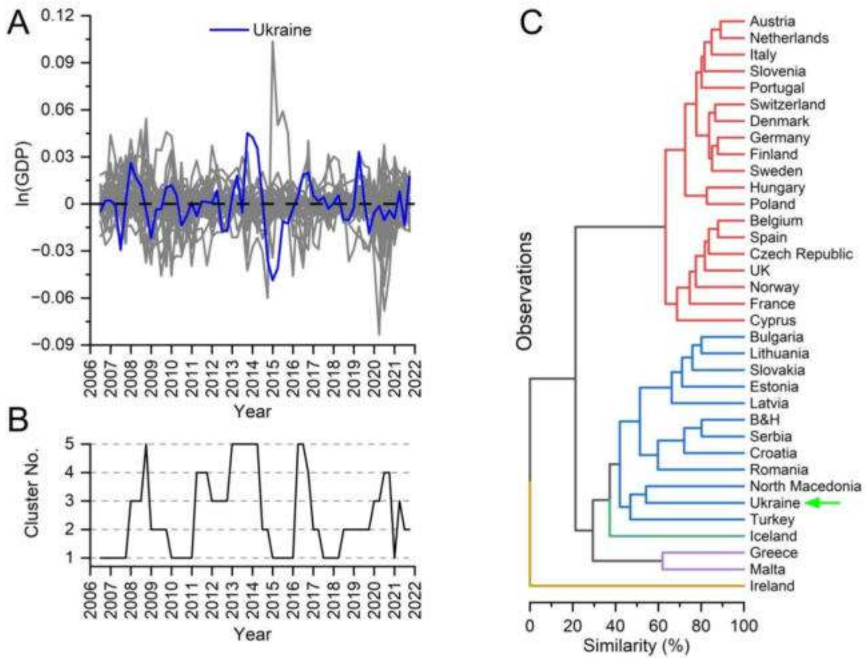

Figure 2 – **Cluster analysis of country-specific components of the detrended real GDP time series of 35 European countries**

Source: compiled by the authors

As illustrated in Fig. 2B, these variables can be categorized to form 5 clusters. Interestingly, when compared to common components in Fig. 1C, substantial country-specific variability is presented in the periods between the shocks, i.e. during 2011-2019. Regarding the observations (countries), the optimal cluster number as established by the Elbow Method was estimated to be 5. According to Hierarchical Cluster Analysis in Origin, Ukraine forms a cluster with 11 other predominantly Eastern European countries (Fig. 2C), with North Macedonia being its nearest neighbor. This suggests that while the business cycle of Ukraine behaves similarly to the group of Baltic and Scandinavian countries in times of global crises, its profile is more similar to those of Eastern European countries in normal times (summarized in Table 1).

Table 1 **Similarity in common and country-specific components of the real ln(GDP) of Ukraine *vis-à-vis* other European countries (top 7 countries are listed in the order from higher to lower similarity)**

Common components	Country-specific components
Lithuania	North Macedonia
Finland	Turkey
Estonia	Romania
Latvia	Croatia
Denmark	Serbia
Norway	Bosnia and Herzegovina
Bulgaria	Latvia

Source: compiled by the authors

Another approach to classify observations and quantify distances between the various elements is by using K-means cluster analysis, which is also implemented in the OriginPro Software [20]. This approach requires that the centroid of the observations, or as a minimum, the number of clusters, should be predefined. Thus, after performing the above described hierarchical cluster analysis, the data representing Cluster Centers were used as the Initial Cluster Centers in our K-means cluster analysis. The results are summarized in Tables 2, 3 and 4.

Table 2 **Summary of K-means cluster analysis**

Cluster No.	Number of countries	Within cluster sum of square	Average distance	Maximum distance
Common components of detrended real ln(GDP) series				
1	19	0,0053	0,01364	0,03421
2	3	0,00273	0,02791	0,04144
3	3	0,00173	0,0214	0,03007
4	10	0,00278	0,01549	0,03062
Country-specific components of detrended real ln(GDP) series				
1	21	0,08232	0,05715	0,12288
2	10	0	0,08048	0,12456
3	1	0	0	0
4	2	0,0081	0,06363	0,06363
5	1	0	0	0

Source: compiled by the authors

Table 3 **Distance between final cluster centers for common components of detrended real ln(GDP) series**

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Cluster 1	0	0,06057	0,1156	0,04834
Cluster 2	0,06057	0	0,15244	0,08116
Cluster 3	0,1156	0,15244	0	0,07254
Cluster 4	0,04834	0,08116	0,07254	0

Source: compiled by the authors

Table 4 **Distance between final cluster centers for country-specific components of detrended real ln(GDP) series**

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster 1	0	0,05504	0,16287	0,12168	0,21904
Cluster 2	0,05504	0	0,15606	0,12803	0,23593
Cluster 3	0,16287	0,15606	0	0,20171	0,30801
Cluster 4	0,12168	0,12803	0,20171	0	0,26436
Cluster 5	0,21904	0,23593	0,30801	0,26436	0

Source: compiled by the authors

For data visualization, X and Y ranges were longitudes and latitudes of capitals of the countries, respectively, while Google Map Import App for Origin was used to overlay a Google map (Fig. 3).

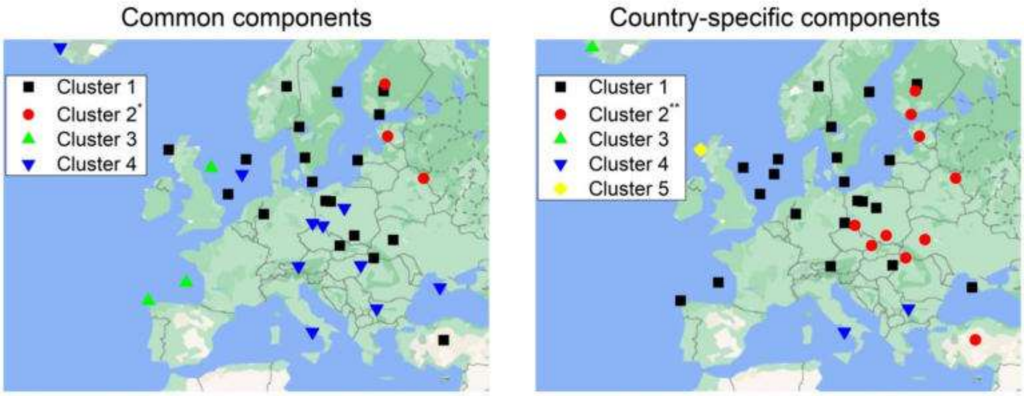

Figure 3 – **Visualisation of the K-means cluster analysis of common and country-specific components of real ln(GDP)**

Source: compiled by the authors

This visually highlights that in the case of country-specific components of ln(GDP), most European countries fall into two major clusters, which, with few exceptions, represent Western and Eastern European countries, Clusters 1 and 2, respectively (Fig. 3, right panel). Notably, Greece and Malta form a more distant Cluster 4, while Clusters 3 and 5 include only one country each, Iceland and Ireland, respectively. In the case of Ireland, this is to be expected in view of its unusually vigorous real GDP growth in 2014-2016. On a similar note, Iceland experienced an analogously atypical period of economic growth in 2015-2018. In the case of common components of ln(GDP), the split appears to instead occur along with north-south axis, which could be reflective of the European sovereign debt crisis that occurred in the first half of the 2010s and which primarily affected southern EU member states.

Conclusions. In this study, cluster analysis was used to characterize the relations between 35 European countries in terms of changes in their detrended real GDP series during 2006-2021. Cluster analysis is sensitive to the method chosen; this is why we complemented the Hierarchical Cluster Analysis with K-Means Cluster Analysis in the OriginPro software The results of the two different algorithms were found to be rather consistent, although as it was already noted by Xu and Tian “each clustering algorithm has its own strengths and weaknesses, due to the complexity of information” [22]; hence some discrepancies are not surprising.

The common component of real GDP series of Ukraine clearly clustered with those of northern EU member states – Lithuania, Finland, Estonia — in the order indicated (Table 1 and Fig. 3, left panel). Regarding country-specific components, both qualitatively as revealed by Hierarchical Cluster Analysis (Fig. 2C), and quantitatively as revealed by K-Means Cluster Analysis (Table 1, Fig. 3, right panel), the country-specific component of the real GDP series of Ukraine clustered with the majority of countries comprising Eastern Europe.

Since our main focus was on comparative analysis of Ukraine with other European countries in view of the Ukraine-EU integration policy, of particular practical significance were the results showing that Ukraine generally clustered with Eastern European countries during the entire analyzed period of 2006Q2-2021Q4. Nevertheless, during the periods of external compound shocks that were caused by the 2008 global financial crisis and the COVID-19 pandemic and are embodied in the common component of the real GDP series, the business cycle of Ukraine clustered more closely with select “core” EU (e.g. Denmark and Finland) (Table 1).

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