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CLUSTER ANALYSIS APPLICATION IN THE EVALUATION OF THE FOREIGN ECONOMIC POTENTIAL OF UKRAINE`S REGIONS

To analyze the market situation and to determine the demand for services provided by freight customs complexes in the regions of Ukraine, it is proposed the application of statistical data analysis methods for a comprehensive regional foreign economic potential assessment. The observation objects were twenty-four regions of Ukraine and the city of Kyiv in the period from 2015 to 2018. A number of indicators reflecting the level of their development were used as regional foreign economic potential assessment factors. As a research tool, such statistical analysis methods as hierarchical cluster analysis techniques and the k-means method in Statistica, the suite of analytics software products, are used. Following the classification results, the regions of Ukraine are divided into five homogeneous clusters based on which it is possible to develop a system of differentiated measures for each cluster of regions with the high, average, and low levels of foreign economic activity development.

Keywords: foreign economic potential of regions; cluster analysis; statistics; export; import.

С целью анализа существующей ситуации на рынке и оценки спроса на услуги грузовых таможенных комплексов по регионам Украины предложено применение методов статистического анализа данных для комплексной

оценки внешнеэкономического потенциала регионов. Объектами наблюдения являлись двадцать четыре области Украины и город Киев в период с 2015 по 2018 год. Для оценки внешнеэкономического потенциала регионов использовались показатели, отражающие уровень их развития. В качестве инструмента исследования применяются такие методы статистического анализа данных как иерархические методы кластерного анализа и метод k-средних в пакете статистического анализа данных Statistica. В результате классификации области Украины распределены по пяти однородным кластерам, что позволит на этой основе разработать систему дифференцированных мероприятий применительно к каждому кластеру регионов: с высоким, средним, низким уровнями развития внешнеэкономической деятельности.

Ключевые слова: внешнеэкономический потенциал регионов; кластерный анализ; статистика; экспорт; импорт.

Доцільність функціонування вантажних митних комплексів в Україні в цілому, а також в окремо взятому регіоні залежить від попиту на митні та логістичні послуги у суб'єктів зовнішньоекономічної діяльності. З метою визначення попиту на послуги вантажних митних комплексів по регіонам України запропоновано застосування методів статистичного аналізу даних для комплексної оцінки зовнішньоекономічного потенціалу регіонів.

Об'єктами спостереження були двадцять чотири області України та місто Київ в період з 2015 по 2018 роки. Як фактори оцінки зовнішньоекономічного потенціалу регіонів використовувалися показники, що відображають рівень їх розвитку: регіональні обсяги зовнішньої торгівлі товарами;експорт і імпорт товарів суб'єктами господарювання за кількістю найманих працівників у розрізі регіонів, кількість активних підприємств за регіонами України та видами економічної діяльності, транспорт, складське господарство, поштова та кур'єрська діяльність;валовий регіональний продукт; кількість суб'єктів господарювання; кількість зайнятих працівників на суб'єктах господарювання; регіональна структура обороту роздрібної торгівлі; капітальні інвестиції за регіонами;регіональна структура роздрібного товарообороту підприємств роздрібної торгівлі; обсяг реалізованої промислової продукції.

Поряд зі стандартизацією вихідних даних, кожному фактору присвоєно певний коефіцієнт важливості, який відображає значимість відповідного показника. Застосовується двоетапна методологія кластерного аналізу: попередня ідентифікація кластерів регіонів України за допомогою ієрархічних алгоритмів (побудови дендрограм) з наступним уточненням класте-

рів за допомогою ітераційної процедури розбиття методом k- середніх в пакеті статистичного аналізу даних Statistica.

В результаті класифікації області України розподілені по п'яти однорідним кластерам, що дозволить на цій основі розробити систему диференційованих заходів стосовно кожного кластеру регіонів: з високим, середнім, низьким рівнями розвитку зовнішньоекономічної діяльності. Застосування дисперсійного аналізу дозволило виділити чинники, котрі суттєво впливають на класифікацію областей по групам, і фактори, вплив яких є незначним.

Ключові слова: *зовнішньоекономічний потенціал регіонів; кластерний аналіз; статистика; експорт; імпорт.*

Problem statement. The important components of management strategy development for freight customs complexes in different regions of Ukraine are the development of their foreign economic potential assessment system, forecasting the volume of export and import freight flows as well as the infrastructure and production capacity level [1, 2].

The rationale for the construction of new freight customs complexes and the improvement of technical, technological, and organizational support in a particular region depend on the demand for their services and prospects for further production and economic development. This determines the relevance of a comprehensive assessment of Ukraine`s foreign economic potential.

Analysis of recent research and publications. At present, there is no clear mechanism for the foreign economic sector comprehensive assessment. However, attempts have been made to develop a methodology for assessing regional foreign economic potential. Such authors as N. E. Kudratov, N.I., Askarov, and B.A. Isakhov [3] proposed a system of indicators for a comparative evaluation of the foreign economic situation in regions.

The theory of cluster economic management is becoming highly relevant. The concept of the cluster is a promising tool for analyzing and assessing the regional economic potential. In the clustering method, regional foreign economic complex management concentrates on the general regulation of economic processes taking place in the region [1].

B.N. Zhyhzhytova [4] has developed methodological approaches to managing regional economy innovative development based on the cluster approach.

The cluster approach and classification methods are also used in the various fields of economy, management, and engineering [5 – 7].

In the paper [5] by applying the Fuzzy-ANP-Weighted-Distance-QC (FAWQC) method to weighted random data, the effectiveness of the method is verified. The method is applied to the 2015 Economics-Energy-Environment (3E) data for 19 provinces in China for a comparative study of the classification of the system structure and evaluation of the low-carbon economy development level.

The paper [6] highlights the relevance of both quantitative and qualitative features of applicants and proposes a new methodology based on mixed data clustering techniques. The cluster analysis may prove particularly useful in the estimation of credit risk. Credit applicants are characterized by mixed personal features, a cluster analysis specific for mixed data can lead to discovering particularly informative patterns, estimating the risk associated with credit granting.

Considering relations among dimensionality reduction, noise trading, and market situations, the paper [7] empirically investigates the effect of dimensionality-reduction methods – principal component analysis, stacked autoencoder, and stacked restricted Boltzmann machine – on stock selection with cluster analysis in different market situations.

Thus, due to the diversity and widespread use of classification methods, it is reasonable to apply the cluster analysis in the evaluation of the foreign economic potential of Ukraine`s regions when assessing the demand for services provided by freight customs complexes.

Aim. The article aims to comprehensively assess the foreign economic potential of Ukraine`s regions as well as to determine the optimal set of statistical methods and the sequence of their application to the initial data, which would give the best result in terms of their subsequent substantial interpretation.

Statement of basic materials. Preparation of initial data. For the comparative assessment of the foreign economic situation in the regions, fifteen factors are singled out, reflecting their development level (Table 1) [1].

The observation objects are twenty-four regions of Ukraine and the city of Kyiv in the period from 2015 to 2018.

The analyzed data is obtained based on a harmonized system of statistical indicators [8]. Despite the fact that it is consistent at the methodological level, it cannot be used without prior preparation. The main problem with the use of the factors is their presentation in different units of measurement, which may not

match. For example, data can be presented in units or thousands of units, in US dollars or the national currency, etc.

Table 1.

Factors reflecting regional economic development

Factor identifier	Factors	Units of measurement
F1	Regional volumes of foreign goods trade, exports	thousand dollars.
F2	Regional volumes of foreign goods trade, imports	thousand dollars
F3	Export of goods according to the number of employees broken down by regions	the number of foreign economic activity participants
F4	Import of goods by economic entities according to the number of employees broken down by regions	the number of foreign economic activity participants
F5	Export of goods according to the number of employees broken down by regions	million US dollars
F6	Import of goods by economic entities according to the number of employees broken down by regions	million US dollars
F7	The number of operational enterprises in the regions of Ukraine and economic activity types, transport, warehousing, postal and courier activities	total units
F8	Gross regional product	million UA hryvnias
F9	The number of economic entities by regions	total units
F10	The number of employees working for economic entities by regions	thousand people
F11	Regional retail turnover structure	million UA hryvnias
F12	Capital investment by regions	million UA hryvnias
F13	Retail trade enterprises` regional retail turnover structure	million UA hryvnias
F14	Sold production of industry by regions	million UA hryvnias
F15	Volume of products sold (work and services) by regions	million UA hryvnias

Therefore, it is necessary to bring them to a uniform format.

Thus, the normalization (or standardization) of the initial data is done by the subtraction of the mean deviation and the division by the standard one. The indicators obtained as a result of standardization have zero mean and unit variance.

Along with the standardization, each factor is assigned a certain importance or weight coefficient indicating the significance of a corresponding indicator.

The weight vector for fifteen factors has the following form:

W = (1,55; 1,55; 1,5; 1,5; 1,45; 1,45; 1,4; 1,35; 1,3; 1,25; 1,2; 1,15; 1,1; 1,05; 1,0).

The product of normalized indices by the corresponding weights allowed identifying the distances between the points in multidimensional space, taking into account the different weights of the factors (Figure 1).

	1 F1	2 F2	3 F3	4 F4	5 F5	6 F6	7 F7	8 F8	9 F9	10 F10	11 F11	12 F12	13 F13	14 F14	15 F15
Vinnytsia region	-0,377712	-0,553864	-0,20356	-0,35362	-0,353347	-0,51813	-0,533718	-0,26564	-0,037285	-0,29669	-0,337293	-0,237554	-0,309186	-0,2246241	-0,2565647
Volyn region	-0,704936	-0,24257	-0,40252	0,2755024	-0,659458	-0,22692	-0,555265	-0,69258	-0,778228	-0,56122	-0,61934	-0,424228	-0,567728	-0,6661745	-0,2811532
Dnipropetrovsk region	3,6699226	1,0459279	0,935684	0,812968	3,4331576	0,978454	1,1187079	1,90411	1,8765226	1,651897	1,7776842	1,0678385	1,6295438	3,667345	0,90102594
Donetsk region	1,7620221	-0,014631	-0,84859	-0,809347	1,6483416	-0,01369	-0,208117	0,470298	-0,276937	0,204878	-0,320255	-0,021445	-0,293567	1,93916711	0,1396388
Zhytomyr region	-0,790196	-0,550796	0,557901	-0,404648	-0,739215	-0,51526	-0,672577	-0,57106	-0,558982	-0,48681	-0,477231	-0,448697	-0,437461	-0,5481517	-0,3575186
Zakarpattia region	-0,210005	-0,184352	0,966143	-0,217654	-0,196456	-0,17246	-0,593092	-0,75465	-0,512079	-0,6052	-0,568847	-0,498986	-0,521443	-0,7355164	-0,4092264
Zaporizhzhia region	0,8969273	-0,165968	-0,31901	-0,538694	0,8390706	-0,15526	-0,169332	0,091941	0,2183984	0,102715	0,1857984	-0,177427	0,1703152	1,09375319	-0,0633202
Ivano-Frankivsk region	-0,735316	-0,486168	-0,04881	0,192963	-0,687877	-0,45481	-0,661085	-0,53163	-0,581161	-0,55971	-0,3789	-0,330939	-0,347325	-0,3980912	-0,367082
Kyiv region	0,0749907	0,6239778	0,497475	0,3956323	0,0701509	0,583719	0,7054818	0,407476	0,6035126	0,346814	0,6469333	0,7415185	0,5930222	0,13394515	0,2061125
Kirovohrad region	-0,863071	-0,633559	-0,98074	-0,990421	-0,807392	-0,59268	-0,719502	-0,63305	-0,931795	-0,64564	-0,686413	-0,461696	-0,629211	-0,6678596	-0,3661276
Luhansk region	-0,978072	-0,586076	-1,40471	-1,142863	-0,914971	-0,54826	-0,878951	-0,85207	-1,364753	-0,71367	-1,098555	-0,597349	-1,007009	-0,6392273	-0,4387248
Lviv region	-0,111157	0,1389306	0,860029	2,093608	-0,103978	0,129969	0,228572	0,262717	1,0378585	0,453686	0,67505	0,2083485	0,6187959	-0,0388882	-0,0376308
Mykolaiv region	0,1256449	-0,421027	-0,86333	-0,909162	0,1175303	-0,39387	-0,216257	-0,48918	-0,492587	-0,51153	-0,469944	-0,327165	-0,430782	-0,3916794	-0,2870743
Odesa region	0,0265205	-0,166114	0,339288	0,3705186	0,0248168	-0,1554	2,7524593	0,284698	1,3994573	0,34076	1,147155	0,0714699	1,0515588	-0,3520976	0,03776962
Poltava region	0,0188838	-0,273467	-0,78031	-0,695935	0,0176608	-0,25582	-0,346976	0,270835	-0,322567	-0,08387	-0,312	-0,092254	-0,286	0,79306177	-0,0924612
Rivne region	-0,913416	-0,600645	-0,61328	-0,15511	-0,854486	-0,5619	-0,624694	-0,69111	-0,885615	-0,62571	-0,6491	-0,494004	-0,595008	-0,5774392	-0,4043458
Sumy region	-0,710163	-0,492174	-0,60935	-0,743283	-0,664351	-0,46042	-0,80186	-0,60356	-0,843925	-0,54196	-0,634635	-0,470516	-0,581749	-0,4953318	-0,3613639
Ternopil region	-0,926477	-0,578504	-0,99155	-0,463033	-0,866705	-0,54118	-0,81	-0,77952	-0,904576	-0,67835	-0,780196	-0,469195	-0,715179	-0,7578868	-0,392496
Kharkiv region	-0,317954	-0,063869	1,122365	0,786016	-0,297447	-0,05974	0,2707086	0,711105	2,1615552	0,8319	1,3913246	0,0481535	1,2753809	0,83873791	0,07619136
Kherson region	-0,993541	-0,628462	-1,01317	-0,983063	-0,929434	-0,58792	-0,473865	-0,7084	-0,71466	-0,65043	-0,521429	-0,472838	-0,477977	-0,6666243	-0,3978639
Khmelnytsk region	-0,853249	-0,562838	-0,72922	-0,488627	-0,798208	-0,52652	-0,598838	-0,55879	-0,349818	-0,48151	-0,534445	-0,319259	-0,489908	-0,5405669	-0,356479
Cherkasy region	-0,766091	-0,576838	-0,66093	-0,720409	-0,716663	-0,53963	-0,351285	-0,43135	-0,534424	-0,43291	-0,49577	-0,402413	-0,454456	-0,2794678	-0,2599085
Chernivtsi region	-1,077243	-0,67211	-0,52043	-0,583963	-1,00774	-0,62875	-0,848785	-0,90184	-0,764941	-0,76033	-0,803624	-0,603593	-0,736655	-0,8423024	-0,4554584
Chernihiv region	-0,756678	-0,527628	-0,60149	-0,907242	-0,707855	-0,49358	-0,561011	-0,61771	-0,876697	-0,602	-0,67577	-0,458619	-0,619456	-0,639086	-0,3569037
Kyiv city	5,5103664	7,1728239	6,312096	6,2872801	5,1548555	6,71006	5,549277	5,678951	4,4337244	5,304886	4,5397999	5,1708469	4,1614832	0,99500519	4,58096455

Fig. 1. Initial data after standardization and the weighting of factors

Cluster data analysis. There is a wide variety of methods for classifying objects. Hierarchical methods and the k-means method are the most common and widespread in statistical data processing packages characterized by relative simplicity, the high quality of obtained results, their interpretability, and wide possibilities for setting partitioning rules [9, 10].

The advantages of hierarchical cluster analysis methods include the possibility of constructing dendrograms, i.e. treeclustering, in which classification stages and the distance between classes are clear. The basis of the algorithm is a distance matrix, which is formed based on consolidation rules and distance calculations.

One of the common hierarchical classification methods is Ward`s method, the algorithm of which consists in determining the distances between groups using variance analysis methods [9, 10].

In k-means clustering, the number of clusters that should be produced is required as input, and the algorithm operates by iteratively assigning points to clusters represented by cluster centroids, which are updated in each iteration. A cluster centroid is calculated by taking the average in each dimension of all data points included in the cluster. The algorithm is initiated by assigning k randomly chosen points in the data set as centroids, and it iterates between two steps until the clusters have stabilized.

The k-means method is considered to be more optimal in comparison with Ward's method both in terms of quantitative and qualitative partition structure. In addition, the result of partitioning with respect to the number of clusters in this method is strictly determined, which is, on the one hand, a positive point because it makes it possible to analyze stable and relatively homogeneous groups over time, and, on the other hand, it presents a problem because this quantity has to be previously determined.

Thus, in the first stage, using Statistica, the suite of analytics software products, a hierarchical classification was applied. Ward`s method was used as a rule for the consolidation of observations into clusters, and the Euclidean distance was applied as the distance between observations. A graphical representation of the hierarchical classification results in the form of a dendrogram is shown in Figure 2.

The dendrogram shows the presence of several groups of neighboring observations, which are grouped into clusters at a short distance of about 1–10 units of the normalized scale. At the same time, there is also a single observation (the city of Kyiv), which is combined with the entire main group at a distance of 38 units and the values of which dramatically differ from the given consolidation. At the same time, the inclusion of the given observation in any cluster will seriously shift its center, leading to the classification distortion.

To determine the optimal number of clusters that the regions should be divided into, a horizontal line was drawn at a distance of 8 units of the normalized scale. Based on the classification results, five clusters are singled out.

Based on the fact that the sample consists of five clusters, the classification of observation by the k-means method was performed. Observations that maximize the initial distances between clusters were chosen as the cluster centroids.
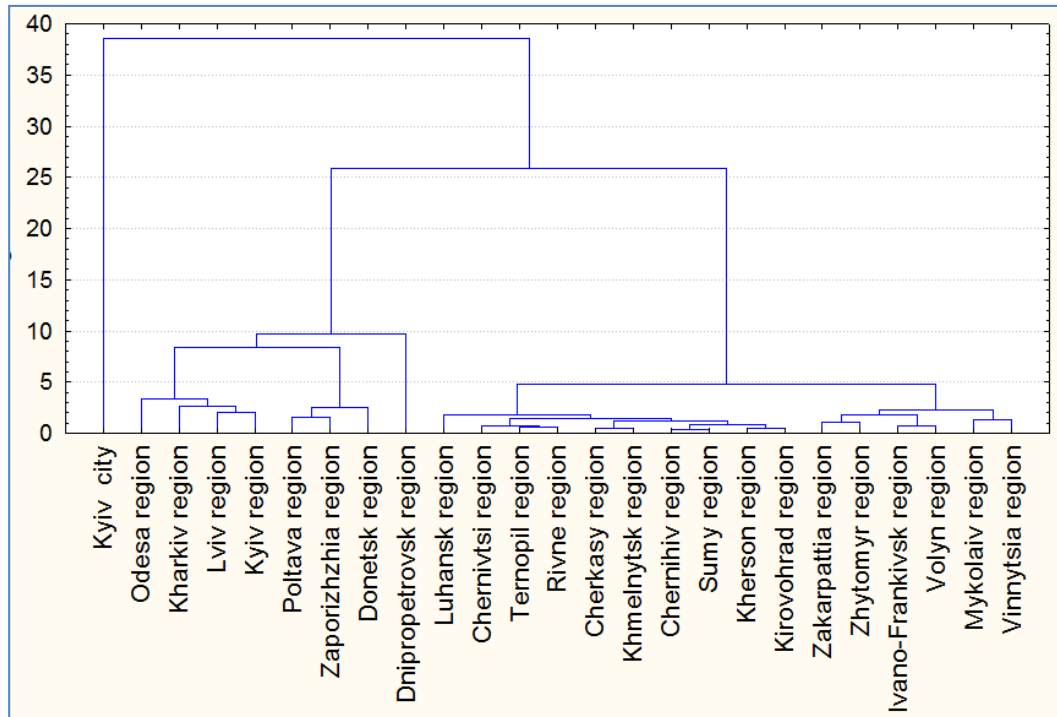
Fig. 2. Graphical representation of the hierarchical classification

As a result of classification by the k-medium method, Ukraine`s regions are distributed by clusters as follows (table 2):

Table 2.

Cluster distribution

Cluster	Number of observations	Regions
Cluster 1	6	Kyiv region, Lviv region, Odesa region, Kharkiv region, Zaporizhia region, Donetsk region
Cluster 2	1	Kyiv city
Cluster 3	7	Vinnytsia region, Volyn region, Zhytomyr region, Transcarpathian region, Ivano-Frankivsk region, Mykolaiv region, Poltava region
Cluster 4	10	Kirovohrad region, Rivne region, Sumy region, Ternopil region, Kherson region, Khmelnytskyi region, Cherkasy region, Chernivtsi region, Chernihiv region, Luhansk region
Cluster 5	1	Dnipropetrovsk region

Figure 3 presents Euclidean distances and squared Euclidean distances between clusters.

Cluster Number	Euclidean Distances between Clusters (KL_W.sta) Distances below diagonal Squared distances above diagonal				
	No. 1	No. 2	No. 3	No. 4	No. 5
No. 1	0,000000	25,29766	0,64675	1,19065	2,75650
No. 2	5,029678	0,00000	32,65159	36,02443	16,06244
No. 3	0,804205	5,71416	0,00000	0,11099	5,55716
No. 4	1,091170	6,00204	0,33315	0,00000	7,00161
No. 5	1,660269	4,00780	2,35736	2,64606	0,00000

Fig. 3. Euclidean distances and squared Euclidean distances

The Euclidean distance (values below the diagonal) is the distance between the sets of variables (F1 – F15) for each cluster of regions and it is equivalent to the distance between the clusters according to the selected indicators. The smaller the distance between objects, the more similar they are. Clusters are at greater distances from each other when Euclidean distances are greater than unity. The squared Euclidean distance (values above the diagonal) is used to give more weight to more distant objects.

The greatest distance is between clusters four and two, three and two, that is, they are the least similar. Clusters four and three ,three and one are almost equidistant from each other since Euclidean distances are less than unity.

The average values for each cluster are presented in a linear graph (Fig. 4).
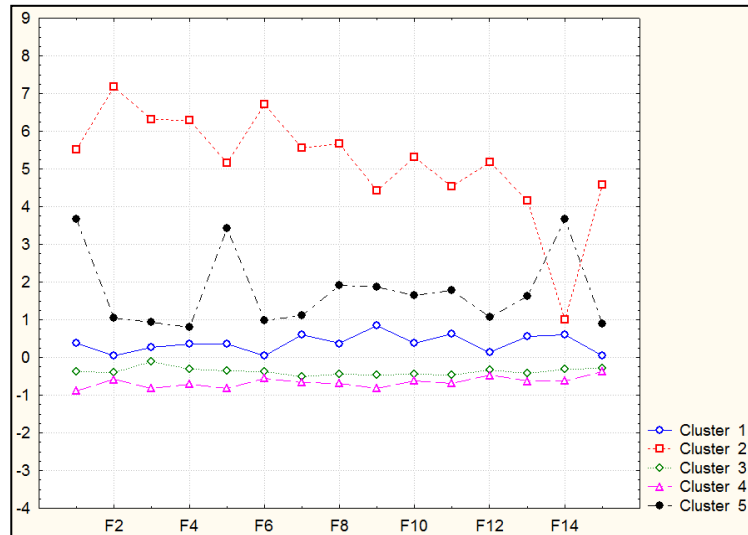

Fig. 4. Linear graph of clusters

The linear graph clearly shows 5 clusters. The average values differ from each other. This indicates a qualitative clustering. As the graph shows, the distance between the average characteristics of the clusters is large, and the total distance between the cluster centroids is significant, which indicates successful clustering.

Figure 5 shows the results of the variance analysis of factors by clusters.

| Variable | Analysis of Variance (KL_W.sta) | | | | | |
	Between SS	df	Within SS	df	F	signif. p
F1	53,57055	4	4,089447	20	65,4985	0,000000
F2	57,04755	4	0,612454	20	465,7295	0,000000
F3	47,85967	4	6,140327	20	38,9716	0,000000
F4	46,78033	4	7,219666	20	32,3978	0,000000
F5	46,88121	4	3,578786	20	65,4988	0,000000
F6	49,92402	4	0,535977	20	465,7289	0,000000
F7	40,45891	4	6,581088	20	30,7388	0,000000
F8	42,61187	4	1,128134	20	188,8599	0,000000
F9	35,80559	4	4,754412	20	37,6551	0,000000
F10	36,87563	4	0,624367	20	295,3043	0,000000
F11	32,24688	4	2,313124	20	69,7042	0,000000
F12	31,05556	4	0,684437	20	226,8694	0,000000
F13	27,09633	4	1,943667	20	69,7041	0,000000
F14	21,01853	4	5,441470	20	19,3133	0,000001
F15	23,85569	4	0,144314	20	826,5212	0,000000

Fig. 5. Variance analysis of factors by clusters

The table shows the values of the between-group (Between SS) and within-group (WithinSS) variances of indicators. The smaller the value of the within-group variance and the greater the value of the between-group variance, the better the factor characterizes the cluster membership of objects and the "better" clustering is. For all parameters, the between-group variance is greater than 21, and the within-group variance is less than 6.58.

The cluster membership of objects is best characterized by the following factors: F2 – regional volume of foreign goods trade, import; F6 – import of goods by economic entities according to the number of employees broken down by regions, F10 – the number of employees working for economic entities by regions, and F12- capital investment by regions since they correspond to the largest difference between intergroup and intragroup variances. Indicator F14 – sold production of industry by regions characterizes the cluster membership to the least extent (it corresponds to the smallest difference of variances).

Factors with the values of p> 0.05 can be excluded from the clustering procedure, since for these indicators there is no significant difference in the

average values of clusters, that is, the factor is not informative when conducting the cluster analysis. In our case, for any indicator $p < 0.05$, which means that we will not exclude any of the factors under consideration. Parameters F and p also characterize the influence of the factor on the division of objects into groups.

Better clustering is achieved with the higher values of the first parameter and lower values of the second one. The table shows that the best indicators specified above correspond to the maximum difference between F and p for factors F15, F2, F6, which significantly affect the classification of regions into groups, and the factor with minor influence on the clustering process is F14.

Conclusions. As a result of the analysis of the factors underlying the division of data into clusters based on the k-means method and the hierarchical method, it was determined that the best result is achieved by a combination of these methods, when at the first stage, the number of clusters is determined with the help of the analysis of hierarchical algorithm visualization (building dendrograms), based on which k-means partitioning is performed.

The cluster analysis results made it possible to single out five clusters and classify observations according to these clusters. The obtained clusters are homogeneous in composition and can be interpreted: the second cluster, which includes the city of Kyiv, and the fifth cluster corresponding to the Dnipropetrovsk region, can be described as clusters with a high level of foreign economic activity development. The first cluster, consisting of 6 observations, includes the following regions with an average level of foreign economic activity development: Kyiv region, Lviv region, Odesa region, Kharkiv region, Zaporizhia region, and Donetsk region. The remaining regions belong to clusters 3 and 4 and are characterized by low foreign economic activity development levels.

The clustering of regions will help to systematize them according to the main problems associated with the development of foreign economic relations, and on this basis to develop a system of differentiated measures for each cluster of regions – with high, average, and low levels of foreign economic activity development.

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