Structural and Dynamic Modelling of the Regions' Foreign Trade Profile Based on Graph Cluster Analysis

Natalia FILIMONOVA
All-Russian Scientific Research Institute of Labor
29, 4th Parkovaya St., 105043 Moscow, Russian Federation
natal_f@mail.ru

Alexey KISLYAKOV
Russian Academy of National Economy and Public Administration under the President of the Russian Federation, Vladimir Branch
59a. Gorky St., 600017 Vladimir, Russian Federation
ankislyakov@mail.ru

Natalia TIKHONYUK
Russian Academy of National Economy and Public Administration under the President of the Russian Federation, Vladimir Branch
59a. Gorky St., 600017 Vladimir, Russian Federation
tasha-ti@yandex.ru

Abstract
The paper argues the necessity of adjusting approaches to forecasting indicators of regional foreign trade using big data and cluster graph analysis methods. There are a large number of international trade forecasting problems, which are identified in this study. The existing methods' disadvantages include the use of irrelevant approaches; the difficulty in forecasting small commodity groups with a random nature of demand or implemented in emerging markets. The research study aims to develop a methodological approach to improve the accuracy of international trade forecasting for regions using economic-mathematical methods to model behavioral activity and create a decision-making system. A four-stage model for constructing the regional trade profile has been proposed. The paper discusses the necessity of using the method of cluster analysis and justifies the choice of the distance metrics method between clusters. The authors offer the methodology for the study of foreign economic relations and the development of regions' foreign trade using network graphs and the cluster approach, which allows to identify stable groups of goods and countries, assess the main trend changes and the potential for regional development. The methodology was tested on foreign trade data from customs statistics of the Russian Federation on exports and imports by country and commodity group description codes with monthly detailing for the last 7 years. We identified features of the graph construction and group connected vertices to find cliques and specify the main stable in time groups of vertices (countries and goods), on which the regional foreign economic activity depends. The paper proposes to expand the typical structure of the trade profile by adding economic complexity indices of the region and the complexity of the product. The calculation of these indices is made for the Vladimir region. The proposed methodology allows to increase the efficiency of international activity management and ensure regional sustainable economic development.

Keywords
***F**oreign trade; cluster analysis; economic complexity index; region's trade profile.*

Introduction

Many international and Russian organizations predict indicators of foreign trade to determine future courses for development and the possibility of applying certain policies, for example, the International Monetary Fund (2021), the Organization for Economic Cooperation and Development (OECD, 2021), the World Trade Organization (2021), the UN Conference on Trade and Development (UNCTAD, 2021), the Bank of Russia (2021), the Ministry of Economic Development (2020), the Accounts Chamber of the Russian Federation (2020). While traditional statistical methods are easy to apply and interpret, they require a large number of hidden patterns that dynamically affect targets, which may not be realistic. Therefore, machine learning is the best and most rational technology capable of predicting trends in international activity in regions.

Export volume forecasting is conducted with the use of a large number of factors, based on classical statistical methods and multivariate regression analysis. Forecasting is supported by strictly formalized predictive models with interpretable algorithms, such as regression or decision trees (Huang, Nie, Zhu, & Du, 2020). The models apply a certain set of factors, strictly regulated by certain forecasting techniques (Kislyakov & Filimonova & Omarova, 2021), which are irrelevant at present. Forecasters pay more attention to the analysis of those commodity groups that have a high share in the structure of exports or imports, such as oil or gas (Kalendjyan & Safonova, 2020). Commodity groups with a small market share are not subject to forecasting and are perceived as a statistical error.

The disadvantages of the methodologies and models used are the lack of possibility to estimate the factors presented in the form of categorical variables, which include the presence of international agreements on economic cooperation, protectionism policy, worsening trade wars, sanctions policy, and other protective and restrictive measures that affect the indicators of foreign economic activity. While traditional statistical methods are easy to apply and interpret, they require a large number of hidden patterns that dynamically affect targets, which may not be realistic. Therefore, machine learning is the best and most rational technology capable of predicting trends in regional international activity.

The study aims to develop a methodological approach to improve the accuracy of international trade forecasting for regions using economic-mathematical methods of modeling behavioral activity and creating a decision-making system.

The study hypothesizes that the use of the economic complexity index and the product complexity index can allow to determine the main directions of foreign trade development for the region and create a region's trade profile.

The proposed methodology allows improving the quality of the selection of macroeconomic indicators that are accepted in international practice and expanding the opportunities to build predictive models of foreign economic activity indicators.

Literature review

International trade is a necessary condition for the development of regions and countries and provides an opportunity to attract foreign investment, expand the market, stimulate development processes and create a competitive environment (McCalman, 2020; Polzunova & Kostygova, 2019; Endovitskaya, Risin, & Treshchevsky, 2019). On the whole, foreign trade is a driving force for economic development (Okenna, 2020).

In world practice, there are many passive approaches for predicting indicators of foreign economic activity: trend models; multifactor regression models; models based on hybrid cognitive maps; complex econometric models; inter-industry balance models; matrix models of international trade; optimization models.

Active forecasting techniques are more effective. They allow building a cause-and-effect relationship between managerial impact and results under dynamically changing conditions. As a rule, such methods focused on informal analysis use expert judgments. This fact leads to a complication of the forecasting process. It is also necessary to consider subjective assessments of the current situation, based on the accumulated experience of the expert group. Scenario-based forecasting methods that combine qualitative and quantitative approaches also require a description of the factors and an indication of how these factors might affect the anticipated events.

Grimme and Lehmann (2020) studied a leading indicator for forecasting German exports, called the ifo Export Climate. This is a survey-based indicator that includes the level of business and consumer confidence of Germany's main trading partners and the country's competitiveness in the global market. The indicator reflects changes in external demand for German goods, modeling international demand and the relative price of German products. The study confirmed the hypothesis that ifo Export Climate is well suited for short-term forecasting of German exports (Grimme & Lehmann, 2020).

Shaikhutdinova and Malganova (2018) analyzed the key factors that harmed imports and exports of the Tatarstan Republic. To forecast international trade, they used the "random walk" method, the essence of which consists of presenting a dynamic series in a certain way oriented random walk process. As a result, the forecasting procedure is reduced to multiple imitations of increments at the lead period and subsequent determination for statistical characteristics of point forecast realizations. The disadvantage of this forecasting method is the non-stationarity of the obtained time series; all future values are equal to the last obtained by fact. As a rule, the random walk method has more frequently for identifying time series than for making predictions. (Shaykhutdinov & Malganova, 2018). Also, this method does not provide an opportunity to consider other factors affecting the target indicator

These difficulties in constructing qualitative predictive models of international trade development require additional research with machine learning methods.

The analysis shows that econometric models are the most frequently used tools for predicting international trade indicators. Modeling and forecasting help to determine the accuracy of the result and change the set of variables until an adequate model is obtained. The advantage of this method is to assess the influence of each factor on the resulting indicator and determine the crucial point at which the dynamics of the system under study will change drastically. At the same time, one of the main limitations is the use of long time-series data to estimate large-scale models, so regression models are more often used in short-term planning.

Research methods

The main steps of our study include the following:
1. Identification, analysis, and classification of factors influencing the formation of the trade profile of the region;
2. Structural-dynamic modeling of regional systems behavioral activity (factors, relationships) using cluster analysis.

Since statistical information on foreign trade in the Vladimir region consists of large amounts of data, it is necessary to use machine learning methods for the analysis. One of such methods is clustering, which is the process of organizing similar objects into groups (Kislyakov, 2020). It allows researchers to simplify further work with the data and understand its structure by dividing it into groups based on similarity. This approach will help identify stable country partners and determine the most promising areas of trade in goods.

Clustering algorithms such as k-means, hierarchical clustering, and Gaussian mixture model are most often used for data analysis. The choice of method depends on the characteristics of the data set and the research problem.

The study of imports and exports of the Vladimir region considers data dispersed in time. Therefore, we used a hierarchical clustering method. High quality is achieved by using agglomerative clustering, in which the main operation is to merge several already existing clusters into a single larger one.

Hierarchical clustering results in a dendrogram, i.e. a binary tree constructed from distance metrics between clusters. The standard distance measures used in the analysis include Euclidean distance, Manhattan distance, Minkowski distance, and Pearson correlation coefficient.

DTW-distance is the most effective algorithm for time series data, which is based on the algorithm of time scale dynamic transformation aimed at achieving an optimal comparison or alignment of several sequences (Hausmann et al., 2014). In other words, the task is to arrange the time series relative to each other to minimize the distance between them.

Clustering with the DTW algorithm allows statistical data to be divided into non-intersecting subsets in such a way that each cluster consists of similar objects, and objects of different clusters differ significantly (Harvard's Growth Lab, 2018). Cluster analysis identifies groups of goods and countries that behave similarly using export and import data. This is necessary for predicting the volume of goods deliveries within groups.

Research results

As a result of the foreign trade forecasting models analysis, we can conclude that most researchers select significant factors and build regression models based on the data on factor variables and resulting attributes. In this study, we tried to forecast international trade to determine the strategic directions of export-import activity development. The analysis was based on the index of economic complexity of the region and the index of product complexity. The proposed approach makes it possible to improve the quality of indicator selection and expand the possibilities of building predictive models for foreign economic activity.

Due to the Covid-19 pandemic, foreign trade development has slowed in 2020. According to the World Trade Organization, total global trade in 2020 is down 7.5% from $19 trillion in 2019 to $17.6 trillion (World Trade Organisation, 2021). The indicators of previous years will not be achieved in the near future, despite the prediction of global trade growth of 7.2% in 2021 (World Intellectual Property Organization, 2021). This negative trend has affected almost every country in the world (Figure 1).

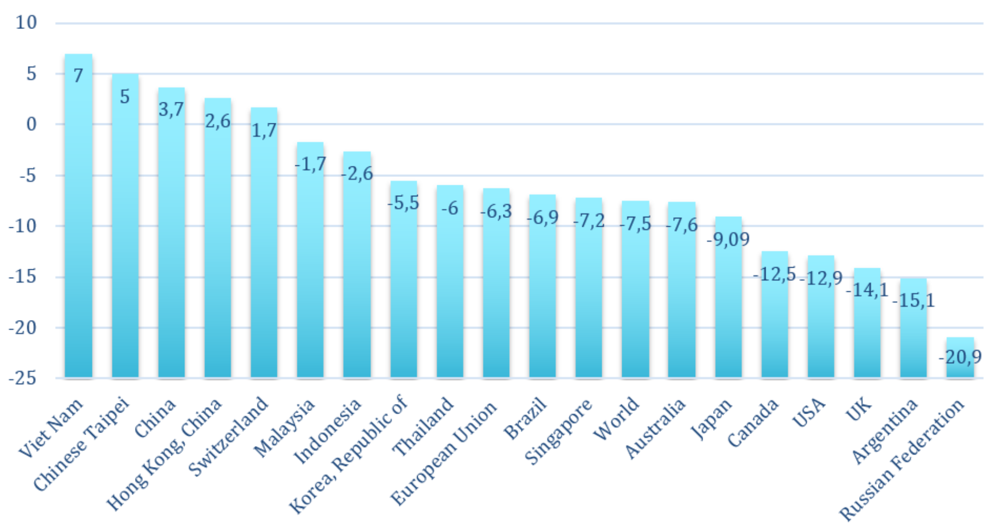


Figure 1. Merchandise exports of selected leading traders, 2020

Similar global trends are typical for the Russian Federation. According to the Federal Customs Service, in 2020 the foreign trade turnover of the Russian Federation decreased by 15% compared with the previous period. The largest decrease occurred in exports, which fell by 20.7% compared to the previous period. The share of net exports fell to 4.8% in 2020 from 7.6% in 2019 due to falling price indices for exported goods (Federal Customs Service, 2021). Figure 2 shows the dynamics of international trade over the period 2014-2020.

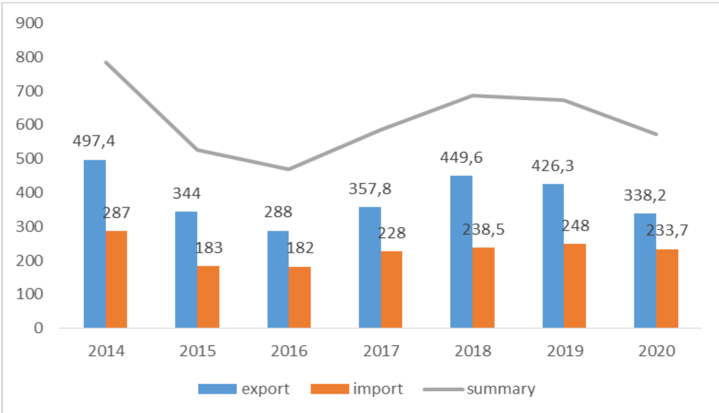


Figure 2. Dynamics of Russia's foreign trade turnover, bln. rub.

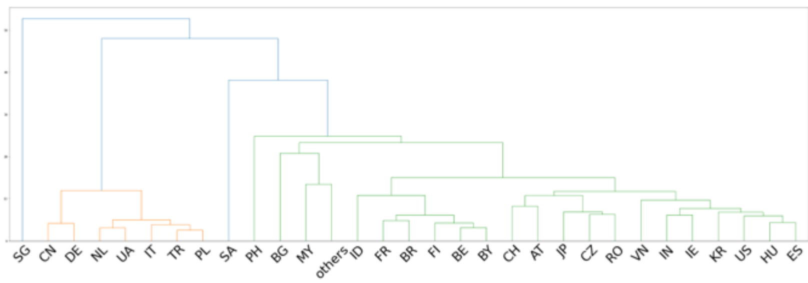
Most of Russia's export structure included primary exports of low-value-added goods. Food, agricultural raw materials, and precious metals compensated for the volume of exports even though oil and gas decreased by 41% and 40% in value terms.

In 2020 the volume of high-tech exports fell by 17% due to a decline in physical export volumes. Most of Russia's export structure included primary exports of low-value-added goods. Food, agricultural raw materials, and precious metals compensated for the volume of exports even though oil and gas decreased by 41% and 40% in value terms (Knobel & Firanchuk, 2020).

Analysis of export and import aggregated indicators for the Vladimir region showed that the key foreign suppliers are China, Germany, CIS countries, Turkey, and Poland. Germany and China supply 25 % of all imported goods. The most important markets for goods are CIS countries, Germany, Poland, Egypt, Estonia. CIS countries account for 56% of all exports of the Vladimir region. The key conditional sectors in the Vladimir region's exports are the timber and glass industries, which accounted for 13% and 12% of the region's total exports in 2020.

To test the agglomerative clustering and DTW-distance clustering methodology (Kislyakov & Tikhonuyk, 2020), dendrograms were constructed. They show groups of countries with similar behavior. The source data for the dendrograms are monthly data for the 30 countries with the highest supply volume. Other countries are based on the monthly average of the supply volumes of countries not included in the top 30. As supply volumes for different countries can vary significantly, the data were normalized by logarithm before the construction of the dendrograms.

The results of clustering by the agglomerative method and the DTW-distance method for imports of the Vladimir region are shown in Figure 3.



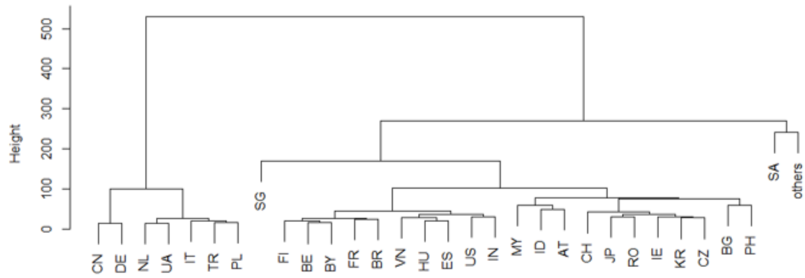


Figure 3. Hierarchical dendrogram by country for Vladimir region imports (top graph-agglomerative method, bottom graph- DTW-distance method)

The results obtained by countries can be divided into 4 groups.

The first group includes 7 countries leaders in the import of goods into the Vladimir region. They are distinguished by stable dynamics and comparable supply volumes for 2019-2020. This group consists of China, Germany, Ukraine, Italy, etc.

The second group comprises the separately standing Singapore and Saudi Arabia. These countries are characterized by irregular spontaneous supplies to Vladimir Region. During the reporting period in some years, these countries do not supply anything at all, while in some years the volume of supplies increases sharply.

The third group includes countries of the second echelon, such as Finland, Belgium, Belarus, etc. These countries do not supply such a large volume as the countries of the first group but also have stable supply dynamics.

The fourth group includes Malaysia, Indonesia, Austria, the Czech Republic, etc. Vladimir Region buys goods from these countries unsteadily, when necessary.

The clustering model for the export partner countries of the Vladimir region is presented in Figure 4.

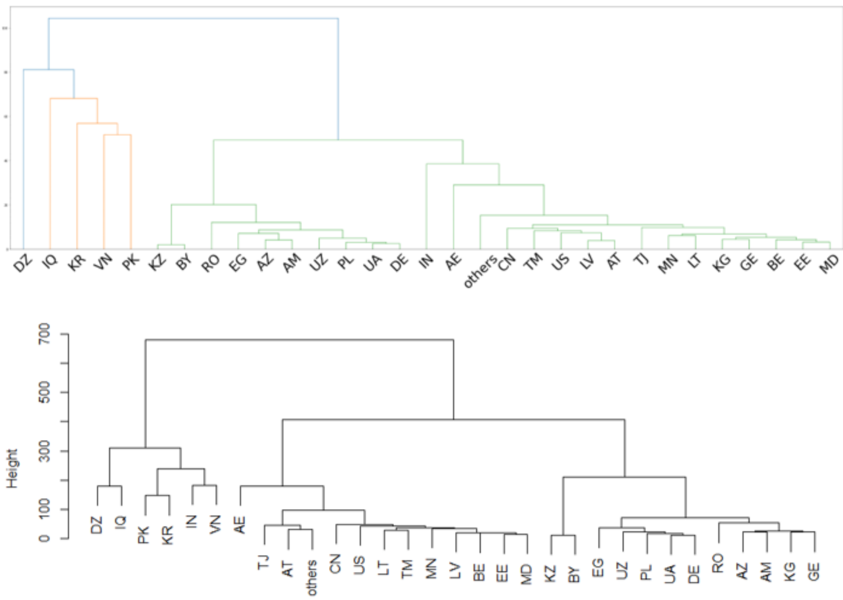


Figure 4. Hierarchical dendrogram of exports of Vladimir region by country (top graph-agglomerative method, bottom graph- DTW-distance method)

In exports, we get a similar result, but in a different direction of trade.

We observe a similar group for the first-tier countries when analyzing exports, but the countries with smaller export volumes are distributed differently. The DTW-distance algorithm compares in pairs the points of two-time series corresponding to the same period, which makes the analysis more relevant from the point of view of supply seasonality. Thus, the obtained clusters of countries unite the countries taking into account the volume and regularity of supplies. As a result, the received groups can be conditionally designated as a group of strategic partners with large and stable volumes of deliveries to the Vladimir region, a group of the second echelon, having small, but stable volumes, and a group with single irregular deliveries.

The first group includes countries of the former Soviet Union influence, it includes closely related Kazakhstan, Belarus, Romania, Azerbaijan, and others. Kazakhstan and Belarus can be conditionally singled out into a separate subgroup as the most important trading partners of the Vladimir region.

The second group includes countries of the second echelon: Estonia, Belgium, Moldova, Lithuania, Mongolia, and others. This group is characterized by a small and irregular volume of purchases of goods from the Vladimir region.

The third group includes countries that purchase goods from the Vladimir region on an occasional and irregular basis, including Vietnam, Korea, Pakistan, and others.

Figure 5 presents a hierarchical dendrogram of the Vladimir region's imports by conditional sectors.

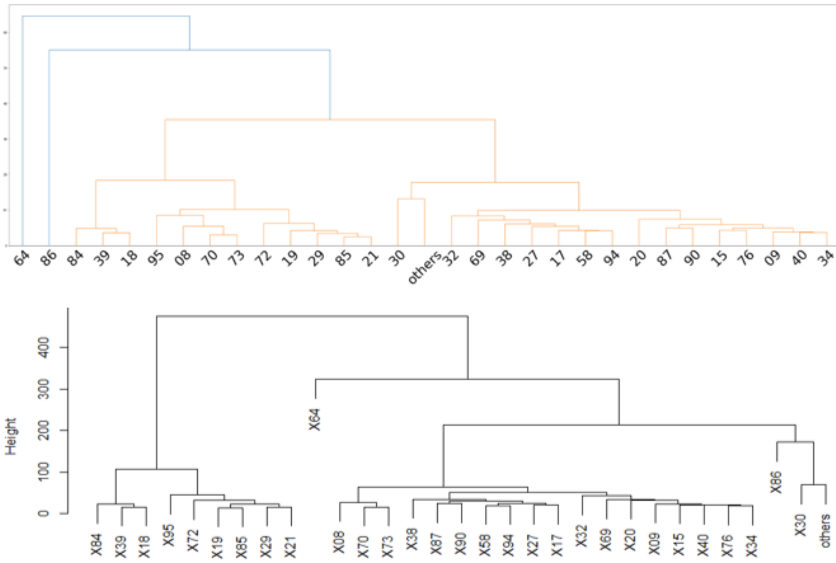


Figure 5. Hierarchical dendrogram of Vladimir region imports by conditional sectors (top graph-agglomerative method, bottom graph- DTW-distance method)

The conditional branches of trade are distributed similarly to the countries. We distinguished the following groups: the stable imports and relatively large supplies group, the stable imports and relatively small supplies group, the relatively small and irregular supplies group, and the one-time purchases of foreign goods.

Figure 6 shows a hierarchical dendrogram of exports of the Vladimir region by conditional sectors.

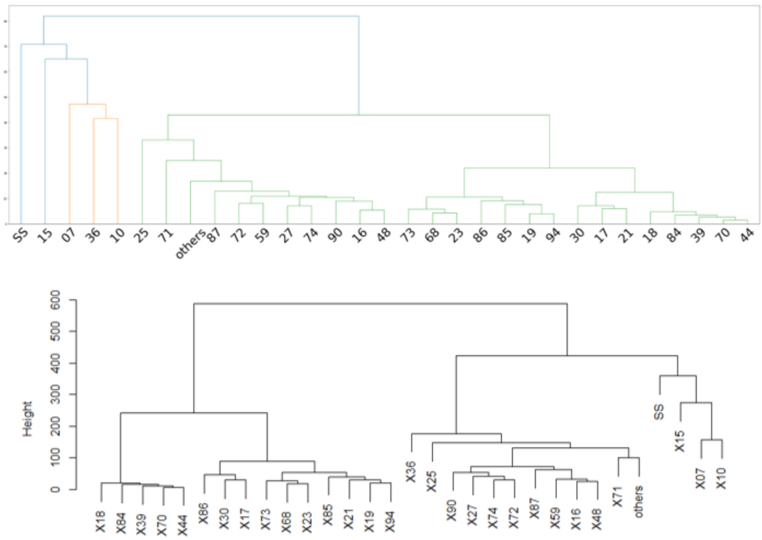


Figure 6. The hierarchical dendrogram on exports of Vladimir region by conditional sectors (top graph-agglomerative method, bottom graph-distance method)

Thereby, the analysis showed that the general tendency of subdivisions into four groups persists. The DTW-distance algorithm allows us to obtain more correct data and easy to interpret results. The advantage of the algorithm is that it considers not only the volume of supply but also tracks seasonality more accurately. Based on these indicators, groups of countries and conditional sectors that behave similarly in trade with the Vladimir region are determined.

In the next step, we used international trade statistics to assess the economic complexity of a region. This index takes into account those products in the production of which a country has a sustainable competitive advantage, in other words, it exports more than the average economy of a similar size. The Economic Complexity Index (ECI) reflects how complex a country's output is.

According to R. Hausmann and C. Hidalgo, the prospects for economic growth are determined by the ability of a particular economy to accumulate knowledge about production. The more complex the structure of knowledge stored in a given economy, the more complex and competitive goods it can produce both for its consumption and export. These ideas formed the basis of the theory of economic complexity, which allows us to answer about the prospects for the competitive economy and the rate of its growth (Hidalgo & Hausmann, 2009).

For further analysis, we have formed a database on exports of the Vladimir region for 97 commodities from 2013 to 2020. This database shows that the region's economy is characterized by opportunities for the production of finished food products, glass, machinery and equipment, wood, chemical products, and plastics.

The index of economic complexity of the Vladimir region is shown in Figure 7.

Between 2015 and 2017, there was a decrease in the region's economic sophistication due to the overall decline in the dollar value of the Vladimir region's exports caused by the economic sanctions against Russia and the fall in oil prices (Kosobutskaya, Ravohanginirina, & Amosova, 2019). Exports of unclassified goods (down 42.9% in 2015, down 22.0% in 2016, down 30.3% in 2017), motor vehicles (down 45.1% in 2015, down 80.4% in 2016, down 91.1% in 2017), railway equipment (down 53.2% in 2015, down 34.8% in 2017), miscellaneous food products (down 67.8% in 2015, down 21.2% in 2016) have dropped significantly over this period. As a result, the share of the following commodity groups decreased: cocoa and cocoa products, miscellaneous foodstuffs, copper, electrical and communication equipment, automotive equipment, optics, instruments and medical equipment, and railway equipment.

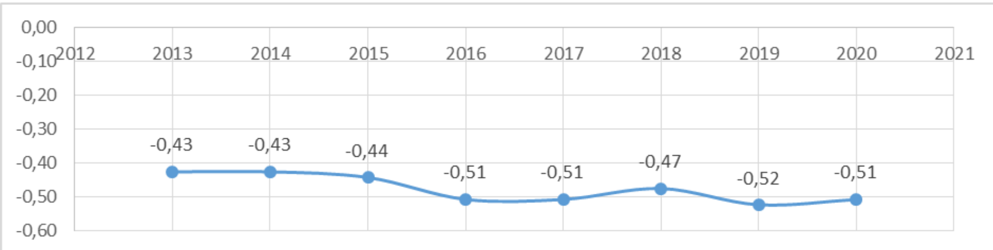


Figure 7. Evolution of the Economic Complexity Index (ECI) of Vladimir region in 2013-2020

The economic complexity index increased slightly in 2018, due to the region's comparative advantage in the following exports: pulp, nonwovens.

But the dollar value of the region's exports fell again in 2019, causing the economic complexity index to fall to -0.52. The reduction in exports occurred in the following commodity groups: unclassified goods (down 99.7%), railway equipment (down 14.1%), mechanical equipment, machinery and computers (21.5%), other metal products (down 47.6%), etc.

The year 2020, marked by a coronavirus pandemic worldwide, led to an increase in the total amount of exports to the Vladimir Region. Exports of pyrotechnics (up 12.8 times), railway equipment (up 128.9%), ready-made flour-based products (up 34.0%), furniture and lighting equipment (up 12.9%), cocoa and cocoa products (up 8.9%), and wood and wood products (up 5.1%) increased. The region's comparative advantages emerged in the areas of special fabrics, unclassified goods.

Thus, in 2020, the economy of the Vladimir region is defined by a medium level of complexity. R. Hausmann's paper concludes that economies with a medium export complexity index have the maximum potential to diversify their export basket.

Further, to determine the competitive advantages of the Vladimir region, we calculated the product complexity index. Generally, loosely related clusters, such as hydrocarbons or agricultural products, have low complexity, which has been revealed as the concept of economic complexity has evolved. In contrast, machines are very complex and interconnected because their production requires similar capital, knowledge, technology, etc. At the same time, clothing, textiles, and food products are less interconnected, and therefore have a low level of complexity. Complex product groups, such as the chemical industry and mechanical engineering, may be weakly interconnected, indicating that these clusters use production capabilities. The implication is that in weakly interconnected clusters it is very difficult to move from one product to another because it requires significant investments, change of technology, and competencies.

The calculation of the economic complexity index is shown in Figure 8.

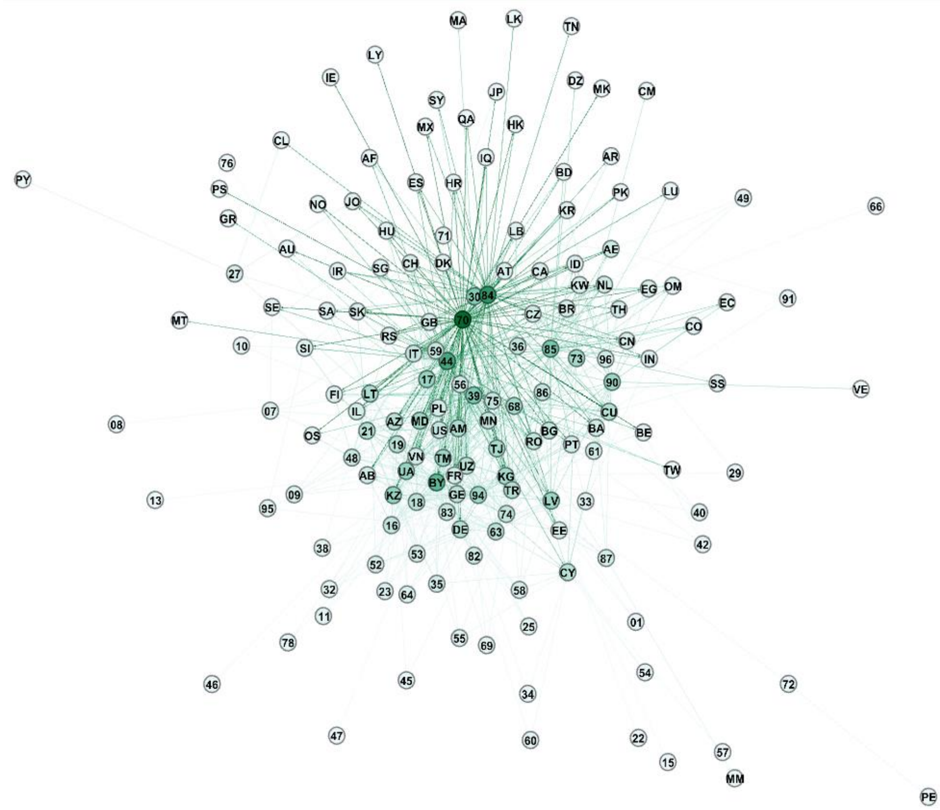


Figure 8. Oriented RCA graph for 2019

The structure of the graphs shows that the relatively stronger sectors of the Vladimir region in exports are glass (70), timber (44), and machine tools and equipment (84). Vladimir region has the closest cooperation with such countries as Belarus, Ukraine, and Kazakhstan. Visual analysis of the graph allows to cut off the countries that buy goods by a secret code. For government agencies involved in export development, the analysis of the RCA indicator will help to identify the most competitive goods and the most attractive countries for partnership development.

Further aggregation of graphs into ensembles will allow evaluating stable connections between vertices. However, to focus on the analysis and identification of groups of vertices connected, we should go to the problem of clique extraction. A clique in a graph is a subset of vertices, each pair of which is connected by an edge of the graph. A maximal clique is a clique that cannot be extended by including additional adjacent vertices. Identification and analysis of the commodity group time series describing the international trade of a region make it possible to determine the main time-stable commodity groups on which foreign economic activity depends.

For example, the analysis of the ensemble of graphs by commodity groups for exports of Vladimir region, created for the adjacency matrix based on the PCI indicator, makes it possible to describe the relationship of individual commodity groups in the overall picture of exports for the region. This graph contains 346 edges and 217 vertices, and it contains 140 cliques, the maximum clique contains 7 vertices with HS codes [1601, 3917, 7412, 7013, 4418, 2521, 3923], which decoding is given in table 1.

Table 1. HS commodity subgroup codes included in the 1st clique

HS code	Name of HS subgroup
1601	Sausages and similar products of meat, meat offal; prepared foodstuffs made from them
3917	Pipes, tubes, hoses, and their fittings (e.g. connections, elbows, flanges), made of plastics
3923	Articles for the transport or packaging of goods, of plastics; corks, closures, caps and other closures, of plastics
7013	Tableware, kitchenware, toiletware, office supplies, articles for home decoration or similar purposes, glassware (other than articles of heading 7010 or 7018)
7412	Copper pipe or tube fittings (e.g. couplings, elbows, flanges)
4418	Joinery and carpentry, timber, building products, including cellular timber panels, prefabricated floor panels, shingles, and shingles for the roofing
2521	Limestone flux; limestone and other limestone stone used for the manufacture of lime or cement (Limestone flux; limestone and other limestone stone used for the manufacture of lime or cement)

Next, we calculated all the statistical characteristics of the time series included in the maximum clique and visualized these time series (Figure 5). Visually, we can assess that one of the generalizing features of these time series is the tendency for the export volumes of the specified goods to increase.

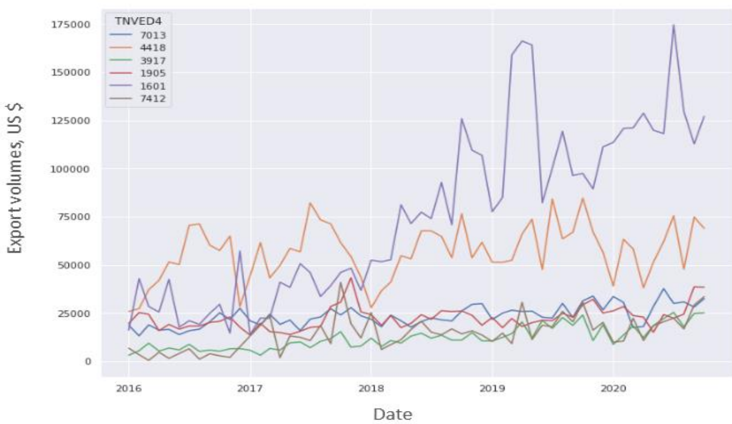


Figure 9. Time series of export volume indicators by commodity group, included in the maximum clique

Conclusion

The main limitation of this study is the use of data before 2020, which complicates the practical application of the model in the post-pandemic period. At the same time, these limitations can be removed if data on foreign economic activity from 2020 onwards would be used.

The economic complexity index and the product complexity index enable to determine the main trends in the development of the foreign economic activity of the region and create a region's trade profile.

Our research has shown that accelerating the economic growth of the Vladimir region requires the complication of its production structure. The most probable is the development of productions in those sectors, for which there are prerequisites, based on already existing industries in the economy. The food industry can be referred to these sectors. However, their contribution to the complexity of the economic structure is low in contrast to the manufacturing industry. The use of methods of cluster analysis, the economic complexity index, and the product complexity index for evaluation allows determining the vector of further regional economic development. However, for this purpose, it is necessary to create appropriate conditions, which will require additional investments and structural transformations.

Further development of the study involves the development of a decision-making mechanism for determining the strategy for the development of foreign trade of the Russian Federation regions. The use of the index of economic complexity and the study of the production structure can become a starting point for further research into the strategic directions of regional economic development and the identification of its competitive advantages. The proposed methodology has been tested in the case of the Vladimir region and can be extended to other regions of the Russian Federation.

The results obtained during the study can be applied in the development of medium-term plans for the international trade of countries with diversified economies.

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