Resilience of Russian regions in the face of COVID-19

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The spread of the COVID-19 pandemic has radically changed our views on regional resilience. This article examines the responses of Russian regional economies to the pandemic, identifying the common features and differences between them.

This study emphasises that regions adapted to the factors of the pandemic in a non-linear manner. Thus, the socio-economic situation in the regions at the beginning of each wave is described by a new data structure. The latter, in its turn, is determined by the adaptation capabilities of the region. An affinity propagation algorithm was employed to cluster these regions. They were then grouped according to their responses to the pandemic.

The results of the analysis showed that regional responses to the pandemic depended on sectoral specialisation, the level of socio-economic development, and the degree of urbanisation. Low-urbanised regions with agro-industrial specialisation demonstrated a higher level of resilience. Innovation-active regions with many external linkages were the most vulnerable to shocks. One of the main conclusions is that economic diversification in the form of 'unconnected diversity' acted as a shock absorber, diminishing the impact of the pandemic.

Keywords:
regional economy,
resilient development,
coronavirus,
cluster analysis

Introduction

Following rapid changes in the socio-economic situation, the notion of resilience has become frequently mentioned in scientific and public discussions (Drobniak 2017). This is due to a set of various external causes (economic, political, environmental, biological, etc.) associated with the spread of the COVID-19 pandemic (Kincses–Tóth 2020, Mitsis 2021, Mitrofanova et al. 2021, Antalóczy et al. 2022, Kapas 2022) that have radically changed our view on regions which were thought to be more resistant to external shocks. At the national level, some regions managed to avoid recessions, while others showed rapid declines in economic activity. The scale of the losses incurred by the regions previously classified as sustainable (according to socio-economic development ratings) requires us to promote a new understanding of regional resilient development during the coronavirus crisis.

Early studies on the impact of the pandemic on regional economies demonstrated a significant difference from traditional economic crises (Howe et al. 2021, Hu et al. 2022). At the same time, some researchers noted that the level of regional resilience is largely determined by the peculiarity of local conditions, as well as the accumulated socio-economic potential (Brada et al. 2021, Ehlert 2021, Barak et al. 2021). In addition, the dynamics of the epidemic situation and the policies implemented by the authorities to limit business and social activity have had a significant impact on the nature of regional economies' responses (Nelson 2021, Nyikos et al. 2021). Thus, resilience indicators differ from region to region. Nevertheless, it seems that regions with similar industry specialisations, degrees of socio-economic development, and socio-demographic features will have similar responses to the factors of the coronavirus crisis. Therefore, the analysis of regional development patterns by identifying similar types of response to external shocks is of great theoretical and practical interest. In particular, it is important to consider the possibility of revealing the specific factors that reinforce regional resilience.

There is a significant lack of empirical research on regional resilience. There is also a demand for analyses of the pandemic's impact on individual regions, which would have to take spatial effects into account. The purpose of this article was thus to study the responses of Russian regional economies to the coronavirus crisis by identifying their common features and differences. In this study, we intended to strengthen the comparative analysis methodology, allowing us to outline the strategies needed to enhance regional resilience.

The remainder of this study is structured as follows. The introduction is followed by a review of current studies on regional resilience. Next, we present a methodology for assessing the response of the Russian regions to pandemic shocks at different stages of the coronavirus crisis. In the next section, using the proposed method, we present the empirical results of our study, namely, how the regional economies of Russia responded to the challenges imposed by the coronavirus crisis. Finally, the conclusions and recommendations for future research are presented.

Literature review

The term 'resilience' is used in many scientific fields to describe the ability of a system to maintain its state in the face of external shocks. For economic systems, the term has gained prominence since regional economies plunged in a 'new reality', accompanied by the economic crisis that began in 2008, the effects of which are still being perceived today.

The concept of resilience in scientific research is ambiguous. This is largely because of the existence of different types of resilience.

Initially, the concept of regional resilience was associated with that of engineering resilience. Engineering resilience implies that the system returns to its initial state after the impact ends.

Within this conceptual framework, regional resilience is understood as the ability of regional economic systems to maintain equilibrium under exogenous shock pressure (McGlade et al. 2012). As Klimanov et al. (2019) note, this model assumes that a crisis displaces the economy from an equilibrium growth path, but some adjusting forces bring it back to its original trajectory. A related concept of resilience suggests that the more resilient an economy is, the less prone it is to changes in the face of various shocks. As an alternative, some authors have noted that the stability of a regional economic system can be expressed in its ability to shift from one state to another, with the latter being more prepared for disruptions and failures (Hill et al. 2008). This interpretation of resilience corresponds to the concept of ecological resilience, which describes a state of affairs in which, as a result of external shocks, the system moves from one equilibrium to another.

However, as Cowell (2013) points out, none of these traditional concepts of resilience are suitable for understanding the specifics of regional responses to external challenges. When regional actors develop responses to emerging shocks, they do not seek to achieve or maintain a new equilibrium. Nor do they strive to return to the previous state, especially if it was initially less desirable. Rather than simply returning to its original state, a resilient system changes in response to new stress. These resilience characteristics define a new type of resilience: adaptive resilience.

In recent years, this type of resilience has been most commonly considered by researchers to characterise different levels of regional vulnerability to stresses and shocks and to explain their respective regional responses. For instance, Martin's (2018) research considers resilience as a non-equilibrium process determined by the ability of market, political, and other institutions not only to withstand or absorb shocks but also to adapt as the regional economy takes a new growth trajectory. Martin sees regional resilience as an endless process of economic evolution.

The key question in the study of regional resilience is as follows: what factors determine why some regional economies are resilient and others are not (Balland et al. 2015). Through attempts to answer this question, the following interrelated viewpoints have emerged that determine the main directions of the research:

– Resilience is shock-oriented. The process of resilience formation is related to the ability of a region to anticipate a shock, prepare for it, and recover with a new and improved growth path after the shock ends (Hassink–Gong 2020).
– The level of regional resilience is largely determined by human factors, social cohesion, and social trust, contributing to the pooling of diverse resources to increase resilience to shocks (Bristow–Healy 2014).
– The level of regional resilience is determined by the nature of shocks and their features (Hu et al. 2022).

The modern concept of resilience is associated with constant development in the face of external perturbations (Martin 2018). Regional resilience is a perpetual process in which economic agents adapt to natural and anthropogenic challenges to ensure sustainable development. Resilience reflects systemic socio-economic opportunities, as well as the ability of a region to mobilise resources to resist the spread of coronavirus in the short term and foster economic recovery in the long term (Hu et al. 2022). However, the level of resilience varies according to the extent to which regional actors learn from their mistakes and achievements, and apply the lessons learned for their adaptation.

There is a discrepancy between the economic consequences of the pandemic and traditional economic crises. Thus, there ought to be different conceptions about what is conducive to building regional resilience. Hu et al. (2022) argued that the nature of COVID-19 gave a particular context to the crisis itself, which should be considered when studying the factors of regional resilience. For example, evidence suggests that highly urbanised regions with broad global supply chain connections showed the highest vulnerability to the coronavirus crisis (Lawreniuk 2020, Turgel et al. 2022). This motivated us to rethink our notion of regional resilience development.

Despite the growing popularity of this imperative, there is ambiguity in the general understanding of regional resilience. There is no uniform approach for assessing it in the form of indicators.

Three main concepts for understanding what factors determine regional resilience can be distinguished:

The first concept focuses on path dependence, which determines the institutions forming in the region, the level of innovation activity, the economic structure, etc. Regional resilience is determined by the level of elasticity of the regional economy, as adaptation is only possible within a specified elasticity threshold (Ibert–Schmidt 2014). The main factors contributing to overcoming the elasticity threshold are considered to be diversification of the economy, the degree of 'connected diversity', a favourable institutional environment, and public policies (Boschma 2015, Tan et al. 2020, Xiao et al. 2018).

The second concept is based on the adaptive process model. According to this concept, resilience potential is formed by accumulated assets and technological innovation. This concept is followed by Martin–Sunley's (2020) study of regional resilience factors. They point out that so-called 'inherited' factors are primarily important for resilience, whereas innovation activity is primarily important for adaptability. Hu–Hassink (2020) also point out that adaptability implies a change in the former actors and resource institutions in the regional economy and can be understood as an innovative action.

The third concept is based on the complexity adaptive system theory of resilience. This concept emphasises the complexity and non-linearity of socio-economic processes. Accordingly, this concept assumes that regional resilience is formed by a set of responses to a wide range of agents (either economic or political) (Chung et al. 2020, Pontarollo–Serpieri 2020). Among the factors determining regional resilience, the authors also include the financial system (Klimanov et al. 2019, Arbolino–Di Caro 2021), industrial structure (Tan et al. 2020), quality of governance (Rios–Gianmoena 2020), level of labour mobility, and geographical location of the region (Diodato–Weterings 2015).

Every empirical study on regional resilience must identify metrics or indicators to assess its level. To date, there is no universally accepted set of indicators.

The assessment of regional resilience is often carried out on the basis of a sole indicator, which mostly reflects the dynamics of economic processes (Giannakis–Bruggeman 2020, Duran–Fratesi 2019, Korolev et al. 2018). GDP (or GRP) and the rate of employment are frequently used as indicators (Di Caro 2015). The appeal of this approach is that it relieves researchers of the need for subsequent aggregation of particular indicators into an integral index. However, in this case, the results of the study largely depend on the indicators chosen for the analysis.

Another common approach is to use a set of indicators, with subsequent reduction to a single sustainability index. Different methods have been proposed for this purpose: calculating the average values of indicators (Rahma et al. 2019), the variance equivalence method (Klimanov et al. 2019), and calculating Mahalanobis distances (Malkina 2020, Gambarov et al. 2017, Stöckl–Hanke 2014).

In addition, there are more complex dynamic models for assessing the stability of socio-economic systems, which involve econometric devices such as vector autoregressive models, etc. (Marasco et al. 2021, Neise et al. 2021, Jomthanachai et al. 2021).

While recognising the importance of these studies for explaining the behaviour of regional economies in the face of external shocks, it should be noted that the proposed models are aimed at solving specific tasks assigned by the authors. There are still not enough studies focusing on the similarities and differences in the responses of regional economies during the coronavirus crisis.

Against this background, our research contributes to the ongoing discussion on the factors of regional resilience. First, we analysed the socio-economic situation in the region. So far, most research has focused on assessing the failures or opportunities for particular sectors of the economy facing external shocks. Second, we focused on the non-linearity of the adaptation process of regional economies during the pandemic. At the beginning of each wave, the economic situation of the regions was described by a unique data structure determined by the regional adaptive capacity. In our opinion, this aspect has not been given much attention in the literature.

Based on the literature review, we decided to use the notion of regional resilience as an adaptive capacity.

The proposed hypothesis implies that the level of regional resilience is reflected by the degree of deviation in key economic indicators from their initial values. By clustering the regions according to the level of variation in the indicators, we can distinguish groups of regions characterised by similar responses to pandemic factors.

Methods

In our study of regional resilience, two key indicators were selected: the industrial production index and retail turnover index.

Our choice can be explained as follows. The industrial production index allows one to characterise regional resilience quite well, as this indicator reflects the magnitude of the spread of crisis phenomena in the economy, leading to structural changes. As Martin et al. (2016) note, one of the fundamental factors shaping regional resilience is the industrial structure. The industrial sector was hit hardest by the COVID-19 pandemic: established supply chains were disrupted, many businesses were forced to reduce production or even completely shut down as a result of the downturn in business activity, and some firms reoriented themselves towards producing goods specifically needed to deal with the pandemic.

Another critical factor in regional resilience is retail trade turnovers. Owing to its structural link to markets for other goods and services, the retail sector is a critical element of the value chain, reflecting, among others, the efficiency of logistics and transport systems. Disruptions in the retail sector have a 'domino effect' on related industries. A study of changes in the retail turnover indicator can also help characterise regional resilience, as adapting to the new demands of a pandemic requires retail turnover stability.

Thus, the selected factors are the most relevant for determining regional resilience, as they set not only the current state of the regional economy but also its capacity for recovery growth.

Clustering of regions according to their level of regional resilience was carried out using the affinity propagation algorithm. Essentially, this algorithm represents a dataset as a network structure. Furthermore, all of the elements of this structure exchange messages with each other about their readiness to become the centre of a potential cluster (Frey–Dueck 2007). After a certain number of iterations or after the boundaries of the clusters stop changing, cluster structures are finally formed around some exemplary points (centres). This algorithm was chosen because, unlike other devices (e.g. the more well-known k-means algorithm), it allows one to find the most similar samples in terms of their features, providing a sufficiently high quality of clustering. At the same time, within each cluster, the most representative sample is defined. In addition, this algorithm makes it possible to use a small dataset when the number of identified clusters is not known in advance and the clusters being formed may differ in size.

The affinity propagation algorithm was applied using the scikit-learn machine learning library (Pedregosa et al. 2011) in the Python programming language. The results were visualised using the Matplotlib library (Hunter 2007). The affinity propagation algorithm has two parameters that determine the result: the damping factor and preference. The first parameter determines the learning rate of the model and is set by default (0.5). The second was set at -2400, because this exact value maximises the explanatory power of the model and does not create too many clusters.

Given that the true clusters were not known, the metrics module of the scikit-learn library was used to assess how well the results corresponded to the data. The silhouette coefficient is a measure of how similar an object in a sample is to other objects in its cluster compared to other clusters (Rousseeuw 1987). For the entire sample, this coefficient is the average of the silhouette coefficients of all objects. This indicator varies from -1 to 1, and the closer it is to one, the better the clustering is. We employed the Euclidean metric as the basis of our calculations. We also checked on an alternative metric, the Davies–Bouldin (1979) index. This index reflects the degree of similarity between clusters, and its minimum value is zero. The closer the index is to zero, the better the data clustering is.

We used the data (the industrial production index and retail turnover index) from the Rosstat publication 'Information for monitoring the socio-economic situation of the constituent entities of the Russian Federation'. All data were structured using an Open Office spreadsheet editor. However, owing to the heterogeneity of the data, we decided to select the months following the entire sample, which corresponded to the onset of particular waves of the pandemic in Russia:

– April 2020 – the beginning of the first wave.
– November 2020 – the beginning of the second wave.
– June 2021 – the beginning of the third wave.
– October 2021 – the beginning of the fourth wave.

The selection of these particular periods is explained by the fact that it is the response to the 'first blow' of the wave that launches the adaptation transformation in the region. The nature of this response determines the trend of changes that arise in the process of adapting the region to the new socio-economic conditions (Albegov et al. 1982). By distinguishing distinct periods in the evolution of the pandemic crisis, we could investigate how quickly regions were recovering after each wave of the pandemic, learning from their experience as a result, which would not be possible if we considered the pandemic as a continuous major shock.

We believed that owing to the non-linearity of regional adaptation to the factors of the pandemic, it was necessary to cluster the regions for each separate stage of the pandemic. The subsequent comparison of the clusters for different waves of the pandemic made it possible to understand how the level of regional resilience changed from one wave to another. The results obtained can shed light on the reasons why these regions showed more or less resistance to the pandemic.

The Russian regions were chosen as the object of this study. However, we excluded all federal cities from the dataset. This was largely motivated by the fact that we considered these regions as integral formations. Thus, our study was conducted using a sample of 79 Russian regions. At the same time, the socio-economic features of Russian regions are distinguished by a high degree of diversity, which makes it possible to identify both regional and national factors of resilient development. The typology of the identified clusters will make it possible to use the positive regional experience of increasing sustainability for other countries and regions under similar conditions.

Research results: Clustering the regions by individual stages of the pandemic

The affinity propagation algorithm identified three clusters of regions for each stage of the pandemic's development in Russia.

At the beginning of the first wave (April 2020), the following clusters were established (Figure A1 in the Appendix):

– The first cluster (blue) is characterised by a moderate decline in industrial production (–6.2%) and more tangible losses in the retail sector (–17.5%).
– The second cluster (green), with a similar decline in industrial production (–5%), is characterised by a stronger contraction in the trade sector (–34.9%).
– The third (red) cluster, more than the two previous ones, felt a loss in the industrial sector (–21.4%), and regarding the dynamics of the decline in retail turnover, it was approximately between the other two (–22.8%).

The silhouette coefficient for this clustering was 0.552. The Davies–Bouldin index was 0.875. Thus, our clusters were well-separated and compact, which demonstrates the effectiveness of the model.

At the beginning of the second wave of the pandemic (November 2020), the following three clusters were established (Figure A2 in the Appendix):

– The first (blue) cluster is characterised by an increase in industrial production (+23%) and a very insignificant drop in trade turnover (–1.1%).
– The second cluster (green) is characterised by a slight increase in industrial production (+1.5%) with a slight drop in trade turnover (–0.7%).
– The third cluster (red) is characterised by a more noticeable decline in industrial production (–8.5%), but the indicator of changes in trade turnover is generally similar to that of the other clusters.

We again used sklearn.metrics to evaluate our model. The silhouette coefficient according to the Euclidean metric was 0.581, and the Davies–Bouldin index was 0.748. Thus, the clustering was in line with the empirical data.

At the beginning of the third wave of the pandemic (June 2021), the following three clusters were obtained (Figure A3 in the Appendix):

– The first cluster (blue) is characterised by a noticeable increase in industrial production and a slight increase in trade turnover (48.5% and 1.4%, respectively).

- The second cluster (green) is distinguished by insignificant growth in both industrial production (+8.3%) and trade turnover (+1.1%), but the retail trade indicator is quite similar to the rest of the clusters.
- The third cluster (red) is characterised by a decline in industrial production (–9.9%) and a very insignificant drop in trade turnover (–0.9%).

The assessment of our model also suggested that the clustering was consistent with the empirical evidence. The silhouette coefficient according to the Euclidean metric was 0.726 and the Davies–Bouldin index was 0.522.

At the beginning of the fourth wave of the pandemic (October 2021), three clusters were obtained (Figure A4 in the Appendix). The silhouette coefficient was 0.629 and the Davies–Bouldin index was 0.566.

All clusters are characterised by the stabilisation of trade turnover, with variance in the growth rates of industrial production:

- The first (blue) cluster features noticeable growth in industrial production (+53.8%).
- The second (green) cluster is characterised by a slight increase in the industrial production index (+13.5%).
- The third cluster (red) is distinguished by a decrease in the industrial production index (–1.3%).

Discussion

According to the Rosstat data, at the beginning of the pandemic, both industrial production and trade turnover indicators significantly decreased in these regions. At the same time, at all stages of the pandemic, the retail trade sector was more sensitive to external shocks than the industrial production sector. The exemplary region with the lowest level of resilience was the Republic of Crimea. The regions in this cluster were characterised by a low level of innovation in manufacturing and a fairly high share of the trade sector in the GRP. These regions were also distinguished by low levels of urbanisation.

A relatively high level of resilience was demonstrated in the agro-industrial regions (southern Russia and the Volga region). At the same time, these regions were characterised by a decrease in retail trade turnover, given its high share in their GRP structure.

In regions with a high degree of economic diversification and a lower population density, the level of resilience appeared to be higher. The most exemplary region in this group was the Smolensk region.

In the second wave of the pandemic, all regions were more resilient to shocks in the retail sector than in the first wave. Retail trade did not grow in any cluster. However, regional industries differed in their sensitivity to the pandemic.

Unexpectedly, regions with low industrial potential and predominant agricultural specialisation showed the greatest resilience in the second wave of the pandemic. An exemplary region of this group was the Republic of Kalmykia. Notably, all regions of the cluster were characterised by rather low indicators of socio-economic development. It can be assumed that the insignificance of their external relations allowed them to quickly reorient themselves to the domestic market. Regions with a high concentration of enterprises actively investing in innovation, which formed the second cluster (such as the Republic of Tatarstan), showed insignificant growth in industrial production. This was due to a gap in the supply chains, which did not allow them to ensure greater industrial growth.

At the beginning of the third wave of the pandemic, more regions consolidated positive adaptation practices and demonstrated growth in both manufacturing and trade. Unexpectedly, significant growth in industrial production was demonstrated by the Republic of Tuva, Republic of Crimea, Primorsky Krai, Yakutia, and Ulyanovsk Oblast. What these regions have in common is the predominantly agrarian specialisation of their economies and low level of urbanisation. At the same time, a significant part of the northern regions, as well as several Caucasian regions, characterised by the lowest socio-economic potential in Russia, continued to stagnate.

At the beginning of the fourth wave, all regions were able to stabilise their development indicators. Regions with agro-industrial specialisation and a relatively low level of urbanisation again demonstrated the greatest resilience.

Thus, the approach of clustering regions according to their responsiveness was effective. We also identified the factors contributing to the level of regional resilience. Based on this analysis, the following conclusions were drawn.

1. When it comes to the impact of the pandemic on regions, there is a significant variance in economic consequences, which depends on sectoral specialisation, the level of socio-economic development, and the level of urbanisation. We believe that, in the early stages of the pandemic, regions with a high concentration of enterprises actively investing in innovation and highly urbanised regions were the most vulnerable. They are characterised by the diversity of economic functioning within territorial clusters and many external linkages. In these regions, the problems of one industry (for instance, a gap in interregional and international supply chains) led to a domino effect in related industries and caused a decline in the growth of industrial production and trade turnover. In addition, a high level of urbanisation contributed to a higher incidence of the disease. Another group of regions that demonstrated a relatively low level of regional resilience was the Siberian regions specialising in the extraction of natural resources with major external supply chains.

2. Agro-industrial regions were more resilient. In our opinion, there are several reasons for this, including 1) working in fresh air limited the disease's spread, 2) the activity of agricultural and agro-industrial enterprises was not suspended during the lockdowns due to its importance for national food security, and 3) localised supply chains and market channels oriented more towards the domestic market.

Conclusions

The scope of this new crisis was unparalleled. Therefore, identifying the common responses of different regions is important for understanding the factors of regional resilience.

To understand regional resilience, our study identified two factors that we believe are the most significant in characterising the adaptive capacity of a region: the industrial production index and the retail trade turnover index. Given that regional resilience is largely determined by the extent to which regions learn from their experience of recovering and preparing for the next wave, we identified four main stages in the development of the pandemic in Russia, corresponding to the beginning of the first, second, third, and fourth waves, covering the years 2020–2021.

Our study of regional resilience was based on cluster analysis. Using the affinity propagation algorithm, we identified clusters of regions with different resilience levels according to the values of the factors selected for analysis for each period under consideration.

Thus, the results of our study showed that regional resilience was highest in agro-industrial regions. However, a number of regions with the lowest socio-economic development demonstrated the least ability to withstand the pandemic crisis. A high level of economic openness had a negative impact on regional resilience, as can be seen in the case of regions with a high concentration of innovation potential. At the same time, the connectivity of sectors within territorial-industrial clusters did not contribute to their ability to withstand external shocks. In this regard, economic diversification (in the form of 'unconnected diversity') contributed to the absorption of the negative impacts of the pandemic in several regions.

Of course, this does not mean that highly urbanised regions, as well as regions that are innovation suppliers, are doomed to lack resilience. However, they showed low levels of regional resilience in the early stages of the pandemic. We argue that the potential for building regional resilience depends largely on the ability of firms and regional public authorities to learn from the pandemic waves. In particular, such lessons learned so far are the following: 1) the so-called unconnected diversity of the economy increases regional resilience, 2) a domestic market orientation improves resilience to shocks, and 3) the use of digital technology enhances adaptive capacity.

In addition, it is important to consider the following major trends that have emerged in the context of the pandemic: the changing structure of consumer demand (personal protective equipment is becoming a priority and interest in healthy lifestyles and improved comfort of living conditions are increasing), the transition of business communications and various forms of leisure activities to the Internet, the increasing popularity of remote jobs, and the development of urban logistics. Obviously, regions should pay attention to these trends in the development of anti-crisis policies as part of their recovery growth.

The results of this study showed that cluster analysis is a valid tool for analysing regional resilience in different regions. Its validity is confirmed by the fact that our findings on the determinants of regional resilience are consistent with the findings of other researchers: the role of linked economic diversity, dependence on global supply chains, trade, etc. Of course, our study has some limitations because we chose a two-parameter model. However, if necessary, the number of investigated parameters can be increased, which will allow us to discover more factors that determine regional sustainability, including region-specific factors. Another limitation of the results is that for the analysis, we used indicators that best reflected the adaptive capacity of the regions for recovery growth. For other types of resilience analysis, different parameters can be applied using our methodology.

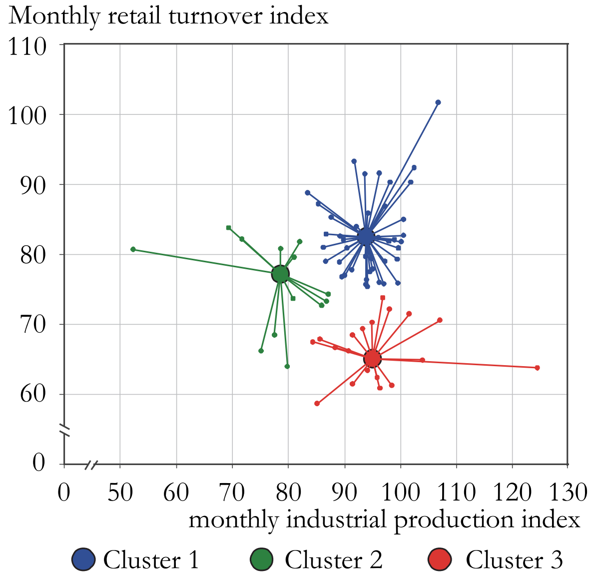
Overall, we believe that we have achieved our research objectives. Conceptually, our study contributes to the literature on regional resilience in the face of the pandemic. This research has produced several implications that may be considered by regional governments interested in adopting policies for economic recovery.

Our hypothesis that the level of regional resilience reflects the degree of deviation of the key indicators of regional socio-economic development from their baseline was confirmed. At the same time, the obtained results set new research objectives related to the study of the extent to which the activities of regional authorities determine the recovery capacity of regions, balancing the economic, social, and environmental objectives of resilient development. This task determines the vector to be used for further research.

Appendix

Figure A1

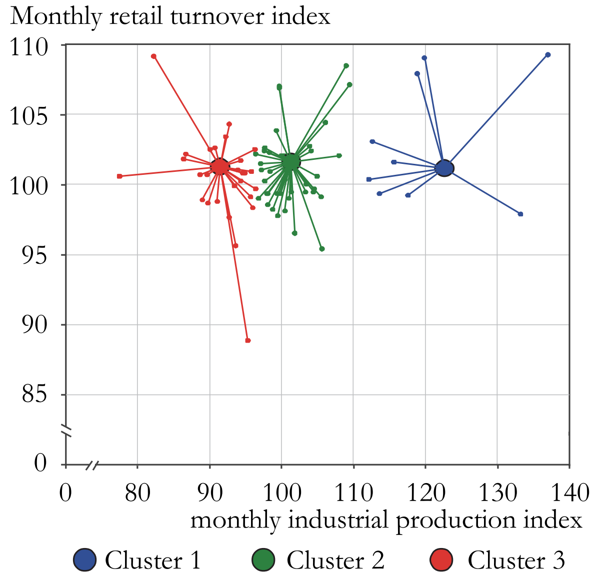
Clustering of Russian regions as of April 2020



Source: Authors' elaboration based on data from Rosstat.

Figure A2

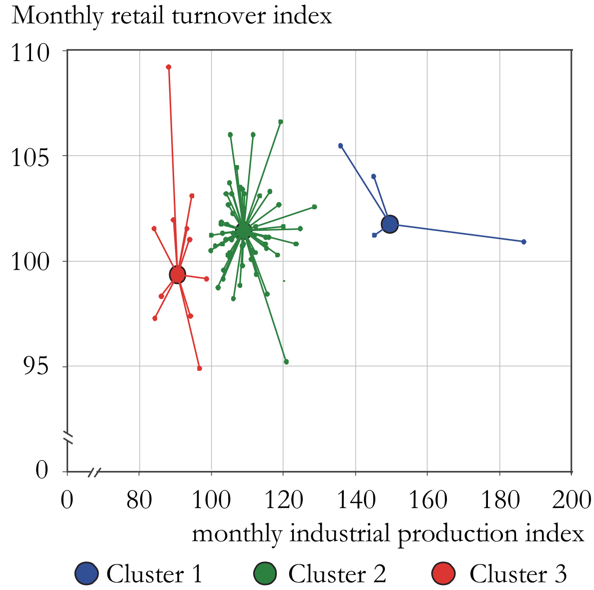
Clustering of Russian regions as of November 2020



Source: Authors' elaboration based on data from Rosstat.

Figure A3

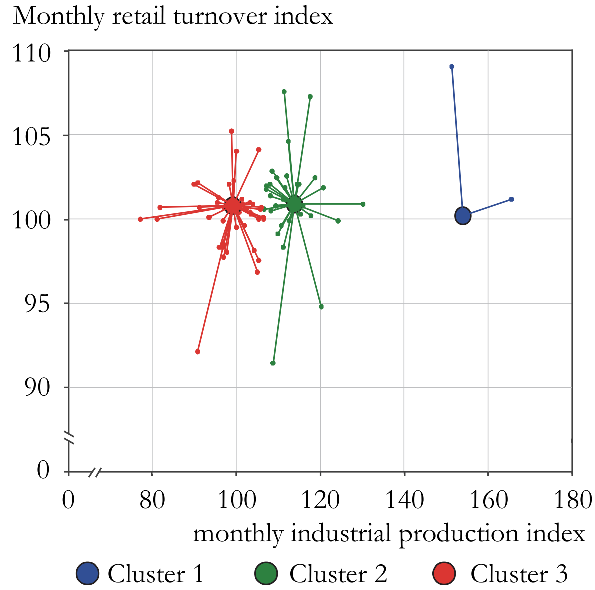
Clustering of Russian regions as of June 2021



Source: Authors' elaboration based on data from Rosstat.

Figure A4

Clustering of Russian regions as of October 2021



Source: Authors' elaboration based on data from Rosstat.

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