

## Original Paper

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## Scenario forecasting of the socio-economic consequences of the COVID-19 pandemic in Russian regions

I.V. Naumov<sup>1,2</sup> ✉, S.S. Krasnykh<sup>1</sup>, Yu.S. Otmakhova<sup>3</sup><sup>1</sup> Institute of Economics of the Ural Branch of Russian Academy of Sciences, Ekaterinburg, Russia; [naumov.iv@uiec.ru](mailto:naumov.iv@uiec.ru)<sup>2</sup> Ural Federal University named after the first President of Russia B. N. Yeltsin, Ekaterinburg, Russia<sup>3</sup> Central Economic and Mathematical Institute of the Russian Academy of Sciences, Moscow, Russia**ABSTRACT**

**Relevance.** There is a perceived lack of methods that can accurately, reliably and comprehensively reflect the epidemiological situation in regions and its impact on their socio-economic development. The approaches that are currently described in research literature do not take into account the multivariate of scenarios of the COVID-19 pandemic, both in time and space.

**Research objective.** The article aims to present a methodological framework that could be used to predict the socio-economic consequences of the COVID-19 pandemic in regions and to detect the most vulnerable regions.

**Data and methods.** The study relies on a set of methods, including the methods of regression modeling, ARIMA forecasting and spatial correlation analysis.

**Results.** The panel regression analysis has confirmed the negative impact of the pandemic on socio-economic development, in particular, the growth of overdue wage arrears, unemployment, arrears, the number of liquidated organizations, and the industrial production index. We have also identified the most vulnerable regions that need to be prioritized for government support.

**Conclusions.** The resulting models and scenarios can be used by policy-makers to set the priorities of state policy for the economic support of the regions and stabilization of the epidemiological situation in the country.

**KEYWORDS**

scenario forecasting, COVID-19, regression analysis, ARIMA forecasting, spatial correlation analysis

**ACKNOWLEDGMENTS**

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**FOR CITATION**

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## Сценарное прогнозирование социально-экономических последствий пандемии COVID-19 в регионах России

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**Актуальность.** Ощущается недостаток методов, способных точно, достоверно и всесторонне отражать эпидемиологическую ситуацию в регионах и ее влияние на их социально-экономическое развитие. Подходы, описанные в настоящее время в научной литературе, не учитывают многовариантность сценариев пандемии COVID-19 как во времени, так и в пространстве.

**Цель исследования.** В статье ставится задача представить методологическую базу, которая может быть использована для прогнозирования социально-экономических последствий пандемии COVID-19 в регионах и выявления наиболее уязвимых регионов.

**Данные и методы.** Исследование опирается на методы регрессионного моделирования, ARIMA-прогнозирования и пространственного корреляционного анализа.

**КЛЮЧЕВЫЕ СЛОВА**

сценарное прогнозирование, COVID-19, регрессионный анализ, ARIMA-прогнозирование, пространственный корреляционный анализ

**БЛАГОДАРНОСТИ**

Исследование выполнено при финансовой поддержке РФФИ в рамках научного проекта № 20-04-60188 «Методы прогнозирования и сценарного моделирования социально-экономических последствий»

**Результаты.** Панельный регрессионный анализ подтвердил негативное влияние пандемии на социально-экономическое развитие, в частности, на динамику индекса промышленного производства, уровня безработицы, просроченной задолженности по выплате заработной платы и числа ликвидированных организаций в регионах России. Мы также определили наиболее уязвимые регионы, которые нуждаются в приоритетной государственной поддержке.

**Выводы.** Полученные модели и сценарии могут быть использованы политиками для определения приоритетов государственной политики по экономической поддержке регионов и стабилизации эпидемиологической ситуации в стране.

от вирусных эпидемий с учетом пространственных и коммуникативных взаимодействий»

#### ДЛЯ ЦИТИРОВАНИЯ

Naumov, I.V., Krasnykh, S.S., & Otmakhova, Yu.S. (2022). Scenario forecasting of the socio-economic consequences of the COVID-19 pandemic in Russian regions. *R-economy*, 8(1), 5–20. doi: 10.15826/recon.2022.8.1.001

## 动态预测新冠疫情 ( COVID-19 ) 对俄罗斯地区社会经济的冲击

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#### 摘要

**现实性:** 现在缺乏能够准确、可靠、全面地反映地区疫情状况及其对社会经济发展影响的研究方法。目前在科学文献中没有考虑到新冠疫情在时间和空间上的多变量动态情景。

**研究目标:** 本文旨在提出一个研究框架, 可用于预测新冠疫情对地区社会经济的冲击。并从而确定受影响最大的地区。

**数据和方法:** 该研究基于回归建模、ARIMA预测和空间相关分析的方法。

**研究结果:** 面板数据回归分析证实了新冠疫情对社会经济发展的负面影响。特别是对俄罗斯地区工业生产指数、失业率、拖欠工资和清算组织数量的动态影响。该研究还确定了需要国家优先支持的最脆弱地区。

**结论:** 政治活动家可以使用该模型来确定国内的一些地区。这些地区可优先获得国家财政支持, 从而稳定流行病期间的社会状况。

#### 关键词

动态预测, COVID-19, 回归分析, ARIMA预测, 空间相关分析

#### 致谢

该研究得到了俄罗斯基础研究基金会的支持(第20-04-60188号赠款“考虑到空间和交流互动的病毒流行的社会经济后果的预测和情景建模方法”)。

#### 供引用

Naumov, I.V., Krasnykh, S.S., & Otmakhova, Yu.S. (2022). Scenario forecasting of the socio-economic consequences of the COVID-19 pandemic in Russian regions. *R-economy*, 8(1), 5–20. doi: 10.15826/recon.2022.8.1.001

### Introduction

The deterioration of the epidemiological situation in Russia caused by the spread of the novel coronavirus infection (Naumov et al., 2021) has spatial heterogeneity. There are poles of growth in the incidence of the COVID-19 (regions with a high concentration of cases), spatial clusters (regions with similar characteristics), and zones of their influence (directions in which the infection is spreading). In other words, the pandemic has affected the socio-economic development of Russian regions differently.

In the light of the above, the research and forecasting of the pandemic's spatial patterns, modeling their impact on socio-economic development

have now become urgent tasks. Such research could provide evidence for policy-makers in setting spatial priorities for the stabilization of the epidemiological situation and in identifying the most vulnerable regions in need of state support.

The purpose of this work is to model and predict the socio-economic consequences of the COVID-19 pandemic in the regions of Russia and to search for spatial priorities of their state support. To achieve them, we set the following tasks: first, to analyze the main methodological approaches to scenario forecasting of the socio-economic consequences of the pandemic; second, to create an approach for scenario forecasting of the pandemic in Russian regions; third, to model

the impact of the pandemic on the indicators of socio-economic development in Russian regions; fourth, to design the most probable basic scenarios of the pandemic in Russian regions and the corresponding forecast scenarios for changing the socio-economic indicators of their development; and, finally, to conduct a spatial analysis of the impact of the pandemic on the socio-economic development of regions and identify the most vulnerable territories.

Thus, our findings could help substantiate the spatial priorities of the state policy to stabilize the epidemiological situation in Russia until 2022.

### Literature review

In the research literature, there are several methodological approaches to predicting the socio-economic consequences of the COVID-19 pandemic in territorial systems of various levels, ranging from municipal to macroeconomic. The most widely used methods include multiple regression on panel data, Box-Jenkins autoregressive moving average models (ARIMA), agent-based modeling, artificial neural networks, SEIR, SIRD and so on. The SEIR and SIRD methods as well as their modified versions were mainly used by Russian researchers to study the localization of the COVID-19 pandemic in Russia (Osipov et al., 2021); to model the impact of the pandemic on household finances (Lebedev & Lebedev, 2021); and to model the spread of the COVID-19 in the Republic of Khakassia (Kozlitin & Shiganov, 2021).

We found that these methods are well suited for predicting the dynamics of the pandemic, but at the same time, they are not sufficient to conduct a full assessment of its impact on the socio-economic development of various territorial systems. Similarly, these methods are not enough to realize the full potential of the scenario approach to forecasting, which implies creating a system of various scenarios to take into account multiple factors.

Agent-based modeling can be used to design various predictive scenarios of the pandemic in different territorial systems and to estimate its socio-economic consequences. This method is suitable for developing a model of a real epidemiological situation in a certain area, taking into account many factors. For example, a team from the Central Economic Mathematical Institute of the Russian Academy of Sciences designed such a model for the municipality of Moscow (Makarov et al., 2020). In this model, human agents pass through

various stages of the disease from infection to recovery or death, and these transitions are modeled not on the group level but on the individual level. This way it is possible to take into account the heterogeneity of the population in terms of the vulnerability to catching coronavirus and the part each individual takes in spreading the disease (Makarov et al., 2020). This model is suitable for creating various predictive scenarios concerning the number of cases and deaths, the date when the peak of the wave is reached, the number of hospital beds needed, including intensive care units in Moscow, taking into account various quarantine measures. However, the model cannot be used to assess the socio-economic consequences of the pandemic in this municipality.

Another study that used agent-based modelling was conducted by Kerr et al. (2021). Their open-source model included the demographic information about age and population size, realistic modes of transmission among the populations including households, schools, workplaces, age-specific incidence rates, dynamics of the spread of the virus, etc. Agent-based modeling is a powerful tool for multivariate scenario modeling and forecasting of the socio-economic consequences of the deteriorating epidemiological situation in territorial systems. However, its main limitation is the need to create a large number of agents that reflect actual socio-economic processes, to construct a complex system of equations describing the influence of various factors on the pandemic in various groups of agents, and its impact on the indicators of the socio-economic development of the given territory. Moreover, such models are not very good at capturing the spatial aspects of the pandemic.

The most popular method of scenario-based forecasting of the impact of the pandemic on the socio-economic development of territories is currently the method of regression analysis. This method was used to form a predictive model for assessing the impact of the COVID-19 pandemic on the economies of some countries in Eastern Europe (Vasileva et al., 2021). The study investigated the impact of the pandemic on the labor productivity index, the growth rate of production and services, the world oil price index, the trade cost index, the growth rate of exports and imports, and other indicators of economic development. As a result, it was predicted that the pandemic would lead to a 6.1% decline in GDP in Eastern Europe by the end of 2020 (Vasileva et al., 2021).



Yiting et al., (2021), using a multiple stepwise linear regression, investigated the impact of the deteriorating epidemiological situation on the indicators of socio-economic development of 39 large cities in China (population size, population density, regional gross domestic product, GDP per capita, number of migrants from rural areas, share of migrants from rural areas, level of urbanization, disposable incomes of the population, number of hospitals and doctors). The authors found that the level of urbanization, socio-economic development, infrastructure, including the urban density, directly affects the number of cases of the coronavirus infection.

Multiple regression analysis was used by Uttrani et al., (2021) to model the impact of the pandemic on global population mobility and mental health. The authors found a significant negative correlation between the reported cases of domestic violence and mobility in the workplace. This indicates an increased level of stress and anxiety in people due to forced isolation during the pandemic.

Regression analysis has also been used to study the impact of the COVID-19 on financial markets in developing countries. The authors confirmed the negative impact of the COVID-19 on the daily market profitability of various sectors of economy, the resilience of the healthcare and banking sector (Rao et al., 2021).

Shimizutani & Yamada (2021), using regression analysis, assessed the impact of the pandemic on food security, financing of basic needs, health care costs, employment, economic and financial well-being of households in Tajikistan.

This tool was also used to assess the impact of the COVID-19 on GDP of developed countries. Yan (2021) studied the impact of the coronavirus on the US economy based on a simple linear regression model. Shanshan et al. (2022) used binary logistic regression to investigate the impact of the COVID-19 on the purchasing power and behavior of consumers and food security in China. This method was also used in (Chan et al., 2021; Ogundokun et al., 2021; Raji, Lakshmi, 2020; Khan et al., 2021).

The main advantage of regression analysis is the ability to establish cause-and-effect relationships between the processes of the pandemic in territorial systems and indicators of their socio-economic development, and to study the factors that are detrimental to the epidemiological situation. Geographically weighted regression modeling can also be applied to take into account

spatial effects when generating data for forecast scenarios.

Regression analysis fully realizes the possibilities of the scenario approach. Moreover, by using regression analysis, we can give due regard to the so-called “controlled variables” in designing predictive scenarios. However, the models built with the help of regression analysis do not always adequately describe the relationship between the processes in question. The relationships between the variables may turn out to be false or change over time, and this requires constant updating and in some cases rebuilding of the regression models.

To assess the impact of the pandemic on the socio-economic development of territories, we also used integrated autoregressive modeling with a moving average according to the Box-Jenkins methodology (ARMA, ARIMA). This method was applied by Davidescu et al. (2021), to predict the unemployment rate, taking into account the dynamics of the incidence of COVID-19. As a result, the authors showed an increase in unemployment in 2020 and predicted its slight decrease until the end of 2023.

Altig et al. (2020) built a regression model to show the uncertainty of the socio-economic development of territories during the pandemic. This method was used to predict the spread of the coronavirus infection in (Ahmar & del Val, 2020; Benvenuto et al., 2020; Bertschinger, 2020; Ding et al., 2020; Kumar et al., 2020; Singh et al., 2020). The main advantage of this forecasting method is that it is easy to use and the resulting data are easy to interpret. The forecasts are sufficiently accurate for the short term if the trends are stable. This method, however, cannot be used to design a system of various scenarios, it is suitable only for building the most probable scenarios (inertial, that is, scenarios assuming that the current trends will continue in the future, extremely pessimistic and optimistic scenarios). The Box-Jenkins models, in contrast to multiple regression, are not suitable for establishing causal relationships between the spread of the infection and indicators of socio-economic development or for studying the spatial characteristics of the epidemiological situation.

The method for predicting the socio-economic consequences of the pandemic that has recently gained popularity is neural network modeling based on a multilayer artificial neural network (MLANN). This method was used by Jena et al. (2021) to study the impact of the COVID-19 on

GDP in developed countries. The authors predicted a decrease in the economic growth rates of eight countries from April to June 2020. Thus, the neural network has proven effective for capturing nonlinearities present in quarterly time series data and for making accurate predictions. The machine learning methods were used in other studies (Gambhir et al., 2020; Majumder et al., 2021; Zoabi et al., 2021; Gavrilov et al., 2021; Kushwaha et al., 2020; Mahdavi et al., 2021). The methods such as ARIMA modeling, however, are capable of predicting with high accuracy the socio-economic consequences of pandemic only in a particular region. These methods cannot identify the spatial patterns of the pandemic but, unlike ARIMA modelling, they can help detect cause-and-effect relationships.

To develop mechanisms for stabilizing the socio-economic situation in regions, a more comprehensive approach is needed that integrates various methods of modeling and forecasting. Such an approach is more suitable for considering the spatial characteristics of the pandemic and for identifying the most vulnerable territories. Thus, not only the most probable basic scenarios can be designed, but a whole system of these scenarios.

## Methodology

As was shown in the previous section, regression analysis is an effective method for predicting the socio-economic consequences of the pandemic. Using the established functional dependencies, this method can be applied to design a system of predictive scenarios, which is why we have chosen it to build the methodological framework of our study.

At the initial stage, we used panel data to assess and build models of the impact of the pandemic on the following socio-economic indicators: the industrial production index, the volume of shipped products, the unemployment rate, overdue wage arrears, the number of liquidated organizations, and the volume of exports of products (see Figure 1 below). The choice of indicators was limited due to the lack of monthly data required for panel regression analysis for 2020 and 2021 in the statistical database of the Federal State Statistics Service.

The regression models using panel data will be used to test the hypothesis about the negative impact of the pandemic on the socio-economic development of the regions. In the process of modeling, we are going to build regressions with

fixed and random effects, assess their adequacy using the Hausman test, Schwarz, Akaike and Hennen-Quinn information tests, analyze the statistical significance of the regression parameters, check the autocorrelation between model errors using the Darbin-Watson test, the normality of the distribution of residuals using the Jarque-Bera test, etc.

The panel data regression models were built with the following variables: the number of cases of coronavirus infection, the industrial production index, the unemployment rate, the volume of overdue wage arrears, the number of liquidated organizations in the regions, and the volume of products shipped. The data were obtained by using the Yandex DataLens service<sup>1</sup> and official statistics from Rosstat<sup>2</sup> for 85 regions of the Russian Federation between March 2020 and August 2021 (1530 observations). Panel models were built using the Gretl software.

The use of panel data in modeling is necessary to take into account space and time as the two key criteria in scenario forecasting to form a significant sample of observations. The models built this way, however, can be used to assess the impact of the pandemic on the economic development of regions in general but they do not reflect the strength of the pandemic's impact on certain regions. Therefore, in order to assess the spatial characteristics of the impact of the pandemic and identify the most vulnerable regions, at the next stage, it is planned to conduct a correlation analysis. The value of the correlation coefficient exceeding 0.7 will indicate a strong negative impact of the pandemic on the socio-economic development of the regions. In addition, it is planned to identify the regions with less significant consequences of the pandemic (with the correlation coefficient ranging from 0.3 to 0.7) and regions that were slightly affected by the pandemic (with the correlation coefficient of less than 0.3). Thus, we will be able to assess and predict the spatial characteristics of the impact of the pandemic and make recommendations concerning the spatial priorities of the state policy.

At the third stage of the study, we will construct regression models of the pandemic's impact on the index of industrial production, the volume of shipped products, the unemployment rate, the

<sup>1</sup> Coronavirus. Dashboard and data / YandexCloud. Retrieved from: <https://cloud.yandex.ru/marketplace/products/yandex/coronavirus-dashboard-and-data>

<sup>2</sup> Operational statistics / Rosstat. Retrieved from: <http://bi.gks.ru/biportal/contourbi.jsp?solution=Dashboard&allsol=1>

amount of arrears on wages, the number of liquidated organizations and the volume of exports in regions with a high correlation. This will help us clarify the models obtained at the first stage and improve their accuracy. This stage is necessary for the construction of scenario and multivariate forecasts of the socio-economic consequences of the pandemic, because panel regression models complicate this process and lead to errors and inaccuracies. The regression models formed at this stage will allow us in the future to design “active” forecast scenarios of changes in the indicators of the socio-economic development of regions, depending on the changes in the dynamics of the COVID-19 morbidity.

To form the basic predictive scenarios of the pandemic in Russia regions, we are going to use integrated autoregressive moving average modeling (ARIMA). This toolkit is suitable for building an accurate inertial forecast, assuming that the trends observed for March 2020-October 2021 will remain stable. We are also going to build two extreme scenarios (optimistic and pessimistic). The assessment of the adequacy of the ARIMA models will be made according to the statistical significance of their parameters, the size of the de-

termination coefficient and information criteria of Akaike, Schwartz, Hennan-Quinn.

The forecasts of the pandemic will be used in the future to design the corresponding forecast scenarios for changes in the socio-economic consequences in the regions according to the models developed at the third stage. For each indicator, we intend to create the most probable inertial scenario, which assumes that the rates of the pandemic will remain stable in the future. We also going to build extreme scenarios (optimistic and pessimistic). The methods of regression analysis and autoregressive modeling by time series (ARIMA) will be applied to design not only basic, but the whole system of different predictive scenarios.

At the final stage, the models will be used to determine the target values of the incidence of coronavirus infection in the regions. After these values are reached, it will be possible to reduce the negative socio-economic consequences.

The proposed approach, in contrast to those currently used, can be applied to systematically assess and predict the socio-economic consequences of pandemic, taking into account the most probable scenarios. The novelty of this approach

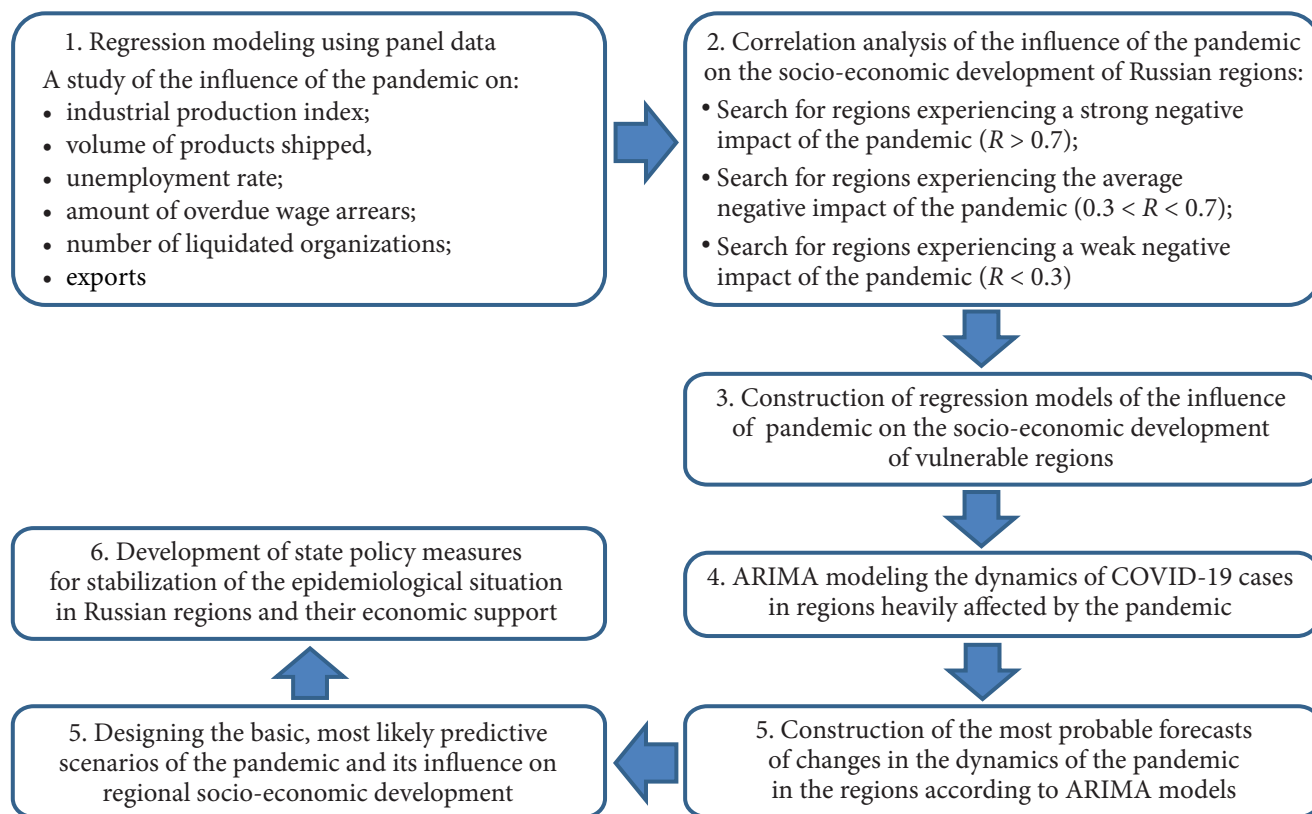


Figure 1. Research methodology  
Source: developed by the authors



lies in the possibility to assess the spatial characteristics of the influence of the pandemic on the socio-economic development of regions by using correlation analysis. By applying this approach, the most vulnerable regions can be identified.

## Results

In accordance with the procedure described above, we built panel regression models of the impact of the number of COVID-19 cases on such indicators as the industrial production index, unemployment rate, overdue wage arrears, the number of liquidated organizations in the regions and the volume of shipped products. We used panel data for 85 Russian regions from March 2020 to August 2021 (1,530 observations). For each indicator, we built three types of models by applying the combined least squares method, with random and fixed effects and assessed their reliability by using the Hausman test and information criteria. As a result, we found the negative impact of the pandemic on the amount of overdue wage arrears (Table 1).

As the regression model shows, an increase in the number of cases in Russian regions leads to an increase in arrears in wage payments. The regression parameters confirming this relationship are statistically significant (regression coefficients have low p-values, less than 5%). The model's reliability is also confirmed by the low values of the information criteria. There is no autocorrelation of residuals and a normal distribution of errors in the model. The model only shows the negative impact of the pandemics on the dynamics of this indicator. For a more detailed study of the spatial

characteristics of this impact, we conducted a correlation analysis (see Fig.2).

We found a close correlation exceeding 0.7 that confirms the strong influence of the pandemic on the growth of overdue wage arrears in Kursk, Tambov, Novgorod, Tyumen, Moscow, Rostov, Lipetsk, Kaliningrad, Krasnodar, Khabarovsk and Stavropol regions, and the Udmurt Republic. The dynamics of overdue debt in these regions may be due to other factors, however. The pandemic had a less significant impact on the growth of arrears in the Republic of Moravia ( $R = 0.68$ ), Crimea (0.61), Nenets Autonomous District (0.54), in Smolensk region (0.35), and in the Republic of Altai (0.32). The dynamics of the incidence of COVID-19 had a weak effect on the indicator under consideration in Oryol (0.27), Amur (0.26), Irkutsk (0.22), Sakhalin (0.1), and Sverdlovsk (0.1) regions. In these regions, other factors contributed to the growth of overdue wage arrears.

To form predictive scenarios concerning the dynamics of overdue wage arrears in regions heavily influenced by COVID-19, we built regression models (see Table 2 below). While according to the results of panel regression analysis, the increase in the incidence of COVID-19 in the regions on average contributed to an increase in overdue debt by 59 rubles, the temporary models built separately for each region showed a more significant increase in this indicator. For example, in Kursk region, an increase in the incidence of coronavirus infection contributed to the growth of the prophesied wage arrears by 1600 rubles; in Khabarovsk region, 1080 rubles; in Tambov

Table 1

Regression model of the dependence of the volume of overdue wages on the number of cases of COVID-19 with fixed effects

|  | Coefficient | Standard error | t-statistic                | P-value      |
|--|-------------|----------------|----------------------------|--------------|
| const  | 20596.7     | 1209.7         | 17.03                      | 1.05e-194*** |
| X1   | 0.059       | 0.012          | 4.87                       | 7.10e-06***  |
| LSDV R-squared   | 0.749       |                | Within R-squared           | 0.015        |
| LSDV F (85, 1359)  | 47.8        |                | P-value (F)                | 0.000        |
| Schwarz criterion  | 33620.3     |                | Akaike Criterion           | 33166.6      |
| Rho parameter  | 0.86        |                | Hennan-Quinn Criterion     | 33335.9      |
| Breusch-Pagan test statistic:  |             |                | LM = 5147,5                | 0.000        |
| Hausman test statistic:  |             |                | H = 9,56                   | 0.0019       |
| Wald test for heteroscedasticity (null hypothesis – observations have total error variance): |             |                | Chi-square (85) = 6,5e+013 | 0.000        |

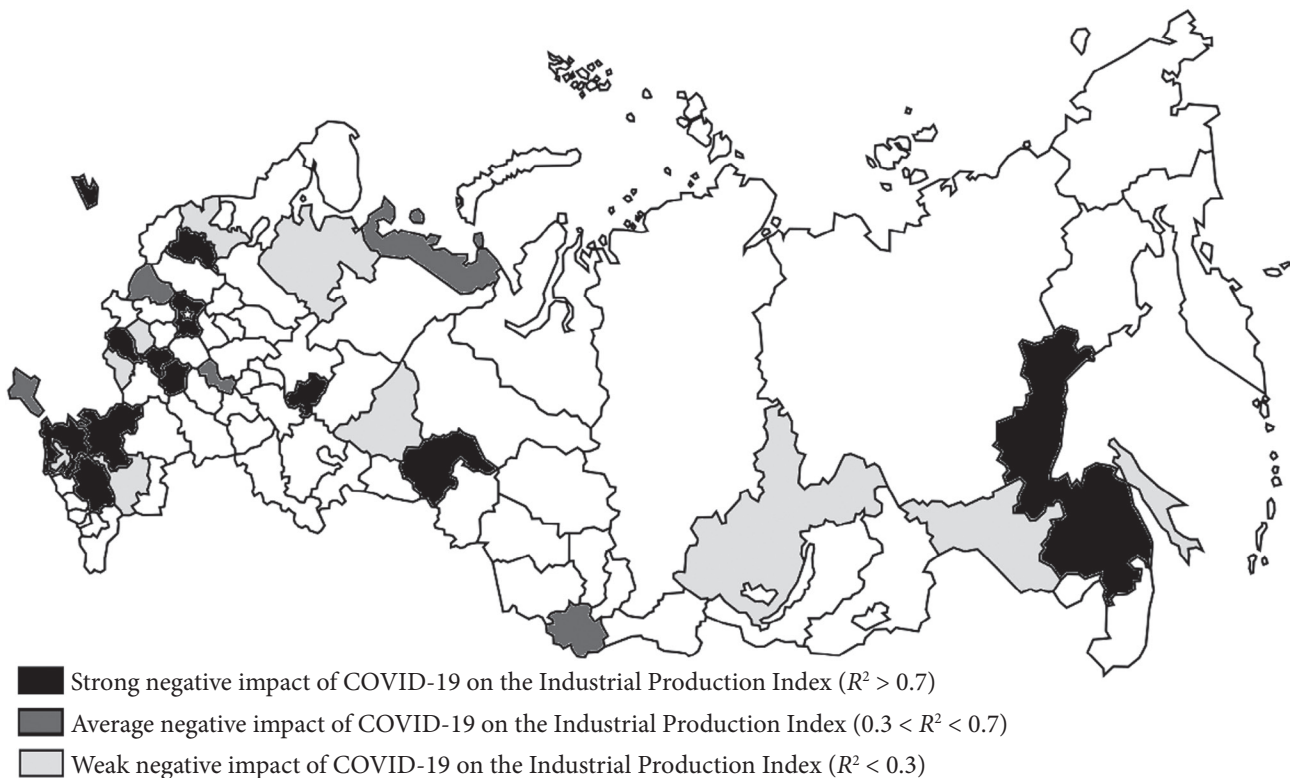
Source: the authors' calculations based on statistical data (Rosstat), indices: Overdue wages, 2021. URL: <https://rosstat.gov.ru/compendium/document/13267>; Yandex Cloud, Coronavirus. Dashboard and data, 2021. URL: <https://cloud.yandex.ru/market-place/products/yandex/coronavirus-dashboard-and-data/> (Accessed: 13.01.2022)

Region, 970 rubles; in Krasnodar region, 670 rubles. The forecast scenarios built on the basis of the regression models and the results of ARIMA modeling indicate a further deterioration in the socio-economic situation of the regions.

The level of overdue debt, according to optimistic forecasts, will be lower than the current value for October 2021, only in a few regions:

Kursk, Novgorod, Moscow, Kaliningrad and Lipetsk. In the rest of the regions, by May 2022, we forecast a significant increase in overdue wage arrears, which will exacerbate the already high level of social tension in the regions.

As a result, we found the negative impact of the pandemic on the unemployment rate in the regions (Table 3).



**Figure 2.** Diagram of the correlation dependence of overdue wage arrears on the number of COVID-19 cases  
 Source: Developed by the authors based on the model

Table 2

**Models of the dependence of the volume of overdue wage arrears on the number of COVID-19 cases and forecast scenarios for this indicator by May 2022, thousand rubles**

|                    | Correlation | Model               | Current value | Forecast scenarios |             |            |
|--------------------|-------------|---------------------|---------------|--------------------|-------------|------------|
|                    |             |                     |               | Inertial           | Pessimistic | Optimistic |
| Kursk region       | 0.94        | $Y = -17113 + 1.6x$ | 85569         | 109099             | 135989      | 82208      |
| Tambov Region      | 0.93        | $Y = 39291 + 0.97x$ | 85087         | 102198             | 113957      | 90441      |
| Novgorod region    | 0.89        | $Y = 820 + 0.31x$   | 15968         | 19396              | 24976       | 13816      |
| Tyumen region      | 0.87        | $Y = -2139 + 0.31x$ | 19182         | 26123              | 31813       | 20433      |
| Moscow region      | 0.86        | $Y = 7456 + 0.24x$  | 128004        | 144392             | 161427      | 127356     |
| Krasnodar region   | 0.85        | $Y = -6250 + 0.67x$ | 47286         | 65197              | 79616       | 50779      |
| Kaliningrad region | 0.85        | $Y = 8326 + 0.14x$  | 17045         | 18480              | 21573       | 15388      |
| Stavropol region   | 0.85        | $Y = 5740 + 0.4x$   | 43818         | 85643              | 116253      | 55034      |
| Khabarovsk region  | 0.74        | $Y = 3938 + 1.08x$  | 103030        | 141826             | 175554      | 108098     |
| Rostov region      | 0.73        | $Y = 5888 + 0.45x$  | 74460         | 98276              | 119390      | 77163      |
| Udmurtia           | 0.70        | $Y = -243.5 + 0.2x$ | 10800         | 18492              | 23239       | 13860      |
| Lipetsk region     | 0.70        | $Y = -933.6 + 0.2x$ | 12941         | 16549              | 21276       | 11822      |

Source: Developed and predicted by the authors based on calculations



Thus, according to the panel regression model with fixed effects, an increase in morbidity per 100 people leads to an increase in the number of unemployed people by an average of 6 people. The correlation analysis showed that the pandemic had the strongest impact on the unemployment rate in Lipetsk region, the Republic of Ingushetia and Dagestan, and the Altai Republic (Figure 3).

The pandemic had a less significant impact on the unemployment rate in Magadan ( $R = 0.68$ ), Astrakhan (0.65), Smolensk (0.64), Novosibirsk (0.57), Moscow (0.48), Nizhny Novgorod (0.43), Tyumen (0.41), Novgorod (0.32), Saratov (0.31) regions, the Altai Republic (0.66), North Ossetia (0.57), Tyva (0.47), Moscow (0.63), the Yamalo-Nenets Autonomous District (0.58), Khan-

Table 3

Regression model of the dependence of the unemployment rate on the number of COVID-19 cases with fixed effects

|   | Coefficient | Standard error | t-statistic               | P-value     |
|---|-------------|----------------|---------------------------|-------------|
| const   | 49196.1     | 295.7          | 166.3                     | 0,000***    |
| X1  | 0.06        | 0.005          | 11.5                      | 2.3e-029*** |
| LSDV R-squared  | 0.95        |                | Within R-squared          | 0.101       |
| LSDV F (865, 1189)  | 300.5       |                | P-value (F)               | 0.000       |
| Schwarz criterion   | 27456.1     |                | Akaike Criterion          | 27013.1     |
| Rho parameter   | 0.84        |                | Hennan-Quinn Criterion    | 27179.5     |
| Breusch-Pagan test statistic:   |             |                | LM = 7020.2               | 0.000       |
| Hausman test statistic:   |             |                | H = 20.3                  | 6.49e-6     |
| Wald test на гетероскедастичность (null hypothesis – observations have total error variance): |             |                | Chi-square (85) = 1.13e+9 | 0.000       |

Source: the authors' calculations based on statistical data (Rosstat), indices: Total number of unemployed, 2021. URL: <https://fedstat.ru/indicator/33414c>; Yandex Cloud, Coronavirus. Dashboard and data, 2021. URL: <https://cloud.yandex.ru/marketplace/products/yandex/coronavirus-dashboard-and-data/> (Accessed: 13.01.2022)

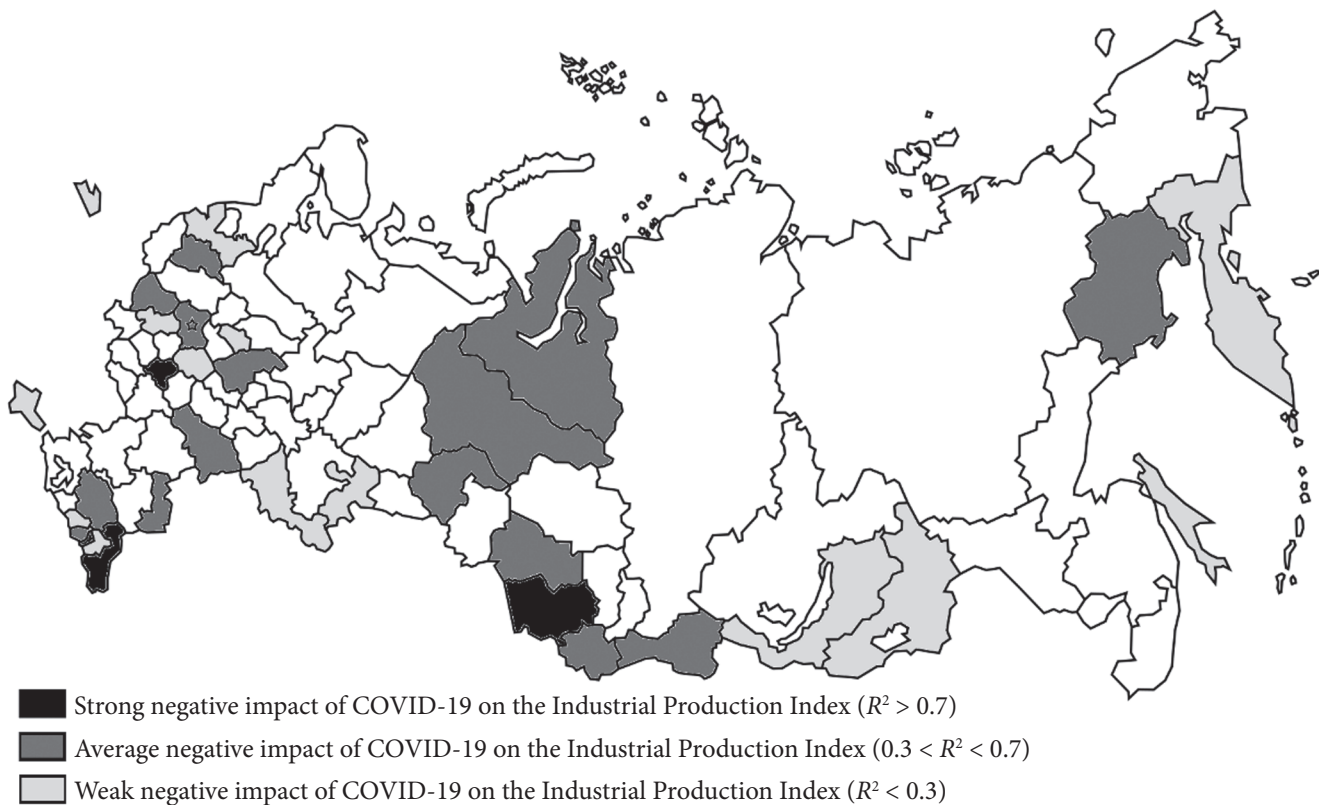


Figure 3. Diagram of the correlation dependence of the unemployment rate on the number of COVID-19 cases in Russian regions

Source: Developed by the authors based on the model

ty-Mansi Autonomous District (0.52) and in Stavropol region (0.38). In other regions, the increase in the unemployment rate is largely caused by other factors that are unrelated to the deterioration of the epidemiological situation. The regression models of the dependence of the indicators on the time series confirmed the significant influence of the pandemic on unemployment in regions with high correlation values (Table 4).

An increase in the number of COVID-19 cases in Dagestan per 100 people provides an increase in the number of unemployed people by 85 people; in Ingushetia, by 79 people; the Altai Republic and Lipetsk region, 15 people. If the growth in morbidity continues by May 2022, the number of unemployed people in Dagestan may increase by 6.6%. In the pessimistic scenario, the number of unemployed people may increase by 9.8%. According to the optimistic scenario, the unemployment rate is expected to exceed the current value in almost all the regions, which signifies serious socio-economic consequences of the pandemic.

We used a regression model with random effects to show the relationship (1) between the industrial production index and the number of cases of COVID-19:

$$IPP = 102,347 + 0.000015 \cdot C \quad (1)$$

where IPP is the industrial production index, %; C is the number of cases of COVID-19 in Russian regions

Although we found a direct relationship between these indicators, the correlation analysis and subsequent regression modeling showed the negative impact of the pandemic in some regions (Figure 4).

According to the correlation diagram, the pandemic has a strong impact on the decline in the industrial production index in Tambov, Sakhalin, Tyumen, Tula, Irkutsk, Voronezh, Sverdlovsk, Volgograd and Amur regions, in the

Kabardino-Balkarian Republic, the Republic of Dagestan, Ingushetia, Karelia, Jewish Autonomous Region, and Chukotka Autonomous District. The correlation coefficient in all of the above regions significantly exceeds the value of 0.7, indicating a close relationship of the indicators (Table 5). These regions faced serious socio-economic consequences of pandemic. For example, an increase in the number of COVID-19 cases per 1,000 people leads to a decrease in the industrial production index by 9.4% in the Chukotka Autonomous District; by 3% in the Jewish Autonomous Region; by 2.1% in the Republic of Ingushetia; and by 1.8 % in the Kabardino-Balkarian Republic. In more resource-rich regions, such as Sverdlovsk and Tyumen regions, the level of decline in the industrial production index is lower. However, there is still evidence of the strong impact of the pandemic on these regions. The regions shown in Table 5 thus should be prioritized for state economic support. The projected forecast scenarios showed that even a significant reduction in the number of COVID-19 cases will not help these regions recover their current level of the industrial production index (as of October 2021) by May 2022.

According to the results of the correlation analysis shown in Figure 4, the pandemic also had a negative impact on industrial production in Arkhangelsk ( $R = -0.62$ ), Vladimir ( $-0.46$ ), Magadan ( $-0.43$ ), Belgorod ( $-0.36$ ), Penza ( $-0.35$ ), Astrakhan and Lipetsk ( $-0.3$ ) regions, Khabarovsk ( $-0.61$ ), Transbaikal ( $-0.39$ ) territories, the Republic of Adygea ( $-0.58$ ), Mordovia ( $-0.56$ ), Chechnya ( $-0.49$ ), Komi ( $-0.4$ ), Altai ( $-0.31$ ), and the Khanty-Mansi Autonomous District ( $-0.38$ ). However, this influence is less significant in comparison with the above considered territories.

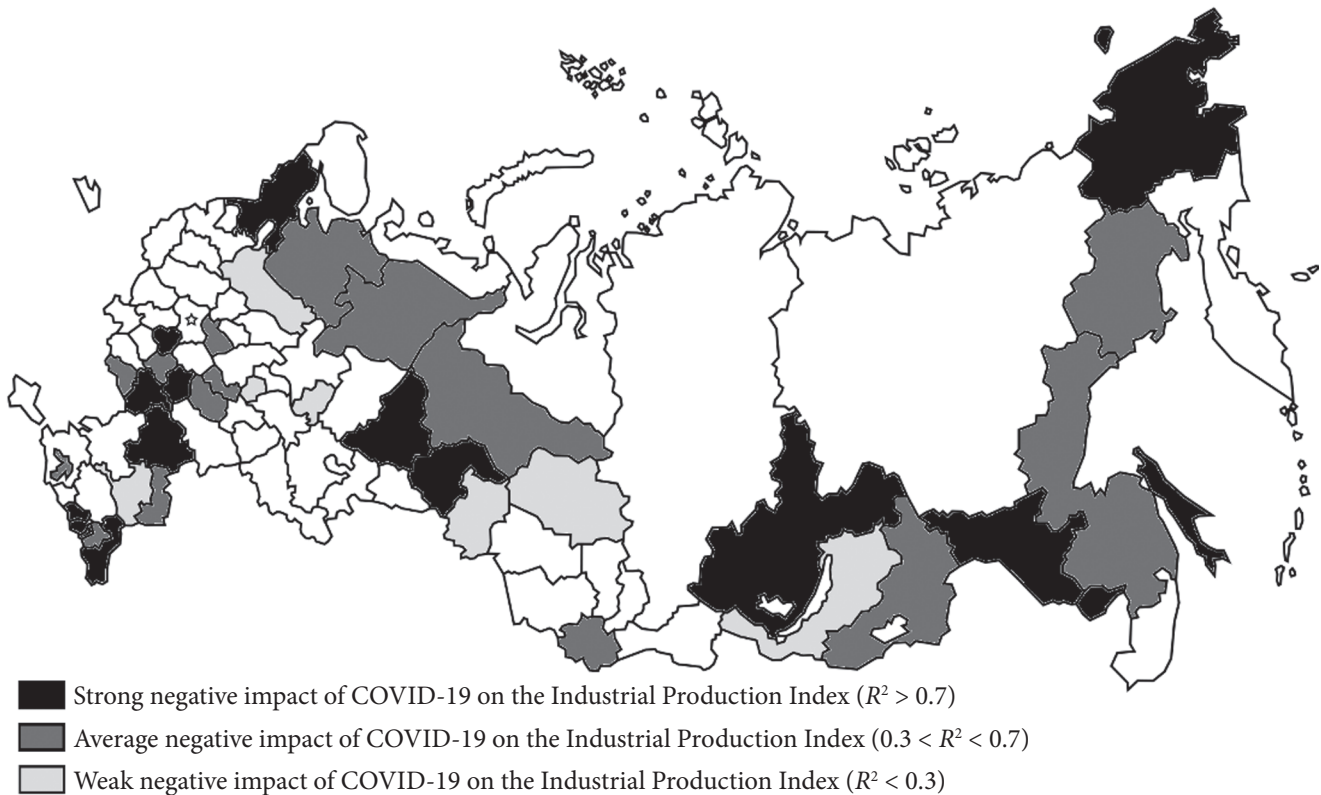
As a result, we showed the negative impact of the pandemic on the number of liquidated organizations (Table 6).

Table 4

**Models of the dependence of the number of unemployed on the number of COVID-19 cases and forecast scenarios for this indicator by May 2022, thousand people**

|                        | Correlation | Model                  | Current value | Forecast scenarios |             |            |
|------------------------|-------------|------------------------|---------------|--------------------|-------------|------------|
|                        |             |                        |               | Inertial           | Pessimistic | Optimistic |
| Republic of Ingushetia | 0.90        | $Y = 73750.8 + 0.789x$ | 89.1          | 94.5               | 98.6        | 90.3       |
| Lipetsk region         | 0.87        | $Y = 24965.6 + 0.146x$ | 33.8          | 36.1               | 39.1        | 33.1       |
| Republic of Dagestan   | 0.84        | $Y = 192682 + 0.853x$  | 236.0         | 251.6              | 259.3       | 243.9      |
| Altai region           | 0.77        | $Y = 63123.5 + 0.154x$ | 76.9          | 80.7               | 84.4        | 77.0       |

Source: Developed and predicted by the authors based on calculations



**Figure 4.** Diagram of the correlation dependence of the industrial production index on the dynamics of COVID-19 cases in Russian regions  
 Source: Developed by the authors based on the model

Table 5

**Models of the dependence of the industrial production index on the number of COVID-19 cases and scenarios for this indicator by May 2022, %**

|                              | Correlation | Model                  | Current value | Forecast scenarios |             |            |
|------------------------------|-------------|------------------------|---------------|--------------------|-------------|------------|
|                              |             |                        |               | Inertial           | Pessimistic | Optimistic |
| Tambov Region                | -0.92       | $Y = 111.8 - 0.0003x$  | 98.2          | 93.0               | 89.5        | 96.6       |
| Sakhalin Region              | -0.96       | $Y = 100.8 - 0.0005x$  | 83.9          | 78.4               | 74.2        | 82.6       |
| Kabardino-Balkar Republic    | -0.96       | $Y = 133.8 - 0.0018x$  | 71.9          | 48.8               | 37.1        | 60.5       |
| Republic of Dagestan         | -0.93       | $Y = 123.1 - 0.00056x$ | 92.3          | 81.4               | 76.0        | 86.8       |
| Tyumen region                | -0.91       | $Y = 136.9 - 0.00069x$ | 89.5          | 74.1               | 61.4        | 86.7       |
| Jewish Autonomous Region     | -0.90       | $Y = 136.9 - 0.003x$   | 81.0          | 73.6               | 54.2        | 93.1       |
| Republic of Ingushetia       | -0.89       | $Y = 121.41 - 0.0021x$ | 72.7          | 59.3               | 46.9        | 71.7       |
| Tula region                  | -0.87       | $Y = 124.7 - 0.0005x$  | 94.8          | 87.0               | 78.1        | 95.9       |
| Chukotka Autonomous District | -0.84       | $Y = 103.3 - 0.0094x$  | 82.0          | 85.4               | 82.5        | 88.3       |
| Irkutsk region               | -0.83       | $Y = 105.1 - 0.00009x$ | 94.4          | 91.5               | 88.8        | 94.2       |
| Republic of Karelia          | -0.80       | $Y = 105.8 - 0.00014x$ | 95.6          | 93.2               | 88.3        | 98.0       |
| Voronezh region              | -0.79       | $Y = 113.2 - 0.00013x$ | 93.8          | 82.8               | 76.5        | 89.1       |
| Sverdlovsk region            | -0.75       | $Y = 104.1 - 0.00007x$ | 93.3          | 91.1               | 89.5        | 92.7       |
| Volgograd region             | -0.68       | $Y = 101.2 - 0.00001x$ | 91.0          | 86.4               | 83.4        | 89.4       |
| Amur region                  | -0.66       | $Y = 102.3 - 0.00024x$ | 93.0          | 89.6               | 85.5        | 93.8       |

Source: Developed and predicted by the authors based on their calculations



According to the regression model with random effects, an increase in the number of cases per 1,000 people on average leads to the liquidation of 6 enterprises. Unfortunately, the correlation analysis has failed to identify the regions where the business bankruptcy rate was seriously affected by the pandemic. As a result, we identi-

fied the territories that are experiencing a medium influence of the pandemic (Stavropol and Kaluga regions and the Nenets Autonomous District) and a weak influence of the pandemic (other regions). Thus, we can conclude that socio-economic factors have a greater impact on the number of liquidated organizations in the regions. The impact of

Table 6

**Regression model of the dependence of the number of liquidated organizations on the number of COVID-19 cases and predictive scenarios for this indicator by May 2022, units**

|  | Coefficient | Standard error | z-score                     | P-value  |
|--|-------------|----------------|-----------------------------|----------|
| const  | 300.86      | 40.37          | 7.45                        | <0.0001  |
| X1   | 0.006       | 0.0004         | 15.97                       | <0.0001  |
| Schwarz criterion                              | 24654.9     |                | Akaike Criterion            | 24644.3  |
| Rho parameter                                  | 0.05        |                | Hennan-Quinn Criterion      | 24648.3  |
| Breusch-Pagan test statistic:                  |             |                | LM = 669.45                 | 1,3e-147 |
| Hausman test statistic:                        |             |                | H = 1895.98                 | 0.000    |
| Wooldridge test for assessing autocorrelation: |             |                | Statistic: F (1, 84) = 6.57 | 0.012    |
| Null hypothesis – normal distribution:         |             |                | Chi-square (2) = 43509.4    | 0.000    |

Source: the authors' calculations based on statistical data (Rosstat), indices: Number of registered and liquidated organizations, 2021. URL: [http://bi.gks.ru/biportal/contourbi.jsp?solution=Dashboard&allsol=1&project=%2FDashboard%2Fcompany\\_statistics/](http://bi.gks.ru/biportal/contourbi.jsp?solution=Dashboard&allsol=1&project=%2FDashboard%2Fcompany_statistics/); Yandex Cloud, Coronavirus. Dashboard and data, 2021. URL: <https://cloud.yandex.ru/marketplace/products/yandex/coronavirus-dashboard-and-data/> (Accessed: 13.01.2022)

Table 7

**Scenarios of changes in the incidence of COVID-19 in regions with serious economic consequences of the pandemic by May 2022, cases**

| Regions                      | Current value | Inertial scenario | Pessimistic scenario | Optimistic scenario |
|------------------------------|---------------|-------------------|----------------------|---------------------|
| Moscow region                | 502,283       | 570,563           | 641,542              | 499,583             |
| Sverdlovsk region            | 153,237       | 185,394           | 207,974              | 162,813             |
| Rostov region                | 152,382       | 205,307           | 252,226              | 158,389             |
| Voronezh region              | 149,620       | 234,070           | 282,385              | 185,756             |
| Irkutsk region               | 119,001       | 151,229           | 181,089              | 121,369             |
| Volgograd region             | 101,459       | 147,260           | 177,127              | 117,393             |
| Stavropol region             | 110,850       | 199,758           | 276,282              | 123,234             |
| Khabarovsk region            | 91,752        | 127,674           | 158,904              | 96,444              |
| Altai region                 | 85,889        | 110,134           | 133,229              | 87,040              |
| Krasnodar region             | 79,905        | 106,638           | 128,158              | 85,117              |
| Republic of Karelia          | 72,745        | 90,390            | 125,076              | 55,703              |
| Tyumen region                | 68,778        | 91,168            | 109,522              | 72,814              |
| Kursk region                 | 64,176        | 78,883            | 95,689               | 62,076              |
| Kaliningrad region           | 62,275        | 72,532            | 94,622               | 50,442              |
| Udmurtia                     | 61,354        | 104,085           | 130,461              | 78,355              |
| Lipetsk region               | 60,324        | 76,011            | 96,562               | 55,459              |
| Tula region                  | 58,695        | 74,061            | 91,478               | 56,645              |
| Republic of Dagestan         | 55,059        | 74,453            | 84,083               | 64,823              |
| Novgorod region              | 48,863        | 59,922            | 77,921               | 41,923              |
| Tambov Region                | 47,212        | 64,853            | 76,975               | 52,732              |
| Amur region                  | 38,800        | 52,979            | 70,240               | 35,717              |
| Sakhalin Region              | 34,415        | 45,715            | 54,247               | 37,184              |
| Kabardino-Balkar Republic    | 34,360        | 47,190            | 53,686               | 40,694              |
| Republic of Ingushetia       | 23,193        | 29,577            | 35,484               | 23,668              |
| Jewish Autonomous Region     | 8,983         | 11,442            | 17,929               | 4,955               |
| Chukotka Autonomous District | 1,847         | 1,903             | 2,207                | 1,598               |

Source: Developed and predicted by the authors based on calculations

the epidemiological situation in the regions is less significant.

Scenario modeling and forecasting of the socio-economic consequences of the pandemic showed that the most vulnerable regions are Moscow, Sverdlovsk, Rostov, Voronezh, Irkutsk, Volgograd, Khabarovsk, Stavropol, Altai, and Krasnodar (see Table 7). Despite the lower number of COVID-19 cases compared to Moscow, Sverdlovsk and other regions, certain regions are strongly affected by the pandemic. These regions include the Republic of Ingushetia, Dagestan, Kabardino-Balkaria, Sakhalin, Amur, Novgorod and Tambov regions, the Jewish Autonomous Region, and the Chukotka Autonomous District.

Correlation analysis confirmed a close relationship between the increase in the incidence of COVID-19 in the regions presented in Table 7 and the decrease in the industrial production index, increase in the number of unemployed people, the volume of overdue wage arrears, and the number of liquidated enterprises. Other regions not presented in Table 7 are less affected by the pandemic. The decline in the indicators of socio-economic development of these regions depends to a greater extent on other factors.

The above findings can be used by policy-makers in developing measures for stabilizing the epidemiological situation and providing support for the most vulnerable regions.

## Conclusion

The proposed methodological approach involves studying the influence of the pandemic on specific indicators of socio-economic development of regions by using panel regression analysis and correlation analysis. The latter is used to assess the tightness of the relationship between these indicators for each region. We have also built regression models to create active predictive scenarios of the pandemic and applied ARIMA forecasting methods to design the most probable (inertial) and extreme scenarios (pessimistic and optimistic).

The panel regression analysis has confirmed the negative impact of the pandemic on socio-economic development, in particular, the growth of overdue wage arrears, unemployment, arrears, the number of liquidated organizations, and the industrial production index. We have also identified the most vulnerable regions with the help of correlation analysis. Scenario modeling and forecasting of the socio-economic consequences of the pandemic showed that the regions that were hit the hardest were Moscow, Sverdlovsk, Rostov, Voronezh, Irkutsk, Volgograd, Khabarovsk, Stavropol, Altai, and Krasnodar. These regions should, in our opinion, be targeted by the state policy for containing the coronavirus pandemic and providing economic support. Our findings can thus be used to develop regulatory tools to minimize the adverse effects of the pandemic on regional development.

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