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RESEARCH ARTICLE

Spread of COVID-19 in the Russian regions in 2020: factors of excess mortality

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Abstract

The paper identifies major factors associated with the pandemic spread in the Russian regions, using econometric models and nonlinear «Random Forest» models to assess their significance. The study is based on data of the Russian regions for March-December 2020, a balanced panel sample included 780 observations. Prevalence of the pandemic was estimated based on the excess mortality rate.

The study has identified a positive relationship between excess mortality and the share of migrants and a negative relationship between excess mortality and the share of pensioners in the region. Importance of climatic factors has been confirmed: high temperatures, other things being equal, reduce excess mortality, while high humidity, on the contrary, increases it. Excess mortality is higher in the regions with lower population mobility. Mortality is higher in the regions with high per capita incomes and regions with significant unemployment. Vice versa, excess mortality is lower in the regions with better doctor and nurse staffing levels.

The study results show that in case of repeated waves of the epidemic or emergence of new viruses, public health policy should be geographically differentiated. Priority should be given to epidemiological situation in the regions with humid climate and low temperatures, high incomes, intensive migration, and high unemployment rates. Significant investments in medical education, higher number of medical specialists and their more even distribution across regions are required. This approach turns out to be more effective in terms of reducing mortality rather than restrictions on population mobility.

Keywords

pandemic; self-isolation; age structure; migration; climate; income; unemployment; healthcare

JEL codes: J11, I12, I18

Introduction

The coronavirus pandemic has been recognized by researchers and politicians as the most important challenge to health systems around the world since the famous «Spanish influenza» in 1918-1920. It had a significant impact on macroeconomic dynamics reducing the growth rate of gross domestic product (GDP), business and household incomes, as well as increasing unemployment in many countries. However, the COVID-19-associated consequences for modern societies should be assessed in terms of lost lives. According to Johns Hopkins Institute[1], as of early May 2022, the pandemic has claimed over 6 million human lives. More than 500 million people worldwide have had the disease (and these are only registered cases). It is not surprising that such a large-scale social phenomenon has become the subject of research by scientists in various fields of science. Hundreds of articles – not counting preprints – have already been published by physicians, demographers, sociologists, mathematicians, economists, specialists in public administration and public health. However, interest in the pandemic is not waning, and the reasons are obvious. First, the virus, although becoming less dangerous, can persist for many years according to experts, and new dangerous infections may appear, and mankind should be ready for such situation. Second, over two years, extensive information has been gradually accumulated making it possible to formally analyze various aspects of morbidity, which used to be almost impossible at the beginning of the pandemic.

In particular, this applies to papers on factors of morbidity or mortality from COVID-19. Early studies in 2020 were mainly based on small samples, used a descriptive approach or studied influence of a small number of factors, leaving aside other possible determinants. Authors of later papers, relying on a rather long series of monthly or daily data on countries or regions of one country, could use regression analysis and nonlinear machine learning models to receive more reliable findings. However, until now, numerous studies have received contradictory results regarding individual factors that affect (or do not affect) morbidity or mortality from COVID-19. Therefore, studying determinants of the pandemic's spread is still relevant, especially in Russia, where only few studies using modern modeling techniques and data for a sufficiently long period have been published so far. The purpose of this study is to identify and evaluate relationship between individual factors and spread of the pandemic in the Russian regions in 2020.

1. What is behind the COVID-19 spread: overview of studies

Migration. The earliest studies conducted in spring, 2020, already showed that the epidemic was initially spreading across regions of individual countries from a large economic center. For example, in Italy, Milano was the epicenter of the infection, which is considered the country's economic capital, and therefore, is the main direction of internal migration. Introduction of lockdown has initiated the process of reverse migration: people who came to Milano to work and study returned home. The majority of internal migrants come from the neighboring regions, and those becoming leaders in the number of COVID-10 cases after Lombardia (Mikhailova and Valsecchi 2020). Moscow, similar to Milano in Italy, is the economic center of Russia, where people come to study

1 https://coronavirus.jhu.edu/ accessed: May,22, 2022.

or in search of a well-paid job. Introduction of lockdown has made many migrants immediately return home to the neighboring regions, which, as a result, had no time to get prepared for the pandemic. Regions located far from Moscow, from which less people come to the capital, had more time to get prepared (Mikhailova and Valsecchi 2020). In Brazil, it is San Paulo, the economic center, that has become the source of the epidemic spread in the country (Nakada and Urban 2021). In the United States, at the early stages of the spread of the virus, influence of population mobility on morbidity and mortality is most clearly traced in the developed cities of the East Coast – New York, Boston and Philadelphia (Glaeser et al. 2020).

Population density and urbanization. A distinctive feature of economic centers is high population density, which, according to conclusions of many studies, is positively associated with the spread of infection. Such results were obtained, in particular, in Brazil (Nakada and Urban 2021), France (Pascoal and Rocha 2022), Iran (Ahmadi et al. 2020), and Turkey (Şahin 2020). However, a study conducted in the U.S. at the regional level shows that population density is not associated with the number of deaths due to the pandemic. The authors explain this result by the fact that in rich regions with a high density of settlement, population has a quicker access to better quality medical services. At the same time, it is worth distinguishing countries by income level. In poor countries, urban agglomerations with high population density are characterized by close informal ties of residents, making social distancing difficult (Hamidi et al. 2020). In addition to population density, researchers use the indicator of the share or number of people living in large cities that shows an average frequency of social contacts in the region – it turns out to be positively associated with morbidity and excess mortality (Ivanov 2020; Zemtsov and Baburin 2020; Kolosnitsyna and Chubarov 2021). However, a study by Pilyasov et al. based on data from the Russian regions failed to reveal any significant relationship between spread of the coronavirus and population density and the level of urbanization (Pilyasov et al. 2021). Another study on the structure of excess mortality in Russia in 2020 demonstrated a faster increase in mortality among urban residents compared to rural residents (Sabgaida 2021). Likewise, a study conducted by Druzhinin and Molchanova (2021) shows a significant positive relationship between increased mortality in the Russian regions in 2020 and the share of urban population.

Population age structure. Since the beginning of the pandemic, the elderly has been declared the most vulnerable group. Indeed, in many countries there was a high mortality rate among the elderly associated, in particular, with concomitant diseases: diabetes, cardiovascular diseases, asthma, cancer, etc. (Singh et al. 2021). In some countries, high mortality rates were mainly due to institutionalization of the elderly, as, for example, in Italy, where infection occurred in nursing homes. In addition, researchers note the fact that older people are tested more often, and therefore the disease is detected more often, thus the registered incidence rate in this group may be overestimated (Danilova 2020). At the same time, both theoretical models of the infection transmission (Kalinin et al. 2020) and empirical studies (Goroshko and Patsala 2021; Zemtsov and Baburin 2020) prove that morbidity and, therefore, mortality among the elderly is lower compared to young people, in particular, because older people have a more responsible attitude towards their health, have fewer social contacts (do not work, do not travel daily by public transport during rush hours) and voluntarily comply with all prohibitions and restrictions, sometimes even after they are officially cancelled. The study conducted by Druzhinin and Molchanova based on the 2020 data of the Russian regions, shows that the share of pensioners turned out to be an insignificant factor in assessing increase in mortality (Druzhinin and Molchanova 2021).

Climatic factors can also influence spread of infections. Both individual countries and regions of large countries (including Russia) significantly differ in climatic characteristics. In literature a special attention is paid to temperature and relative humidity among all climatic factors, because they protect the human respiratory tract from infectious diseases (Lowen and Steel 2014; Mecenas et al. 2020). It is proved that there is a negative relationship between air temperature and rates of spread of the coronavirus infection, that is, the higher the temperature, the lower the rate. Impact of relative humidity is dependable upon temperature. If high temperatures prevail in a country/region, then high air humidity reduces rates of the virus spread (De Angelis et al. 2021; Sun et al. 2021). At low temperatures, on the contrary, high air humidity increases rates of the infection spread (Lin et al. 2020). Thus, a significant relationship between climatic factors and spread of the coronavirus infection has been shown using the statistical method of «random forest» on the basis of the Russian regional data (Pramanik et al. 2022). At the same time, results of the study conducted by Sabgaida and Zubko on the basis of data on the 2020 two coldest months– November and December – show that low temperatures contribute to decreased transmission of the SARS-COV-2 virus (Sabgaida and Zubko 2021).

Prevalence of urban vegetation is also an important environmental factor. Using the method of "path analysis", it was proved that a 1% increase in green space in the city reduces spread of the coronavirus infection by 2.6%, other things being equal (You and Pan 2020). Urban greening helps to fight many other challenges of the XXI century rather than the coronavirus infection alone. Urban greening has several impact vectors. First, it improves the air quality, which leaves much to be desired in modern megacities. Second, green spaces produce a positive effect on emotional state of people, improving mental health (Hartig and Kahn 2016).

Political factors are numerous. First of all, these are the measures that governments are taking to curb spread of infection: from soft recommendations to complete lockdowns. The U.S. regional data show that actions aimed at reducing the COVID-19 spread are effective, both at the federal and regional levels (White and Hébert-Dufresne 2020). Not only decisions themselves are important, the speed of their adoption matters as well: in the United States, a two-day delay in introducing restrictions in the state increased the number of the infected by 20% (Adolph et al. 2021). In the UK, immediate introduction of social distancing standards in March 2020 made it possible to reduce the infection rate 4 times (Jarvis et al. 2021).

Both rigidity of the measures taken and severity of the punishment for non-compliance play a significant role. Initially, it was assumed that the stricter the measures, the slower the spread. However, the example of Sweden, where maintaining of social distancing was only advisory in nature from the very beginning of the pandemic, showed that this is not necessarily the case (Adolph et al. 2021). Perhaps the reason is a negative psychological perception of strict restrictions. That is why an important factor is a level of public confidence in government and willingness to follow its decisions (Lewnard and Lo 2020). After all, it is clear that the spread of infection is influenced by actual behavior of people, which does not necessarily follow the established norms. In turn, compliance with the established measures can be accounted for by both a sense of social responsibility and fear of getting sick (Maloney and Taskin 2020). Therefore, during a sharp rise in morbidity, restrictions will be better respected compared with periods of decline.

A large-scale testing program is no less important: according to many researchers, countries that have initiated testing from the very beginning of the pandemic managed to better cope with the epidemic (Brotherhood et al. 2020). Intensive testing can minimize population loss due to the pandemic, as well as ensure isolation and timely treatment of the infected, slowing down the infection spread and reducing deaths, therefore, it is a close replacement for lockdowns (Wells et al. 2021). However, there are studies that fail to find any significant relationship between lockdowns, border closure or testing programs and mortality from COVID-19 (Chaudhry et al. 2020).

Directly or indirectly, *economic factors* influence the coronavirus infection spread. The more severe restrictive measures, the harder economic consequences for people, therefore, only a rather well-off population can afford to comply with self-isolation. In the U.S., a relatively high mobility was registered in poorer areas of the country. This is due to the fact that the poor population was forced, despite the lockdown, to go to work to cover their basic needs (Khalatbari-Soltani et al. 2020). A similar relationship was found in the Russian municipalities – mobility was higher where wages were lower (Dokhov and Topnikov 2021). In the UK, in poor areas the COVID-associated mortality was twice as high as in rich areas (Caul 2020). There are several explanations to the relationship between poverty and the COVID-associated morbidity and mortality. First, the poorer population is mainly involved in low-skilled work that cannot be done remotely. In addition, the low-income population travels by public transport, where more social contacts occur (Rachele et al. 2015). Poor areas are characterized by higher population density, making social distancing more difficult. A study based on the German data collected during the first wave of the pandemic proved significance of low-skilled employment as a proxy variable of poverty (Ettensperger 2021).

A study conducted in Mexico showed that the probability of dying from infection for the lower income decile population is 5 times higher compared to people from the upper decile (Arceo-Gomez et al. 2022). Many studies show that unemployment rates are positively associated with mortality from the coronavirus infection rather than the poverty level alone (Sun et al. 2021). However, there are studies with the opposite findings. For example, a positive relationship has been identified between GDP per capita and the COVID-associated mortality per 100 000 population at the macro level for 50 countries (Chaudhry et al. 2020).

A study conducted by Druzhinin and Molchanova (2021) povides estimation of the mortality growth regression in the Russian regions in 2020 wich showed insignificance of income variables. A study by Pilyasov et al. (2021) assessing excess mortality in Russia, showed that per-capita income variable turned out to be insignificant either. Zemtsov and Baburin, on the contrary, register a higher disease incidence in rich regions, explaining this by the fact that population of rich regions travels more and has better opportunities for diagnosing the disease (Zemtsov and Baburin 2020).

Finally, factors of the *health system* are of particular note. It is only logical to assume that better resource provision, including human, material, and financial, other things being equal, should at least reduce mortality, if not the disease incidence itself. However, in the first months of the pandemic, both morbidity and mortality grew at a catastrophic rate in rich countries with the developed and modern health systems. And vice versa, China, a relatively poor country with less medical resources, has quickly and effectively suppressed the first wave of the epidemic. This means that availability of medical services alone does not solve the problem if other necessary anti-infection policy measures are missing. Attempts to identify impact of health indicators on spread of the epidemic face an obvious challenge of endogeneity: increased disease incidence in many countries or regions made the authorities quickly respond to the deteriorated situation and expand capacity of medical institutions, increasing funding. Therefore, for example, such indicator as relative number of hospital beds increased following the increased number of patients. It is not surprising that in Italy, which was most affected at the beginning of the pandemic, a positive relationship between the number of hospital beds in provinces and both COVID-19 incidence and mortality was identified (De Angelis et al. 2021). Only the indicator of relative number of doctors (which cannot be quickly increased) turned out to be associated with excess mortality in the «right» way: in the Italian regions with high number of doctors, mortality significantly decreased (Buja et al. 2022). A study conducted for all countries of the European Union showed insignificance of such factor as the number of hospital beds, while relative number of doctors in the country reduced mortality from coronavirus infection (Cifuentes-Faura 2021). Studies based on the Russian data failed to find any significant relationship between morbidity and the number of hospital beds in the region (Zemtsov and Baburin 2020) but do confirm a negative relationship between mortality and relative number of doctors and nurses (Stepanov 2020).

As review of studies shows, factors of the coronavirus infection spread are numerous and diverse in their effect, but in general they can be grouped into the following five main groups:

- *demographic* (population age composition, migration, population density, urbanization);
- *environmental factors* (temperature, humidity, urban greening);
- *political factors* (state actions – restrictive policy measures and degree of compliance with them, testing programs, subsequently – vaccination);
- *economic factors* (income level, poverty, inequality, housing conditions, employment specifics, unemployment);
- *characteristics of the health system* (availability of material and human resources, financing).

In this study, we will try to assess the relationship between all groups of factors and the coronavirus infection spread in the Russian regions in 2020 using econometric modeling and construction of nonlinear models.

2. Empirical analysis of factors of changes in excess mortality in the Russian regions during the pandemic

2.1 Data

The study uses data of the Federal State Statistics Service of the Russian Federation (Rosstat) (https://rosstat.gov.ru/). The sample included data on 82 regions of Russia, including the Tyumen and Arkhangelsk regions, without distinguishing districts. The observation period is limited to 10 months from March to December 2020, that is, from the beginning of the epidemic up to the initiation of mass vaccination in the country. In addition to Rosstat data, the study used information from Yandex's public data visualization and analysis service, Yandex DataLens[1], and Weather Archive website[2].

1 Yandex DataLens URL: https://cloud.yandex.ru/services/datalens

2 Weather Archive URL: http://weatherarchive.ru/

2.2 Variables

The indicator of excess mortality per 100 000 population in the region – excess mortality – was used as a dependent variable in the construction of models. Following the majority of researchers, we have deliberately refrained from using the indicators of morbidity and/or mortality from COVID-19 provided by official statistics.

Already in early stages of the pandemic, experts pointed out obvious advantages of using excess mortality rate as the most objective indicator for comparisons (Leon et al. 2020). Indeed, morbidity statistics have an obvious drawback: the registered number of cases significantly depends upon intensity of testing, which may vary by country/region of one country / time periods. They more often test vulnerable groups, for example, the elderly, which can distort the detected morbidity structure (Danilova 2020). Many people get sick asymptomatically, the share of undetected cases is not known exactly and depends, in turn, upon availability of medical services. In addition, different criteria for determining COVID-19 as the official cause of death can be used (Ivanov 2020). It is also important that the coronavirus infection increases the likelihood of death from other diseases, acting as an indirect cause of death. Excess mortality is an excess of the actual mortality rate over the expected one, therefore it includes both official mortality from COVID-19 and unregistered cases as well as cases that are indirectly accounted for by the pandemic. Estimates of excess mortality over the two years of the pandemic, from January 1, 2020 to December 31, 2021, conducted by specialists in 191 countries, showed that excess mortality exceeds the official COVID-19 mortality rates more than three times (COVID-19 Excess Mortality Collaborators 2022).

There are different ways of evaluating excess mortality. This article used the following approach: first, the indicator of relative (per 100 000 population) mortality in each region was calculated for each month of each year – from 2017 to 2019. Then, for each region, a three-year average relative mortality for each month was calculated. Further, for each region, the average relative mortality in the same month in 2017-2019 was subtracted from the relative mortality for each month (from March to December) in 2020. Thus, we have obtained excess mortality for each region of Russia for every month in 2020:

$$EM_{ij2020} = M_{ij2020} - \sum_{t=2017}^{2019} \frac{M_{ijt}}{3}, \tag{1}$$

M – actual deaths;
EM – excess mortality;
i – region index;
j – month index;
t – year index, *t* = 2017-2019.

In some papers, only the previous year 2019 is used as a basis for comparison (Druzhinin and Molchanova 2021), however, this method seems inaccurate, because random fluctuations in mortality can be observed in one individual year. Using the average for several years as a basis makes it possible to even out such fluctuations. In their study, Goroshko and Patsala use the average indicator for 5 years as a basis (Goroshko and Patsala 2021), however, in recent years mortality in Russia has been significantly reducing, in particular, due to cardiovascular component, so the average for 5 years can turn out to be higher than the 2020 actual indicators. Even using a three-year average as a basis, we have identified some negative values in monthly indicators of excess mortality by region. Since the linear-logarithmic form of the mortality function will be used later in the study, the variable of excess mortality per 100 000 population was transformed by adding to all its values a constant equal to the sum of the modulus of the highest negative value and figure of one.

Independent variables for modeling were selected in accordance with the groups of morbidity and mortality factors identified above (Table 1). To take into account *demographic factors*, the following three variables were used: the number of pensioners per 100 000 population, the share of internal migrants calculated as net in-migration per 100 000 population, and the share of population living in the capital of the subject of the Russian Federation and other cities with population over 300 000 people. A pensioner is a citizen of the Russian Federation who has realized the right to receive a pension.

The share of pensioners reflects, first, the age structure of the region, and second, what is important for this study, roughly shows the share of the non-employed elderly. Indicator of the number of pensioners per 100 000 population is available on a quarterly basis.

Table 1. Variables used in modeling

Name	Description	Measurement and frequency of observations
	Dependent variable	
excess mortality	excess mortality	people, per 100 000 population of the region; monthly measurements
	Independent variables	
	Demographic factors:	
pensioners	share of pensioners	people per 100 000 population of the region; quarterly data
migrant	share of internal migrants	people per 100 000 population of the region; monthly data
capital	share of population residing in big cities	share of population living in the capital of the Russian subject and cities with population over 300 000 people, %; annual data
	Environmental factors:	
temp	average air temperature	°C; monthly data
humidity	relative air humidity	%; monthly data
plants	urban greening	share of green spaces within the city limits per 1 hectare, %; annual data
	Political factors:	
self.isolation.aver	self-isolation index	from 1 to 5; monthly data
	Economic factors:	
income	per capita monetary income	in Russian rubles, in prices as of December, 2020; monthly data
flat	total residential premises per inhabitant	m^2; annual data
unemployment	unemployment rate	share of the unemployed in the workforce, %; monthly data
	Health system factors:	
medicine	number of doctors and nurses	people, per 10 000 population; annual data

The number of internal migrants was calculated as the sum of the number of interregional and intraregional migrants, this indicator is available by month. Indicator of the share of population living in the capital of the subject of the Russian Federation and other cities with population over 300 000 people was manually calculated for each region as the sum of the number of all residents living in large cities of the region, attributed to the population of the region. This is an annual indicator.

To assess *environmental factors*, the following variables were used: average temperature and relative air humidity, and the share of green spaces within the city limits per 1 hectare. Data on average temperatures and humidity were taken for each region by month from WeatherArchive website. In winter months, the average temperature in most regions is below zero, therefore, to meet purposes of further logarithmation, the indicator had to be converted. A constant was added to each observation equal to the sum of the modulus of the highest negative value (-37.3 in December 2020 in the Republic of Sakha (Yakutia)) and figure of one. In order to obtain the share of green spaces within the city limits per 1 hectare, for each region, indicator of the total area of green spaces within the city limits was divided by the total area of urban land within the city limits.

Political factors are presented in the analysis as Yandex self-isolation index variable. Self-isolation of population is one of the major non-medical measures to control spread of the epidemic. In order to measure severity of the applied policy, researchers use various indicators. Some of them collect official data on all measures introduced or canceled and compile integral indexes for individual regions of the country or entire countries. This principle is used, in particular, to construct a well-known OxCGRT Severity Index (Oxford Coronavirus Government Response Tracker). Others use population geolocation indicators, which are usually collected by cameramen and other specialized companies, for example, Google Mobility in the U.S. or Baidu Maps in China (Brodeur et al. 2021). In Russia, to assess mobility of population, Yandex self-isolation index has been developed – an integral indicator that is calculated daily based on data on the use of various Yandex applications and services from the very first days of the epidemic. It compares the level of urban activity on a particular day and a regular day before the epidemic. If the activity level is the same as during rush hours of a regular weekday, it means that the self—isolation index is low, 0 point. If the city is quiet as at night, the index equals to 5 points.

Naturally, the Yandex index shows how the anti-infection measures are actually implemented rather than a formal set of anti-infection measures in effect in the region. In this sense, it can be considered as a proxy variable of the measures applied, adjusted for “compliance” of the population. At the same time, it is precisely this approach to taking into account policy measures that seems to be correct – after all, it is actual mobility that affects morbidity/mortality rather than decrees of the governor or resolutions of Rospotrebnadzor (Federal Service for the Oversight of Consumer Protection and Welfare). And vice versa, integral indices compiled on the basis of a set of measures taken require adjustments to the level of their implementation. The Yandex index has already been used in studies on prevalence of COVID-19 on the basis of the Russian data (Dokhov and Topnikov 2021; Egorov et al. 2021).

Yandex website only presents graphical distribution of the index by day and city, its quantitative values by region are not publicly available. To receive quantitative data, the authors requested the Research Department of Yandex LLC on an individual basis. Since this is a daily index, its monthly average for each month was calculated for each region.

Population per capita monetary income, total average area of residential premises per inhabitant, and unemployment among population aged 15 years and older were used as *economic indicators*. Monthly per capita monetary incomes were adjusted to constant prices in December 2020 using the basic consumer price index (CPI) for goods and services of the Federal State Statistics Service. Rosstat data on the total average area of residential premises per inhabitant of the region are available by month. Data on the unemployment rate among population aged 15 and older are available on a monthly basis.

Of all factors characterizing the *health system*, the study uses the number of doctors and nurses for one very important reason. The number of hospital beds, as well as expenditures of the healthcare system during the pandemic significantly increased, precisely as a response to the increased morbidity and mortality. Therefore, inclusion of these indicators in the model as independent variables does not seem well-grounded due to obvious endogeneity. Unlike beds and monetary expenses, it is impossible to increase the number of medical personnel in a short period of time, since medical professions require special and long-term education.

As outliers, we have removed data on Moscow, St. Petersburg and Sevastopol from the sample. The outliers are values of the indicator "the share of population living in the capital of the subject of the Russian Federation and other cities with population over 300 000 people" for Moscow, St. Petersburg and Sevastopol, because the indicator in the subject cities equals to 100%. In addition, the Chukotka District was excluded from the sample due to lack of data on the self-isolation index. In order to avoid duplication of information, data on autonomous districts within regions were not used. After removing the outliers, a balanced panel sample was obtained with a total of 780 observations in 78 regions over 10 months.

2.3 Descriptive analysis

Distribution of excess mortality by region is shown on the map (Appendix). For visualization, we have selected October with one of the highest excess mortality rates. The value volatility of the dependent variable is high, excess mortality is unevenly distributed across the country. The leaders include the Krasnodar Krai, Volgograd, Saratov and Belgorod regions and some other regions. If we consider dynamics in the country's average excess mortality by month (Figure 1), we see that the growth is observed throughout 2020 with August as the only exception.

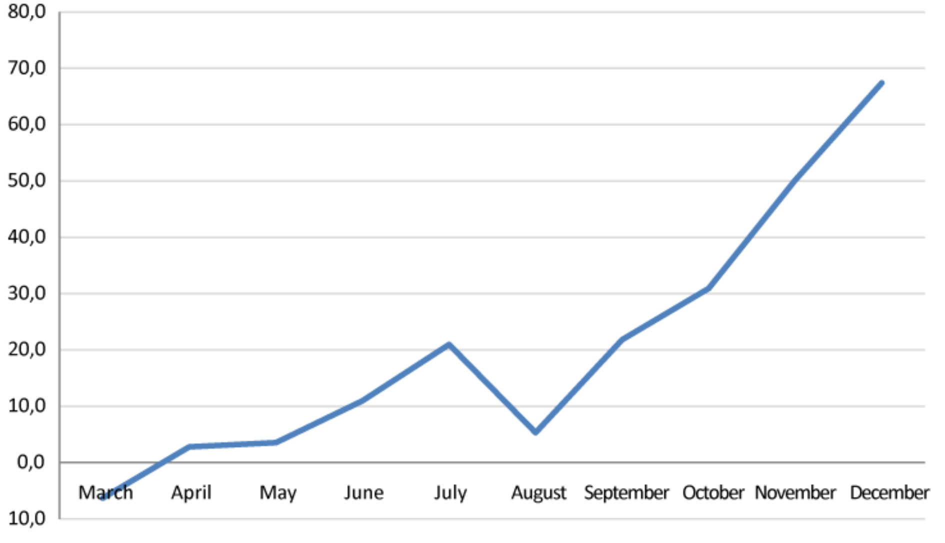

Fig. 1. Average excess mortality per 100 000 population in Russia by month, 2020. *Source:* authors' calculations based on Rosstat data.

Dynamics in Yandex self-isolation index shows peak values across the country in April, which is quite expected, since it was April when the lockdown was in effect in most regions with the strictest restrictions on population movement (Figure 2).

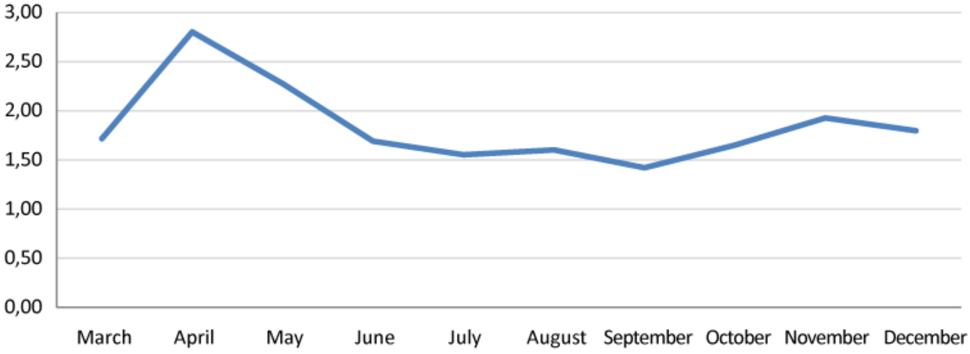

Fig. 2. Average Yandex self-isolation index in Russia by month, 2020. *Source*: authors' calculations based on Yandex DataLens data; URL: https://cloud .yandex.ru/services/datalens

Table 2 shows descriptive analysis of data used in the study. There is a significant value variation in variables by month and region: the minimum gap in indicators such as the number of medical specialists, share of pensioners or air humidity is about two times, while the spread of independent variable values – excess mortality – ranges from minus 30 to plus 126. Thus, all selected variables demonstrate a significant volatility and can be included in the regression analysis. The correlation matrix constructed for the selected variables did not show any high pair correlation (above 0.6), which indicates absence of multicollinearity and possibility to use all variables in the model simultaneously.

Table 2. Descriptive analysis of variables used in the study

	Measurement item	Average	Standard deviation	Mean	min	max
excess.mortality	People per 100 000 population of the region	20.35	26.83	13.16	-30.42	125.64
pensioners	People per 100 000 population of the region	30 581	3 445	30 742	21 684	38 589
migrants	People per 100 000 population of the region	222.82	95.92	218.56	25.80	550.40
capital	%	38	11	38	5	66
temp	°C	8.26	9.98	9.7	-37.30	26.90
humidity	%	72	10	72	42	92
plants	%	22	11	20	2	55
self.isolation.aver	-	1.89	0.48	1.80	0.80	3.60
income	in standard prices as of December, 2020, Russian rubles	32 502	12 870	29 017	13 875	99 274
flat	square meter	27.20	3.96	27.56	14.29	34.18
unemployment	%	7.19	4.21	6.10	1.50	31.20
medicine	People per 100 000 population of the region	155	20.96	154	109	217

2.4 Hypotheses

Based on theoretical models of health economics and empirical studies conducted in other countries or earlier in Russia and with due regard to the pandemic complex nature and its both medical and social specific features, we expect that excess mortality will be associated with five groups of factors, namely: demographic characteristics of the region; peculiar features of the natural environment; restrictive policy in force in the region; and economic factors and state of the health system.

2.5 Modeling and results

The study used regression models of panel data as the main method. For the ease of result interpretation, a linear-logarithmic form of the model has been selected. Therefore, at the stage of data preparation, we have transformed variables of excess mortality and average temperature so that values of all observations became positive. The mortality function looks as follows (2):

$$\log(excess\_mortality) = \beta_0 + \beta_1 \times \log(pensioners) + \beta_2 \times \log(migrants) + \beta_3 \times \log(capital) + \\ + \beta_4 \times \log(temp) + \beta_5 \times \log(humidity) + \beta_6 \times \log(plants) + \beta_7 \times \log(self.isolation.aver) + \\ + \beta_8 \times \log(income) + \beta_9 \times \log(flats) + \beta_{10} \times \log(unemployment) + \beta_{11} \times \log(medicine).$$

Three regression models have been evaluated: ordinarily least squares method (OLS or pooled regression), and fixed and random effect models (RE and FE). The models were evaluated using the R statistical package, version 4.0.2.

A consistent comparison of the estimated models using the Hausman specification test, Breusch–Pagan test and F-test suggests that a fixed effect model is more preferable. However, in this model we lose a number of important variables for which monthly values are not available. Due to peculiar features of the panel model with fixed effects, impact of all variables, which are annual, "goes" into effects of the regions. Therefore, we further interpret the coefficients of both the FE model and the OLS model, which turned out to be statistically significant.

As Table 3 shows, estimates of both models indicate a statistically significant positive relationship between excess mortality in the region and relative number of migrants. Excess mortality is positively associated with air humidity and negatively with its average temperature, with humidity factor being more important. The estimates of both models also confirm a positive correlation of the dependent variable with indicators of per capita income and unemployment. In addition, the FE model reveals a negative relationship between excess mortality and relative number of pensioners in the region and a positive relationship with the self-isolation index. The OLS model re-confirms a significant and negative dependence of the mortality variable upon relative number of medical specialists.

To test results' robustness of the linear econometric models, we have used the Random Forest model, a powerful algorithm based on the method of decision trees. It allows to establish nonlinear relationships between the selected variables. The models included the same factors that we used for regression models. At the first step, the sample was divided into a training and a test one in the proportion of 75:25. The number of trees was set to equal to 500. After testing the model on both samples, at the next stage, individual factors were checked for importance. The estimates obtained by the Random Forest method do not have an exact quantitative interpretation, like coefficients in linear regression models, but they

Table 3. Evaluation results of excess mortality regression models

Veriable	OLS model	FE model
Pensioners	-0.01	-36.81***
	(0.23)	(5.79)
Migrants	0.19***	0.43***
	(0.05)	(0.08)
Capital	0.08	
	(0.03)	
Temp	-0.32***	-0.16*
	(0.07)	(0.07)
Humidity	0.98***	0.47*
	(0.14)	(0.14)
Plants	-0.07	
	(0.03)	
Self.isolation.aver	0.01	0.24***
	(0.05)	(0.06)
Income	0.31***	1.52***
	(0.08)	(0.20)
Flat	0.22†	
	(0.18)	
Unemployment	0.18***	0.90***
	(0.06)	(0.14)
Medicine	-0.48***	
	(0.18)	
Constant	2.56	
	(2.41)	
R-squared	0.25	0.54
F-statistics	22.90	114.74
Number of observations	780	780
Number of objects of observation	78	78

Standard deviation is indicated in brackets

*** – 0.1%, ** – 1%, * – 5%, † – 10%

make it possible to understand which factors are more important in the model. Figures 3 (a) and 3 (b) present results of the modeling carried out in different ways. In both cases, the horizontal axis shows significance of each factor in the model. The modeling results showed that the most important variables associated with excess mortality are as follows: relative air humidity (*humidity*); average temperature (*temp*); self-isolation index (*self.isolation.aver*); number of internal migrants per 100 000 population (*migrants*); per capita monetary income (*income*). Just as in the regression models, the share of urban population, housing provision and share of green spaces in cities turned out to be least significant.

Using the "Random Forest" method, we proved that most of the factors that turned out to be significant in the regression panel model with fixed effects were also significant in the nonlinear model. Thus, the modeling results turned out to be quite sustainable.

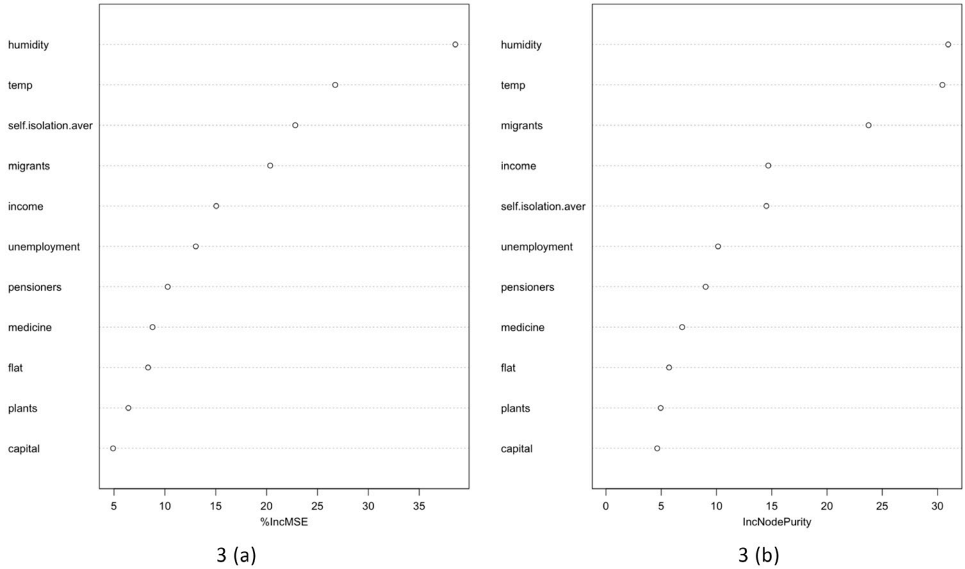

Fig. 3. Factor significance in the "Random forest" model

2.6 Discussion of the results

In general, the study hypotheses have been confirmed: in each of the five groups of the factors identified during literature review and descriptive data analysis, the modeling has identified variables that were statistically significantly associated with excess mortality rates.

Among demographic factors, a positive relationship between excess mortality and number of migrants has been confirmed, which is consistent with studies conducted both in Russia and other countries (Nakada and Urban 2021; Mikhailova and Valsecchi 2020). As expected, the coronavirus infection, like other similar diseases, spreads faster in those regions where population mobility is higher.

An interesting result is a relatively low excess mortality in regions with higher relative number of pensioners. It would seem that mortality among the elderly should be higher (Singh et al., 2021). However, people of this age group, first, do not work and objectively have fewer social contacts, and second, they are more careful and voluntarily comply with self-isolation requirements, even in the established restrictions are invalid (Kalinin et al. 2020). Therefore, disease incidence in this group is lower compared to younger population reducing average mortality in the region. This result is consistent with earlier studies (Goroshko and Patsala 2021; Zemtsov and Baburin 2020; Pilyasov et al. 2021).

The paper confirms significance of climatic factors: other things being equal, high temperatures reduce excess mortality, while high humidity, on the contrary, increases excess mortality. This conclusion confirms results of the study (Pramanik et al. 2022) regarding COVID-19 prevalence in Russia, although it disagrees with findings of another study (Sabgayda and Zubko 2021) based on data on two cold months of 2020.

The self-isolation index turned out to be significantly and positively associated with excess mortality. This means that in those regions and in those months when the index is higher and mobility is lower, mortality rates are higher as well. Apparently, there is an inverse relationship out here: poor epidemiological situation makes people stay home regardless of formal restrictions, either because of illness and quarantine, or simply because of the fear of getting infected. This fact is consistent with conclusion of the study (Maloney and Taskin 2020). However, such conclusion obviously contradicts the claims about effectiveness of the compulsory large-scale isolation of population, which was used by authorities in many countries, including Russia, in the first months of the pandemic.

Among significant economic factors, per capita income especially noteworthy. Its positive association with excess mortality was confirmed by all models used in the work. It is natural that in richer regions with well-developed industry, transport and wholesale trade, the level of business activity is higher and more people continued to work even during the lockdown, therefore both morbidity and mortality were relatively higher. The obtained conclusion contradicts results of many foreign and one Russian work (Khalatbari-Soltani et al. 2020; Caul 2020; Ettensperger 2021; Dokhov and Topnikov 2021) but does comply with results of a cross-country study (Chaudhry et al. 2020) and studies based on data of the Russian regions (Zemtsov and Baburin 2020; Pilyasov et al. 2021).

Another economic factor – unemployment –turned out to be positively associated with excess mortality as well. One can assume that people who lost their job due to closure of enterprises were made search for vacancies or part-time jobs and could not work on a remote basis. For the first time ever such conclusion was made based on the Russian data and does correspond to findings of studies conducted in other countries (Sun et al. 2021).

Finally, a negative relation between excess mortality in the region and number of medical specialists is another important result of the study. This conclusion is consistent with findings of many foreign studies (Buja et al. 2022; Cifuentes-Faura 2021) and one Russian study (Stepanov 2020). Unlike number of hospital beds, which follows development of the epidemic and therefore positively correlates with both morbidity and mortality, the number of doctors and nurses is exogenous, at least in the short term. Thus, one can argue that regions with high number of medical specialists better coped with morbidity and, subsequently, had relatively low excess mortality, other things being equal.

Findings of this study may be used for developing public health policy in case of repeated waves of the epidemic or emergence of new viruses. Vast extent of the Russian territory and significant variation in climatic and socio-economic characteristics of its regions require differentiated policy measures, rather than its standardization. In particular, priority should be given to epidemiological situation in regions with humid climates and low temperatures, high incomes, intensive migration, and high unemployment – for example, in the framework of the next vaccination program. The COVID-19 pandemic has clearly demonstrated the need for significant investments in medical education to increase the number of medical specialists, which is extremely unevenly distributed across regions nowadays. This approach turns out to be more effective in terms of reducing mortality rather than restrictions on mobility.

2.7 Limitations of the analysis and prospects for further research

Limitations of the study are mainly related to shortcomings of information. Thus, individual statistical indicators are presented in Rosstat databases by region only on an annual or quarterly basis, significantly limiting capabilities of the analysis. Information on anti-infection policy measures implemented by regions is either unified nor systematized. There are no reliable data on the scale of population testing by region and in dynamics, making it impossible to include this important factor into modeling.

Furthermore, in this study, we have intentionally used information for 2020 only, when mass vaccination was yet to be initiated in the country. However, a further analysis, starting from 2021, does require inclusion of this factor. Meanwhile, there are no official data on the number of vaccinated by region and in dynamics yet. It is possible to use findings of sociological surveys of population and employers along with such data accumulation.

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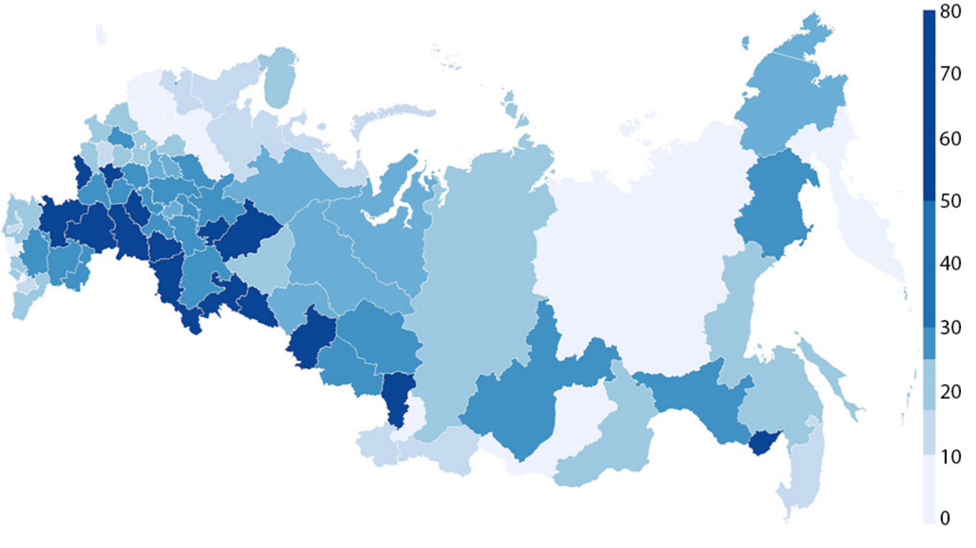
Appendix

Excess mortality by 100,000 of population, October 2020



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