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RESEARCH ARTICLE

Socio-economic and Demographic Factors of Excess Mortality Due to the Coronavirus Pandemic in Regions of Russia

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Abstract

This paper examines the factors associated with excess mortality in Russian regions during the coronavirus pandemic, analyzing them separately for different waves of the pandemic. The study utilizes data from 85 Russian regions on excess mortality – calculated as the number of deaths in each month exceeding the expected number based on the trend of the previous four years – along with socio-economic characteristics (income, unemployment, inequality, migration), vaccination rates, healthcare system characteristics, and the self-isolation index. The analyzed period spans from April 2020 to February 2022.

Based on these data, panel regressions with fixed effects and OLS models of accumulated mortality were constructed separately for the second wave (September 2020 – February 2021) and the third wave (July 2021 – February 2022) of the pandemic.

The key findings indicate that in both the second and third waves, there was a positive relationship between excess mortality and average per capita income. Only in the second wave was a positive relationship observed between excess mortality and the level of self-isolation, the number of doctors per capita, and migration, while a negative relationship was found with unemployment. In contrast, only in the third wave was there a negative relationship between excess mortality and vaccination rates, migration, unemployment, and the number of hospital beds per capita.

Keywords

excess mortality, coronavirus pandemic, life expectancy, mortality factors, inter-regional inequality

JEL codes: J10, J11, J18

Introduction

The coronavirus pandemic began in China in December 2019 and quickly spread to nearly all countries. On March 11, 2020, the World Health Organization (WHO) declared the outbreak a pandemic. Despite the relatively low mortality rate of coronavirus infection, the high transmission rate, the absence of specific treatments and established protocols, as well as the lack of vaccines in the early stages, led to significant mortality in many countries (Karlinsky and Kobak 2021).

As a result of the coronavirus pandemic, life expectancy at birth in Russia dropped to the level observed in 2013. In 2021, life expectancy for men was 65.5 years – two years higher than the twentieth-century peak recorded in 1990 – while for women, it was 74.5 years, nearly returning to the highest life expectancy observed in the twentieth century (Rosstat 2023). By the end of 2022, life expectancy had almost returned to pre-pandemic levels, indicating that the coronavirus pandemic was a temporary shock to life expectancy. On May 5, 2023, WHO announced that the coronavirus pandemic was no longer considered a public health emergency (WHO 2023).

According to Rosstat, the number of deaths attributed to COVID-19 in Russia was approximately 670.000, while excess mortality exceeded 1 million. The coronavirus pandemic effectively nullified Russia's progress in increasing life expectancy. Mortality during the pandemic followed a wave-like pattern, with three distinct periods of high mortality: May–July 2020, September 2020 – February 2021, and June 2021 – March 2022. However, excess mortality varied by region in each wave, suggesting that the factors influencing mortality and their impact differed between the second and third waves. This distinction underscores the need to analyze these waves separately.

In its recommendations, WHO continues to highlight the significant threat posed by potential new waves of coronavirus and future epidemics (WHO 2023). Therefore, understanding the factors influencing mortality during the pandemic is crucial for developing effective measures to mitigate demographic losses in future health crises.

The aim of this study is to identify the factors influencing the regional differentiation of excess mortality in Russia, considering the division of the pandemic into waves. The analysis is based on data from 85 Russian regions, covering excess mortality – calculated as the number of deaths exceeding the expected level for each month, based on trends from the previous four years – along with socio-economic characteristics (income, unemployment, inequality, migration), vaccination rates, healthcare system indicators, and the self-isolation index for the period from April 2020 to February 2022.

The key findings indicate that excess mortality in Russian regions was positively associated with average per capita income, the self-isolation index, the number of doctors per capita, and migration. Conversely, excess mortality exhibited a negative relationship with vaccination rates, the number of hospital beds per capita, and unemployment.

The structure of this paper is as follows: first, the differentiation of Russian regions in terms of demographic losses during the pandemic is analyzed across different waves. Next, the factors contributing to excess mortality are systematized, and their relationship with the level of excess mortality in Russian regions is examined. The final section discusses the study's limitations and outlines prospects for future research.

Data

When assessing the demographic losses caused by the coronavirus pandemic, it is essential to consider not only the direct impact – deaths directly attributed to COVID-19 – but also the indirect effects. These include fatalities resulting from the inability to provide medical care for other chronic and acute diseases, suicides, and other related factors. Existing literature also suggests that official COVID-19 mortality data may be underestimated (Kobak 2021). Furthermore, the accuracy of diagnosing "coronavirus infection" may vary across regions due to differences in diagnostic rules and regulations (Remuzzi and Remuzzi 2020). As a result, official data on COVID-19 deaths may not fully reflect the true mortality burden of the pandemic.

To address these limitations, many researchers propose using excess mortality as a more comprehensive indicator. Excess mortality is defined as the number of deaths exceeding the expected level for a given period, accounting for both the direct and indirect effects of the pandemic (Shkolnikov et al. 2022; Kontis et al. 2020; Beaney et al. 2020).

A key aspect of this approach is the construction of an expected mortality rate, which can be estimated using various methods, such as the mortality rate from a previous period, the average value over several preceding periods, or a projected mortality rate. Shkolnikov et al. (2022) argue that, due to long-term trends in declining mortality, the latter approach is preferable, as it prevents the underestimation of losses.

Following this reasoning, our study extrapolates the historical time series of crude mortality rates (CMR) to establish an expected mortality level that aligns with the long-term trend.

Monthly CMR values were calculated using data on mortality dynamics (Karlinsky and Kobak 2021) and the average annual population (RosBRiS) according to the following formula:

$$CDR_{REG,Y,M}^{observed} = \frac{D_{REG,Y,M}}{N_{REG,Y}/12}, \tag{1}$$

where $CDR_{REG,Y,M}^{observed}$ is the observed CMR in region *REG,* in year *Y,* month *M*; $D_{REG,Y,M}$ – the number of deaths in region *REG,* year *Y,* month *M*; $N_{REG,Y}$ – the average annual population in the region *REG,* year *Y.*

The expected mortality rates were obtained by extrapolating the ACS time series for 2016-2019 to 2020-2022. The expected value of the CMR was calculated using the formulas:

$$CDR_{REG,Y,M}^{expected} = CDR_{REG,2019,M}^{observed} \times K_{REG,M} \text{ for 2020}, \tag{2}$$

$$CDR_{REG,Y,M}^{expected} = CDR_{REG,Y\text{-}1,M}^{expected} \times K_{REG,M} \text{ for 2021 - 2022}, \tag{3}$$

where $CDR_{REG,Y,M}^{expected}$ is the expected CMR in region *REG,* in year Y, month *M*; $CDR_{REG,2019,M}^{observed}$ is the observed CMR in region *REG,* 2019, month *M*; $CDR_{REG,Y\text{-}1,M}^{expected}$ is the expected CMR in region *REG*, in year *Y*-1, month *M*; $K_{REG,M}$ – the average growth rate of CMR for month *M* during 2016-2019, calculated using the geometric mean formula: $K_{REG,M} = \sqrt[4]{\prod_{Y=2016}^{Y=2019}\left(\frac{CDR_{REG,Y,M}^{observed}}{CDR_{REG,Y\text{-}1,M}^{observed}}\right)}$.

Thus, the predicted CMR values (Fig. 1) align with both the long-term mortality trend and seasonal fluctuations.

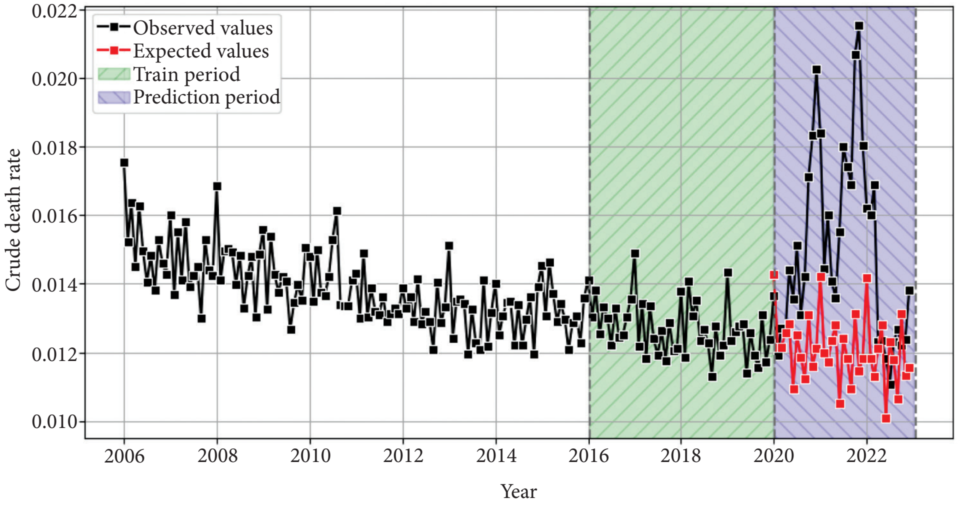

Figure 1. An example of forecasting excess mortality in the Russian Federation. *Source:* calculated by the authors based on data from Rosstat (Karlinsky and Kobak 2021) and RosBRiS

Excess mortality was calculated as the difference between the observed and expected values of CMR:

$$CDR^{excess}_{REG,Y,M} = CDR^{observed}_{REG,Y,M} - CDR^{expected}_{REG,Y,M}, \tag{4}$$

where $CDR^{excess}_{REG,Y,M}$ is the observed CMR in region *REG*, in year *Y*, month *M*; $CDR^{observed}_{REG,Y,M}$ is the observed CMR in region *REG*, in year *Y*, month *M*; $CDR^{expected}_{REG,Y,M}$ is the observed CMR in region *REG*, in year *Y*, month *M*.

Mortality rates were not standardized, despite the fact that comparing non-standardized rates is generally considered problematic due to the varying age structures of populations across Russian regions. However, since COVID-19 disproportionately affects the elderly population, using a standardized coefficient could potentially distort the relationship between the factors under study and excess mortality. Models were calculated using both standardized mortality rates and general excess mortality rates; no significant differences were found between the results (Appendix 1). To account for differences in age structure across regions, the proportion of the elderly population in each region was included in the model.

Excess mortality in Russia varies across regions and over time. Figure 2 presents a heat map of excess mortality across 85 Russian regions by month (red indicates high excess mortality, green indicates low). The figure clearly shows two major waves of the pandemic: September 2020 – February 2021 and June 2021 – March 2022. The first wave of the pandemic is also evident in May–July 2020; however, due to the strict restrictive measures imposed by authorities, excess mortality during this period is less pronounced compared to the second and third waves.

It is important to note that excess mortality may occur with a delay relative to infection rates, as death does not immediately follow infection. In this study, we focus on mortality waves, rather than waves of infection.

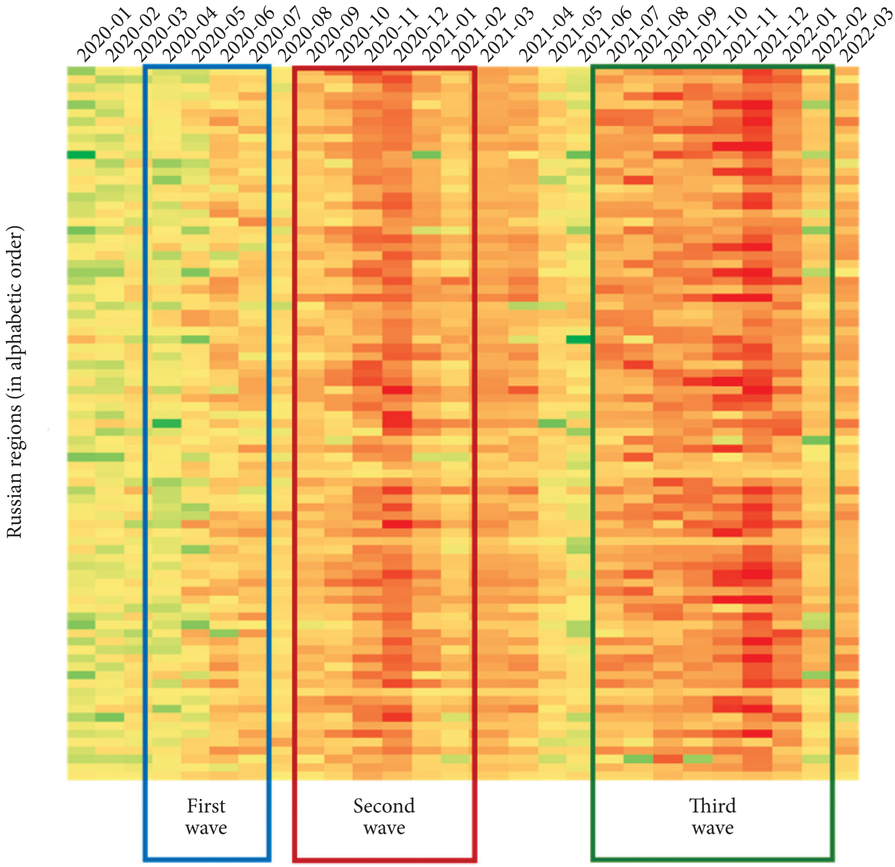

Figure 2. Excess mortality rate in the regions of Russia. January 2020 – March 2022, per capita (red indicates a high coefficient, green indicates a low coefficient). *Source:* compiled by the author based on Rosstat data

In addition, excess mortality varied between regions during the second and third waves – some regions experienced higher mortality in the second wave, while others had higher mortality in the third.

Researchers have not yet reached a consensus on the relationship between excess mortality and certain factors. Different studies sometimes arrive at directly opposite conclusions regarding the same determinants (Kalabikhina and Maksimov 2023) (Table 1).

Thus, some authors have found a negative relationship between excess mortality and average income levels, both in studies based on Russian data (Dokhov and Topnikov 2021) and in studies using foreign data – Mexican (Arceo-Gomez et al. 2022) and German (Ettensperger 2021). The authors explain this correlation by suggesting that people living in wealthier regions have better access to medical services, which in turn lowers mortality rates.

However, other studies show a positive relationship between income and excess mortality. Such findings were demonstrated in a study based on data from all of 2020 in Russian regions (Kolosnitsyna and Chubarov 2022) and in a study focusing solely on the first

Table 1. Factors of excess mortality in previous studies

Factor	The direction of communication, *the country/territory under study is indicated in italics (the period of analysis in parentheses)*
Income	**Positive** – *Russia (March – May, 2020)* (Zemtsov and Baburin 2020); *Cross-country study* (Chaudhry et al. 2020); *Russia (2020)* (Kolosnitsyna and Chubarov 2022)
	Negative – *Russia (first wave)* (Dokhov and Topnikov 2021); *Germany (first wave)* (Ettensperger 2021); *Mexico (2020)* (Arceo-Gomez et al. 2022)
	Unrelated – *Russia (First Wave)* (Pilyasov et al. 2021)
Inequality	**Positive** – *USA (first wave)* (Oronce et al. 2020); *Cross-country Studies (OECD) (2020)* (Sepulveda and Brooker 2021; Wildman 2021); *British Municipalities (2020-2022)* (Gaia and Baboukardos 2023)
Unemployment	**Positive** – *Iran (2020-2021)* (Mirahmadizadeh et al. 2024)
	Negative – *England (first wave)* (Sun et al. 2021); *Russia (2020)* (Kolosnitsyna and Chubarov 2022)
Migration	**Positive** – *Russia (2020)* (Kolosnitsyna and Chubarov 2022); *Scandinavia (2020)* (Diaz et al. 2021)
	Negative – *Italian municipalities (first wave)* (Valsecchi and Durante 2021)
	Unrelated – *Russia (March – May, 2020)* (Zemtsov and Baburin 2020)
Availability of doctors and beds	**Positive** – *Russia (first wave)* (Stepanov 2020); *Russia (2020)* (Kolosnitsyna and Chubarov 2022); *Italy (first wave)* (Buja et al. 2022); *EU (first wave)*: (Cifuentes-Faura 2021)
	Negative – *England (first wave)* (Sun et al. 2021)
Compliance with restrictive measures	**Positive** – *Russia (2020-02.2021)* (Kotov et al. 2022); *Russia (2020)* (Kolosnitsyna and Chubarov 2022)
	Negative – *Scandinavia (first wave)* (Conyon et al. 2020, Juranek and Zoutman 2020); *USA (first wave)* (Charoenwong et al. 2020)

Source: compiled by the authors based on a literature review

wave of the coronavirus pandemic (Zemtsov and Baburin 2020). A similar conclusion was reached by the authors of a cross-country study analyzing the 50 countries with the highest number of coronavirus cases as of May 2020 (Chaudhry et al. 2020).

The authors interpret this result by arguing that higher income levels are typically found in areas with greater population density and higher regional development. These factors contribute to increased social interactions, leading to a higher number of infections and, consequently, more deaths from COVID-19.

An alternative approach to assessing economic well-being links excess mortality not to average income but to income inequality. A study based on U.S. data found that states with higher levels of inequality experienced higher COVID-19 incidence and mortality rates (Oronce et al. 2020). Similar findings were observed in studies on OECD countries (Sepulveda and Brooker 2021; Wildman 2021).

A positive relationship between income inequality and excess mortality was also identified in research using data from British municipalities across all age groups. The authors note that high inequality amplifies the negative effects of other factors on excess mortality. Based on these findings, they conclude that addressing income inequality should be the primary focus before tackling the negative impact of other factors (Gaia and Baboukardos 2023).

Migration is another important socio-economic factor. Some studies based on Russian data have found a positive association between migration and excess mortality – regions with higher migration rates experienced higher excess mortality (Kolosnitsyna and Chubarov 2022). However, other studies found no significant effect of migration on mortality (Zemtsov and Baburin 2020).

At the same time, a positive relationship was observed in studies based on data from Scandinavian countries (Diaz et al. 2021) and Italian municipalities during the first wave of the pandemic. The authors highlight the ambivalence of this relationship. On one hand, a larger influx of migrants can lead to a higher number of infections within a municipality. On the other hand, migrants may have greater awareness of how to manage the virus. For example, in Italy, migration flows moved from more infected areas to less infected ones, which suggests that their presence may have had a positive impact on mortality rates in some municipalities (Valsecchi and Durante 2021).

A similar contradictory result was found for unemployment. A negative relationship between unemployment and excess mortality was observed in Iran (Mirahmadizadeh et al. 2024), while a positive relationship was identified in studies based on data from Russia and England (Sun et al. 2021; Kolosnitsyna and Chubarov 2022). The authors suggest that unemployment may not have a significant relationship with excess mortality, as many countries introduced substantial unemployment benefits during lockdowns. As a result, many people chose to quit their jobs, which led to an increase in unemployment during the same periods when excess mortality was rising.

Regarding healthcare systems, the authors also highlight the connection between healthcare system characteristics and excess mortality. Studies based on Russian, Italian, and EU data have shown a positive relationship between excess mortality, the availability of doctors, and the number of hospital beds (Stepanov 2020; Kolosnitsyna and Chubarov 2022; Buja et al. 2022; Cifuentes-Faura 2021). The authors do not offer a clear explanation for this relationship. It is possible that the number of medical staff and beds is not the primary factor, but rather the effectiveness of current protocols for hospitalizing and treating COVID-19 patients.

In contrast, data from England indicate that greater geographical accessibility to hospitals is negatively associated with excess mortality (Sun et al., 2021)

A number of studies demonstrate that compliance with non-pharmacological infection prevention measures – such as social distancing, self-isolation, and wearing masks – can reduce coronavirus mortality, even in the absence of government enforcement (Conyon et al. 2020; Juranek and Zoutman 2020). Some authors use data from Google's Community Mobility Reports (Sulyok and Walker 2021) or similar mobility data from other IT platforms (Charoenwong et al. 2020) as a proxy for adherence to movement restrictions. In studies of Russian regions, the Yandex self-isolation index (Kotov et al. 2022) is used as a similar proxy variable. However, Russian data yielded a counterintuitive result: higher levels of self-isolation were associated with higher excess mortality (Kolosnitsyna and Chubarov 2022).

The inconsistency in the relationships between factors and excess mortality, as identified in previous studies, is noteworthy for another reason: the studies differ in the periods and frequencies of data selected for analysis. Some studies consider mortality data on a monthly basis, while others analyze it cumulatively over the entire period of the pandemic (usually from spring 2020). As noted earlier, excess mortality varies over time, and in our view, the factors contributing to high (or low) mortality in a particular area are most relevant during periods when a specific pandemic wave is "active."

Previous researchers, using Russian data, examined mortality continuously over the pandemic, without distinguishing between periods of high and low mortality (Kolosnitsyn and Chubarov 2022; Kotov et al. 2022; Zemtsov and Baburin 2020). However, we believe that this approach may bias the results, as it prevents us from identifying whether a factor directly affects excess mortality, or whether it only influences the onset of a new wave.

In other words, we *hypothesize that the relationship between factors and excess mortality may vary significantly during the growth waves of the pandemic and between them*. For this reason, the study separately examines the factors contributing to excess mortality in the second and third waves, excluding the months between the waves when excess mortality was relatively low.

The first wave is not considered in this study, as strict restrictive measures were implemented across all regions of the country during that period, resulting in relatively low excess mortality. Additionally, during the first wave, the virus primarily entered from other countries (as opposed to domestic regions, as will be shown later for the second and third waves). In the spring and summer of 2020, the greatest losses were seen in regions with high human traffic from abroad (Paterlini 2020). Given that coronavirus restrictions had a significant protective effect during this period, it seems unnecessary to examine other socio-economic factors.

Thus, the study analyzes factors that could be associated with excess mortality separately during the second and third waves of the coronavirus pandemic.

In mortality studies, authors typically rely on the framework of Grossman's model of demand for health (Grossman 1972, 2000). According to Grossman's logic, the factors to be examined in this study can be categorized into three groups: behavioral factors (related to population activity), medical care factors (related to the healthcare system), and technological factors (socio-economic characteristics). Additionally, demographic characteristics of the region will be considered separately.

We use per capita monetary income data from Rosstat, the unemployment rate, and the Gini coefficient as indicators of income inequality within regions, which serve as socio-economic characteristics. We hypothesize that higher income, lower unemployment, and lower inequality are associated with lower excess mortality. Conversely, lower income or higher inequality may limit individuals' financial and other resources to protect themselves from the coronavirus, and may also restrict access to medical services, thereby increasing the likelihood of death from the virus.

As demographic characteristics, we use the percentage of the population over the age of 65 (individuals beyond the working age) on a monthly basis. An attempt was also made to use the proportion of the population under the age of 15 (individuals below the working age), as it is known that schools can act as hotbeds for coronavirus transmission. Children and adolescents are often 'super-spreaders,' as they may be asymptomatic but capable of infecting a large number of individuals (White et al. 2022). However, assessing the significance of this factor is challenging due to the difficulty in evaluating the policy of transitioning schools to remote learning in Russia. The issues with monitoring the severity of these restrictions are discussed below, making the interpretation of this factor complex.

The inclusion of the proportion of the population above working age is based on the fact that the mortality rate from coronavirus increases with age. For instance, a study conducted in the state of Indiana showed that the probability of hospitalization (a key indicator of case severity) was 0.4% for individuals under the age of 40, and 9.2% for those over the age of 60 (Menachemi et al. 2021). The association between the proportion of the elderly population and excess mortality has been confirmed in previous studies. Notably, Russian studies found a negative relationship (Kolosnitsyna and Chubarov 2022), while global studies showed a positive relationship (Sun et al. 2021).

As indicators of the healthcare system, we consider the number of doctors and beds per capita in the region, based on Rosstat data. The number of doctors per capita reflects the availability of human resources in the region to treat a large number of patients, while the number of beds represents the capacity for patient hospitalization. In Russia, the principle of 'first-come, first-served' primarily applies when hospitalizing patients, meaning that medical organizations admit all patients who require hospitalization on a first-come, first-served basis. Patients for whom there are insufficient available beds must wait until space becomes vacant. In critical health situations, this principle means that not all patients will have access to beds, and some may die without receiving medical care. Therefore, having available beds for new patients is crucial.

It is important to note that both variables are available only on an annual basis, which necessitates caution in their use. The number of beds fluctuated non-linearly throughout the year, while the number of doctors includes not only those in COVID hospitals but also general district specialists. Additionally, the number of doctors is less sensitive to external shocks and cannot be increased rapidly, as all medical professionals require training. In contrast, the number of beds can be expanded more quickly.

Another indicator we include as part of the healthcare system is the level of vaccination within the population. Data on the percentage of individuals vaccinated with two doses of the COVID-19 vaccine are sourced from gogov.ru, which compiled vaccination data from the websites of regional operational headquarters throughout the pandemic. Mass vaccination in Russia began in January 2021 (Rossiyskaya Gazeta 2021), but high levels of collective immunity were only achieved by the end of 2022. While this study does not address the reasons for the slow increase in vaccination rates, it is important to note that the vaccination campaign progressed at different rates across regions. Our hypothesis is that higher vaccination rates in a region are associated with lower excess mortality. However, it is also possible that high vaccination levels could lead to changes in population behavior – individuals may become less cautious, assuming the pandemic has subsided.

Among the indicators of social contact activity in the region, we include the Yandex self-isolation index and the migration indicator, measured by the number of arrivals per capita to the region for permanent residence each month.

The self-isolation index was calculated by Yandex from March 2020 to September 12, 2021 (Yandex 2020), covering the entire first and second waves, but not the third. Therefore, it is not possible to analyze the relationship between the self-isolation index and excess mortality during the third wave. The index is an aggregated measure of population activity, calculated based on the use of Yandex services by users (such as maps, navigator, food delivery, etc.). It is computed for all settlements in the country with a population of more than 50,000, with the data then averaged for the settlements within each region. According to Yandex's methodology, the index can take values from 0 to 5, where 0 represents a low level of self-isolation (comparable to 'rush hour on a weekday'), and 5 indicates high self-isolation ('as quiet as night in the city'). The company used the average activity from March 2–5, 2020, as the baseline (a period just before coronavirus restrictions were implemented and when no cases had been recorded in the regions).

The index reflects the extent to which people have reduced their social contacts. In this sense, the self-isolation index can be considered an indicator of compliance with restrictions. However, the index has significant limitations, which will be discussed in the section on the study's limitations. Despite these drawbacks, the Yandex index will be used in this study, as no other services provided specific indicators for Russia.

Since the index was calculated by Yandex on a daily basis, we recalculated the data into monthly terms by taking the arithmetic average of the index for each month. Additionally, to facilitate interpretation, the self-isolation index was multiplied by 20. In the final version of the study, the self-isolation index is measured in percentage points, where 0 percentage points represents maximum self-isolation, and 100 percentage points indicates maximum activity. The final formula for calculating the index looks as follows:

$$SI_{i,REG} = \frac{\sum_n SI_{n,i,REG}}{N_i} \times 20, \tag{5}$$

where i – month, year; REG – region; n – day in month i; N_i – a number of days in month i.

Migration in this study is measured by the number of permanent residents in the region per capita (according to Rosstat). In previous studies, migration has been measured either by migration balance (Kotov et al. 2022) or by the sum of arrivals and departures for permanent residence in the region (Kolosnitsyna and Chubarov 2022). However, in our view, excess mortality was primarily influenced by arrivals to the region, rather than departures. Individuals moving into the region could already be infected, potentially bringing the virus from one part of the country to another. This could offset the region's success in controlling the virus within its borders, thus contributing to higher morbidity and mortality. While the virus could also have been imported by people not coming for permanent residence (e.g., shift workers, tourists, etc.), such data is not available for the regions of Russia during the period of interest.

The study will use the number of infections in the region per capita per month as a measure of the "strength" of the pandemic:

$$Z_{i,REG} = \frac{\sum_n Z_{i,REG,n}}{\underline{P}}, \tag{6}$$

where i – month, year; REG – region; $\underline{P}$ – average annual population of the region; n – a day in month i.

The data are taken from the official reports of the operational headquarters of the Russian Federation for the fight against coronavirus (stop coronavirus.rf). These data have limitations, as they reflect the number of detected cases rather than the actual number of infections, since they only represent those who tested positive.

A large number of infections could lead to an overload of the healthcare system, as seen in Brazil (da Silva and Pena 2021) or India (Rocha et al. 2021). However, most cases of infection do not require mandatory hospitalization (Menachemi et al. 2021). Therefore, a more adequate parameter for assessing the burden on the healthcare system would be the number of hospitalizations per capita. Unfortunately, for Russian regions, full data on coronavirus hospitalizations have only been published since January 2022. Prior to this, the data were fragmented and not available for all regions, making it impossible to use this indicator.

Methods

Some of the factors we are considering vary over time, while others are relatively stable and represent permanent characteristics of the regions. To account for the influence of both categories of factors, we base our analysis on two independent strategies:

- Panel regressions of excess mortality by month for each of the two waves, which include factors that fluctuate during the coronavirus pandemic, such as migration, the self-isolation index, and vaccination rates.
- Cross-sectional regressions of accumulated excess mortality for each wave, which include variables that cannot be tracked on a monthly basis and would be inappropriate to include in the monthly model.

A panel data model with fixed effects is used to assess the impact of variable factors (migration, self-isolation, vaccination) on excess mortality. A random-effects model seems inappropriate, as we do not include all possible factors that could explain the variation in excess mortality, and we cannot be certain that the random-effects model would be correct. In evaluating a fixed-effects model, it is not possible to estimate coefficients for variables that do not change over time. This is another reason why additional regressions for accumulated excess mortality for each of the waves are conducted to assess the influence of some of the factors.

To assess the relationship of variable factors with excess mortality, panel data models with fixed effects were constructed:

$$In\left(CDR^{excess}_{REG,Y,M} + const\right) = \mu + \beta InX_{REG,Y,M} + \gamma InX_{REG,Y,M\text{-}1} + u_{REG} + \varepsilon_{REG,Y,M}, \quad (7)$$

where $X_{REG,Y,M}$ – vector of explanatory variables (shown in the Table 2 and 3), $X_{REG,\ Y,M\text{-}1}$ – vector lagged variables.

All variables are taken in logarithms. In the case of mortality during the pandemic and the factors under consideration, it seems that the relative changes in the indicators are more important than the absolute changes. To take the logarithm of variables with negative values (in particular, the excess mortality rate), these variables were first converted into positive values by adding the same positive constant to all variable values.

Some variables may have a delayed effect on excess mortality, so the model includes lagged variables for the number of detected cases, the self-isolation index, and migration.

Death from coronavirus does not occur immediately upon infection but after some time. Accordingly, the current mortality rate from coronavirus depends not only on the number of infected people in the current month, but also on the number from the previous month. A similar logic justifies the inclusion of the lagged self-isolation index in the model. If the population restricted their social contacts more in the previous month, then the excess mortality rate should be lower in the current month.

Migration may also have a delayed effect: people entering the region may have been in the early stage of the incubation period, while those already infected were likely unable to freely enter the region due to quarantine restrictions. Those who entered the region could have infected others, who might become seriously ill and potentially die as early as the following month.

For control, the model includes unemployment levels and per capita income in the region. In the third wave, instead of the self-isolation index (for which there is insufficient data), the level of vaccination is included as a factor specific to the coronavirus pandemic.

When considering the model for the second wave, two regions were excluded – the Chukotka Autonomous Okrug and the Nenets Autonomous Okrug – due to the lack of data on the Yandex self-isolation coefficient for these regions. As a result, the number of regions analyzed in the second wave was 83. In the third wave, data are available for all variables under consideration for all months, so the number of regions increases to 85.

In Tables 2 and 3, descriptive statistics for the variables used in the panel models are provided. These tables show that excess mortality in the third wave was higher than in the second wave, while the median was lower than the mean in the second wave, and vice versa in the third wave. This may indicate that, in the third wave, excess mortality was more widespread across regions.

Table 2. Descriptive statistics of variables in the second wave of the coronavirus pandemic (09.2020 – 02.2021)

Variable	Average	The median	St. deviation	Min.	Max.
Excess mortality rate	3.79	3.05	2.95	-3.38	15.40
Migration per 1.000 people	1.515	1.147	1.227	0.322	14.59
Persons over 65 years of age per 100.000 population	30251	30353	3222	21817	38146
Per capita income	34620	30113	15776	14215	99006
Unemployment	7.16	6.00	4.34	2.40	32.4
Self-isolation index	37.4	38.1	6.77	16.1	55.9
Detected cases per thousand people per month	3.71	3.02	2.94	0.105	20.8

Source: compiled by the authors

Table 3. Descriptive statistics of variables in the third wave of the coronavirus pandemic (07.2021 – 02.2022)

Variable	Average	The median	st. dev.	Min.	Max.
Excess mortality rate	5.64	5.31	3.54	-3.42	19.31
Migration per 1.000 people	1.532	1.216	1.082	0.28	8.47
Persons over 65 years of age per 100.000 population	29517	29558	3031	21720	37172
Per capita income	37840	32970	16779	15018	108400
Unemployment	5.35	4.20	3.68	1.50	30.4
Detected cases per thousand people per month	8.09	5.21	9.88	0.231	92.4
Vaccination rate (%)	35.81	35	13.07	4.9	71.2

Source: compiled by the authors

The simulation results are presented in Table 4.

In the second wave of the coronavirus, a negative association was found between excess mortality and the migration rate from the previous month, which contradicts our initial assumptions. At the same time, the positive association between excess mortality and the proportion of older people was consistent with the initial assumptions. The relationship between excess mortality and other factors was the opposite of what was initially hypothesized: both the level of per capita income and the self-isolation index were positively associated with excess mortality.

Table 4. The results of the evaluation of panel models with fixed effects. The dependent variable is the logarithm of the excess mortality coefficient (with robust standard errors)

All variables are in logarithms	**(1) 2nd wave (09.2020–02.2021)**	**(2) 3rd wave (07.2021–02.2022)**
Migration per 1.000 people in the current month	0.05 (0.04)	-0.21* (0.04)
Migration per 1.000 people in the previous month	-0.18*** (0.07)	0.083* (0.046)
Persons over 65 years of age per 100.000 population	11.83*** (2.96)	8.27*** (2.83)
Per capita income	0.34*** (0.09)	0.898*** (0.097)
Unemployment	0.16 (0.11)	0.029 (0.117)
Detected cases per 1.000 people in the current month	0.08* (0.046)	0.058*** (0.0154)
Detected cases per 1.000 people in the current month	<0.0001 (0.037)	-0.058*** (0.012)
Vaccination rate (%)		-0.046 (0.17)
Index of self-isolation in the current month	0.45*** (0.11)	
Index of self-isolation in the previous month	0.058 (0.112)	
R-square	0.59	0.51
Number of observations	498	680

Source: compiled by the authors. *Note:* *** 1%, ** 5%, * 10% levels of significance

In the third wave of the coronavirus, as per the initial assumptions, the proportion of people over 65 and the level of migration from the previous month were positively related to excess mortality. However, the remaining variables exhibited counterintuitive relationships – migration in the current month was negatively associated with excess mortality, while the income level was positively associated with it.

For both waves, the number of coronavirus cases was significant and positively associated with excess mortality. In the third wave, the negative relationship between the number of cases from the previous month and excess mortality was also significant.

To assess the impact of constant factors, an OLS model is constructed in which the accumulated excess mortality in the region over the entire period of the wave serves as the dependent variable. This regression includes the average per capita income in the region, unemployment, the Gini index, the number of beds and doctors per capita in the region (as of early 2021, since more recent data by region was unavailable), and the proportion of the population over 65 years old. The monthly indicators were averaged for each wave. In this case, we did not use logarithmic variables, as we are primarily interested in the direction of the relationship rather than its strength. Descriptive statistics are provided in Table 5.

Table 5. Descriptive statistics of variables in the model of accumulated excess mortality

Variable	Average	The median	St. deviation	Min.	Max.
Per capita income – 2nd wave	42053	36630	17808	21396	107.500
Per capita income – 3rd wave	35986	30995	15959	17954	97358
Excess mortality rate – 2nd wave	4.33	4.38	1.24	1.37	6.91
Excess mortality rate – 3d wave	6.45	6.7	1.838	1.97	9.654
Persons over 65 years of age per 100,000 population (as of early 2021)	30466	30582	3335	21849	38308
Unemployment – 2nd wave	7.252	6.1	4.296	2.6	31.2
Unemployment – 3d wave	5.295	4.2	3.584	1.5	29.7
Number of beds per 100,000 population (2021)	817	795.5	139	438	1317
Number of doctors per 10.000 people (2021)	37.8	36.69	7.637	23.49	64.01
Gini Coefficient (2021)	0.3676	0.364	0.02423	0.329	0.44

Source: compiled by the authors

To assess the relationship between the region's slowly changing characteristics over time and excess mortality, OLS models are constructed:

$$CDR_{REG}^{excess} = \mu + \beta X_{REG} + \varepsilon_{REG}, \tag{8}$$

where X_{REG} – vector of explanatory variables (shown in Table 5).

The simulation results are presented in Table 6.

Table 6. Results of the evaluation of OLS models. Dependent variable is the excess mortality rate for the entire wave (robust standard errors)

	(3) 2nd wave (09.2020–02.2021)	(4) 3rd wave (07.2021–02.2022)
Constant	-0.777 (3.08)	3.65 (4.58)
Per capita income	-0.0001** (<0.001)	0.00001 (<0.001)
Persons over 65 years of age per 100.000 population	0.0001*** (<0.001)	0.0001*** (<0.001)
Unemployment	-0.104** (0.044)	-0.162*** (0.051)
Number of beds per 100.000 population	-0.0013* (0.0006)	-0.001 (0.0011)
Number of doctors per 10.000 people	0.02* (0.012)	-0.02 (0.025)
Gini Coefficient	9.895 (6.99)	-3.87 (9.05)
R-square	0.28	0.31
Number of observations	85	85

Source: compiled by the authors. *Note:* *** 1%, ** 5%, * 10% levels of significance

In contrast to the results of the panel model, in the second wave, the level of per capita income showed a negative relationship with excess mortality. At the same time, unemployment was significantly negatively associated with excess mortality, which aligns with the findings of previous studies on this topic. In the second wave, a negative relationship was also found with the number of hospital beds per capita – meaning that the more beds available in the region, the lower the excess mortality. However, the relationship with the number of doctors was positive, and this counterintuitive result requires further explanation.

Results and discussion

Average per capita income

In panel models (1) and (2), a positive relationship was found between excess mortality and per capita income in the region, which contradicts the initial hypothesis. Several explanations can be offered for this connection.

Firstly, higher average per capita income may indicate a larger proportion of the region's population living in urban areas. According to statistics in Russia, most of the poor population resides in rural areas (Lezhnina 2014). Living in urban areas can influence the likelihood of dying from coronavirus in several ways. On the one hand, residents of large cities have greater access to medical services and more opportunities for self-isolation, as they can use digital technologies to order products and access government services (Sun et al. 2021; Kalabikhina and Maximov 2023). On the other hand, large cities tend to have higher population densities, which increases the likelihood of contracting the virus and potentially dying from it compared to rural areas (Martins-Filho 2021).

Secondly, a higher level of per capita income may be due to the fact that in such regions, people spend more time in public places (bars, cafes, cinemas, etc.) (Alekseenok 2012). Given that the restrictions imposed in Russia were not always strictly enforced, or the restrictions themselves were not particularly severe (in particular, public catering facilities were not fully closed in any month in nearly all regions, except during the nationwide lockdown in the first wave), people could continue their activities as they did before the pandemic. The positive relationship between per capita income and excess mortality may actually indicate that people in higher-income regions continued to visit public places, became infected, and died at a higher rate than those in less affluent regions. This observation is also supported by sociological data – according to the 29th wave of the RFMS, only 35% of Russians strictly observed coronavirus restrictions in 2020 (Kozyreva and Smirnov 2021). Since the coronavirus restrictions were much milder in 2021, it can be assumed that the proportion of the population ignoring these restrictions only increased over time.

The third possible explanation is that in Russia, the level of per capita income in the regions is closely correlated with income inequality (Fig. 3). Thus, the higher the average per capita income in a region, the higher the regional inequality. As mentioned earlier, income inequality is an important factor in differentiating excess mortality (Sepulveda and Brooker 2021; Wildman 2021; Gaia and Baboukardos 2023). Therefore, the positive association between excess mortality and per capita income likely reflects a link to the level of inequality in the region, rather than the income of the population itself. Furthermore, the results of model (3) generally support this conclusion – per capita income is significantly negatively associated with excess mortality across the waves.

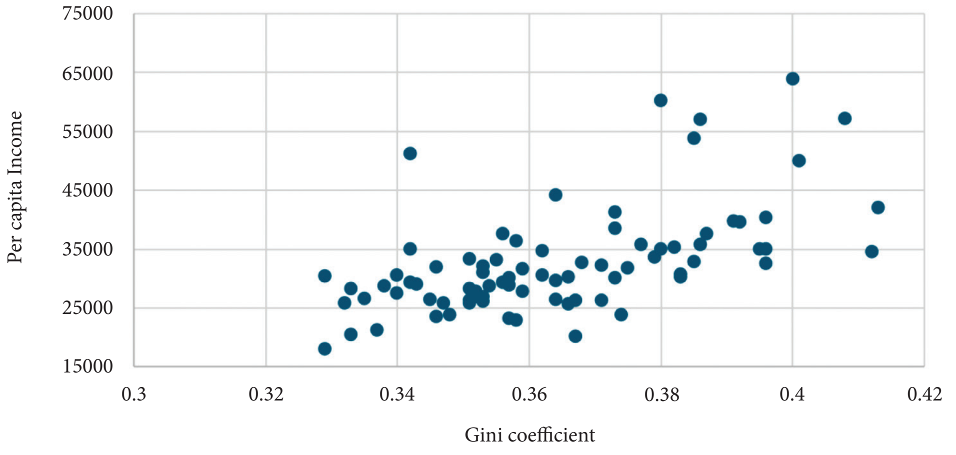

Figure 3. Diagram of the dispersion of Russian regions by average per capita income and the Gini index. *Source:* compiled by the author based on Rosstat data

The arguments presented above about the relationship between inequality and per capita income raise the question of why the Gini index itself turned out to be insignificant in the corresponding models (3) and (4). In our view, the issue lies in the "summation" of monthly excess mortality within the models. As we observed in Fig. 2, excess mortality varies over time. Previous studies have shown that inequality begins to affect excess mortality only during periods of high stress on the healthcare system (Oronce et al. 2020; Gaia and Baboukardos 2023). Therefore, using accumulated excess mortality as a measure may be problematic, as it combines periods when inequality had an effect on access to healthcare and other services, and periods when inequality did not exert a similar influence. In contrast, per capita income reflects not only individual characteristics but also the region's capacity to manage the pandemic, making its impact on excess mortality more stable. This interpretation offers a fresh perspective on excess mortality from COVID-19 and suggests that greater attention should be paid to individuals with low socio-economic status. This finding is consistent with previous studies on life expectancy and mortality in Russia's regions prior to the pandemic (Andreev and Shkolnikov 2018).

Migration

The positive association between migration in the previous month and excess mortality aligns with intuitive logic (model (1)). However, the negative relationship observed in the third wave model (model (2)) is unexpected. The most likely explanation for this discrepancy is that during the third wave of COVID-19, the dominant strain was the Omicron variant, which, according to research, had a significantly higher transmission rate – spreading 1.5 to 2 times faster than previous variants such as Alpha, Beta, and Gamma, which were prevalent in the second wave (Lundberg et al. 2022).

The second wave of COVID-19 began in the fall of 2020, coinciding with the return of vacationers from southern regions, where mortality had started rising earlier. Due to the slower spread of the virus at that time, new arrivals from other regions could have had a substantial impact on the number of infections and subsequent deaths (Druzhinin et al. 2021).

At the same time, the third wave in Russia occurred during autumn and winter of 2021, a period when international flights had resumed, and regional populations were observing fewer restrictions while traveling more actively between regions and abroad. As a result, the introduction of a new virus strain into a region could have happened at the very beginning of the wave, with its subsequent spread driven more by internal factors rather than by interactions with other regions.

In our view, the negative association observed in the third wave may be explained by a feedback effect – people may have been moving to regions where the COVID-19 situation was more stable. However, this hypothesis requires further investigation.

Another possible explanation for this relationship lies in the limitations of our migration data. The indicator used does not directly measure the number of people arriving in a region but instead reflects only the number of "individuals who registered their residence with the territorial authorities of the Federal Migration Service of Russia during the reporting period.[1]" The dynamics of the pandemic are influenced, among other factors, by people who arrive in a region without registering, primarily tourists. However, Rosstat only began estimating tourist flows in 2022 (Rosstat 2021). Additionally, pendulum migration between certain regions is even more difficult to quantify, making it nearly impossible to assess its scale accurately (Makhrova 2017). Nevertheless, despite these limitations, the observed association between migration and excess mortality remains valuable.

Level of self-isolation

The level of self-isolation in both the current and previous months showed a positive and significant association with excess mortality. This likely reflects an inverse relationship – regions with worsening coronavirus situations saw greater reductions in social contacts. This finding aligns with previous studies on Russia (Zemtsov and Baburin 2020; Kolosnitsyna and Chubarov 2022).

However, the coefficient for the self-isolation index in the previous month is also significant and positive, suggesting that this result cannot be solely attributed to feedback. This may indicate that the relationship between excess mortality and self-isolation is not linear. It is possible that beyond a certain "critical" level of self-isolation, the effect on excess mortality shifts to a negative impact – an assumption that requires further investigation.

Caution is necessary when using the Yandex self-isolation index due to two key limitations.

Firstly, the self-isolation index was calculated by Yandex based on the use of its electronic services on mobile devices (Yandex 2020). Naturally, not all individuals rely on Yandex services in their daily activities, particularly the elderly and children. As a result, the index may not fully capture population-wide activity, especially for older individuals – the group most vulnerable to COVID-19. Currently, no studies have assessed the accuracy of this index as a comprehensive measure of mobility and isolation.

Secondly, the self-isolation index varies significantly within a single month, making the use of monthly averages potentially misleading. On certain days, self-isolation levels may have been much lower than on others, but these fluctuations are not reflected in the average. A clear example of this issue arises in January, when the first 1.5 weeks consist of long public holidays, leading to reduced activity. However, the monthly average does

1 Practical instructional and methodological manual on demographic statistics. Approved on 07.12.2007. Rosstat

not indicate whether these holiday periods had any meaningful effect on mortality. In fact, based on our model, the expected impact would be the opposite of what might intuitively be assumed.

To improve the analysis of self-isolation's effect on excess mortality, it would be beneficial to explore alternative methods of measurement or consider a more precise approach to assessing mobility patterns over time.

Identified cases of infection

The relationship between the number of detected infections and excess mortality aligns with expectations – higher infection numbers in the current month correspond to increased excess deaths. Additionally, in model (2), the number of infections in the previous month was also significantly associated with excess mortality in the current month. This result is intuitive, as different variants of the virus exhibited varying timeframes from infection to death. In the second wave, the dominant variant had an incubation-to-death period of approximately 2–3 weeks, whereas in the third wave, this interval shortened to 1–2 weeks (Lundberg et al. 2022).

The observed relationship in the third wave reflects the natural progression of the pandemic – when a high number of infections occurred in the previous period, fewer deaths were recorded in the current one. This could be due to a combination of acquired immunity, improved treatment protocols, or changes in testing and reporting strategies.

When interpreting this indicator, several limitations must be considered. First, it does not represent the total number of infections but rather the number of positive test results among those tested. This means the data only capture cases where individuals sought medical attention and underwent testing. Second, reporting biases and potential data manipulation – whether intentional or accidental – may affect the accuracy of these figures. Not all patients displaying COVID-19 symptoms were necessarily infected with the virus (Danilova 2020), and conversely, not all symptomatic patients were tested. Finally, diagnostic accuracy has evolved over time. Early in the pandemic, testing was prone to false positives and false negatives, but these issues were largely addressed by early 2021 (Vandenberg et al. 2021).

Vaccination

The study finds a negative relationship between vaccination rates and excess mortality, aligning with the conclusions of previous research. However, it is important to interpret this result with caution. In Russia, mass vaccination coincided with the spread of the Omicron variant, which had a lower mortality rate compared to earlier strains (Lorenzo-Redondo et al. 2022). As a result, the observed lower excess mortality in regions with higher vaccination rates may not be solely due to vaccine efficacy but also influenced by the characteristics of the Omicron wave itself. The potential benefits of vaccination require further investigation, which falls beyond the scope of this study.

Characteristics of the healthcare system

Our analysis of the healthcare system's characteristics is constrained by the availability of data, as most indicators are reported only on a quarterly or annual basis. The negative relationship between the number of hospital beds per capita and excess mortality, as observed in model (3), is challenging to interpret. The number of hospital beds fluctuates non-linearly in response to healthcare demands, meaning this relationship does not necessarily reflect the actual burden on the healthcare system during the pandemic. Furthermore, it does not clarify whether an increase in hospital beds helped prevent excess mortality. Additionally, for COVID-19 patients, the availability of oxygen-equipped and ventilator-supported beds was crucial, but such data is not available for Russian regions.

A similar challenge arises with the number of doctors. Without data on their specialization or workplace distribution, it is difficult to explain the counterintuitive finding of a positive association between the number of doctors and excess mortality. It is also important to consider that, during the pandemic, many doctors were reassigned from general medical departments to "red zones" dedicated to COVID-19 treatment.

Overall, the lack of detailed, month-by-month data on the healthcare system's functioning in Russian regions presents a significant limitation. Without such data, it is impossible to precisely assess the quality and effectiveness of medical services provided during the pandemic.

Age structure of the population

The proportion of the elderly population is significantly associated with excess mortality in both waves of the pandemic, with the coefficient being lower in the third wave. Perhaps this is due to the collective immunity acquired by the elderly population by the fall of 2021, but the coefficients should be interpreted with caution.

Results

Summing up this section, we will briefly formulate the main conclusions of the study:

1. The positive association of excess mortality with income is actually a reflection of the link between excess mortality and income inequality in the regions of Russia.
2. The self-isolation index shows an inverse relationship – higher excess mortality corresponds to higher self-isolation rates among the population.
3. Migration is positively associated with excess mortality in the second wave and negatively in the third – most likely due to the characteristics of strain transmission specific to each wave.

The main limitation of the study is the lack of publicly available high-frequency data on the healthcare system (e.g., number and specialization of beds, number of medical staff), morbidity, hospitalization, and mortality by age (as the relationship of each factor may vary across age groups), as well as population movement between regions and short-term relocations within regions (which are not fully captured by the indicator used). Since mortality varies significantly over time, the use of aggregated indicators may introduce bias.

Including high-frequency data in the analysis, which is typically not publicly available, would improve the accuracy and completeness of the study. Additionally, the study could be supplemented with data on education, as research shows that mortality rates tend to be lower in regions with a more educated population (Meara et al. 2008; Shkolnikov et al. 2006). However, there is a lack of high-quality, regionally specific education data, particularly in a dynamic format (except for census data), so access to such data would enhance the study's results.

Research perspectives

The analysis presented above provides a general understanding of the potential factors contributing to excess mortality in Russian regions during the coronavirus pandemic. However, it also highlights several areas that require further research.

First, additional studies are needed to explore the relationship between excess mortality and inequality in the region. The mechanisms through which inequality impacts excess mortality may be varied. For instance, income inequality could reduce the ability of low-income individuals to access healthcare services. Conversely, lower-income individuals may have fewer opportunities to limit their social contacts – such as through remote work or other means of social distancing.

Inequality is not limited to income alone. Inequality in access to healthcare services is a critical factor that influences mortality rates during epidemics. This was demonstrated in studies from the UK (Sun et al. 2021) and the United States (Mishra 2021). In Russia, access to healthcare services is also unequal, with regions that have better healthcare infrastructure often showing higher levels of inequality in access (Kazantsev and Rumianceva 2022). Thus, further analysis should examine other dimensions of inequality, including healthcare access, to validate the finding that inequality has a detrimental effect on mortality during the pandemic. Understanding the mechanisms of inequality's impact on excess mortality will be essential for more nuanced insights into the pandemic's socio-economic dynamics.

Another possible way to expand the analysis is to use an alternative method to the self-isolation index for assessing the limitation of contacts among the population. In particular, it would be possible to combine the analysis of the self-isolation index with an analysis of the severity of restrictions on contact imposed by the state. In Russia, coronavirus restrictions were mostly imposed at the regional level. When trying to analyze the differences in the restrictions imposed during the second and third waves of the coronavirus, the following obstacles to the use of these variables were identified:

- firstly, until August 2021, there was no single service that would aggregate the restrictions in detail. An attempt to isolate the types and frequency of restrictions from the relevant decrees of the regional heads presents a difficult task due to the varying approaches of regional executive authorities in updating their decrees. In some regions, new restrictions were introduced by amending previous resolutions (for example, in Moscow, restrictions were adjusted by amending Decree No. 68-UM "On the stages of lifting restrictions imposed in connection with the introduction of a high-alert regime"), while in other regions, new decrees were adopted each time (or amendments were made with the wording "to state the text of the resolution in the following wording"), which makes tracking the changes a complex task;
- secondly, the restrictions imposed by the regions often copied one another. In some regions, some authority for imposing restrictions was transferred to the municipal level. Due to the lack of reliable COVID statistics at the municipal level, it is difficult to use this data;
- thirdly, some restrictive measures were introduced for a short period (1-2 weeks), making it unclear how they should be accounted for when analyzing monthly fluctuations in mortality.

For further research, it is necessary to analyze in detail the restrictions imposed and their observance.

Due to the lack of the ability to monitor the effects of the restrictions imposed on specific territories of Russia and the lack of high-quality data, this idea had to be temporarily abandoned. The hypothesis was that the excess mortality rate in a region could be influenced by the proportion of workers employed in certain professions:

1. In some industries, close and regular contact with other people is inevitable. Even with strict adherence to preventive anti-epidemic measures, the level of infection and, consequently, excess mortality will likely be higher if these activities are not restricted (for example, schools should be switched to remote operation to limit the spread within them).
2. In other industries, there is no close and regular contact between people, but these types of activities cannot be suspended (for example, industrial enterprises, housing and communal services, and so on). In such cases, regions with a large proportion of people employed in these sectors may experience higher excess mortality rates.

Additionally, the impact of the coronavirus varies across individuals from different age groups, so it would be beneficial to separate the analysis by age in future research.

It is also important to consider that we are dealing with a spatial context – Russian regions are geographically close, and high levels of excess mortality in one region may, in part, be influenced by similarly high levels in neighboring regions. In this case, spatial models should be explored. Since this study did not aim to analyze the spatial patterns of excess mortality, we limited ourselves to using panel data models and OLS models. Spatial analysis can serve as a foundation for further research.

Conclusion

The results obtained in the study (considering the limitations noted earlier) show that the differentiation in excess mortality across the regions of Russia is related to income levels, inequality, and the size of migration flows. It also indicates the absence of a positive effect of self-isolation on excess mortality during the second and third waves, which may suggest both the imperfection of the Yandex self-isolation index and the insufficient restriction of social contacts during these periods to reduce excess deaths.

An important finding of the study is the positive association between excess mortality and the level of per capita income in the region. However, this result more likely reflects a positive relationship between excess mortality and income inequality in the region.

The study raises several questions that require further investigation. It is crucial to clarify the mechanism through which inequality affects excess mortality in the regions, assess whether the restrictive measures taken in the regions were effective in preventing excess mortality, and determine which age groups were most affected by specific factors. Another open question is the impact of the healthcare system's burden on excess mortality, for which it is necessary to identify appropriate monthly regressors that could serve as reliable proxy variables.

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Appendix 1

Validation of Model Results for Sustainability Using Standardized Mortality Rates

The method of indirect standardization was employed to standardize the coefficients. Mortality rates in the Russian Federation for 2021 were used as the standard. Excess mortality rates were converted into the number of excess deaths using regional population data.

The age factor (proportion of individuals over 65 years old) was excluded from the models, as the influence of age structure should be accounted for through the standardization process. The results of the simulation are presented in Table A1.

Table A1. Results of the panel model evaluation with fixed effects. The dependent variable is the logarithm of the excess mortality coefficient, with robust standard errors

All variables are in logarithms	(5) 2nd wave (09.2020–02.2021)	(6) 3rd wave (07.2021–02.2022)
Migration per 1.000 people in the current month	0.05 (0.03)	0.001 (0.03)
Migration per 1.000 people in the previous month	-0.01*** (0.004)	0.011*** (0.003)
Per capita income	0.23*** (0.006)	0.038*** (0.008)
Unemployment	0.022*** (0.007)	0.0015 (0.008)
Detected cases per 1.000 people in the current month	0.003 (0.003)	0.008*** (0.0007)
Detected cases per 1.000 people in the current month	0.004 (0.03)	-0.001 (0.0012)
Vaccination rate (%)		-0.01*** (0.0017)
Index of self-isolation in the current month	0.018** (0.007)	
Index of self-isolation in the previous month	0.012 (0.008)	
R-square	0.54	0.47
Number of observations	498	680

Source: compiled by the authors. *Note:* *** 1% , ** 5%, * 10% levels of significance

Compared to the model shown in Table 5 (for non-standardized mortality rates), the proportion of the vaccinated population has become significantly negative. This may indicate that, during the third wave of the pandemic, vaccination coverage was indeed associated with a reduction in COVID-19-related deaths. At the same time, all other variables of interest showed similar signs and significance. Therefore, we conclude that the use of both standardized and general mortality rates is equivalent in this study.