Демографическое обозрение / Demographic Review
2024;11(2) 4-20 DOI: https://doi.org/10.17323/demreview.v11i2.21824

Convergence of mortality rates and life expectancy in Russia's major cities before and after the pandemic

Ekaterina Vetrova
(ekat.vetrova@gmail.com),
Lomonosov Moscow State University, Russia.

Natalia Kalmykova
(natalia-kalmykova@yandex.ru),
Lomonosov Moscow State University, Russia.

Abstract: *This study examines mortality convergence and divergence trends across major Russian cities with populations between 100,000 and 1 million before, during, and after the COVID-19 pandemic. These cities account for approximately 37,9 % of the urban and 28,4 % of the total Russian population. Using official data on death counts and mid-year population estimates from the Federal State Statistics Service (Rosstat) for 2012–2022, we apply beta- and sigma-convergence models to life expectancy at birth, to interval (truncated) life expectancy between ages 0-15, 15-35, 35-65, and remaining life expectancy at age 65.*

Our findings provide evidence of strong mortality convergence across large cities prior to the pandemic, driven primarily by improvements in child and young adult age groups (0-15 and 15-35 years). In contrast, convergence was weakest among adults aged 35-65 – a group that remains the greatest potential for reducing mortality disparities and increasing overall life expectancy in Russia. The pandemic disrupted these trends: although beta-convergence persisted, sigma-convergence weakened, and disparities in life expectancy widened again in 2022 due to uneven recovery across cities.

Overall, the results highlight both the progress and fragility of mortality convergence in Russian urban population. While younger age groups contribute to convergence, high mortality and persistent inequality in older working ages (35-65 years) indicate that lagging cities are not adopting the practices of leading cities. The COVID-19 pandemic slowed convergence and underscored the vulnerability of certain populations and health systems to external shocks.

Keywords: *major Russian cities, mortality, life expectancy, convergence, COVID-19 pandemic.*

For citation: *Vetrova E., & Kalmykova N. (2024). Convergence of mortality rates and life expectancy in Russia's major cities before and after the pandemic. Demographic Review, 11(2), 4-20.*
https://doi.org/10.17323/demreview.v11i2.21824

Introduction

Russia entered the 20th century with a very high total but very low effective fertility. Yet from the point of view of the demographic and, moreover, socio-economic reproduction of society, what matters is precisely effective fertility, which measures not only the number of children born, but also how many of those who are born survive, socialize, participate in economic life, become adults and replace their parents. Children who die in infancy or as they are approaching adulthood are, from a demographic and socio-economic point of view, an unjustified waste of the reproductive potential of the human population. In contrast, children who reach certain socially determined age thresholds become more and more valuable capital for society and the family.

The more that the number of children reaching adulthood, the age of marriage and parenthood differs from the total number of children born, the lower the demographic and social effectiveness of fertility and the economy of the population reproduction regime as a whole. The greater the child mortality, the greater must be fertility's compensatory component and, consequently, fertility as a whole, to maintain a given social norm of family size. The reduction of child mortality is the most important trigger for the modernization of the entire process of population reproduction. The convergence of total and effective fertility is, on the one hand, evidence of the growth of this effectiveness, an indicator of the demographic progress achieved in the course of modernization, while on the other hand it is the objective basis for a significant decrease in fertility, a strengthening of the intra-family birth control that occurred during the first demographic transition, that is, the transition to the modern regime of population reproduction, in which population growth depends barely at all on early mortality.

20 years ago, F. Mele and J. Vallin wrote in one of their articles that the health transition, which involves a gradual convergence of mortality rates between countries, goes through several stages of convergence and divergence caused by different levels of health development and by the sociocultural and economic characteristics of different countries. At the same time, the authors noted that "it would be useful to develop (these ideas) further to see how applicable they might be to the mortality trends and differences observed *within countries*, either in terms of internal geographic differences or even in terms of economic, social, cultural, gender and other differences" (Vallin, Meslé 2004: 38). The example of Europe shows that countries with similar levels of economic development are gradually undergoing a path of convergence in mortality, albeit at different rates (Coleman 2002).

Most studies analyze mortality convergence at the cross-country level (Mackenbach 2013; Liou et al. 2020) or for regions of the world (Aksan, Chakraborty 2023). Convergence within a country is studied less frequently. For example, (Edwards, Tuljapurkar 2005) analyzed age patterns of mortality in the United States, in particular the variation in the average age of death among adults, ethnic groups and population groups with different levels of income and education. The works (Hrzic et al. 2023; van Raalte et al. 2020) compared the dynamics and convergence of life expectancy at birth in the regions of Western and Eastern Germany.

One would assume that a similar convergence in mortality should be observed in Russia as well. Previous studies have repeatedly emphasized the significant heterogeneity of Russian regions in terms of mortality rates (Danilova 2017; Shchur, Timonin 2020; Andreev, Kvasha, Kharkova 2014). For Russia, the problem of inequality in mortality, with a pronounced center-periphery gradient, is an important one (Shchur 2018; Shchur, Timonin 2020; Zubarevich 2007).

At the same time, indicators of large cities outpace the average indicators of their regions; no convergence of mortality rates within regions is observed.

The research question is this: Is there convergence in mortality between large cities in Russia? Differences between large cities in access to health care, high-quality food, a healthy lifestyle and employment opportunities can make an urban environment less attractive to residents. This in turn provokes internal migration and increases the economic development gap between cities (Bortz et al. 2015).

In our work, the hypothesis of convergence in mortality was tested on the entire set of Russian cities with a population of over 100 thousand people. This definition of the sample ensures a similar level of socio-economic development and human capital between objects, and helps to reduce the problem of the center-periphery gradient. Cities with a population of over a million are not included in the analysis, since previous studies (Shchur 2018) show that the mortality structure in such cities is too individual, there is no general trend towards convergence or divergence of million-plus cities in terms of life expectancy over the past 30 years. The process of convergence in mortality between regions was uneven even in the years of growth in life expectancy before the external shock of the pandemic (Timonin et al. 2017). The choice of the subject of this work is based on the findings of studies of territorial differences in mortality in Russia (Shchur 2018; Shchur, Timonin 2020; Zubarevich 2007; Popova 2019).

We test hypotheses of beta- and sigma-convergence for life expectancy in large cities of of Russia, as well as for interval life expectancy in the age groups 0-15, 15-35, 35-65 and 65 years and older. The concept of beta-convergence is that in less developed cities, with low life expectancy (LE) at birth, LE grows faster than in cities with an initially higher level. That is, the growth rate of the indicator depends on its initial value. Sigma-convergence suggests a decrease in the dispersion of LE at birth between cities over time.

Using the example of the United States (Bianchi, Bianchi, Song 2023), the uneven impact of the COVID-19 pandemic on different social groups was revealed. Similar trends are noticeable for Russian cities. Therefore, the work considers separately the periods before (2012-2019), during (2020) and after the COVID-19 pandemic (2021-2022), and also assesses the impact of the pandemic on the rate of convergence in large cities of Russia.

Data and methods

The empirical basis of the study is data from the Federal State Statistics Service: 3TS tables "Tables of mortality and life expectancy" from 2012 to 2021 for cities of Russia with a population of over 100 thousand people. The data contain mortality tables for five-year age intervals separately for men, women and both sexes. The sample includes 150 large cities. This is a complete list of cities whose population, according to Rosstat, exceeded 100 thousand people throughout the entire period.

The study used interval life expectancies for the age intervals of 0-14, 15-34, 35-64, and 65 years and older. Interval life expectancy is calculated based on five-year life tables using the formula:

$$ {}_{x+n}e_x = \frac{T_x - T_{x+n}}{l_x}, \tag{1}$$

where ${}_{x+n}e_x$ is the average life expectancy in the interval from x to x+n years, T_x is the number of person-years of the future life of the generation aged x years and older, and l_x is the number of people who survived to the exact age of x years.

To test the hypothesis about the convergence of mortality rates in large cities, beta- and sigma-convergence models are used. Although these models were initially created within the framework of macroeconomic theory, their application to demographic data has also become widespread (Edwards 2011; Edwards, Tuljapurkar 2005; Coleman 2002; Kashnitsky, De Beer, Van Wissen 2017; Kalabikhina, Shatalova, Fang 2020).

The main assumption of the beta-convergence model is that cities with initially lower life expectancy will experience higher growth in this indicator than cities with a higher initial level. Thus, lagging cities will gradually catch up with the leaders.

The main regression of the model is described by the expression:

$$\log\left(\frac{E_{i,t}}{E_{i,t-1}}\right) = \alpha + \beta \log\left(E_{i,t-1}\right) + \varepsilon_{i,t} \ , \tag{2}$$

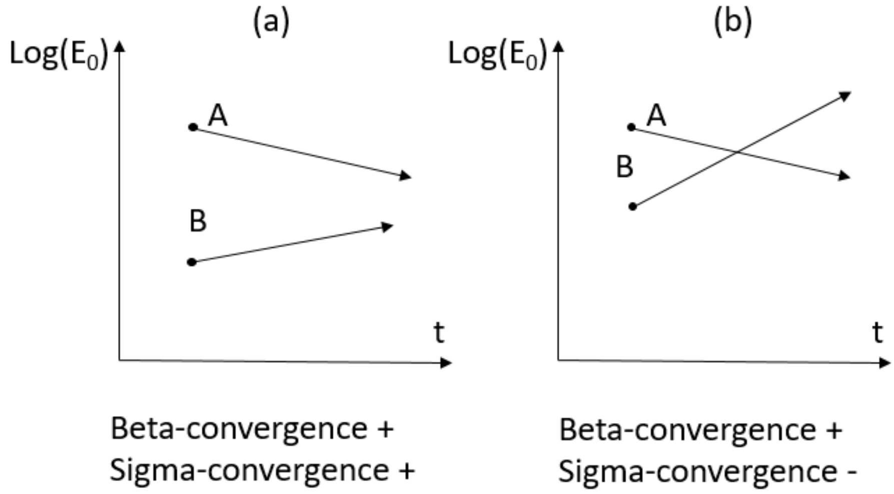
where $\log\left(\frac{E_{i,t}}{E_{i,t-1}}\right)$ shows the growth in life expectancy at birth and $\varepsilon_{i,t}$ are random errors. The coefficient α can be considered as the average growth rate. The beta-convergence hypothesis is confirmed if the coefficient $\beta < 0$, i.e. the higher the life expectancy level at the current moment, the less its growth will be in the next period.

Sigma-convergence is said to occur when the spread of the values of the indicator of interest decreases over time. In this paper, the auxiliary regression of the sigma-convergence model is described by the following equation:

$$SD(E_t) = \gamma + \delta * \mathrm{t} + \mu_t \ , \tag{3}$$

where $\mathrm{SD}(\mathrm{E_t})$ is the standard deviation of life expectancy in cities for year t and μ_t is a random error. If the coefficient δ is significant and negative, sigma-convergence is present in the data.

Figure 1. Life expectancy dynamics depending on the combination of beta- and sigma-convergence



Source: Based on the article (Sala-i-Martin 1996.)

We look at several options for combining beta- and sigma-convergence. One of the possible combinations is that both hypotheses are confirmed, and both beta-convergence and sigma-convergence are present in the data. In this case, cities lagging behind in life expectancy catch up with the leaders, and the spread of values decreases (Figure 1a). However, a situation is possible when beta-convergence is observed in the data, but sigma-convergence is absent. This means that in cities with a lower initial level of life expectancy, the value of the indicator increases faster than in cities with a high initial level, but the spread of values does not decrease (Figure 1b) (Sala-i-Martin 1996). This situation is less favorable, since it means that the leaders lose their advantage, and the cities develop unevenly. Leaders and outsiders change places. In this case, it is necessary to pay attention to cities that are losing their initial advantage, since the value of life expectancy in them is likely to decrease or remain at the same level, while the decline in mortality in other cities is accelerating.

In the study, the beta- and sigma-convergence hypotheses are tested for life expectancy at birth, as well as for interval life expectancy in the age groups 0-15, 15-35, 35-65 and 65 years and older for people who have survived to the beginning of each of the age intervals. Testing the hypotheses for interval life expectancy allows us to draw conclusions about which groups are responsible for the convergence of life expectancy at birth, as well as to identify promising age groups due to which convergence could be enhanced.

To test the hypothesis about the impact of the pandemic on convergence, two model specifications were estimated taking into account the binary variable COVID-19, equal to 1 for 2020 and 2021 and 0 for all other years. For 2022, an additional binary year variable (*after*) was introduced, since the recovery process after the pandemic may affect the rate of convergence differently than the external shock itself.

In order to take into account the effect of the pandemic, an extended specification of the beta-convergence model was estimated:

$$\log\left(\frac{E_{i,t}}{E_{i,t-1}}\right) = \alpha + \beta \log(E_{i,t-1}) + \gamma * \log(E_{i,t-1}) * Covid_{19} + \partial * \log(E_{i,t-1}) * after + \varepsilon_{i,t} \quad (4)$$

For the period “before the pandemic”, the regression equation looked like this:

$$\log\left(\frac{E_{i,t}}{E_{i,t-1}}\right) = \alpha + \beta \log(E_{i,t-1}) + \varepsilon_{i,t} \quad (5)$$

For the pandemic period:

$$\log\left(\frac{E_{i,t}}{E_{i,t-1}}\right) = \alpha + (\beta + \gamma) * \log(E_{i,t-1}) + \varepsilon_{i,t} \quad (6)$$

In 2022:

$$\log\left(\frac{E_{i,t}}{E_{i,t-1}}\right) = \alpha + (\beta + \partial) * \log(E_{i,t-1}) + \varepsilon_{i,t} \quad (7)$$

If the coefficient γ is significant, the pandemic has a significant impact on the convergence rate. The significance of the coefficient ∂ will indicate the impact of the recovery process after the pandemic on the convergence rate.

For data analysis, regression construction and visualization, R and RStudio software were used.

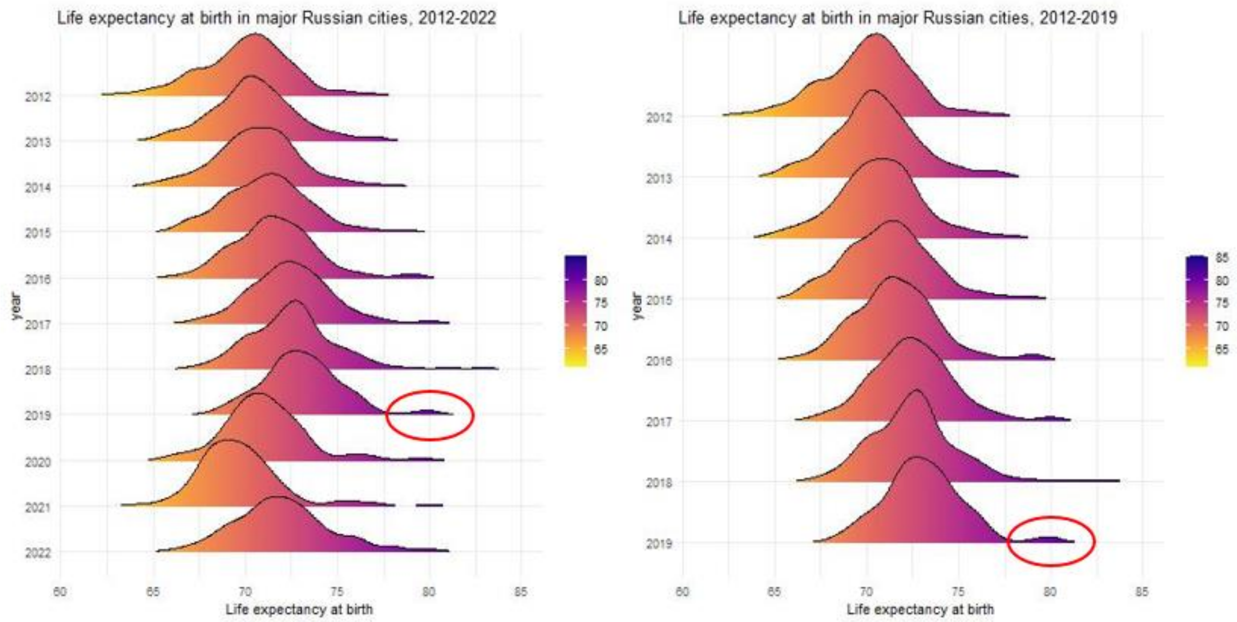
Results

The distribution of cities by life expectancy at birth becomes more compressed from 2012 to 2019 (Figure 2). In 2012, there was a noticeable plateau in the distribution at 67-68 years of life expectancy, which is below the average. By 2019, the cities on the left side of the distribution are approaching the average life expectancy, and the average life expectancy itself is growing. The left edge of the distribution is a large group of cities with an indicator below the average. In 2020-2021, the distribution is compressed even more, but the average life expectancy is decreasing due to the COVID-19 pandemic. In 2022, the spread of cities increases again due to the uneven recovery of life expectancy in cities.

Due to significant changes in the dynamics of life expectancy after 2019, the hypotheses about beta- and sigma-convergence were further tested separately for the intervals 2012-2019 and 2012-2022. Before 2019, the distribution of cities by life expectancy becomes significantly more compressed, the first and third quartiles of the distribution converged in values (Table A1 of the Appendix). However, by the end of the period, a right "tail" of the distribution emerges, representing cities significantly ahead of the average level of life expectancy at birth.

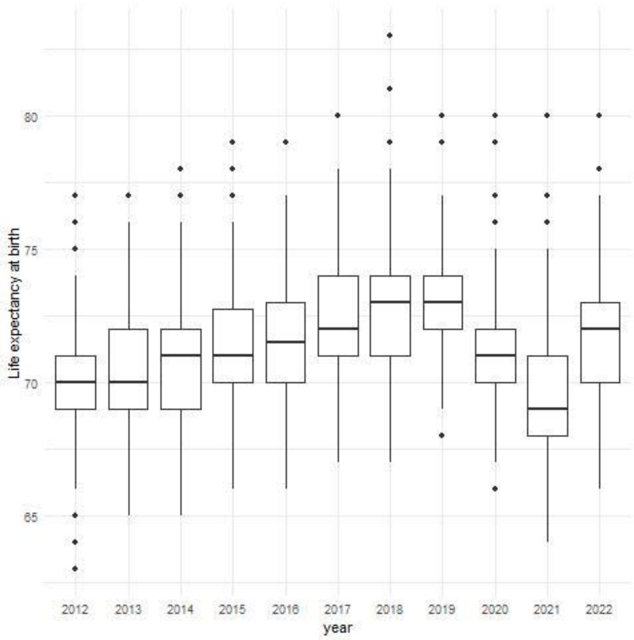
In Figure 2, this feature of the distribution is highlighted in red. If we consider the statistics of cities by life expectancy at birth (Figure 3), the highlighted "tail" is individual points that differ from the general distribution. Four cities with values above 77 years fell into this category (Makhachkala, Kaspiysk, and Khasavyurt (Republic of Dagestan), as well as Nazran (Republic of Ingushetia)). Other studies (Mkrtchyan 2019) discuss the abnormally high life expectancy in the Caucasian republics, so we will consider this result as an outlier rather than a stable trend.

Figure 2. Distribution of cities by life expectancy at birth from 2012 to 2022



Source: Authors' calculations.

Figure 3. Distribution of cities by life expectancy at birth from 2012 to 2022



Source: Authors' calculations.

Mortality convergence in large cities before the pandemic

To assess convergence without taking into account the external shock, Model 1 is built on data from 2012 to 2019. Model 2 includes 2020 and 2021 to check whether the convergence between cities was maintained during the pandemic (Table 1). Model 3 also includes 2022, which saw the recovery of life expectancy after the pandemic. The table presents the results of estimating the models for all cities in the sample, but the models were tested for robustness and built without taking into account the cities that were classified as outliers according to the preliminary analysis. The results are robust, and the significance and direction of the influence of the variables are preserved. The model coefficients change by less than 0.01.

Table 1. Results of estimating the beta-convergence regression using the ordinary least squares (OLS) method

Variable	Model 1 2012-2019	Model 2 2012-2021	Model 3 2012-2022
Const (α)	0.146 *** (0,020)	0.101 *** (0,02)	0.069*** (0,02)
Initial level of LE (β)	- 0.033 *** (0.005)	-0.024 *** (0.005)	-0.016*** (0.005)
R^2	0.254	0.143	0.067

*Note: Standard errors are given in brackets; *** – significance at the 1% level.*

Regression analysis shows the presence of absolute beta-convergence of life expectancy between large cities. That is, in cities with a lower initial level of life expectancy, the indicator grows faster than in cities where life expectancy was initially higher. But the external shock of the pandemic contributed to the dynamics of the life expectancy at birth in cities, and the recovery process is uneven. The strongest beta-convergence is observed in the data before 2019. In model 1, the β coefficient reaches its largest absolute value. After the pandemic, the convergence becomes weaker, although it still remains statistically significant.

The results of the sigma-convergence regression estimate are shown in Table 2. Before 2019, sigma-convergence is also present in the data. The coefficient for the time variable is negative and significant, which indicates that the spread of life expectancy at birth values (standard deviation) decreases over time. However, taking into account the pandemic years, sigma-convergence in the data disappears. From 2020 to 2022, the beta-convergence process continued, but the spread of values did not decrease.

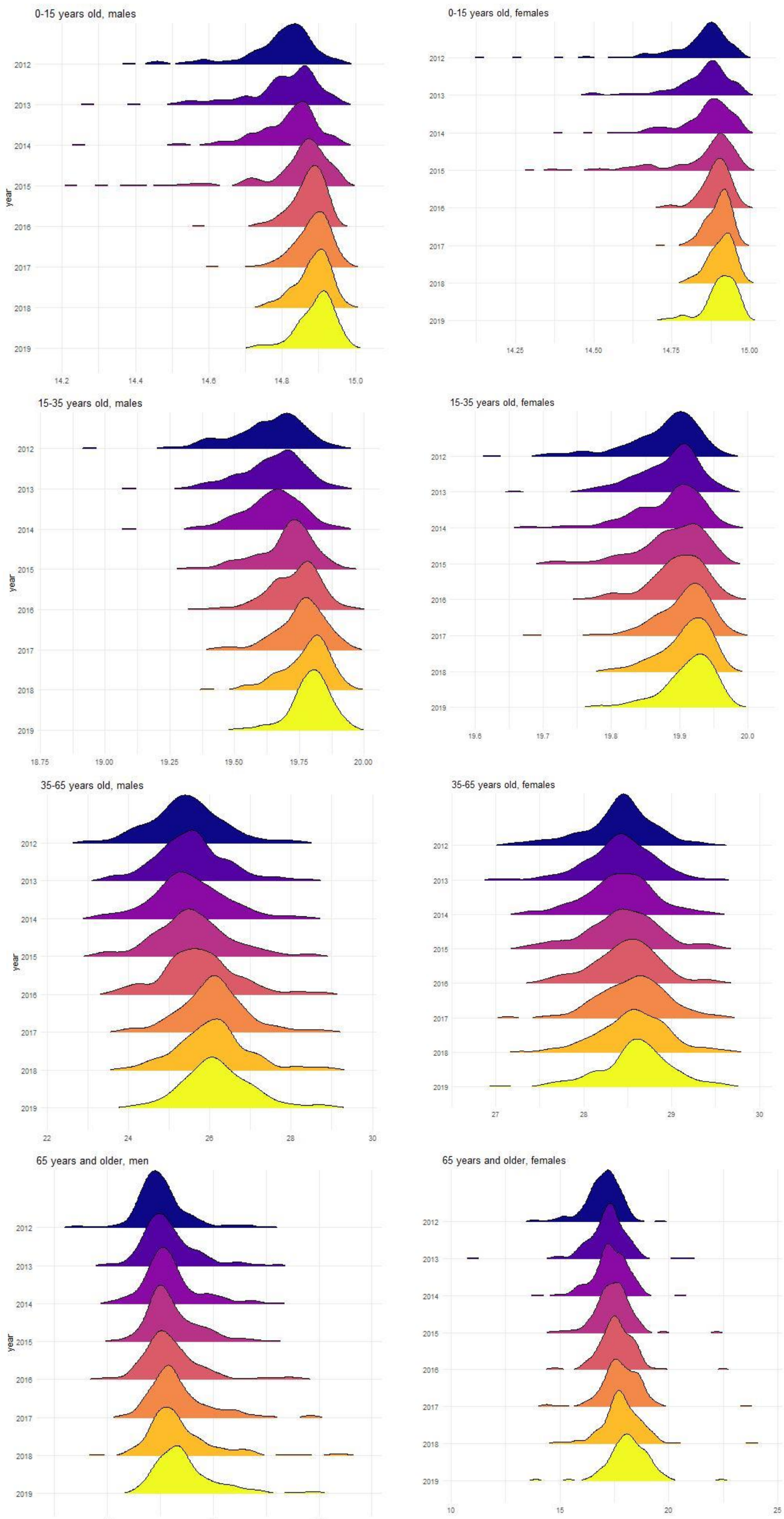
Table 12 Results of sigma-convergence regression estimation using the OLS method

Variable	Model 3 2012-2019	Model 4 2012-2021	Model 5 2012-2022
Const	0.923 ** (0.318)	0.434 (0.27)	-0.021 (0.34)
Time	-0.0004 ** (0.0002)	-0.0002 (0.0001)	0.00002 (0.0001)
R^2	0.57	0.22	0.003

*Note: Standard errors are given in parentheses; ** – significance at the 5% level*

As a result of the obvious change in trends during the COVID-19 pandemic, it is necessary to consider the convergence process before 2019 and after 2020 separately.

Figure 4. Dynamics of the distribution of large cities by interval life expectancy in age groups, men and women, 2012-2021



Source: Authors' calculations.

Regarding the convergence that took place before 2019 inclusive, it is necessary to highlight the age groups that were the drivers of this process, as well as those age groups whose mortality differences still vary greatly between cities. In order to identify the most vulnerable groups and the most promising ones in terms of increasing life expectancy, an analysis of interval life expectancy was conducted in the age groups 0-15, 15-35, 35-65 and 65 years and older. The difference in the structure of causes of death in these age groups was identified in earlier studies (Danilova 2017). Interval life expectancy was chosen as a key element of the analysis as an analogue of life expectancy, allowing us to assess the convergence between age groups.

The main drivers of convergence are the 0-15 and 15-35 age groups for both men and women. The lowest convergence is observed in the 65+ age groups for men and women, as well as 35-65 years for men (Figure 4). To illustrate the distribution dynamics within each group over time, the dimensions of the axes are different.

The highest convergence is observed in the 0-15 and 15-35 age groups. In these age groups, the left "tail" of the distribution (cities with the lowest life expectancy in this age range) is pulled towards the average value from 2012 to 2019. The peak of the distribution is growing, which indicates a high concentration of cities with approximately the same life expectancy. These groups are the drivers of convergence of cities in overall life expectancy. This is confirmed by the decomposition of the contribution of age groups to the gap with the leading cities in life expectancy at birth. Figure A in the Appendix shows a graph of the contribution of age groups to the gap between city groups and the leader in life expectancy in Russia - Moscow. According to calculations, at this stage the age groups 0-14 years and 15-34 years make a minimal contribution to other cities' lag behind Moscow or even have a lower mortality rate. This confirms the fact that there is a convergence process within these age groups. The pandemic has hardly reduced the average life expectancy in these age groups, and the distribution of cities in 2020-2021 remained compressed.

The highest differentiation of cities in life expectancy is observed in older working ages (35-65 years). In this age group, the growth in the average life expectancy is insignificant. The spread was high in both 2012 and 2019. During the pandemic, life expectancy in this age range decreased, and the distribution of cities in 2021 returned to the 2012 level.

In the age group of 65 years and older, there is also high differentiation, but it is of a slightly different nature. At retirement ages, there is a pronounced right "tail" of the distribution: cities that are significantly ahead of the average in life expectancy. However, the population accounting at retirement ages is not always carried out correctly (Mkrtchyan 2012). In this age group, the decrease in life expectancy is most noticeable. These findings are confirmed by other studies (Kuchmaeva, Kalmykova, Kolotusha 2021).

Brief results of the analysis of beta- and sigma-convergence by the method of constructing regressions for age groups are presented in Table 3. Full results of regression estimates are presented in Tables A2-A5 of the Appendix.

β-coefficients in all equations are negative and significant at the 1% level. Thus, statistical tests confirm beta-convergence in life expectancy in large cities.

The hypothesis is confirmed that the strongest convergence is present in the age groups up to 15 and from 15 to 35 years. For these age intervals, the β coefficient is the largest in absolute value. The weakest convergence is observed in the older working ages of 35-65 years. However, for this age group, the convergence of cities is also statistically significant.

Sigma-convergence is observed only in the age groups from 0 to 35 years. Thus, the convergence process, i.e., the convergence of initially lagging cities to the leading cities in life expectancy, occurs primarily due to children's and young working-age groups. In these groups, the spread of life expectancy values in age intervals is reduced.

Table 3. Brief results of regression estimates for beta- and sigma-convergence in large cities of Russia by age groups, 2012-2019

	Men	Women
LE at birth	$\beta = -0.3^{***}$ $\delta = -0.0002$	$\beta = -0.04^{***}$ $\delta = -0.0004$
0-15	$\beta = -0.12^{***}$ $\delta = -0.0007^{**}$	$\beta = -0.12^{***}$ $\delta = -0.0007^{**}$
15-35	$\beta = -0.10^{***}$ $\delta = -0.0005^{***}$	$\beta = -0.09^{***}$ $\delta = -0.0001^{***}$
35-65	$\beta = -0.03^{***}$ $\delta = -0.0005^{*}$	$\beta = -0.03^{***}$ $\delta = -0.00006$
65+	$\beta = -0.03^{***}$ $\delta = 0.002$	$\beta = -0.03^{***}$ $\delta = -0.0002$

*Note: * – Significance at the 10% level; ** – significance at the 5% level; *** – significance at the 1% level. The groups for which the hypotheses of the work are confirmed are marked in green: there are significant beta- and sigma-convergences. The groups for which the hypotheses of the work are confirmed with a low level of significance of the results are marked in yellow; groups for which the hypothesis of the presence of sigma-convergence was not confirmed are marked in red.*

In the 35-65 age group, sigma-convergence is practically insignificant, and for ages over 65, sigma-convergence is completely absent. The cities lagging behind in life expectancy are gradually catching up with the leaders, but the spread of life expectancy values remains significant over the years. These age groups are currently slowing down the process of convergence of life expectancy at birth. Since the group of older working ages (35-65 years) makes a greater contribution to life expectancy at birth, it is the most promising for further reduction of mortality in lagging cities. The focus of social policy should be primarily on reducing mortality in older working ages.

The impact of the external shock of the pandemic on mortality convergence in large cities

According to the scatter plot of life expectancy at birth (Figure 2), since 2020 the distribution of cities has shifted to the left, and the average life expectancy has decreased. However, in 2020 and 2021 the distribution remains compressed. In 2022, the recovery process from the pandemic begins, but is uneven. The distribution of cities by life expectancy at birth becomes wide again, as in 2012. To test the significance of the pandemic's impact on the convergence process, an extended specification of the beta-convergence model (formula 4) was estimated.

Based on the results of the model estimation presented in Table 4, the coefficients γ and ∂ turned out to be significant and positive. Therefore, the pandemic and the process of recovery of mortality patterns in cities after the pandemic had a significantly negative impact on beta-convergence. The coefficient at the initial level of life expectancy at birth decreased both during the pandemic in 2020-2021 and in 2022 during the recovery period.

Table 4. Beta-convergence model of life expectancy at birth taking into account the effect of the pandemic, 2012-2022

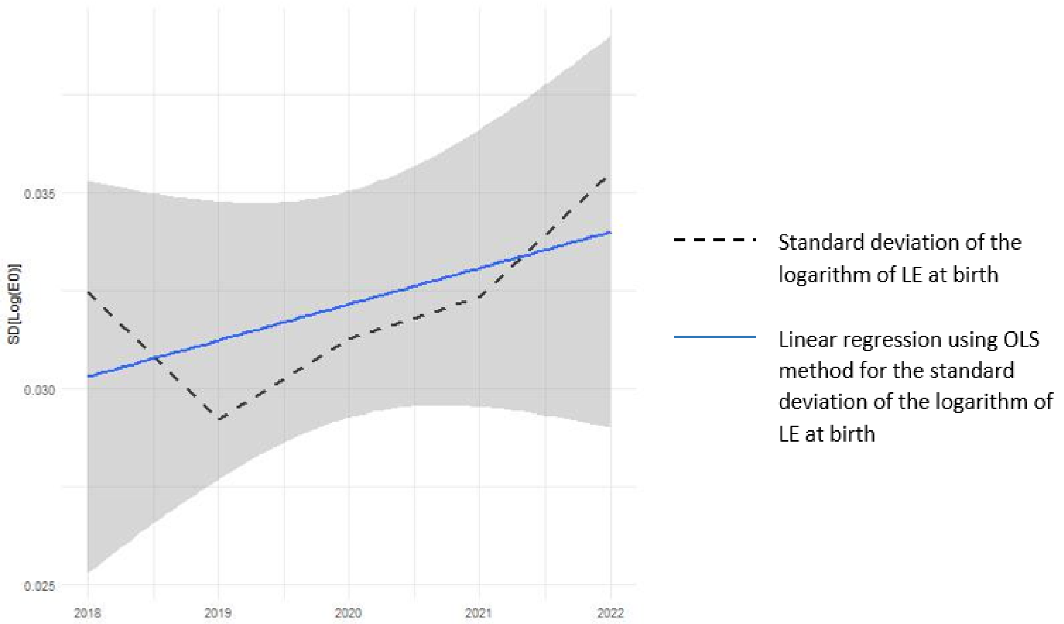
	Beta-convergence model taking into account the pandemic
Const	0.37 *** (0.05)
β	-0.09 *** (0.01)
β*COVID-19	0.0008 *** (0.0002)
β*After	0.0009 *** (0.0003)
R^2	0.05

Note: Standard errors are given in parentheses;

**** – significant at the 1% level.*

Sigma-convergence during the pandemic and immediately after it becomes insignificant. The spread of values increases in the period from 2019 to 2022, and the standard deviation of life expectancy at birth increases during this period (Figure 5).

Figure 5. Standard deviation of the logarithm of life expectancy at birth by year, linear regression, 2018-2022



Source: Authors' calculations.

Conclusions and discussion

Over the past 10 years, convergence in life expectancy has been observed between Russian cities with a population of 100 thousand to 1 million people. This is an important result, since previous studies by regions and cities of Russia, as a rule, showed significant heterogeneity in mortality. For example, for cities with a population of over a million, researchers do not reveal any obvious convergence, but for smaller cities, life expectancy levels out (Andreev, Kvasha, Kharkova 2016; Shchur 2018; Kvasha, Revich, Kharkova 2017). Perhaps the explanation is that cities with a population of over a hundred thousand are closer in terms of economic indicators and level of infrastructure development. In the future, this study can be supplemented by including economic factors in the analysis, as well as the administrative status of cities.

Convergence in life expectancy occurs primarily due to young ages. The strongest convergence is observed in the 15-35 age group, with the second strongest convergence being in the 0-15 age group. The weakest convergence is found in older working ages, 35-65 years. Cities also differ significantly in life expectancy in the 35-65 age range. It is this age group that determines the trends in life expectancy at birth in recent years. The differentiation in life expectancy in this age range has hardly decreased over the years, which means that lagging cities are not borrowing the practices of leading cities.

The COVID-19 pandemic has negatively affected the overall convergence trend. The convergence process continues, but the pace has slowed down. In addition, it should be noted that the recovery of cities in 2022 after the pandemic is uneven. The spread of life expectancy values has increased again almost to the level of the beginning of the period under review - 2012. The convergence process is often uneven, which is a consequence of changes in the structure of causes of death (Vallin, Meslé 2004). However, identifying the vulnerable groups that contributed to the downturn helps mitigate the impact of the shock through targeted social policies. A separate task for future research is to identify the categories of cities in which the recovery process is the least successful, since this slows down the convergence process.

In this paper, a number of questions remain open about the reasons for the presence of convergence and its slowdown in large cities, as well as its drivers. For accurate answers, studies are needed that include an analysis of the economic and social characteristics of cities with a population of over 100 thousand people.

Mortality in childhood and adolescence is usually affected by the level of healthcare and the development of the emergency care infrastructure, as well as by the level of education. Unfortunately, not all of these indicators are presented in municipal statistics. However, it is the level of infrastructure and education that can explain the fact that differences in mortality rates between regions remain significant, while for cities with a population of over 100,000 people, a convergence process is underway.

To explain the differences in the rate of convergence in age groups, additional research into the leading causes of death is required. It can be assumed that in older age groups, the convergence process is slower, since the leading classes of causes of death for these age groups (circulatory diseases, neoplasms) depend on people's behavior throughout their lives. Thus, with an increase in the level of education and quality of life, there is a delay when a new generation matures and enters the 35-64 or 65+ age group. It takes time to change the habits of preventive behavior of the population (limiting unhealthy practices, eating healthier, regular medical examinations), which are becoming more accessible with the growth of the level of medicine and the level of well-being.

The slowdown in convergence during and after the pandemic may be caused by the increased burden on the healthcare system in large cities where catch-up growth was occurring. In addition, the pandemic primarily affected the oldest ages, for whom the convergence process was already experiencing significant difficulties before the pandemic.

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Appendix

Table A1. Descriptive statistics of the dynamics of LE at birth in large cities, 2012-2022

Feature\Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Minimum	66	65	65	67	66	67	68,0	69	67	64	66
First quartile	69	69	69	70	70	71	71,0	72	70	68	70
Median	70	70	71	71	71	72	72,5	73	71	69	72
Third quartile	71	72	72	72	73	74	73,0	74	72	71	73
Maximum	74	76	75	75	77	77	76,0	77	75	75	77
Standard deviation	2.19	2.07	2.06	2.06	1.97	1.95	2.02	1.90			

Table A2. Beta-convergence models by age groups, men, 2012-2019

Variable	Men all ages	Men 0-15 years	Men 15-35 years	Men 35-65 years	Men 65+
Const (α)	0.12 *** (0.02)	0.32 *** (0.015)	0.28 *** (0.013)	0.1 *** (0.016)	0.1 *** (0.022)
Initial level of LE (β)	-0.03 *** (0.005)	-0.12 *** (0.005)	-0.10 *** (0.004)	-0.03 *** (0.005)	-0.03 *** (0.009)
R^2	0.13	0.76	0.75	0.18	0.09

*Note: *** significance at 1% level.*

Table A3. Beta-convergence models by age groups, women, 2012-2019

Variable	Women all ages	Women 0-15 years	Women 15-35 years	Women 35-65 years	Women 65+
Const (α)	0.17 *** (0.02)	0.32 *** (0.012)	0.27 *** (0.019)	0.09 *** (0.02)	0.11 *** (0.02)
Initial level of LE (β)	-0.04 *** (0.005)	-0.12 *** (0.004)	-0.09 *** (0.006)	-0.03 *** (0.006)	-0.03 *** (0.008)
R^2	0.24	0.84	0.59	0.11	0.11

*Note: ***significance at 1% level.*

Table A4. Sigma-convergence models by age groups, men, 2012-2019

Variable	Men all ages	Men 0-15 years	Men 15-35 years	Men 35-65 years	Men 65+
Const	0.4 (0.37)	1.41 ** (0.43)	0.95 *** (0.07)	0.99* (0.5)	-3.32 (2.14)
Time	-0.0002 (0.0002)	-0.0007 ** (0.0002)	-0.0005 *** (0.00003)	-0.0005* (0.0002)	0.002 (0.001)
R^2	0.13	0.64	0.96	0.38	0.3

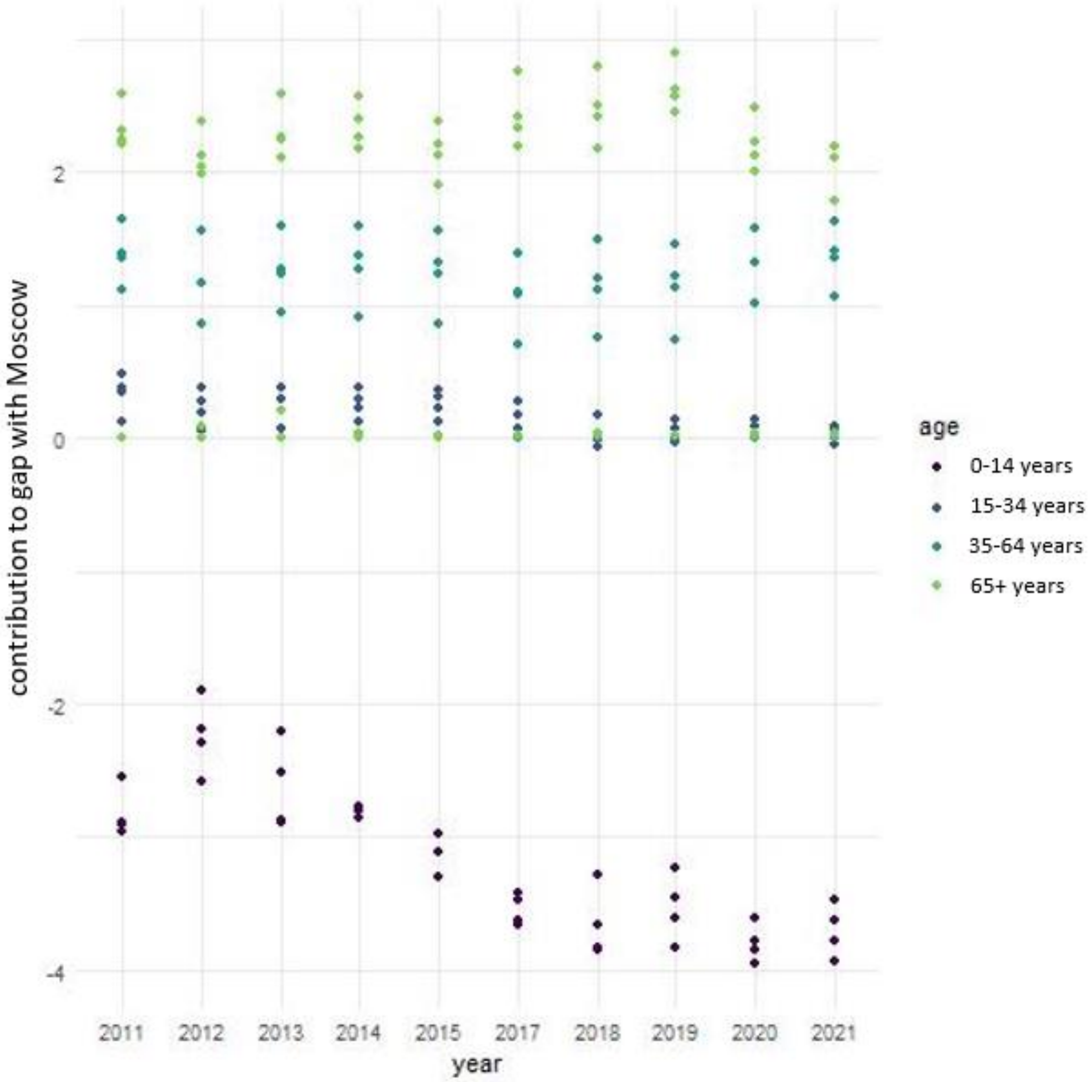
*Note: *significance at 10% level; ** significance at 5% level; ***Significance at 1% level.*

Table A5. Sigma-convergence models by age groups, women, 2012-2019

Variable	Women all ages	Women 0-15 years	Women 15-35 years	Women 35-65 years	Women 65+
Const	0.75 (0.42)	1.44 ** (0.56)	0.30 *** (0.06)	0.15 (0.19)	0.53 (1.46)
Time	-0.0004 (0.0002)	-0.0007 ** (0.0003)	-0.0001 *** (0.00003)	-0.00006 (0.0001)	-0.0002 (0.0007)
R^2	0.32	0.52	0.8	0.07	0.02

*Note: ** significance at 5% level; *** significance at 1% level.*

Figure A. Contribution of age groups to the gap between cities and Moscow, decomposition of life expectancy at birth



Source: Authors' calculations.