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Rural-urban migration within Russia: Prospects and drivers

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ABSTRACT

This study investigates migration flows between urban and rural areas in Russia from 2011 to 2020 and explores potential drivers using a combination of Markov chain and spatial interaction modelling approaches. The findings indicate a high likelihood of rural-to-urban migration, leading to increased urbanization pressure and depopulation of rural areas in the country, further worsened by high mortality and low fertility rates. Socioeconomic and environmental factors, including population size, wages, employment, housing availability and precipitation, have a significant impact on migration flows, and the effects tend to vary according to whether the origin and destination are rural or urban. In general, origin effects are more pronounced than destination effects, meaning that the decision to migrate in Russia is mainly influenced by departure factors.

1. Introduction

Considerable social and economic disparities exist between regions in Russia, particularly between urban and rural areas. Rural areas comprise over 70 percent of the national territory and are home to less than a quarter of the Russian population (approximately 144 million in 2023). Poverty levels are generally one and a half times higher in the countryside than in the cities (Zubarevich, 2019), which are characterized by significantly higher average earnings, as Moscow with an average income 33 percent higher than the rest of Russia (Borison, 2019). In addition, social and employment services are often less efficient in rural settlements, due to their low population density and geographical remoteness (Amini and Nivorozhkin, 2015). These and other differences contribute to social insecurity and the desire for higher living standards (Guriev and Vakulenko, 2015), leading to steady rural depopulation and unbalanced urbanization processes (World Bank, 2024) that undermine the country's economic growth and development (Mareeva, 2020).

Internal migration flows have significant impacts both on origin and destination areas. In rural areas that are the origin of consistent outflows, migration primarily affects the region's agricultural sector (United Nations, 2017; Abdulraheem and Iderawumi, 2019) by altering labor availability, land use, innovation, and production techniques. Furthermore, it reduces the efficiency of public and social services (Cañal-Fernández and Álvarez, 2022), which leads to a lower level of regional development (Tacoli et al., 2015; Jia et al., 2017; Vakulenko, 2019). On the contrary, urban residents have generally better access to economic and social opportunities and tend to have greater occupational and geographic mobility (Butler et al., 2002). However, the excessive concentration of migration flows in a few urban areas puts undue pressure on social services, infrastructure, and housing, which can undermine their efficiency (Margolies, 1978; Zhang and Song, 2003; Rodríguez-Pose and von Berlepsch, 2018a, 2018b) and hinder regional development.

Besides internal migratory pressures, other factors like population decline and climate change contribute to the strain. COVID-19 pandemic has significantly affected spatial mobility patterns worldwide, leading to changing migratory systems (González-Leonardo et al., 2022). In various countries, there was a migration phenomenon marked by a substantial population shift from urban to rural areas (Fielding and Ishikawa, 2021; Vogiazides and Kawalerowicz, 2022; Rowe et al., 2022). It could be the case with Russia, which experienced a natural population growth decline of 0.72 percent in 2021, with deaths outnumbering births by 1.04 million. The COVID-19 pandemic exacerbated this situation, resulting in high mortality

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rates, particularly in metropolitan areas (Nikitin et al., 2023). Conversely, climate change, a problem to which neither Russia nor any other country is oblivious, is altering the comparative advantage of regions and driving increased migration to urban areas (Adger et al., 2020). These developments present both opportunities and uncertainties, highlighting the need for a cautious yet proactive approach to address the risks and benefits of migration between rural and urban areas for the economic growth, well-being, and sustainable development of a country (FAO, 2018).

To effectively design and adapt interventions in this regard, it is essential to monitor present and future prospects of migration movements within a country. It is important to recognize where and why people are moving to reduce future costs and facilitate adaptation to economic, social, and climatic changes within and outside national borders. The academic literature currently lacks up-to-date evidence on migration flows in Russia, specifically when distinguishing between rural and urban areas. Additionally, there is insufficient evidence linking current migration to environmental conditions, such as increasing temperatures or changes in rainfall patterns. This study aims to cover these gaps and explore what are the prospects and drivers of migration flows within Russia, considering the rural or urban nature of origin and destination regions.

To achieve this goal, the study incorporates two complementary analyses. Firstly, we provide an overview of the current trends and prospects of migration flows within Russia's federal districts using a Markov chain approach. For this analysis, we obtained the most recent publicly available data from Rosstat on migration flows between rural-to-urban (RU), rural-to-rural (RR), urban-to-rural (UR), and urban-to-urban (UU) areas at the federal district level between 2011 and 2020. We then integrated the database on migration flows with the physical, economic, and social characteristics of each urban and rural area. This resulted in a panel dataset that was analyzed using a spatial interaction regression model to explore the main drivers behind intraregional and interregional migration flows, taking into account both origin and destination effects as well as network spillover effects.

The structure of this paper is as follows. Section 2 reviews rural-urban migration and related pressures in the Russian context, highlighting gaps and methodological approaches in the literature. Section 3 provides a detailed description of the collected data (Section 3.1) and the methods used in this study, including a Markov chain approach (Section 3.2) and a spatial interaction regression model (Section 3.3). The following section presents and discusses the primary findings on the current prospects (Section 4.1) and drivers (Section 4.2) of rural-urban migration in Russia. Concluding remarks and policy recommendations are provided in the last section (Section 5).

2. Literature review

Rural-urban migration is a crucial aspect of demographic transitions and urbanization trends. According to Niva et al. (2023), internal migration has grown rapidly over the past decade and dominates over international migration; the 'urban pull-rural pressure' phenomenon (Jedwab et al., 2017) characterizes it, with a positive net migration in urban areas and a negative net migration in rural areas. However, there is a wide variation in migration rates around the world and the global trend of urban attraction and rural depression may become less consistent when analyzing migration patterns at national and subnational scales. Indeed, it is necessary to conduct (sub)national analyses to better inform policies, encourage national and international cooperation, and promote shared responsibilities in migration management (Niva et al., 2023).

The Russian Federation consist of eight federal districts (Fig. 1), which are integral part of the state administration and responsible for the implementation of key strategic goals for the sustainable development (Cherkasov, 2008; Fedorez, 2018). Rural-urban migration patterns in Russia involve movements both within and among federal districts. Before the end of the Soviet Union, there was high inward mobility in the eastern and northern regions, including rural areas; after the collapse of the Soviet Union, the direction has shifted in the opposite direction (Kalamanov et al., 2003), concentrating in western and metropolitan areas, specifically within the Central, Northwestern, and Southern Federal Districts. Since then, the rural population of Russia has gradually declined (Mkrtchyan, 2019), losing about 3.7 million people (World Bank, 2024). However, the decline of the rural population has recently slowed due to markedly positive rural migration in

Fig. 1. Map of Russian federal districts illustrated regarding a population (millions of people) and net migration (thousands of people) in 2021 based on the Federal State Statistics Service (Rosstat). Source: Own elaboration.

some districts (Niva et al., 2023). Our paper analyzes these flows in more detail, examining the extent of the 'urban pull-rural pressure' phenomenon among Russian federal districts, and explores what social, economic, demographic, and environmental factors may influence them.

There is substantial academic literature investigating the socio-economic and demographic factors affecting migration flows within a country. Firstly, population size plays a key role in shaping migration patterns. A larger population in the origin region is expected to positively influence migration flows by increasing the likelihood of migration, while regions with larger populations act as magnets for migrants due to their greater demand for goods and services, leading to more robust labor markets and attracting individuals and businesses from other areas (Lewer and Van den Berg, 2008). Another principal stimulus for migration is the scarcity of economic prospects; individuals strive for improved job opportunities, wages, and living standards in the destination areas (Vakulenko, 2019; Zhang and Song, 2003, 2011). Wage levels and unemployment rates are often used as indicators to assess the economic well-being and labor market conditions within a region. A destination region's appeal is expected to rise with higher wage levels and a decrease in unemployment rates (Anderson and van Wincoop, 2003); as for the origin size, higher wage levels might both disincentive out-migration and potentially increase the number of people who can afford migration, making its impact on the origin region ambiguous (Sardadvara and Vakulenko, 2020). In the case of the unemployment rate, it is likely to be positively associated with out-migration. Additionally, Lewer (2008) suggests including in migration analysis how well destination and source regions respectively provide housing stock, as the availability of housing can be a significant factor in attracting or repelling migrants. Finally, there are also evidences for which migration patterns are related to environmental conditions (Backhaus et al., 2015; Tol, 2017), such as rising temperatures or changes in rainfall patterns, which especially affects rural areas where, for example, recurrent droughts can lead to a decrease in productive farmland.

Several authors have analyzed distinct aspects of migration flows in the Russian Federation. The empirical study by Guriev and Vakulenko (2015) examines the barriers to labor mobility and the geographical poverty traps resulting from the intra-country movements. Examining net region-to-region migration flows in Russia from 1996 to 2010, the authors identify a lack of affordable housing, poor infrastructure and difficulty finding a job in the destination region among the factors limiting labor mobility. The study concludes by emphasizing how internal migration can help break these poverty traps and promote interregional convergence in the country. Recently, Makhotaeva and Nikolaev (2023) demonstrate the significant influence that socio-economic factors have on the migration behavior of highly skilled specialists, resulting in a favorable impact on the economic progress of both the regions from which they depart and those to which they relocate. As Tacoli (2015), Abdulraheem and Iderawumi (2019), and Makhotaeva and Nikolaev (2023) have highlighted enhanced education access and improved healthcare accessibility stand out as the primary factors driving young people from rural to urban regions. Accordingly, Kovanova and Badmaeva (2018) suggests that rural areas are more likely to be populated by older, less educated or married people (Cuadrado-Roura, 2001) than younger people, especially those who are educated, unmarried or not interested in the agricultural sector and do not consider starting a household farm as an easy job. Moreover, women demonstrate a greater inclination to migrate than men (Bednaříková et al., 2016). Finally, examining migration movements between 1998 and 2010, Sardadvara and Vakulenko (2020) indicate that it is easier to understand migration patterns in Russia by acknowledging the existence of different regions of origin and destination, specifically the West (Europe) and East (Asia) regions, according to previous evidence (Sardadvar and Vakulenko, 2016). The same authors also suggested estimating and interpreting internal migration movements in Russia, considering network effects, including social ties and information flows. These factors notably affect migration patterns in Russia and refine the accuracy of the analysis, yielding policymakers with enhanced understanding of mobility-related factors.

In terms of methods, the study of migration processes has gained importance since the beginning of the 20th century, when population movements within and between countries increased (Korepina, 2017); since then, different approaches and methodologies have been developed on the topic. One of the well-established approaches in the literature is the Markov chain theory; based on a stochastic approach, Markov chains illustrate a system's development over time contingent on the previous epoch's state (Bertsekas and Tsitsiklis, 1996). In the migration domain, chains result in trends depicting flow of individuals between areas over time, influenced by their previous movements. This article applies the Markov chain approach to reveal current trends in internal (rural-urban) migration flows in Russia, emphasizing patterns and dynamics. However, this approach does not provide any information on the factors driving the migration trends. Thus, to complete the descriptive analysis of Markov chains, a complementary analysis is needed to deepen the knowledge of the emerging prospects by exploring possible drivers. For this purpose, two main strands of literature exist.

The first one uses the well-established gravity model approach (Poot, et al., 2016). These models, based on the principles of Newton's law of gravity, assume that flows between two regions are directly proportional to their size (economic or demographic) and inversely proportional to the distance between them (Todaro and Smith, 2020; Ramos, 2016). The gravity models are then extended with variables related to different attracting and pushing factors of migration. Nevertheless, such models neglect spatial relationships among different observations, which are instead considered by spatial econometrics (LeSage and Pace, 2008a).

In this second strand (see LeSage 2008 for a comprehensive overview of spatial econometric models and methods), the analysis recognizes that the value of a variable in one location may be influenced by the values of the same variable in neighboring locations. Spatial interaction models (LeSage and Fischer, 2016) extend the traditional gravity model by using spatial connectivity matrices for origins and destinations to account for the spatial spillovers from neighboring regions. Thus, these models clarify the intricate interplay of factors and spatial dependencies in migration processes through multiple effects. Origin effects refer to the influence of characteristics or attributes of the origin location on the flow between two regions. Destination effects are the attributes of the destination location that influence the interaction between regions. Network origin and destination effects involve the influence of network structures at the origin and destination, respectively, on migration between locations. Finally, intra-regional effects can also be isolated, highlighting the internal dynamics and interactions within the same region.

Spatial panel models have recently also gained popularity due to the increasing availability of datasets that track different spatial units over time. Panel data provides greater opportunities for research modelling compared to single-equation cross-sectional data. It is typically more informative, exhibiting reduced collinearity between variables and more variation. Using panel data allows for greater degrees of freedom, which enhances estimation efficiency and enables more sophisticated behavioral hypotheses. In this paper, we investigated potential drivers for the trends outlined by the Markov chains, alongside a ten-year panel-based spatial interaction model as described in the next section.

3. Material and methods

3.1. Data collection

To attain our research goals, we gathered data on migration flows and constructed a so-called Tally matrix for each year of the time frame

(T) of 2011–2020[2] (Table S1 in the Supplementary Information provides an overview of the available data). The off-diagonal elements x_{ij} in a Tally matrix represent the number of persons who migrated from place i to place j at time t; whereas the diagonal elements of the matrix represent those persons who continued to live in the same region, including persons who moved within the same region (intra-regional migration). The Rosstat publicly shares migration statistics that distinguish between rural and urban origins and destinations across each Federal District. Based on this data, each of the eight federal districts is figuratively split into a rural (e.g., Rural Central Federal District) and an urban region (e.g., Urban Central Federal District) and we developed ten matrices detailing within and between movements of people among 16 regions (n = 16). Given this feature, migration flows can be of four types: rural to rural (RR), rural to urban (RU), urban to rural (UR) and urban to urban (UU). Furthermore, migratory flows can be differentiated between interregional (from region i to region j) and intraregional (within the same region i) population movements. To complete the needs of the Markov chain analysis, we also collected the births and deaths for each year.

Moving on to the needs of the spatial regression analysis, we constructed a panel dataset. The migration flows from the Tally matrices, excluding residents who did not move (reported in the diagonals), are organized in a destination-centric order according to LeSage and Fischer (2016). The first n rows represent all flows to $i = 1$ from origin $j = 1,2,\ldots,16$ for the first year, the rows from $n+1$ to $i = 2$ from $j = 1,2,\ldots,16$, and so on for the same year. This pattern repeats for each subsequent years. Next, for each year, we collected and added the explanatory variables for urban or rural region.

As explanatory variables, the panel dataset includes key indicators that capture the economic, social, and environmental conditions of each region, representing both attractive and/or hindering forces. These socioeconomic factors encompass the primary determinants of migration choices recognized in academic literature, including population, average wage (adjusted for constant 2020 prices), unemployment rate, and housing availability (measured as residential building area in square meters per capita). Regarding potential environmental effects, we followed the approach proposed by Dell et al. (2014) to incorporate population weights into climate data to provide a more accurate understanding of how climate variations affect people within a specific region. All data were collected from Rosstat's Annual Russian Statistical Book, except for wages for urban areas, which are available through the annual Rosstat's collection 'Regions of Russia. Main Socio-Economic Indicators of Cities.' Table 1 presents the descriptive statistics of the dataset, which includes 2816 observations for ten years and seven explanatory variables. Data management and analysis were performed using R-software (version 4.2.3).

3.2. Markov chain

This study analyzes migration patterns within the country by utilizing Markov chain theory and estimating a non-stationary transition matrix, as proposed by Hierro and Maza (2009), to account for changes in intra-distribution dynamics over time. We began by taking the average of two consecutive Tally matrices outlined in the preceding section, resulting in a sequence of nine transition count matrices. Next, we accommodated the birth and death processes. Following Collins (1975), we arranged the sample population of births and deaths alongside the original transition count matrices by adding the births of the most recent year as the bottom row and deaths of the prior year as the additional right-hand column. Thus, the transition count matrices are a square ($17x17$) matrix. To complete the matrices, we assigned the bottom right box, defined as the reservoir acting as a source of potential inputs and outputs from the system, a value such that the average of the Russian population was 145.6 million people. As reported and demonstrated by Collins (1975), any considerable number in the reservoir is sufficient and does not affect the final prediction of the model.

After the construction of these matrices, we computed the probabilities of moving from one location to another and constructed the sequence of transition probability matrices $P(t_{2011},t_{2012})$, $P(t_{2012},t_{2013})$, …, $P(t_{2019},t_{2020})$. The elements of $P-$matrices represent the probability of transitioning from state i to state j for a single time step, and the rows of P sum to 1. According to Hierro and Maza (2009), based on the Chapman-Kolmogorov equation, the non-stationary transition matrix $P(t_{2011},t_{2020})$ is equivalent to the product of all yearly transition matrices.

Once the non-stationary transition matrix was estimated, we constructed a Markov chain (Casella and Berger, 2002) by multiplying the initial state of the systems $p^{(0)}$ (referring to the state of the system in 2011) with each successive power of the initial transition matrix. In our case, the new vectors refer to the expected distribution of the Russian population among rural and urban territories for the state systems in 2011, 2021, 2031, and so on.

3.3. A spatial interaction regression model

A spatial interaction regression model is implemented to explore and clarify the underlying drivers explaining the dynamics of migration flows as described by the Markov chains, considering the spillover effects that one region may have on the surrounding or nearby regions. We modeled the spatial interaction of endogenous and exogenous variables[3] using the model proposed by LeSage and Fischer (2016) as applied in a similar panel form by Sardadvar and Vakulenko (2020):

$$M = \alpha + \tau + \widetilde{X}_O\beta_O + \widetilde{X}_D\beta_D + X_I\beta_I + \rho_o W_o M + \rho_d W_d M + W_O\widetilde{X}_O \theta_O + W_D\widetilde{X}_D\theta_D + \varepsilon \quad (1)$$

The dependent variable M of annual flows is represented by a $n^2T \times 1$ stacked vector assuming a destination-centric organization. The ($n^2T \times 1$) vectors α and τ represent the stacked vectors of pairwise and time fixed effects, respectively. Next, defining X as the ($nT \times k$) matrix of $k(=6)$ characteristics for each region and year, we constructed the $X_O = \iota_n \otimes X$ and $X_D = X \otimes \iota_n$ matrices, sized $n^2T \times k$, using the Kronecker product ($\otimes$) with the ($n \times 1$) identity vector ι_n to create a matrix of characteristics associated with each origin (destination) region. To isolate the intraregional effects, we then computed the $n^2T \times k$ matrices for the origin and destination region as $\widetilde{X}_O = (X_O - X_I)$ and $\widetilde{X}_D = (X_D - X_I)$, respectively; these matrices exclude the values of the explanatory variables where the origin and destination regions are identical (i.e., intraregional migration), which are instead isolated in the $n^2T \times k$ matrix X_I. Based on this framework, the β_O, β_D, and β_I ($k \times 1$) vectors represent the coefficients associated with the origin, destination, and intraregional effects, respectively.

Endogenous spatial interactions are modelled as $\rho_o W_o M$ and $\rho_d W_d M$. This type of interaction refers to situations where feedback on flow magnitudes from neighboring regions of origin and destination leads to a reaction (LeSage and Pace, 2008b). The ρ_O and ρ_D are the coefficients associated with origin-based and destination-based dependence, respectively. To quantify the spatial relationships that exist among the features in the dataset, we defined a contiguity $n \times n$ spatial weights

[2] Although the current federal districts in Russia were established in 2000, there were significant changes in the statistics in 2010 (Rosstat). Thus, the comparability of data for previous years is compromised, and for this reason, our data collection begins from 2011. Moreover, we included 2020 as any other year, despite the pandemic. The Russian authorities did not insist on a total closure or quarantine measures. The main measure was a 'no-work period' between April and May, which had no effect on domestic migration. Extra-national migration was the most affected, but it is not considered in the analysis.

[3] Given the spatial aggregation of the study, we did not consider lagged socioeconomic explanatory variables, as we do not believe that there is a significant reverse causality effect.

Table 1
Descriptive statistics.

		Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
	Total flows (people)	48.00	1060.00	2836.00	15340.00	10060.00	410180.00
	Total population (mln people)	143.05	143.67	146.41	145.63	146.78	146.88
Rural	Population (1000 p)	1504.00	2285.00	4925.00	4736.00	6164.00	8625.00
	RR flows (people)	48.00	458.50	905.50	5833.70	2119.20	93716.00
	RU flows (people)	207.00	1344.00	2488.00	14612.00	5917.00	205036.00
	Wage (RUB, 2020 price)	17071.00	23782.00	27629.00	32468.00	32790.00	86088.00
	Unemployment rate (%)	4.60	5.83	7.55	8.13	9.70	17.50
	Housing availability ($m^2/capita$)	34.00	69.25	109.50	120.99	143.50	255.00
	Air temperature (°C)	-16.90	-5.13	2.10	1.46	7.14	12.75
	Average precipitation (mm/month)	19.00	40.00	48.50	49.01	57.38	82.50
	Weighted air temperature	-0.27	-0.09	0.04	0.09	0.33	0.53
	Weighted annual precipitation	0.32	0.84	1.53	1.63	2.22	3.95
Urban	Population (1000 p)	4670.00	8003.00	10904.00	13525.00	15832.00	32454.00
	UR flows (people)	164.00	1169.00	2712.00	12369.00	5583.00	169885.00
	UU flows (people)	895.00	5292.00	10868.00	28545.00	22616.00	410180.00
	Wage (RUB, 2020 price)	31159.00	38952.00	44549.00	49754.00	57346.00	86088.00
	Unemployment rate (%)	2.60	4.10	5.20	5.48	6.03	12.30
	Housing availability ($m^2/capita$)	34.00	182.20	273.00	327.40	372.80	898.00
	Air temperature (°C)	-16.90	-3.08	3.05	2.47	8.88	12.75
	Average precipitation (mm/month)	19.00	40.00	48.50	49.70	58.50	82.50
	Weighted air temperature	-1.15	-0.20	0.33	0.29	0.67	2.05
	Weighted annual precipitation	1.00	2.01	4.04	4.92	5.24	18.10

Note: mln = million; RR = Rural to rural; RU = Rural to urban; UR = Urban to rural; UU = Urban to urban; RUB = ruble currency; m^2 = meter squared; °C = Celsius degree; mm = millimeters; Weighted = average population-weighted (Dell et al., 2014).

matrix W based on whether two regions share a common border. Having divided a federal district into an urban and a rural region, we assumed that these two spatial units are contiguous with each other and share the same federal district boundaries; diagonal elements of W are instead set to zero to prevent self-contiguity. The matrix is then row-standardized, such that the sum of the weights is equal to 1, allowing the spatial lag to be interpreted as a weighted average of the neighboring features. Finally, the W is expanded based on the relationships between dependent and explanatory variables to $W_o = W \otimes I_{nT}$ and $W_D = I_{nT} \otimes W$, with I_{nT} being an $nT \times nT$ identity matrix. Similarly, spatial lags of the exogenous variable are modelled as $W_O\widetilde{X}_O$ and $W_D\widetilde{X}_D$. These specifications indicate the spatial spillover impacts of neighboring source and destination regions, acknowledging that a change in the characteristics of a neighboring region could affect the magnitude of flows between regions. The θ_O and θ_D represent the coefficients associated with the network origin and destination effects, respectively.

The estimation is based on maximum likelihood assuming a Poisson distribution feasible for migration flows, as they are counts (LeSage and Pace, 2009). Eq. 1[4] is used to estimate five specifications to take account of the fact that rural and urban regions may differ; the first estimate relates to all observations, while the remaining ones relate only to specific types of migration (UU, UR, RU, or RR). The analysis was performed via R package 'fixest' (Berge et al., 2023).

Both the dependent and independent variables are in log form, but the coefficient estimates cannot be interpreted directly as elasticities (Thomas-Agnan and LeSage, 2021). Spatial extensions cause changes in the characteristics of a single region to produce numerous responses in the flow matrix, rather than changes in a single observation. To address this issue, we rely on the cumulative scalar summary measures proposed by LeSage and Thomas-Agnan (2015), which reflect the partial derivative expressions to quantify the effects arising from changes in the explanatory variables of the model. Specifically, these effects summarize the average impact of a change in a characteristic at a representative region on all flows to and from that region (intraregional effects), on outgoing flows only (origin effects), on incoming flows only (destination effect), and on flows that neither depart from nor arrive at that region (network effects). Thibault Laurent et al. (2023) demonstrate how to compute these cumulative scalar summary measures in a general spatial autoregressive interaction framework including endogenous and exogenous interaction effects, and developed dedicated R functions for this scope.

4. Results and discussion

4.1. The prospects of rural-urban migration within Russia

Using a Markov chain analysis (Section 3.2), we examined the internal migration patterns between urban and rural areas in Russia by Federal District. We then projected these trends into the future (until 2051), stressing the current prospects if the patterns remain unchanged. Thus, the results provide insights into which rural and urban areas are currently attracting more people, which are more relatively stable in terms of population, and which are experiencing depopulation trends.

Table 2 displays the current migration patterns obtained through Markov chain analysis. We present both absolute and relative values of the urban and rural population across Federal Districts in Russia over time. In terms of absolute figures, the country exhibits a decrease in population due to mortality, with the total population of Russia projected to decrease from 142.9 million in 2011–140.9 million in 2051, which is not as negative as the UN estimate of 133 million (United Nations, 2022). Nevertheless, in relative terms it is evident that the population is becoming more concentrated in urban areas. Fig. 2 emphasizes this observation by illustrating the relative changes in population distribution compared to the 2011 baseline.

The proportion of individuals residing in rural regions drops across all districts except for the North Caucasus and South, whilst experiencing a surge in all urban areas except for Volga and Siberia. There are different rates of change between rural (Fig. 2a) and urban (Fig. 2b) areas based on expected interregional migration patterns. Among rural regions, the Central district shows the highest rate of change, with a 25.5 percent decrease in the share of Russian residents living in this area compared to the 2011 level. On the other hand, Fig. 2b illustrates

[4] Using likelihood-ratio (LR) tests (LeSage and Pace, 2008), we compared restricted versions of the Eq. 1 assuming: (i) $\rho_o = \rho_d = 0$; (ii) $\theta_o = \theta_d = 0$; or (iii) $\rho_o = \rho_d = \theta_o = \theta_d = 0$. Table S2 displays the log-likelihood values, alongside an LR test of the imposed restrictions for each model versus the unrestricted one. Eq. 1 dominates all other versions of the model, exhibiting significant lower likelihoods.

that among the urban areas, the North Caucasus has the highest rate of change, with a 34 percent increase in the proportion of Russian residents. The chart indicates that positive changes are expected only in the South and North Caucasus regions of both rural and urban areas, in relation to the 2011 figures. As mentioned previously, to gain more insight into these perspectives, we combined the descriptive Markov chain framework with a spatial interaction regression analysis, examining potential drivers for these trends.

4.2. *Potential drivers of urban-rural migration patterns*

The results of the spatial interaction regression analysis for all five specifications are reported in Table 3, while Table 4 reports the scalar summary measures of the different intraregional effects (IE), origin effects (OE), destination effects (DE), network effects (NE), and total effects (TE). As the dependent and independent variables are both in logarithmic form, the values in Table 4 can be interpreted as elasticities.

From Table 3, we can first see that a non-spatial interaction specification of a traditional gravity model would suffer from omitted variable bias due to the exclusion of significant spatial lags. ρ_o is positive and significant in all specifications, indicating a spatial dependence between neighbors at the origin. Thus, migration flows in a given origin, whether urban or rural, are affected by the magnitude of migration in locations close to the origin. In contrast, the spatial autoregression of the destination shows non-significant effects.

Next, we see that a larger region of origin in terms of population leads to an increase in migration flows in all specifications, except when people move from urban to rural federal districts (UR). The same can be said for larger destinations, when people move between urban (UU) or rural (RR) areas of different federal districts. The positive and significant population coefficients are consistent with expectations; a larger population may increase the likelihood of migration at origin or indicate a more attractive destination with more job opportunities, better infrastructure and services, and a more vibrant economy (Lewer and Van den Berg, 2008). The intraregional effects of population are also positive for all regions and RR specifications, suggesting more intraregional flows for larger (rural) federal districts area, which makes intuitive sense (Fischer and LeSage, 2014; Sardavar and Vakulenko, 2020). Regarding the network effects, spatial spillovers from the larger regions neighboring the source and destination regions are negative when significant, i.e., in all specifications except for the UU for origin network effects and the opposite for destination network effects. A negative coefficient for regions close to the origin or destination means that an increase in population in neighboring regions decreases flows from origin to destination, perhaps because migrants take the opportunity to travel shorter distances or because the destination becomes less attractive, suggesting a destination competition effect associated with larger urban areas (Sardavar and Vakulenko, 2020).

Regarding wages, the models show significant different behavior depending on whether the origin wage is referred to. With the exception of UR, wage coefficients are significant as an origin effect. In contrast, no significance is found for the destination effect. When people move between the same types of area (rural or urban) of different federal districts, an increase in wages in the origin location increases migration flows. One of the possible explanations is that higher wages in the origin location may indicate a growing economy and higher living standards, which lead to an increase in the cost of living and make it more difficult for some people to afford to live there. In this case, migration from the place of origin may be a way for people to seek more affordable living conditions elsewhere. When the coefficient is negative, as in the ALL regions specification, it suggests instead that higher wage levels in the origin discourage migration flows; individuals seem to be less likely to migrate, possibly due to the availability of suitable employment and good income prospects in their local communities. A correlation observed also in Zhang and Song (2003), Zhang and Song (2011), and Jia (2017). Intra-regional effects are also positive

Table 2
Successive absolute (mln people) and relative values (p^n).

Period	Rural								Urban								Total
	Central	North West	South	North Caucasus	Volga	Ural	Siberian	Far Eastern	Central	North West	South	North Caucasus	Volga	Ural	Siberian	Far Eastern	Russia
2011	7.1	2.2	5.2	4.8	8.7	2.4	4.6	2.4	31.3	11.4	8.7	4.6	21.2	9.7	12.6	6.0	142.9
	(5.0%)	(1.6%)	(3.6%)	(3.4%)	(6.1%)	(1.7%)	(3.2%)	(1.7%)	(21.9%)	(8.0%)	(6.1%)	(3.3%)	(14.8%)	(6.8%)	(8.8%)	(4.2%)	(100%)
2021	5.3	2.0	5.2	5.5	6.9	2.1	3.8	1.9	32.8	12.0	9.7	5.5	20.2	10.2	12.2	5.6	140.9
	(3.8%)	(1.5%)	(3.7%)	(3.9%)	(4.9%)	(1.5%)	(2.7%)	(1.4%)	(23.2%)	(8.5%)	(6.9%)	(3.9%)	(14.3%)	(7.3%)	(8.7%)	(4.0%)	(100%)
2031	5.2	2.1	5.3	5.9	6.5	2.0	3.6	1.8	33.2	12.3	10.2	6.0	19.3	10.3	11.9	5.3	140.9
	(3.7%)	(1.5%)	(3.8%)	(4.2%)	(4.6%)	(1.4%)	(2.6%)	(1.3%)	(23.5%)	(8.7%)	(7.2%)	(4.3%)	(13.7%)	(7.3%)	(8.4%)	(3.7%)	(100%)
2041	5.2	2.1	5.3	6.0	6.4	2.0	3.6	1.7	33.2	12.3	10.3	6.1	19.2	10.3	11.8	5.2	140.9
	(3.7%)	(1.5%)	(3.8%)	(4.3%)	(4.5%)	(1.4%)	(2.6%)	(1.2%)	(23.6%)	(8.7%)	(7.3%)	(4.3%)	(13.6%)	(7.3%)	(8.4%)	(3.7%)	(100%)
2051	5.2	2.1	5.3	6.0	6.4	2.0	3.6	1.7	33.3	12.3	10.3	6.1	19.2	10.3	11.8	5.2	140.9
	(3.7%)	(1.5%)	(3.8%)	(4.3%)	(4.5%)	(1.4%)	(2.6%)	(1.2%)	(23.6%)	(8.7%)	(7.3%)	(4.4%)	(13.6%)	(7.3%)	(8.4%)	(3.7%)	(100%)

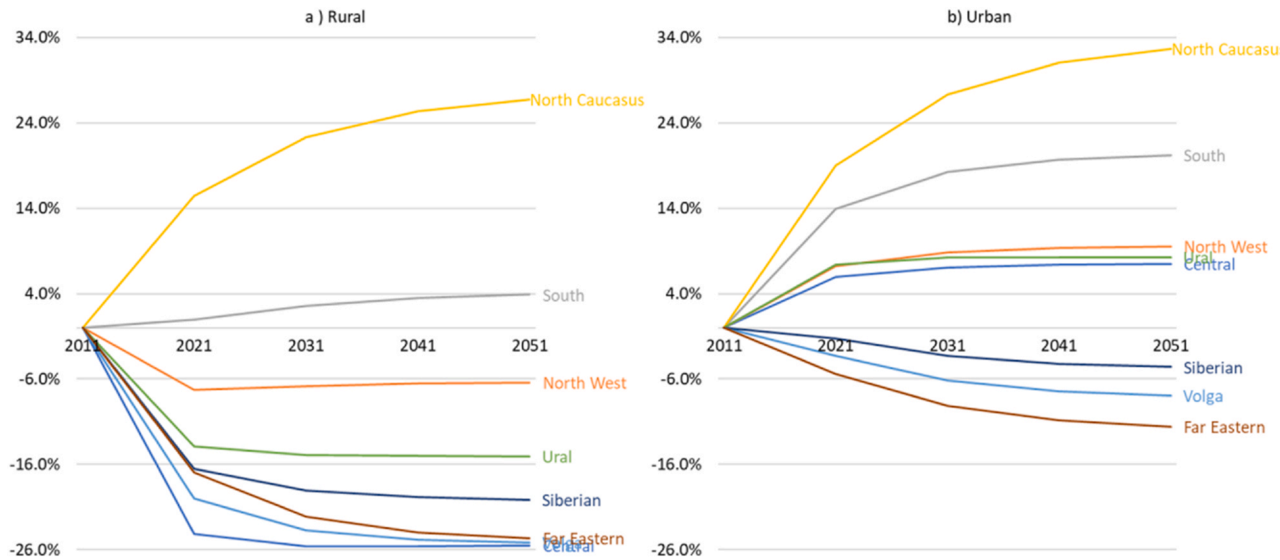

Fig. 2. Trends of the change in the distribution of the projected population in Russia from the initial state in 2011 for rural (a) and urban (b) territories.

Table 3
Results for the contiguity spatial interaction specification.

Model:	All regions	Urban to urban	Urban to rural	Rural to urban	Rural to rural
ρ_d	0.00 (0.01)	0.01 (0.03)	0.03 (0.02)	0.01 (0.01)	-0.01 (0.03)
ρ_o	0.78*** (0.03)	0.58*** (0.09)	0.82*** (0.03)	0.94*** (0.05)	0.32*** (0.08)
Origin effects					
Population	0.51*** (0.11)	0.22 (0.18)	0.31** (0.14)	0.84*** (0.08)	0.70*** (0.13)
Wage	-0.34*** (0.10)	0.33** (0.15)	-0.02 (0.14)	-0.46** (0.21)	0.21** (0.10)
Unemployment rate	0.26*** (0.10)	0.60*** (0.22)	0.23** (0.10)	0.31*** (0.11)	-0.01 (0.11)
Housing	0.09* (0.05)	0.10 (0.13)	0.01 (0.05)	0.22* (0.13)	0.08 (0.07)
Temperature	0.06 (0.09)	0.07 (0.11)	-0.01 (0.06)	0.18 (0.25)	-0.10 (0.22)
Precipitation	0.06* (0.03)	0.08* (0.04)	0.07*** (0.03)	-0.04 (0.06)	0.01 (0.06)
Destination effects					
Population	0.04 (0.06)	0.30** (0.15)	0.04 (0.06)	0.07 (0.09)	0.42*** (0.11)
Wage	0.17 (0.11)	0.13 (0.11)	-0.02 (0.09)	-0.01 (0.14)	0.21 (0.15)
Unemployment rate	0.03 (0.04)	-0.11 (0.14)	-0.08*** (0.03)	0.08 (0.08)	-0.07 (0.13)
Housing	0.11*** (0.04)	0.12** (0.06)	-0.03 (0.05)	0.19 (0.15)	0.01 (0.04)
Temperature	-0.01 (0.06)	-0.06 (0.07)	-0.17 (0.19)	-0.02 (0.06)	-0.12 (0.22)
Precipitation	-0.02 (0.02)	0.03 (0.03)	-0.05 (0.03)	0.04* (0.02)	0.00 (0.07)
Intraregional effects					
Population	0.52*** (0.14)	0.30 (0.24)			0.90*** (0.17)
Wage	-0.22 (0.13)	0.19 (0.18)			0.25*** (0.08)
Unemployment rate	0.35*** (0.07)	0.61*** (0.16)			0.04 (0.14)
Housing	-0.06 (0.05)	-0.08 (0.05)			0.06 (0.06)
Temperature	0.02 (0.11)	-0.02 (0.13)			-0.07 (0.27)
Precipitation	0.04 (0.04)	0.05 (0.05)			0.03 (0.08)
Network origin effects					
Population	-0.57** (0.26)	-0.07 (0.32)	-0.98* (0.54)	-0.82*** (0.19)	-0.55*** (0.15)
Wage	1.16** (0.50)	0.62*** (0.12)	0.12 (0.23)	0.74* (0.41)	0.24 (0.44)
Unemployment rate	-0.29 (0.29)	0.05 (0.47)	0.02 (0.44)	-0.53** (0.21)	-0.32 (0.21)
Housing	-0.07 (0.23)	-0.12* (0.07)	-0.04 (0.08)	-0.10 (0.08)	-0.09 (0.08)
Temperature	-0.04 (0.17)	-0.09 (0.12)	0.03 (0.13)	0.05 (0.32)	-0.33 (0.53)
Precipitation	-0.03 (0.06)	-0.06 (0.05)	-0.12** (0.06)	0.10 (0.09)	-0.08 (0.13)
Network destination effects					
Population	0.02 (0.03)	-0.07*** (0.02)	-0.14 (0.09)	-0.03 (0.07)	0.00 (0.04)
Wage	-0.03 (0.03)	0.06** (0.03)	0.01 (0.07)	0.04 (0.09)	-0.02 (0.07)
Unemployment rate	-0.02 (0.03)	0.06** (0.03)	0.19*** (0.04)	0.03 (0.06)	0.08 (0.05)
Housing	0.01 (0.05)	0.08*** (0.02)	0.01 (0.04)	0.11*** (0.04)	0.00 (0.04)
Temperature	0.06 (0.04)	0.09 (0.06)	0.13 (0.11)	-0.01 (0.08)	0.07 (0.14)
Precipitation	-0.03 (0.05)	0.05* (0.03)	0.13* (0.07)	-0.02 (0.05)	0.02 (0.04)
Model characteristics					
Observations	2560	640	640	640	640
Log-likelihood	-134218.20	-62234.30	-16863.90	-13052.00	-11211.60

Note: Clustered (Years) standard-errors in parentheses
Significance codes: ***: 0.01, **: 0.05, *: 0.1

Table 4
Scalar summary measures of effects for the contiguity spatial interaction specification.

Model	Variables	OE	DE	IE	NE	TE
ALL	population	0.53	0.14	0.08	-0.55	0.20
	wage	-0.05	0.96	0.03	3.30	4.23
	unemployment	0.27	0.09	0.05	-0.43	-0.02
	housing	0.08	0.45	0.03	0.02	0.57
	temperature	0.08	-0.02	0.00	0.27	0.33
	precipitation	0.06	-0.10	0.00	-0.05	-0.09
UU	population	0.23	0.67	0.08	-0.02	0.95
	wage	0.48	0.40	0.06	1.85	2.79
	unemployment	0.70	-0.19	0.07	0.98	1.56
	housing	0.09	0.27	0.02	0.07	0.45
	temperature	0.07	-0.13	-0.01	0.10	0.03
	precipitation	0.08	0.05	0.01	0.07	0.22
UR	population	-0.13	-0.07	0.00	-5.01	-5.20
	wage	0.04	-0.09	0.00	0.65	0.59
	unemployment	0.41	-0.29	0.00	2.38	2.50
	housing	-0.02	-0.18	0.00	-0.14	-0.33
	temperature	-0.02	-0.94	0.00	0.80	-0.15
	precipitation	0.08	-0.27	0.00	0.43	0.23
RU	population	0.90	1.37	0.00	-0.60	1.67
	Wage	0.05	0.15	0.00	6.55	6.75
	unemployment	0.08	1.23	0.00	-3.85	-2.55
	Housing	0.85	3.82	0.00	5.14	9.81
	temperature	0.53	0.04	0.00	4.27	4.83
	precipitation	0.08	0.82	0.00	0.81	1.71
RR	population	0.65	0.55	0.14	-0.44	0.90
	Wage	0.22	0.31	0.05	0.36	0.94
	unemployment	-0.02	-0.12	0.00	-0.31	-0.45
	Housing	0.07	0.00	0.01	-0.08	0.00
	temperature	-0.11	-0.20	-0.02	-0.38	-0.71
	precipitation	0.01	-0.01	0.00	-0.07	-0.08

and statistically significant in the overall and RR specification, suggesting more intra-regional movement with higher wages, especially between rural areas of the same federal district. The positive spillover effects of wages indicate a competitive influence, i.e., higher wages in neighboring regions stimulate increased migration from the origin regions, except for migration to rural areas. On the other hand, an urban destination becomes less attractive when higher wages are available in neighboring regions, as suggested also in Vakulenko (2019).

For the unemployment rate variable, an increase in the proportion of unemployment would increase outflows from the origin, except for RR movements, playing the role of pull-factor and suggesting that migration can be a response to a lack of employment opportunities (OECD, 2023). On the destination side, movements from urban to rural areas are negatively correlated with a higher unemployment rate in the rural destination region. As in the case of larger rural regions, the effect of unemployment on within region migration flows is positive; note that population and unemployment are the only variables displaying statistically significant intraregional effects. The effects of higher unemployment rates relative to neighboring regions is negative and significant only in the RU specification, meaning that inflows from neighboring regions would be smaller in this case. In contrast, the effects of higher unemployment rates in the neighboring regions of the destination are positive and significant in the case of urban origins, suggesting a greater inflow to destination regions (urban or rural) that have neighbors with fewer job opportunities.

Overall, housing availability has positive and significant effects on origin and destination, as well as in the RU specification for origin effects and in the UU specification for destination effects. An increase in the housing availability in the destination (urban) locations would therefore, as expected, increase the migration flows to this region. Conversely, a positive origin effect could be due to previous population losses, as motivated by Sardavar and Vakulenko (2020), who found the same evidence as we do here. The effect of housing availability on migration flows within the same region is not significantly different from zero, suggesting that the retention and competition effects are offsetting (Fischer and LeSage, 2014). The spillover effect of more housing availability in regions neighboring the origin is negative but significant only in the UU specification, suggesting that inflows from neighboring regions would be lower in this case. Such effect is significant opposite in regions neighboring urban destinations (i.e., in UU or RU specifications), which means that there are more inflows to the destination districts that have neighbors with a higher housing supply.

Regarding the environmental factors, temperature shows insignificant effects, suggesting that it does not influence decisions to move from one place to another. On the contrary, precipitation does in certain circumstances. The origin effects of precipitation are positive and significant in the overall model and in the specifications when the origin is urban, indicating that higher precipitation levels coincide with more significant migration flows. It is possible that heightened rainfall will have adverse repercussions on the economy, infrastructure, and access to clean water, which would stimulate emigration from a given area (Backhaus et al., 2015; Tol, 2017), due to, for instance, floods, landslides, and mudslides (Black et al., 2011; McLeman, 2011). Spatial spillover effects due to rainfall in regions close to the place of origin are negative and significant only in the UR specification, implying a retention effect for urban areas surrounded by those with higher precipitation. On contrary, spatial spillover effects of higher rainfall in the neighboring regions of the destination region is positive and significant for UU and UR specifications, suggesting higher inflow from urban areas to destination regions that has neighboring regions with higher rainfall, a competition effect.

5. Conclusion and recommendations

This study was designed to analyze the prospects and drivers of recent migration flows within Russia, addressing the rural or urban nature of origin and destination regions. We provide insights into the expected rural-urban distribution within Russia's federal districts by mid-century using a Markov chain analysis. The results confirm a general trend of depopulation and urbanization, with the total population decreasing and relatively more people moving to urban areas; only the North Caucasus and Southern Federal Districts show a positive trend for both their rural and urban areas.

We then applied a spatial regression analysis to investigate the plausible causes of these trends, considering origin-destination, intra-regional and spatial spillover effects. The results provide several important insights into the determinants of migration flows in Russia. First, given the importance of spatial dependence between neighboring regions, traditional gravity models would suffer from omitted variable bias if ignoring spatial interactions. Population size, both at origin and destination, tends to increase migration flows. Regarding wages, higher pay is a significant factor that motivates individuals to move between similar areas (rural to rural or urban to urban) in search of better job opportunities. The unemployment rate also plays a significant role, acting as a push factor in response to a lack of job opportunities. The housing availability also influences migration; in particular, greater housing availability in destination regions encourages migration to those regions. In terms of the environment, temperature does not seem to play a key role, but rainfall can stimulate certain migration flows due to its direct or indirect impacts on the region. The overall results underline the complex interaction of these factors, especially when distinguishing between rural and urban areas, and highlight the predominance of origin factors in influencing migration decisions in Russia.

The generalizability of these results is subject to certain limitations. One main limitation of the study regards the aggregation level of data. Publicly available data on migration flows within Russia, accounting for urban or rural origin and destination, are available at the federal districts level, which made us assume the contiguity matrices of the rural and urban area. Furthermore, it was not possible to assess key demographic attributes of migrants, as gender, age, or education, which literature show a correlation. Regarding the Markov chain analysis, one main limitation concerns the fact that the probability of moving from one region to another is constant over time, which may not be the case. Changes in economic, social, or political conditions may change migration patterns and make them deviate from expected trends based on past data alone. Future research should address these limitations by using alternative data and models that allow for more robust and flexible estimates of migration patterns and drivers. In this respect, much more work needs to be done to determine the influence of alternative destinations on bilateral migration rates, so-called multilateral resistance (Maza et al., 2019).

Decision-makers can benefit from the evidence gathered in this paper to design targeted interventions to support rural areas and address the challenges of urbanization. The South and North Caucasus Federal Districts stand out as the only federal districts where, in contrast to the others, both rural and urban areas are experiencing positive relative population growth. It is also likely, according to our results, that these two neighboring regions are influencing each other through spatial effects. This unique trend calls for policymakers and other stakeholders to examine the factors contributing to this positive outlook and to draw lessons that can be applied in other federal districts, such as successful initiatives to promote balanced population growth between rural and urban areas. By implementing these targeted policies, the government can create employment opportunities, improve living standards, and reduce the pressure on rural residents to migrate to urban areas in search of a better quality of life.

Regional scientists have proposed several policies to address rural depopulation, as it is a widespread problem in almost all developed countries (Santos and Fernández, 2023). As also emphasized in our findings, the primary drivers of demographic shifts are the economic pull of urban areas and the relative lack of opportunities in rural regions (Santos and Fernández, 2023). Therefore, policies recommendations advocate for supporting productivity growth and structural change in rural regions (Henning et al., 2023). In this regard, agricultural intensification and specialization, common practices in Russia, can marginalize less productive areas, eroding biodiversity, social systems, and traditional knowledge (Castillo et al., 2023). Policymakers can target these abandoned areas to mitigate these negative consequences and reintroduce abandoned lands through holistic planning, considering biophysical, economic, social, and cultural factors (Castillo et al., 2023).

Concentrating solely on rural areas, however, may not be effective, as pointed out by Westlund and Borsekova (2023). Rural areas often lack the necessary resources, such as purchasing power or human capital, for endogenous development, which makes interaction with urban areas necessary for growth. Thus, policy makers should foster regional urban-rural interactions. This requires the use of existing rural governance structures and the involvement of multi-level governance in the implementation of efficient monitoring and evaluation systems of long-term planning (UN-Habitat, 2019). It is also advisable to prevent over-population in a small number of metropolitan areas, as happening in Russia. This can be achieved by addressing the lack of affordable housing, which forces households to leave urban areas despite the local economic opportunities, as our findings suggest. To increase inclusivity and affordability in urban housing markets, policymakers can implement measures such as increasing the supply of social housing, implementing rent controls, and providing financial support to low-income households (Castillo et al., 2023).

Finally, teleworking is also becoming an area of policy focus, as it can help relocate individuals to attractive but remote rural areas and promote regional rural-urban interaction (Westlund and Borsekova, 2023). Raagmaa (2023) and Henning et al., (2023) demonstrated that the COVID-19 pandemic and the rise of remote work have enabled high-productivity workers to relocate to rural areas in Estonia and Sweden, respectively. To replicate this trend in Russia, however, policies must also enhance rural areas with public infrastructure and transportation systems, as well as to bridge the digital gap between rural and urban centers.

Compliance with Ethical Standards

The authors declare that they have no conflicts of interest

Declarations

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CRediT authorship contribution statement

Anastasia Chaplitskaya: Conceptualization, Formal analysis, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Johan van Ophem:** Conceptualization, Supervision, Writing – review & editing. **Wim Heijman:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Gianmaria Tassinari:** Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.rspp.2024.100053.

References

Abdulraheem, M.I., Iderawumi, M.A., 2019. Effect of Rural-Urban Migration on Education and Economic development. Am. J. Trade Policy 6 (1), 7–12.

Adger, W.N., Crépin, A.S., Folke, C., Ospina, D., Chapin, F.S., Segerson, K., Wilen, J., 2020. Urbanization, migration, and adaptation to climate change. One Earth *3* (4), 396–399. https://doi.org/10.1016/j.oneear.2020.09.016

Amini, C., Nivorozhkin, E., 2015. The urban–rural divide in educational outcomes: Evidence from Russia. Int. J. Educ. Dev. *44*, 118–133. https://doi.org/10.1016/j.ijedudev.2015.07.006

Anderson, J.E., van Wincoop, E., 2003. Gravity with gravitas: A solution to the border puzzle. Am. Econ. Rev. 93 (1), 170–192. https://doi.org/10.1257/000282803321455214

Backhaus, A., Martinez-Zarzoso, I., Muris, C., 2015. Do climate variations explain bilateral migration? A gravity model analysis. IZA J. Migr. 4 (1), 1–15. https://doi.org/10.1186/s40176-014-0026-3.cd

Bednaříková, Z., Bavorova, M., Ponkina, E.V., 2016. Migration motivation of agriculturally educated rural youth: The case of Russian Siberia. J. Rural Stud. 45, 99–111. https://doi.org/10.1016/j.jrurstud.2016.03.006

Berge L., Krantz, S., & McDermott, G. (2023). Type Package. Title Fast Fixed-Effects Estimations. Version 0.11.1. January 10, 2023. Available at: 〈https://cran.r-project.org/web/packages/fixest/fixest.pdf〉 [accessed 28/08/2023].

Bertsekas, D.P., Tsitsiklis, J.N., 1996. Introduction to Probability. Athena Scientific.

Black, R., Adger, W.N., Arnell, N.W., Dercon, S., Geddes, A., Thomas, D., 2011. The effect of environmental change on human migration. Glob. Environ. Change 21, 3–11. https://doi.org/10.1016/j.gloenvcha.2011.10.001

Borison, G., 2019. Econ. Inequal. Russ. Available at:〈https://www.colorado.edu/polisci/2019/04/26/economic-inequality-russia〉.

Butler, L.K., Donahue, M.G., Rohwer, S., 2002. Molt-migration in Western Tanagers (Piranga ludoviciana): Age effects, aerodynamics, and conservation implications. Auk *119* (4), 1010–1023. https://doi.org/10.1093/auk/119.4.1010

Cañal-Fernández, V., Álvarez, A., 2022. Explaining the Decline of Rural Population in Spain (1900–2018). J. Interdiscip. Hist. *53* (1), 25–47. https://doi.org/10.1162/jinh_a_01797

Casella, G., Berger, R.L., 2002. Statistical inference, 2nd ed. Duxbury Press.

Castillo, C.P., van Heerden, S., Barranco, R., Jacobs-Crisioni, C., Kompil, M., Kučas, A., Lavalle, C., 2023. Urban–rural continuum: an overview of their interactions and territorial disparities. Reg. Sci. Policy Pract. 15 (4), 729–769. https://doi.org/10.1111/rsp3.12592

Cherkasov, K.V., 2008. Federal districts: essence and place in the federal structure of Russia. Gos. i Pravo 12, 67–75.

Collins, L., 1975. An Introduction to Markov Chain Analysis. Brothers Ltd The Invicta Press Ashford Kent and London.

Cuadrado-Roura, J.R., 2001. Regional convergence in the European Union: From hypothesis to the actual trends. Ann. Reg. Sci. *35*, 333–356. https://doi.org/10.1007/s001680100054

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52 (3), 740–798. https://doi.org/10.1257/jel.52.3.740

FAO (2018). The State of Food and Agriculture. Migration, agriculture and rural development. Rome, FAO, Italy, 200.

Federal State Statistics Service, Russian Federation (Rosstat) Available at: 〈https://rosstat.gov.ru/〉[accessed 03/09/2022].

Fedorez, M.N., 2018. Federal districts: significance and role in the state-territorial structure of the Russian Federation. Gos. i Pravo (10), 136–140.

Fielding, T., Ishikawa, Y., 2021. COVID-19 and migration: a research note on the effects of COVID-19 on internal migration rates and patterns in Japan. Popul. Space Place 27 (6), e2499. https://doi.org/10.1002/psp.2499

Fischer, M.M., LeSage, J.P., 2014. Spatial regression-based model specifications for exogenous and endogenous spatial interaction. 54th Congr. Eur. Reg. Sci. Assoc.: "Reg. Dev. Glob.: Best. Pract." 26–29. 〈http://hdl.handle.net/10419/124380〉.

González-Leonardo, M., Rowe, F., Fresolone-Caparrós, A., 2022. Rural revival? The rise in internal migration to rural areas during the COVID-19 pandemic. Who moved and Where? J. Rural Stud. *96*, 332–342. https://doi.org/10.1016/j.jrurstud.2022.11.006

Guriev, S., Vakulenko, E., 2015. Breaking out of poverty traps: Internal migration and interregional convergence in Russia. J. Comp. Econ. 43 (3), 633–649. https://doi.org/10.1016/j.jce.2015.02.002

Henning, M., Westlund, H., Enflo, K., 2023. Urban–rural population changes and spatial inequalities in Sweden. Reg. Sci. Policy Pract. 15 (4), 878–893. https://doi.org/10.1111/rsp3.12602

Hierro, M., Maza, A., 2009. Non-stationary transition matrices: An overlooked issue in intra-distribution dynamics. Econ. Lett. *103* (2), 107–109. https://doi.org/10.1016/j.econlet.2009.02.005

Jedwab, R., Christiaensen, L., Gindelsky, M., 2017. Demography, urbanization and development: Rural push, urban pull and… urban push? J. Urban Econ. 98, 6–16. https://doi.org/10.1016/j.jue.2015.09.002

Jia, P., Du, Y., Wang, M., 2017. Rural labor migration and poverty reduction in China. China World Econ. *25* (6), 45–64. https://doi.org/10.1111/cwe.12220

Kalamanov, V.A. et al. (2003). Management of migration processes: textbook / - M: GSU, 223.

Korepina, T.A., 2017. Comparative analysis of approaches to migration modelling. Vopr. Territ. 'nogo Razvit. 1 (36), 6.

Kovanova, E.S., Badmaeva, N.V., 2018. Migration of Rural Residents in Russia's Regions: Issues, Trends, and Focus Areas. Int. J. Eng. Technol. (UAE) *7* (4.38), 288–291.

Laurent, T., Margaretic, P., Thomas-Agnan, C., 2023. Generalizing impact computations for the autoregressive spatial interaction model. Geogr. Anal. 55 (4), 728–758. https://doi.org/10.1111/gean.12358

LeSage, J.P., Thomas-Agnan, C., 2015. Interpreting spatial econometric origin-destination flow models. J. Reg. Sci. 55 (2), 188–208. https://doi.org/10.1111/jors.12114

LeSage, J.P., Fischer, M.M., 2016. Spatial regression-based model specifications for exogenous and endogenous spatial interaction. Springer International Publishing, pp. 15–36.

LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. CRC Press, Boca Raton.

LeSage, J., Pace, R., 2008a. Introduction to Spatial Econometrics. CRC Press, Boca Raton.

LeSage, J., Pace, R., 2008b. Spatial Econometric modelling of Origin-Destination Flows. J. Reg. Sci. 48 (5), 941–967. https://doi.org/10.1111/j.1467-9787.2008.00573.x

Lewer, J.J., Van den Berg, H., 2008. A gravity model of immigration. Econ. Lett. Volume 99 (1), 164–167. https://doi.org/10.1016/j.econlet.2007.06.019

Makhotaeva, M., Nikolaev, M., 2023. Migration of Specialists with Higher Education in Russia: Assessment of Factors and Modeling of Processes. J. Appl. Econ. Res. 22 (1), 120–141. https://doi.org/10.15826/vestnik.2023.22.1.006

Mareeva, S., 2020. Socio-economic inequalities in modern Russia and their perception by the population. J. Chin. Sociol. 7 (1), 1–19. https://doi.org/10.1186/s40711-020-00124-9

Margolies, L., 1978. Rural-urban migration and urbanization in Latin America. Curr. Anthropol. 19 (1). https://doi.org/10.1086/202010

Maza, A., Gutiérrez-Portilla, M., Hierro, M., Villaverde, J., 2019. Internal migration in Spain: Dealing with multilateral resistance and nonlinearites. Int. Migr. 57 (1), 75–93.

McLeman, R.A., 2011. Climate and Human Migration: Past Experiences, Future Challenges. Cambridge University Presshttps://doi.org/10.1017/CBO9780511973921

Mkrtchyan, N.V., 2019. Migration in rural areas of Russia: territorial differences. Popul. Econ. 3 (1), 39–51. https://doi.org/10.3897/popecon.3.e34780

Nikitin, B., Zakharova, M., Pilyasov, A., et al., 2023. The burden of big spaces: Russian regions and cities in the COVID-19 pandemic. Lett. Spat. Resour. Sci. 16 (1), 16. https://doi.org/10.1007/s12076-023-00341-z

Niva, V., Horton, A., Virkki, V., Heino, M., Kosonen, M., Kallio, M., ... Kummu, M., 2023. World's human migration patterns in 2000–2019 unveiled by high-resolution data. Nat. Hum. Behav. 7 (11), 2023–2037. https://doi.org/10.1038/s41562-023-01689-4

OECD (2023). Migration and unemployment. Available at: 〈https://www.oecd-ilibrary.org/migration-and-unemployment_5jm0wzm1h5bp.pdf〉 Accessed 24/04/2023. [accessed 15/04/2023].

Poot, J., Omoniyi, A., Cameron, M.P., Mare, D.C., 2016. The Gravity Model of Migration: The Successful Comeback of an Ageing Superstar in Regional Science. IZA Doc. 10329. https://doi.org/10.2139/ssrn.2864830

Raagmaa, G., 2023. Estonian population and regional development during the last 30 years—back to the small town? Reg. Sci. Policy Pract. 15 (4), 826–845. https://doi.org/10.1111/rsp3.12623

Ramos, R., 2016. Gravity models: A tool for migration analysis. IZA World Labor 239. https://doi.org/10.15185/izawol.239

Rodríguez-Pose, A., von Berlepsch, V., 2018a. Does population diversity matter for economic development in the very long term? Historic migration, diversity, and county wealth in the US. Eur. J. Popul. 35 (5), 873–911. https://doi.org/10.1007/s10680-018-9507-z

Rodríguez-Pose, A., von Berlepsch, V., 2018b. Internal migration and regional development in Europe. Reg. Sci. Urban Econ. 68, 1–13.

Rowe, F., Calafiore, A., Arribas-Bel, D., Samardzhiev, K., Fleischmann, M., 2022. Urban exodus? Understanding human mobility in Britain during the COVID-19 pandemic using Meta-Facebook data. Popul., Space Place *29* (1), e2637. https://doi.org/10.1002/psp.2637

Santos, J.L., Fernández, M.T.F., 2023. The spread of urban–rural areas and rural depopulation in central Spain. Reg. Sci. Policy Pract. 15 (4), 863–878. https://doi.org/10.1111/rsp3.12605

Sardadvar, S., Vakulenko, E., 2016. Interregional migration within Russia and its east-west divide: Evidence from spatial panel regressions. Rev. Urban Reg. Dev. Stud. *28* (2), 123–141. https://doi.org/10.1111/rurd.12050

Sardadvar, S., Vakulenko, E., 2020. Estimating and interpreting internal migration flows in Russia by accounting for network effects. Socio-Econ. Plan. Sci. 69, 100685. https://doi.org/10.1016/j.seps.2019.01.007

Tacoli, C., McGranahan, G., Satterthwaite, D., 2015. Urbanization, rural-urban migration, and urban poverty. Human Settlements Group, International Institute for Environment and Development, London, UK.

Thomas-Agnan, C., LeSage, J.P., 2021. Spatial econometric OD-flow models. Handb. Reg. Sci. 2179–2199. https://doi.org/10.1007/978-3-662-60723-7_87

Todaro, M.P., Smith, S.C., 2020. Economic development. Pearson UK.

Tol, Richard S.J., 2017. Population and trends in the global mean temperature. Atmosfera 30 (2), 121–135. https://doi.org/10.20937/atm.2017.30.02.04

United Nations (2017). World Urbanization Prospects: The 2017 Revision. United Nations, Department of Economic and Social Affairs, Population Division.

UN-Habitat – United Nations Human Settlements Programme. (2019). Urban-Rural Linkages: Guiding Principles. United Nation. Available at: 〈https://unhabitat.org/urban-rural-linkages-guiding-principles〉. [accessed 15/04/2023].

United Nations (2022), Department of Economic and Social Affairs, Population Division (2022). World Population Prospects 2022: Summary of Results. UN DESA/POP/2022/TR/NO. 3.

Vakulenko, E., 2019. Motives for internal migration in Russia: what has changed in recent years? *Appl. Econ., Russ.* Pres. Acad. Natl. Econ. Public Adm. (RANEPA) 55, 113–138.

Vogiazides, L., Kawalerowicz, J., 2022. Urban Exodus in Covid Times: Who Moves Out of the Inner City of Stockholm and where Do They Go? Stockholm Research Reports in Demography. Stockholm University.

Westlund, H., Borsekova, K., 2023. Rural problems, policies and possibilities in a post-urban world. Reg. Sci. Policy Pract. 15 (4), 717–728. https://doi.org/10.1111/rsp3.12664

World Bank (2024). Rural population (% of total population). Available at: 〈https://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=RU〉 [accessed 04/01/2024].

Zhang, K.H., Song, S., 2003. Rural-urban migration and urbanization in China: Evidence from time-series and cross-section analyses. China Econ. Rev. 14, 386–400. https://doi.org/10.1016/j.chieco.2003.09.018

Zhang, K., Song, S., 2011. Rural-Urban Migration and Urbanization in China. Ser. Contemp. China 14, 279–300. https://doi.org/10.1142/9789814287814_0011

Zubarevich, N.V., 2019. Poverty in Russian regions in 2000-2017: factors and dynamics. Popul. Econ. 3 (1), 63–74. https://doi.org/10.3897/popecon.3.e35376