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ORIGINAL PAPER

Community Roots of COVID-19 Infection Rates Between Population Composition and Regional Systems in Romania

Dumitru Sandu[1]

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Abstract

This is an analysis of conditions favouring the cumulative COVID-19 infection rates between February 2020 and April 2021 in Romania, as an Eastern European society, at the local community level. What are the socio-demographic and location profiles of the local communities by considering their infection rates with SARS-COV-2 at the beginning of the pandemia as a dependent variable? This is the research question that structured the approach. The general hypothesis that is tested is that reported infections with the new coronavirus are higher in communities of higher social interactions. The theoretical model is tested by multiple regression analysis working on more than 2500 local communities, out of the 3200 local administrative units of the country. Data basis for testing the model are coming from the National Institute of Public Health and the National Institute of Statistics. Higher COVID infection rates are favoured by socio-human capital, the regional capital, migration abroad experience, and modernity at a local level. Other factors are captured by the cultural areas as subregions of historical regions of the country, formed by neighboured similar counties. Nuclei of higher infections with COVID-19 are located in developed communities around large cities, high modernity areas, and communities of high emigration abroad. Principles for health public policies are formulated at the end by considering the role of decentralisation, and better ways to do a rapid and good diagnosis at local levels. To our knowledge, this is one of the very few studies that address determinants of COVID-19 infections at the local community level for a whole country in Europe. New research questions are formulated as an outcome of conclusions. They could be answered only by supplementary multilevel research. Limitations of analysis are derived from the fact that we are using only ecological, spatially aggregated data, and not multilevel ones. Relations that were recorded to the community could not be transferred to the individual level.

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Extended author information available on the last page of the article

Keywords Covid-19 infections · Cultural areas · Community capitals · Social interactions

Introduction

The disease in general, the pandemic in particular, has a strong social determination. Naturally, in the confrontation with COVID-19, the speed of the spread of diseases and, especially, the reduction of its incidence and consequences, mattered and counted. This is why official infection rates have been calculated and reported over certain periods, usually 14 days. However, understanding the social mechanisms of contagion also requires reporting for longer periods. This is what we will do next, for the case of Romania, using a set of data available at the locality level, regarding the incidence rates of infections from February 2020 to the end of April 2021.

The mainstream of the emerging sociological literature on COVID-19 focuses mainly on the consequences of this pandemic crisis, on the pandemic patterns at the national level (Sigler et al., 2021) or on changes that are induced in different societies (Matthewman & Huppatz, 2020). The diffusion of COVID in the same society is addressed here mainly at the county or regional level (Andersen et al., 2021, Mitrică et al., 2021, Bylok, 2022). The analysis we are introducing focuses on factors contributing to the spread of the disease at the local level of local administrative units (LAU 2) in a particular society in Eastern Europe. To what degree do local and regional patterns of social interaction contribute to the spread of the disease from its launch in February 2020 up to starting of its decline at the end of April 2020 in the Romanian society? This is the research question of this approach. In the mainstream literature, the spatial approach of the diagnosis was focused mainly on countries and regions by neglecting comparisons of rural communities, towns and cities covering a whole country. Our approach develops multiple comparisons among over 2500 rural communes, towns and cities considering the socio-demographic and location factors that could predict the differential rates of infection with SARS-COV-2.

At the beginning of the pandemic, social interactions leading to COVID-19 infection were associated with places of higher development and social interaction by business or migration (Allain-Dupré et al., 2020, Signorelly et al., 2020). In the Romanian media, the phenomenon was especially associated with the movement of migrants or temporary trips abroad. Does migration abroad remain a significant factor in favouring COVID infections even when the period of analysis for more than a year? Spatially, the identification of community environments with several cases of infection was associated with the location of communities on the border of the country or with increased population density, specific to large cities. The high population density and social interactions in the big cities and the migratory circulation abroad (Hâncean et al., 2020) were the main factors associated in the media with explaining the appearance of the outbreaks of infection. This is the context in which the new rules of social distancing (in fact socio-spatial) have become increasingly difficult to follow. Why so? For the simple reason that the life of large urban centres close to such centres is based on a high density of social relations, on multiple interactions, strongly rooted in the local culture. The population density goes, in many cases, together with the size of the locality. The larger the locality, the higher the population density. Are there any size thresholds for localities, depending on which infection rates vary significantly? Did the city, commune or micro-region structured around big cities, development centres or national borders matter especially in the process of spreading the pandemic? And if regions matter, what kind are they? Urban, developmental, historical or cultural areas?

We did not find in the literature than few studies that are close to our approach of predictors of COVID-19 infections at small areas level, for the early stages of the pandemics. This is the case of multivariate analysis of 177 neighbourhoods in New York City (Whittle & Diaz-Artiles, 2020). The dependent variable of the study was the cumulative rate of positive cases of COVID-19 recorded on April 5th 2020 at the level of Zip Code Tabulated Areas in New York City. The key findings indicate higher infection rates in neighbourhoods of high population density, and low median income, lower percentages of the white population, and high shares of the population under 18 years old.

On a larger scale, the same type of analysis is developed for 1624 counties that had at least 16 cases of COVID-19 infections, cumulatively, in May 2020, in the United States (Zhang & Schwartz, 2020). They used two regression models having as dependent variables incidence and mortality rates of COVID-19. Population density, the share of people of + 65 years old and the percent of tested people for COVID-19 are the predictors that are statistically significant and positive for the variation of the incidence rates. Percentages of the minority population, population under the poverty line, and the tested people against COVID-19 are not significant predictors. Sensitivity analysis (Treiman, 2014) for the same approach proved that if one takes only the population in the rural counties, density is no more a significant predictor.

The next section of this analysis presents the methodological frame of the approach. The following sections are devoted to the results of the analysis based on the meanings identified for the specific effects of different blocks of variables used to predict the cumulative rates of infection of the local population with the new coronavirus. A last section of the results introduces the findings of the relations between COVID-19 as infections and vaccinations at the locale level. More technical tables with the results of the multiple regression analyses are included in the Appendixs.

Methods and Data

The data we are using for all the variables from Fig. 1 are measured at the level of local administrative units (LAU 2) and are provided by the National Institute of Public Health (for the dependent variable—the cumulative rate of COVID-19 infections) and the National Institute of Statistics (for the independent variables). Ordinary least square regression was run on a set of 2577 rural communes/towns/cities out of the total of 3181 localities. Listwise deletion was used for very small or missing data communities. Similar regression models were run with all the LAU2 units and, separately, by each of the eight development regions (Appendix

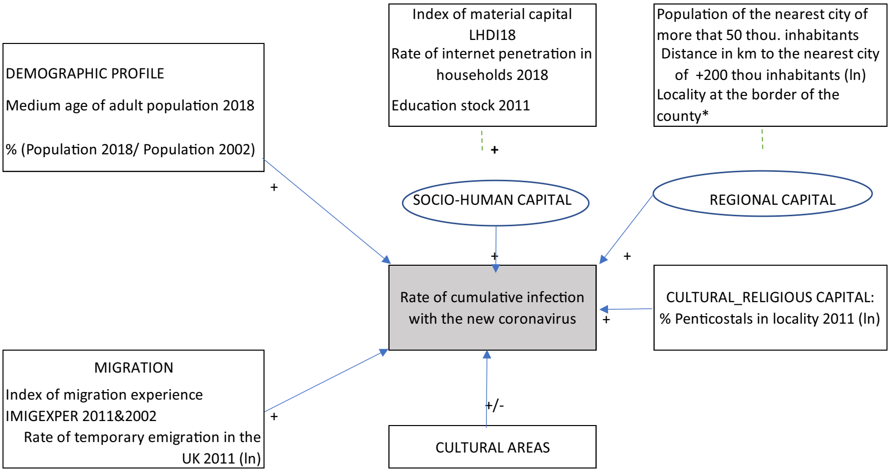

Fig. 1 Blocks of variables used in predicting cumulative rates of infection with COVID-19. Ellipses are, as in AMOS analyses, latent variables, not directly measured. By rectangles, we represented directly measurable variables. Continuous line arrows represent causal relationships and dotted lines measure measurement relationships between latent variables and those used to estimate them. Initially, the factorial score for regional capital was a measure with inverse scaling, with maximum values for isolated localities. By multiplying by − 1 we obtained a direct scaling of the score in the sense that the maximum value is assigned to the maximum intensity of the reference phenomenon. The relations of direct proportionality, positive, are marked by + and those of inverse proportionality, negative, by −. The model from this figure is tested by a multiple regression presented in Appendix 1. Correlations among independent variables are not represented in the diagram in the hypothesis of a usual multiple regression (Steiner 2005) with rather independent predictors or with low correlations among them (as tested by VIF—variation inflation factor)

1 and Appendix 3). To better understand the significance of the migration experience in predicting the intensity of infections with SARS-COV-2 we also computed a regression model taking the local modernity index as a dependent variable (Appendix 2). All the regression models are tested by computing variance inflation factors to avoid colinearity. Sensitivity analysis (Treiman, 2014) proved the stability of the results if one changes some predictors.

The hypothesis from which we started claims that the infection rates at the level of localities in Romania, cumulated for the period February 2020–April 2021, were favoured by a series of factors relevant to their specific social interaction in the reference areas. Such models/patterns derive, in turn, from the sociocultural and economic profile of the localities. We took the concept of community capital from the community development analyses (Emery & Flora, 2006) and we built for each locality the related profiles. Based on the available data, we determined profiles on six blocks of variables, relevant, in turn, for six types of community capital—vital or demographic, socio-human, regional, migration, cultural-religious and cultural area. We adopted six working assumptions based on the six types of community capital considered.

The demographic profile was measured by the average age of the adult population in the locality and the total population increase (Fig. 1). The expectation is that in the dynamic localities, with a marked increase in population, the interactions will be of high density and, consequently, the infection rate with the new covid will be high. The high average age of the local population increases the risks of contamination with the new covid and, implicitly, can lead to high infection rates.

Similarly, we assumed that the social interactions that could affect the transmission of the new coronavirus were also dependent on the educational profile of the population, and the local socio-human capital. From three indicators we built an index of the socio-human capital of the locality, similar, in many respects, to the human development index calculated by the United Nations Development Programm (UNDP) at the national level. The constitutive indicators, aggregated by factor score, are the stock of education, the internet penetration rate at the level of households in the locality, and the material capital index (revenues to the local budget from own sources, consumption of gas for household consumption and living space per dwelling). This index is strongly correlated with the local human development index, variant 2018 (LHDI18), built for a different analysis (Sandu et al., 2020, 2020a; Sandu et al., 2020b).[1]

In the series of population composition indicators, we also included those related to migration abroad. The data for this aspect are older and come from the National Institute of Statistics (NIS), the 2011 population census. Although in the meantime the state of migration flows abroad has changed, the differences between localities in terms of migration have likely remained largely the same. We first used an index of local migration experience based on data from 2011 and 2002, IMIGEXPER (Sandu, 2016), and secondly, the rates of temporary emigration from the locality to the UK (2011). We have retained in the analysis model only emigration to the UK—although we had similar measures for destinations Italy, Spain, Germany, and France—after experimenting with the multiple regression model in Appendix 1. The expectation is that in the localities with high rates of departures abroad, intense phenomena of contamination with the new coronavirus will be registered.

In the series of indicators of the cultural composition of the population, we tested by multiple regression, before making a decision, the effect of ethnicity (Hungarians, Roma) and religious denomination (Adventist, Pentecostal, Catholic) depending on the data available locally, from the last census since 2011. The only significant predictor for new local coronavirus infections remained membership in the Pentecostal religious cult and we maintained this variable in the series of predictors. Another reason for not keeping other ethnicity/religion variables among the current predictors in the regression from Appendix 1 is that keeping them there would increase the VIF (variation inflation factors) over the threshold of 4 for some cultural areas where the shares of these cultural groups are higher. The decision is meant to increase the stability of the multiple regression model (Treiman, 2014).

[1] In fact, two of the constituent indices for the socio-human score (material capital and internet penetration rate) are also included in the composition of the LHDI18. The correlation between the LHDI18 and the socio-human capital index (SHC) introduced by this material is very high, at 0.96.

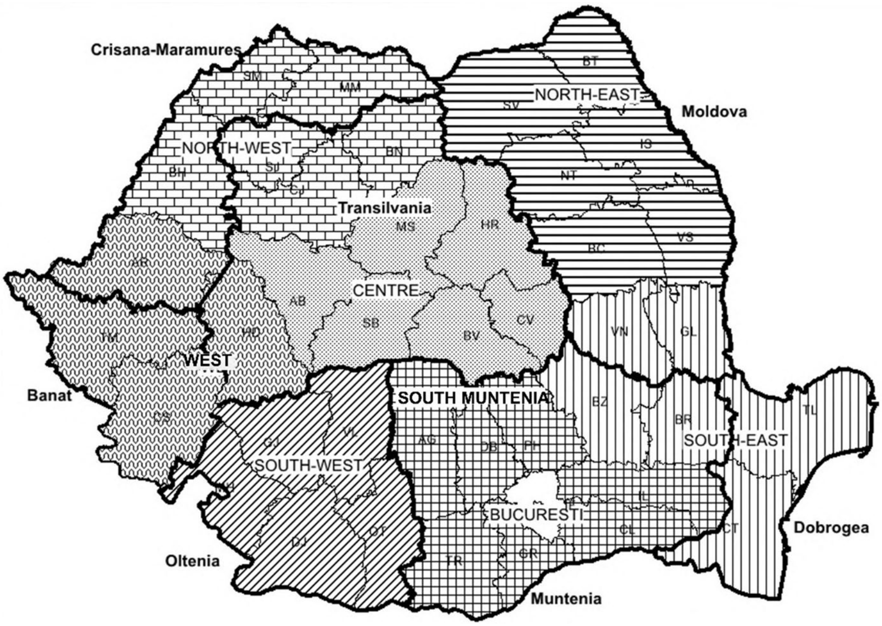

Fig. 2 Historic and development regions of Romania. Borders of historical regions are marked by bold lines. Development regions are clusters of neighbouring counties with identical patterns of grids. Their names are in capital letters. The historical region of Moldova in Romania, for example, is formed by eight counties. Sex of them (SV, BT, NT, IS, BC, VS) form the North-East development region. VN and GL are also part of the Moldova historical region and are included in the South-East development region, together with BZ-BR (from Muntenia) and TL-CT forming the historical region of Dobrogea

Regardless of other factors, the relevant social interactions for the transmission of the new coronavirus were, most likely, conditioned by the position of the locality in the urban-regional system. We assumed that the social interactions are stronger for the localities that are closer to large urban centres and are central, in the county system, in the sense that it is not on the edge of the county (Sandu, 2003: 262).

Another set of position indicators in the regional system is given by the locality belonging to one of the 15 current cultural areas of the country (Sandu, 2020a), as subregions of historical regions, consisting of counties with similar profiles by demographic, economic, cultural and social indicators. We expect that the localities that are in the cultural areas of some big cities, such as Timiş, Cluj, Sibiu and Braşov, for example, will have, caeteris paribus, high rates of infection with the new coronavirus. Similarly, localities in Ilfov county, near the capital city of Bucharest, are expected to record high rates of infection.

The sensitivity of COVID infection rates to regional configurations will be tested by using not only cultural areas as subregions of historical regions (Moldova, Dobrogrea, Muntenia, Oltenia, Banat, Crisana-Maramures, and Transilvania) but also development regions as NUTS2 (Fig. 2).

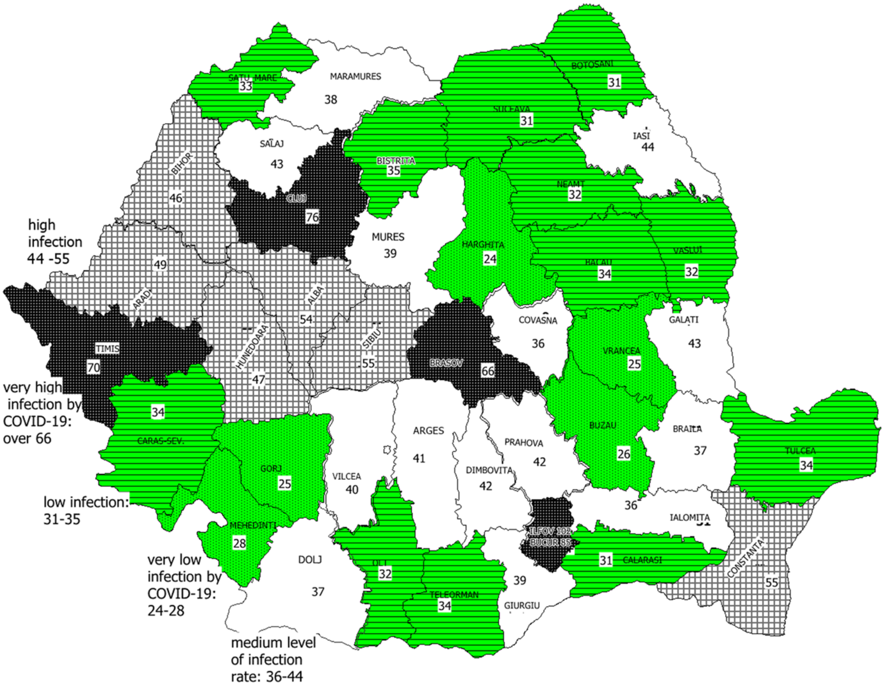

Fig. 3 Cumulative infection rates by COVID-19: locality averages by counties. Primary data source: National Institute for Public Health (NIPH). Cumulative infection rates by COVID-19 for the period February 2020–April 2021. Averages weighted by locality population, by counties. Figures in the county indicate the cumulative rate of COVID-19 infections as weighted averages for all the localities in the county. Data series divided by natural breaking points. Figures indicate limits of intervals as cumulative infections by 1000 people. Own graphics and computation. Example: Timis county is in the category of counties with maximum infection rates of 70 rate of infections per 1000 inhabitants

The only normative regions (EUROSTAT, 2010) with fixed limits and institutional functions are counties and development regions (Sandu, 2013). Cultural areas and historical regions are analytical or functional regions. All these types of regional configuration will be considered here from the point of view of inequalities among infection rates of localities.

Results

Regional Location

A first regional overview of COVID-19 infections is provided by the map in Fig. 3. Localities from counties including large urban centres had the highest average rates of new Covid infections. This is the case of the counties Timis, Cluj, Braşov and Ilfov (considered together with the capital city of Bucharest). Timis-Cluj-Brasov is part of the same cultural area as clusters of counties of high socio-cultural similarity

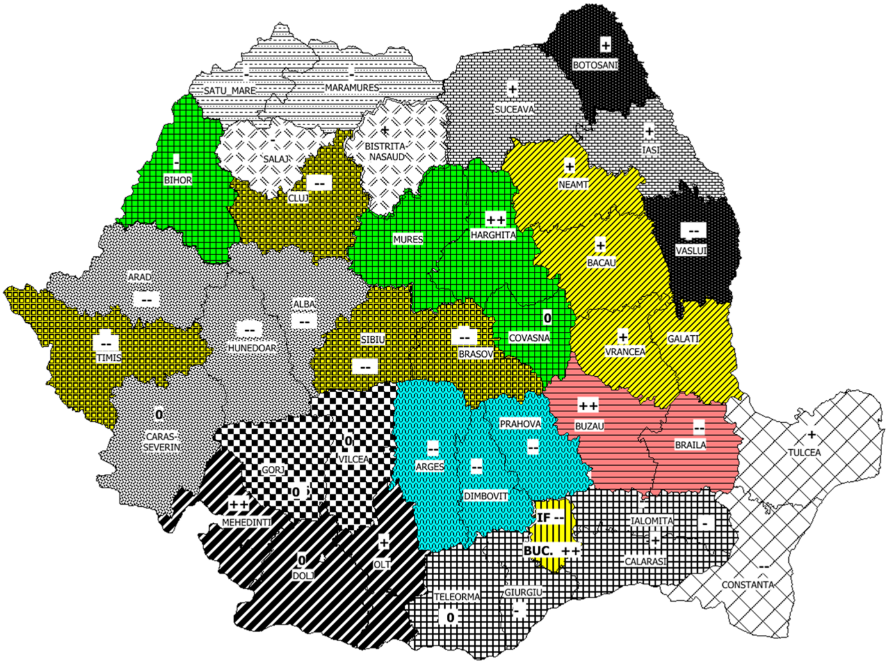

Fig. 4 Counties favouring (−) or disfavouring (+) infections with the new coronavirus within cultural areas. Cultural areas are historical subregions made up of counties that have a high degree of socio-cultural similarity (Sandu, 2020a). By (− −) we marked the counties for which a very high rate of infection of the localities with the new Covid is specified. By (−) are marked the counties with high infection. Counties that have very low rates of infection of localities, so fewer diseases with COVID-19, are marked by (+ +). The (+) marker is used for the low infection rate. The counties that are on average are marked with 0. The analysis was performed by adjusted standardized residues, in a table that intersects the type of locality in terms of the degree of infection with the new coronavirus (five categories demarcated by quintile values on the series of infection rates local COVID-19) and the county of affiliation. Adjusted standardized residue calculations were performed under data weighting conditions with the locality population. For example, Timiş County was specific for localities with very high cumulative infection rates with the new covid (quintile 5), at the end of April 2021

(Sandu, 2020a). Infection rates in the counties that are close to large urban centres, as is the case for Arad-Hunedoara-Alba counties are not so high as in counties of large urban centres but are also high. The majority of counties in this situation are, also, part of the same cultural area.

Medium rates of infection are specific for localities in Arges-Dambovita-Prahova, another cultural area of the country in the historical region of Muntenia.

A more stable image of the relations between county location of localities and the intensity of Covid infections could be obtained if one considers the significance of the relationship between the county and the quintiles of Covid infections (Fig. 4). Localities from the cultural areas of large urban centres from Timis-Cluj-Brasov-Sibiu systematically favoured high rates of local infections with Covid. In the North cultural area of Maramures-Satu Mare recorded a similar trend of higher probability of infections with Covid. Localities from the North Muntenia cultural area, from

Table 1 Cumulative rates of infection with the new covid by development regions and size categories of localities (‰)

	Development regions	Types of residence and demographique size of localities:							Total
		communes of - 4000 inhabit.	communes of +4000 inhabit.	towns of - 20 thou. inhabit	cities of 20_50 thou. inhabit.	cities of 50_100 thou inhabit.	citiies of 100_200 thou. inhabit.	cities of 200 thou. inhabit.	
4	Oltenia (South-West)	20	22	28	40	51	55	57	34
3	South Muntenia	25	32	42	45	64	59	59	39
2	Low Danube (South-East)	16	25	34	38	49	48	66	39
1	North and Central Moldova (East)	20	24	28	38	50	53	69	35
6	North-West	29	40	37	50	65	57	82	49
5	Banat+AR+HD (West)	34	62	41	45	57	71	84	54
8	Bucuresti_Ilfov	51	97	125	105			86	89
7	Central Transilvania (Centre)	26	36	37	49	70	70	86	48
	Total	24	34	38	48	59	58	78	47

Data source at locality level: National Institute of Public Health (INSP) for COVD-19 infections during February 2020–April 2021 and INS for the population after residence in 2018. Own calculations by reporting infections accumulated over the entire period, at 1000 inhabitants. Example: The average infection rate in the cities of 20 thousand-50 thousand inhabitants in the Bucharest-Ilfov region was 105 ‰, the maximum in the table. AR—Arad County. HD—Hunedoara county is affiliated with the West development region. For the configuration of development regions see Fig. 2.

counties Arges-Dambovita-Prahova, also favoured high rates of Covid infections. On the contrary, counties from the cultural area of South–East Moldova (from counties Neamt-Bacau-Vrancea) had a lower probability of Covid infections. A similar trend of low Covid infection was registered in localities from Iasi-Suceava, another cultural area of the Moldova historical region.

Even if the trend was to have rather homogeneous effects on Covid infections from counties of the same cultural areas, there were also exceptions to heterogeneous effects. This is the case, for example, with the counties of Vaslui and Botosani that form a poor cultural area in the historical region of Moldova. The first one significantly favoured high Covid infections, contrasting with Botosani county systematically disfavoured Covid infections.

It is clear that one has to go beyond bivariate relations to include not only regional profiles but also characteristics of localities.

The impact of the various community profile variables, mentioned in the methodological section (Fig. 1), is analysed by using the data of a multiple regression model (Appendixs 1 and 2). We start by contextualising their effect on Covid infections by an overview of the impact of locality demographic size.

How Important is the Size of the Locality?

If we disregard the dynamics of the infection process and take into account only the cumulative rates of this contamination, it results that the tendency has been for the local infection rates to be higher in localities of large demographic size. The specific impact was, as expected, maximum for cities with more than 200 thousand inhabitants (Table 1). The communes with less than 4 thousand inhabitants were the ones with the lowest COVID infection rates. Differentiated effects appear between the two extremes. Localities, communes or cities, with a population between 4 and 20 thousand inhabitants are part of the category of those who have disadvantaged

COVID infection effects. Small towns with 20 thou–50 thou. inhabitants are typical of the national average infection rate of about 38 infections per 1000 inhabitants.

Cities with a population of over 50 thousand inhabitants have favoured, in the statistical logic, not case by case, high infection rates.

However, if we look at the patterns of infection in development regions, the images are different. The highest infection rates occur in Transylvania, within the development regions 5 (West), 7 (Center), and in the south, in Bucharest-Ilfov. Here, the big cities of over 200 thousand inhabitants recorded by far the highest infection rates, over 80‰. In the Old Kingdom (Moldova, Muntenia, Dobrogea and Oltenia), the main nucleus of the concentration of infections was in Ilfov county.

In very large cities (on the scale of Romania, of course) the measures of social distancing were the least observed, in conditions of maximum social heterogeneity, high density and high-intensity migratory circulation. The reverse is valid for communes with less than 4 thousand inhabitants. Of course, over time, as the pandemic process unfolded, other factors acted to influence infection rates. This is the case with vaccination, for example. However, we did not have a dynamic situation at the local level in this respect. Similarly, factors such as social interactions related to migration are likely to have differentially influenced COVID-19 contamination over time. Specific data related to such an approach are again not available to me. The reference to migratory circulation considers all types of migration—internal and external, external for long or short periods and also circulatory-external, shuttle type abroad. The latter is practically unquantified but most likely expanding.

After specifying the regional context of Covid infections one can go further and see better-specified models that consider Covid infections function of local community characteristics and cultural areas including them.

Socio-Human and Regional Capital

The new analysis (Appendix 1) allows for the identification of the specific effects of different factors (Fig. 1) on COVID contamination. From there we learn that it was not the size of the cities as such that counted as an independent factor in determining the infection rates with the new covid, but the socio-human capital[2] associated with the size of the cities. Social interactions tend to be more intense in cities with a high level of education, developed communication infrastructure and a good financial situation. Here, in localities with high socio-human capital, we record increased rates of infection with the new Covid. There seems to be a style of life of higher educated people, with better internet connection and good material situation that favours

[2] If the multiple regression equation in Appendix 1 also includes the variable on locality size, this variable does not appear to be a significant predictor of COVID-19 infections. Removing the socio-human capital index from the equation makes locality size a statistically significant predictor. It follows that locality size is a significant factor in predicting COVID infection rates due to its strong association with socio-human capital stock. The education stock, in essence, tends to be higher the larger the locality is by population.

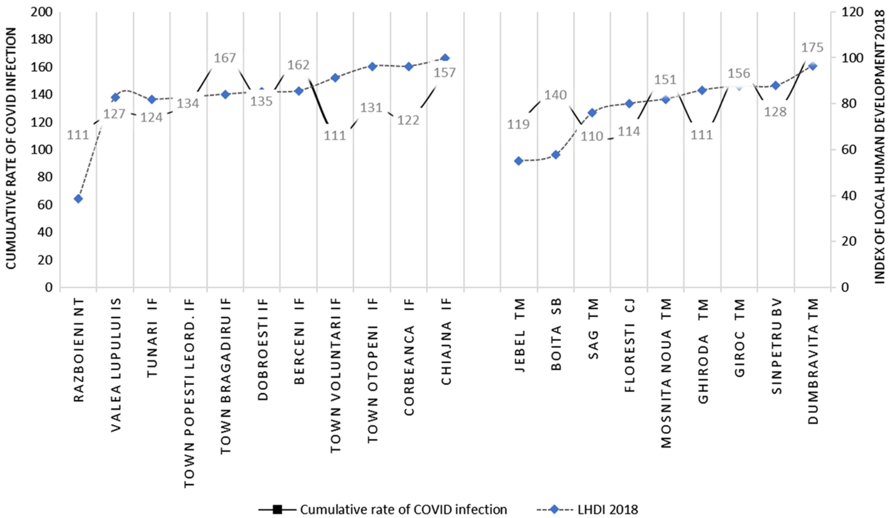

Fig. 5 Top 20 localities with maximum cumulative COVID-19 infection rate. Data source: INSP, own calculations. Infection rates are calculated by reporting the number of infections in the period February 2020–April 2021 reported per 1000 inhabitants with permanent domicile in the locality, in 2018. (National Institute of Statistics, NIS, calculates only at the census the population with usual residence in the locality.) The graph shows, by way of example, the first 20 localities with the maximum infection rate. To the left of the figure is the scale of infection rates. The series from which the data regarding the infection rates are extracted has a minimum value of 1.1 ‰ for Dubova commune from Mehedinţi county and a maximum of 175 ‰ for Dumbrăvişa commune from Timiş. The simple average of the series is 27.6 ‰, and the weighted average with the population of the localities is 47.1 ‰. Example: for the city of Bragadiru in Ilfov county, the cumulative rate of COVID-19 infections was, at the end of April 2021, 167 ‰, the second-largest, after that of Dumbrăviţa in Timiş. The local human development index (LHDI 2018) for 19 of the 20 localities in the graph was very high, on a scale between 0 (minimum development) and 100 (maximum development). The city of Chiajna, with a very high infection rate, had a maximum LHDI 2018 of 100. For Dumbăviţa, the level of development was also very high, with LHDI 2018 worth 97

higher social interactions and territorial mobility. All of these favoured higher rates of Covid infections at the local level.

The proximity to the big cities also made a notable contribution to the spread of the Covid-19 pandemic. An overview, in this sense, provides the 20 localities in the country that had the highest Covid infection rate at the end of April 2021 (Fig. 5). Most of them are communes or small towns in Ilfov and Timiş counties. The highest infection rate, of 175 ‰ was registered in the commune of Dumbrăviţa from Timiş, very close to the city of Timişoara. But also in the series of this chart appear common or strongly developed cities near Bucharest, Cluj, Iasi, Sibiu. With the data of the updated local human development index (LHDI18), Chiajna, Corbeanca, Otopeni, Voluntari and Dumbrăviţa are the first five localities in terms of human development level in Romania.

We now find that such peri-urban localities are not only highly developed but also "favourable" to COVID infections. Where does this situation come from? We do not have complete data for the answer. It is very likely that in their case, or those similar to them, it is a composite effect. In this effect, we will find both socio-cultural and economic components. The rich population, in most cases, for such localities, was motivated by its way of life of intense territorial circulation, in the country and abroad, by the multiple social interactions it has, to carry out several diagnostic tests of possible COVID-19 infections. In addition, the increased financial facilities available to the population of localities close to large cities have facilitated testing by financial resources. Several tests could also lead to the detection of several infections.

The validity of the above findings could be questioned on the assumption that the population residing in communities close to large cities would be under-registered more than for other categories of localities. Consequently, the denominator given by the population of the locality used to calculate the infection rates would be, in reality, higher. This set of figures would result in an overestimation of COVID infection rates for communities near large cities. Hypotheses are contradicted but by the partial data we have: the population growth rate between 2002 and 2018 is 118% for localities close to large cities, larger than for other categories of localities depending on the distance they are located from large cities (calculations not shown here). In addition, the estimation gap between the local population by domicile, the known one, and the one by usual residence, at the local level, but unknown, is well controlled in the regression equation in "Appendix 1" by the migration index abroad and by the total growth rates of the population between 2002 and 2018. The results of the multiple regression analysis are fully interpretable. If the distortions given by the unknown ratios between the population by domicile and by usual residence were very high, the interpretability of multivariate analyses would be problematic.

What about migration? In the series of initial questions, we mentioned it as the primary source of COVID-19 interactions. Does this factor still matter when the analysis is done with cumulative data throughout over a year and controlling for several other factors? In addition, migration data at the locality level are old, from 2011, since the last census in Romania. Meanwhile, the levels and the intensity of migration flows have changed.

Migration Interactions

Yes, the migration from 2020 to 2021 is no longer the one from 2011. Despite this, the migration experience measured at the level of the 2011 census continued to be significant for the COVID-19 contamination mode in the local–regional profile. According to the results of the analysis in "Appendix 1", the localities that had many people abroad in 2011 and 2002 had high rates of COVID-19 infection the years later. Why? For the simple reason that, although the configuration of local migration fields from Romania to certain foreign countries has changed in the meantime, the hierarchies of migration experiences between localities have had, very likely, strong inertia over time. Migration social networks with those abroad and with those at home have been maintained. Job losses abroad due to the economic crisis associated with the pandemic have led to more or less forced returns to the country, permanently or temporarily. Such changes inevitably had consequences on the probabilities of COVID-19 infection. In addition, increased labour demand, especially in the agriculture of immigrant countries such as Germany, the United Kingdom, France and the Netherlands, has stimulated emigration or re-migration decisions in the country. This kind of economic migration through strong demand on the labour market abroad has favoured, directly or indirectly, social interactions which, in turn, have favoured COVID infections.

With analysis data that we do not present here, it resulted that COVID infections were favoured especially for the localities that had a tradition of migration on the Romania-Great Britain corridor. Why is this so? More data on the subject that we do not have could clarify the problem.

The local experience of migrating abroad counts for the rates of infection with the new coronavirus not only about social interactions with people from different contexts and social networks. It also counts as an experience that brings modernization, with a specific lifestyle, based on multiple social contacts, rationality, etc. That this is the case is also proved by the fact that the localities with an increased index of demographic, housing and institutional modernity are not only with a large number of inhabitants, increased education stock and high-level urban-regional capital but also communities with a strong tradition of temporary migration abroad (Appendix 2).[3]

Commuting from rural areas to large cities and high internal out-migration from the same rural areas are, also, favourable to large shares of COVID-19 infections. An extension of the regression model from "Appendix 1" indicates that localities with a high percentage of the occupied population in locality working as commuters in other localities or being temporary out-migrants in the country are also localities of high infection rates with SARS-COV-2 (see footnote to the Table in "Appendix 1"). Rural communes that are close to large cities tend to be more developed and with a larger share of people working as commuters in large urban centres or as temporary out-migrants in urban centres (regression analysis not presented here).

Migration experience, socio-human capital of locality and COVID-19 infections scores go together by locality size. The larger the size of the locality, the larger migration experience values, socio-human capital and infection rates of COVID-19 at the locality level (Table 2). It is very likely that locality size conditions, in a positive way, the migration experience and its socio-human capital. These two factors facilitate higher social interactions within and out of locality and, implicitly, higher rates of COVID-19 infections.

Cultural Areas

In addition, it is verified the expectation that the COVID contamination phenomena in Romania have a strong dependence on the historical sub-regions of the country,

[3] If in the regression equation in "Appendix 1" we additionally introduce the predictor 'degree of local modernization', the effect of the migration index on infection rates becomes insignificant because local modernity is also significantly determined by the intensity of the local migration experience ("Appendixe 2").

Table 2 Variation of COVID-19 infections by settlement type, socio-human capital and local migration experience

Category of settlement	Cummulative infection rate with COVID-19 ‰	Index of socio-human capital	Index of local migration experience IMIGEXPER
commune of -4 thou. inhabitants	24	36	46
commune of +4 thou. inhabitants	34	41	56
towns of - 20 thou. inhabitants	38	49	63
towns of 20-50 thou. inhabitants	48	55	74
towns of 50-100 thou. inhabitants	59	57	81
cities of 100-200 thou. inhabitants	58	59	87
cities of + 200 thou. inhabitants	72	63	91
Bucharest	85	68	98
Total	47	50	70

Primary data sources: National Institute for Public Health for COVID-19 data and National Institute of Statistics for socio-demographic data. All the figures are averages weighted by locality population 2018. For IMIGEXPER, a Hull score, see shorturl.at/sDENQ. The index of socio-human capital (SHC) is a factor score (Smith 1962) of education stock 2011, internet penetration rate 2018, and an index of material capital (Sandu 2020b). SHC is transformed by a Hull score to have a variation

designated here as cultural areas (Fig. 2). Several factors not explicitly included in the present analysis, associated with the socio-cultural profile of some groups of counties, contributed to the manifestation of differential rates of COVID-19 infection at the regional level. The cultural area consisting of counties consisting of large cities in Transylvania, acted, for example, in this regard. These are the counties of Timiş-Cluj-Sibiu-Braşov. Similarly, in Transylvania, they acted to favour increased COVID infection rates and factors associated with the specifics of localities in the cultural areas Alba-Arad-Hunedoara-Caras-Severin, near Timisoara. The counties in the south of Muntenia Teleorman-Giurgiu-Călăraşi-Ialomiţa near Bucharest and Botoşani-Vaslui near Iaşi form cultural areas of lifestyle, with a similar function of favouring high cumulative rates of COVID-19 infection.[4]

Is COVID-19 only an effect of social interactions in certain local–regional contexts? To what degree it could be considered a cause of the intensity of COVID-19 vaccinations? This is what we analyse in the last section of the article.

[4] We performed a regression analysis with all the variables in "Appendix 1" which we added as predictors and measures of the intensity of flows to Germany, Italy, the UK, Spain and France, using old data from 2011 (temporary emigration rates, logarithms). The only statistically significant predictor for a positive relationship is the rate of emigration to the UK.

COVID-19 Infections and Vaccinations

The rates of COVID-19 infections are predictors of the high relevance of COVID-19 vaccinations at local levels. A regression model that used a set of predictors that are very close to those in "Appendix 1" proved that the infections with COVID-19 are an important predictor of the local rates of vaccinations even if one controls for community context variables (Sandu, 2021). The higher the recorded rates of COVID-19 infections, the higher the vaccination rates against the virus at the local level. Territorial vaccination patterns tend to be similar to those of infections. Localities of higher development levels that are better connected to large cities and with a higher migration abroad experience have, also, higher rates of vaccination against COVID-19. The regional patterns by cultural areas are not so similar. What is constant is the fact that localities from a cultural area of large urban cities, like Brasov-Sibiu-Cluj-Timis, had not only high infection rates but also high rates of vaccinations. On the contrary, localities in Ilfov, in the proximity of Bucharest, the capital city of the country, recorded, on average, high rates of COVID-19 infections but low rates of vaccinations against this virus. Further research is needed to find the explanation.

Conclusions

As expected, local communities acted as important matrices in favouring or disfavoring social interactions with a direct impact on the cumulative rates of SARS-CoV-2 infection. The material presents the findings of an analysis that tries to answer the question "what about from the profile of communes and cities in Romania has favoured/disadvantaged the cumulative rates of infection of the population?". Data provided by the National Institute of Public Health at the local level were related to social, demographic, economic, cultural and regional characteristics of the communes and cities in the country.

Cumulative infection rates for more than one year were strongly dependent on community characteristics with a direct impact on social interactions. Large cities, with their increased socio-human capital, and migration abroad seem to have played a key role in the process of infesting the population with SARS-CoV-2. Social interactions specific to large cities and communities close to them acted, very likely, as environments of immediate relevance for the speed of infestation and its spread. The cultural areas around large cities such as Bucharest, Timisoara, Cluj, Sibiu, Brasov and Iasi stood out, especially as living and production environments that favoured high levels of COVID-19 infection. Municipalities and communes in the peri-urban areas of the mentioned large cities have been registered as places of maximum intensity infection, beyond the variability of the health system conditions or the local health policies adopted.

A second family of factors that favoured COVID infections is given by the social interactions associated with migration abroad. Although the data for measuring the community migration experiences we have been able to work with locally are old, they continue to be relevant, given the very high inertia of migration processes. As in a huge social experiment, we managed to control, through appropriate statistical procedures, the role of some factors to highlight the impact of others factors on the phenomenon in question. Thus, we could find that COVID-9 infections were significantly higher in communities with large indices of migration abroad experience.

Of course, this cannot be a complete analysis. It would have been optimal to work with data that combine individual characteristics with community characteristics. Such data exist in Romania, but they are not publicly available. Based on the available data, so far, we have obtained the first image at the national level of the community-regional conditions that have favoured the social interactions relevant to the spread of COVID-19 infections. There is no doubt that a better specification of local data by mentioning infections by periods and vaccination rates would have helped us considerably in better understanding the process analyzed.

A whole series of fertile questions come along the lines of this analysis. Why does the migratory circulation to Great Britain bring, more than the one on other corridors on which the Romanians circulate, an increased probability of COVID-19 infection? Why does the poor cultural area of Botoşani-Vaslui favour the type of infection in question? Is the explanation already suggested, regarding the proximity of the two counties to the strong urban centre of Iaşi, sufficient? Why in the localities with a higher share of Pentecostals, caeteris paribus, were the COVID-19 infection rates higher? Is there a connection between the registration of this relationship and what happened in Suceava at the beginning of the pandemic? Is the explanation for the high level of COVID-19 infections in the cultural area of Southern Muntenia about the Bucharest effect sufficient? Probably not. Why did the small, highly developed communes and towns in the peri-urban big cities have maximum COVID-19 infection rates? Did only the culture, the proximity to the big cities and the high degree of development matter? Again, we don't think so. Details on the demographic composition of the population and other similar issues should be seen. Why, for example, Dumbrăviţa, one of the most developed communes in Romania, has the highest COVID-19 infestation rate? How much did the migration corridor to Germany or the share of religious minorities matter here, apart from the explanatory factors already mentioned?

Research into the consequences of the COVID-19 epidemic in Romania is emerging. Demographic aspects at the national level are investigated by Vasile Gheţău (2021). The relationship between infection-vaccination at the local–regional level cannot yet be addressed in the absence of the necessary data in the public space.

Even if this paper is not policy-oriented, some recommendations/questions for preventive policies emerge. As far as the contagion effects of COVID-19 infections are visible among neighbouring territorial units, are decentralised policies recommended for the case of Romania as for other similar situations (Laroze et al., 2021). Social interactions by commuting between rural communities at the periphery of large cities and large cities' populations seem to be an important way of spreading infections. Local administrations are, very likely, in better positions than central administration to identify how local social interactions among neighbouring territorial units favour such contagion. Is this valid only for the first waves of contamination?

As an emigration country, Romania has a lot of migrants abroad and diverse and strong connections between non-migrants at home and migrants abroad.

Restructuring in the European labour markets and the impact of pandemia largely stimulated circular and return migrations. Hard to control the streams of migration in such a context. What could be done to improve the communication flows between origin and destination communities on health topics, supported by the local administration in the migration corridors? Such communication networks could be important not only in conditions of pandemic contagion but, also, for transnational development.

A better diagnosis and treatment at the community level in the conditions of contagion diseases involve, also, a need for better and rapid estimations of incidence rated at the territorial level. This cannot be done as far as one computes the estimations of infection and mortality rate by referring to the population by domicile and not to the population of usual residence. This is the case in Romania where the population by residence is estimated only at the country and regional but not at the local communities level. The situation is expected to change after to current population census in 2022.

Appendix 1: Predictors of Rates of Infection with COVID-19 at the Local Level

Predictors		Coef	Beta	$p > \mathrm{t}$
Vital capital	Average age of adult population 2018	1.267	0.186	0.000
	% (Population 2018/Population 2002)	0.144	0.207	0.000
Socio-human capital (rate of internet penetration 2018, education stock 2011, material capital 2018)		11.963	0.441	0.000
Regional capital (large population in the nearest city, small distance to the nearest city of + 200 thou inhabit, locality that is not at county border)		4.361	0.201	0.000
Migration	Index of migration experience IMIGEXPER 2011 & 2002	0.049	0.035	0.051
	Rate of temporary emigration to the UK 2011 (ln)	1.649	0.059	0.000
% Penticostals in locality 2011 (ln)		1.333	0.065	0.000

Predictors		Coef	Beta	$p>t$
Cultural area (reference category BN SJ)	Bucureşti Ilfov	31.121	0.210	0.000
	TM SB BV CJ	6.587	0.106	0.000
	BT VS	5.529	0.076	0.000
	South Muntenia	4.846	0.069	0.000
	AB AR HD CS	3.222	0.051	0.006
	North Muntenia	2.505	0.041	0.030
	SM MM	0.704	0.008	0.541
	SV IS	0.568	0.008	0.653
	CV HG MS BH	0.258	0.004	0.819
	NT BC VR GL	−0.192	−0.003	0.875
	North OLTENIA	−0.982	−0.013	0.413
	Dobrogea	−1.307	−0.016	0.311
	South Oltenia	−1.919	−0.025	0.110
	BZ BL	−5.778	−0.067	0.000
Constant/intercept		−43.164		0.000
R2		0.63		
N		2576		

Data source: National Institute of Public Health for data on COVID-19 infection rates from the beginning of the pandemic to the end of April 2021, reported per 1000 permanent residents in 2018, and INS for population data. Own linear regression calculations in STATA using robust standard errors. The significance levels are conventional because it is not a question of a sample of 3200 localities but of 2576 localities for which we obtained data on all the variables in the analysis. Random factors play, however, in this case as well, through errors in measuring the inevitable variables. The interpretability of the results is, however, a way of validation. I used the dot as a decimal marker. No variance inflation factor (VIF) value for predictors is higher than 4, indicating low collinearity among predictors. Beta are regression coefficients that are comparable by the fact that they are computed on standardised variables as z scores.

The model is tested by sensitivity analysis (Treiman, 2014) by replacing the regional capital variable with an index of urban competitiveness IURCON (Ionescu-Heroiu et al., 2013: 247) and thepattern of statistical significance for regression coefficients kept the same configuration. Similarly, the model keeps a similar pattern of significant regression coefficients if one adds the proportion of the employed population out of residence locality but within the country (values from 2011 census, NIS). The new predictor has a positive significant net effect. Only two cultural areas are no more significant predictors (North Muntenia and AB AR HD CS). R2 is slightly increased to 0.638.

We experimented with applying the same regression model using, instead of the cultural area as a predictor, the historical region, or the urban or developmental region. The resulting multiple determination coefficients are lower than the one recorded in the model presented here, but with very close values. It follows that cultural areas are relevant categories of regions for social interactions associated with COVID-19 infections.

Appendix 2: Predictors of the Degree of Local Modernity

Predictors	Coef	$p>t$
Population 2018 (ln)	2.384	0.000
Regional capital	1.304	0.000

Predictors		Coef	$p > t$
Education stock 2011		8.584	0.000
Index of migration experience IMIGEXPER 2011&2002		0.141	0.000
Cultural areas (reference BN SJ)	Bucureşti Ilfov	9.298	0.000
	TM SB BV CJ	4.449	0.000
	CV HG MS BH	3.778	0.000
	AB AD HD CS	1.816	0.006
	SM MM	1.157	0.174
	Dobrogea	−0.702	0.386
	South Muntenia	−1.254	0.076
	North Muntenia	−2.758	0.000
	BZ BL	−3.458	0.000
	NT BC VR GL	−7.223	0.000
	SV IS	−7.259	0.000
	South Oltenia	−9.580	0.000
	North OLTENIA	−9.726	0.000
	BT VS	−11.648	0.000
Constant/intercept		−45.256	0.000
R2		0.778	
N		2577	

Data source: NIS. See for IMIGEXPER Sandu, D. 2016. Migration abroad experience and modernity at the local level in Romania (sav file), https://www.researchgate.net/publication/301607751_Migration_abroad_experience_and_modernity_at_the_local_level_in_Romania_sav_file (consulted 23 May 2021).

Linear regression in STATA, with robust standard errors. Dependent variable – degree of local modernity as a factor score of three factor scores referring to demographic, housing and institutional modernity (https://www.researchgate.net/publication/301608144_Migration_abroad_experience_and_modernity_at_the_local_level_in_Romania_excel_file, consulted June 1st 2021).

Appendix 3 Predicting Rates of Infection with COVID-19 by Development Regions

Predictors		North-East	South-East	South-Muntenia	South-West	West	North-West	Centre	Bucharest_IF
Vital capital	Average age of adult population 2018	1.153***	0.314	0.723***	0.982***	2.017***	0.800***	0.834*	4.041

Predictors		North-East	South-East	South-Muntenia	South-West	West	North-West	Centre	Bucharest_IF
	% (Population 2018/ Population 2002)	0.061**	0.128***	0.030	0.116**	0.215***	0.083***	0.130***	0.325
SHC Socio-human capital (rate of internet penetration 2018, education stock 2011, material capital 2018)		13.572***	10.344***	9.710***	6.305***	13.642***	14.824***	14.436***	13.541**
REGC Regional capital (factor score of population in the nearest city, distance to the nearest city of + 200 thou inhabit, locality that is not at county border * − 1). The higher the value of the factor score*−1 the higher the regional capital		4.321***	2.325***	3.202***	2.573***	8.858***	7.160***	4.398***	2.116

Predictors		North-East	South-East	South-Muntenia	South-West	West	North-West	Centre	Bucharest_IF
Migration	Index of migration experience IMIG-EXPER 2011&2002	−0.028	0.061	0.163***	0.088	−0.024	−0.123*	−0.068	0.626
	Rate of temporary emigration to the UK 2011 (ln)	0.335	1.813 *	−0.186	3.272**	2.616	0.240	6.324***	20.095
% Penticostals in locality 2011 (ln)		1.432***	1.177	−0.463	−1.135	1.369	1.145	1.017	10.682
Constant/intercept		−19.834	−0.755	−8.433	−36.059	−77.369	1.813	−14.315	−197.636
R2 coefficient of multiple determination		0.405	0.502	0.392	0.272	0.648	0.571	0.5	0.834
N number of communes		437	314	462	363	234	374	303	31
Population weighted averages for:	COVID-19 infection rate	34.4	39.2	39.3	33.5	52.9	48.3	48.1	86.3
	Socio-human capital (H)	41.5	46.9	46.2	45.4	53.6	51.3	53.0	67.4
	Regional capital (H)	48.0	49.5	50.7	46.6	49.8	45.1	47.4	79.2
	Index of migration experience IMIG-EXPER 2011&2002	72	70	55	56	70	72	71	91

Primary data sources: NISP, NIS. OLS regressions by development regions as specified by columns. H-Hull score = 50 + 14*z score. In the rgression models, SHC and REGC are not transformed by H scores (Smith, 1962). Ln—logharitmic transformation. Significance levels 0.05 *, 0.01 **, 0.001 ***.

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Declarations

Conflict of Interest No conflict of interest.

Ethical Approval Not the case.

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Authors and Affiliations

Dumitru Sandu[1]

Dumitru Sandu
dumitru.sandu@gmail.com

1 University of Bucharest, Street Schitu Maguranu, no. 9, Sector 1, 010181 Bucharest, Romania