Geography of COVID-19 outbreak and first policy answers in European regions and cities

Mounir Amdaoud, Giuseppe Arcuri, Nadine Levratto, Marianna Succurro, Damiana Costanzo

Geography of COVID-19 outbreak and first policy answers in European regions and cities[1]

Mounir AMDAOUD
EconomiX, CNRS, université Paris Nanterre
Mail : mounir.amdaoud@economix.fr

Giuseppe ARCURI
EconomiX, CNRS, université Paris Nanterre
PRISM, université Paris 1 Panthéon sorbonne
Mail : giuseppe.arcuri@univ-paris1.fr

Nadine LEVRATTO
EconomiX, CNRS, université Paris Nanterre
Mail : nadine.levratto@parisnanterre.fr

Marianna SUCCURRO
Università della Calabria
Mail : marianna.succurro@unical.it

Damiana COSTANZO
Università della Calabria
Mail : damiana.costanzo@unical.it

[1]This paper is taken from a study, coordinated by EM Normandie Business School (France), produced for ESPON, a European Program. It results from the Work package 1 of the project which was led by EconomiX (France) in collaboration with the University of Calabria (Italy), and EM Normandie Business School. **This study has been funded by the ESPON 2020 Cooperation Programme framework, partly financed by the European Regional Development Fund.**

The developed analyses and comments in this document engage only their authors and do not necessarily reflect the opinions of members of the ESPON 2020 Monitoring Committee**.**

Table of Contents

1. Introduction

In the first months of 2020, COVID-19 has affected the life of millions of people around the world. The pandemic has led national and local governments to operate in a context of uncertainty, and have to deal with difficult trade-offs given the health, economic and social challenges. Beyond the health emergency and the human tragedy, the disease triggered a social, human and economic crisis. The severe lockdown and social distancing policies put a stop on global economic growth. This led to a declining economic activity, a contraction of consumption and massive job losses.

In the second quarter 2020, still marked by COVID-19 containment measures in most Member States, seasonally adjusted GDP decreased by 12.1% in the euro area and by 11.9%in the EU, compared with the previous quarter, according to a preliminary flash estimate published by Eurostat, the statistical office of the European Union. Among the Member States, for which data are available for the second quarter 2020, Spain (-18.5%) recorded the highest decline compared to the previous quarter, followed by Portugal (-14.1%) and France (-13.8%). Lithuania (-5.1%) recorded the lowest decline (Eurostat, 2020).

Clinical data and surveillance reported at an early stage two important aspects of the epidemic: (i) elderly male population (over the age of 65) and for patients with co-morbidities such as diabetes, hypertension, chronic respiratory diseases, cancer, and cardiovascular disorders are at higher risk of dying from Covid-19 in the pandemic (Du et al., 2020), and (ii) a strong territorial dimension in SARS-CoV-2 pandemic spread (OECD, 2020). In this train of thought, a multitude of local features (social, demographic and economic) have been attributed as potential determinants for the observed variety in the Covid-19 outcome.

The importance of local parameters in explaining the health of populations and mortality rates is widely demonstrated in the literature (Cambois and Jusot, 2007). This dimension is also found in the declaration of the Millennium Development Goals signed in September 2000, which underlines the importance of the fight against poverty and the improvement of the conditions of care on the reduction of the mortality especially those of the children. In addition, these factors have been associated with other epidemics in the past and there is no reason why this should not be the case for this new disease. For instance, Linard et al. (2007) found that environmental and socio-economic factors play a crucial role in determining the spatial variation of Puumala and Lym e borreliosis infection in Belgium. Stanturf et al. (2015) arrive at the same observation in their study on the Ebola epidemic in 2014 in three West African countries (Liberia, Sierra Leone, and Guinea). It follows that taking these contextual elements into account is essential in the study of health-related questions and that their omission would lead to a partial understanding of the phenomena studied as underlined by Geronimus et al. (1999) or, more recently and on the Covid-19 in Italy, Bayer and Kuhn (2020). The latter thus envisage that family structures and the presence within the same dwelling of families with several generations differ according to the regions and would thus explain the geographic differences observed.

We put forward the assumption that spatial dependence between the regions across different channels explains the variety in the spread of Covid-19. To analyze the unequal spatial diffusion of the epidemic across Europe, we use for that an original dataset covering 377 European regions in 28 countries. For each region we calculate an indicator to describe the prevalence of the pandemic in the territory. It is defined as the ratio between the number Covid-19 related deaths over the number of inhabitants. Data on Covid-19 related deaths were collected at three moments of the pandemic first wave (end of March, end of May and end of July).

The empirical study is based, on the one hand, on an explanatory analysis of Covid-19 spatial diffusion which makes it possible to account for the level of dependence of the death rate linked to Covid-19 at different places in space. On the other hand, we use spatial regression models and Geographical weighted regression to capture the diffusion effect and the role of different groups of factors in this process. Spatial and geostatistical techniques have been used widely in several contributions dedicated to viruses, such as Hepatitis C infection, MERS-CoV, H1N1 influenza, HIV, dengue, and recently Covid-19 (Bourdin et al., 2020; Amdaoud et al., 2020).

The document is structured as follows. The second section gives an overview of the spread of the Coronavirus (Covid-19). The kinetics of the epidemic across European regions are analysed in the third section. The fourth section shows the advantages and limitations of spatial technique used. The fifth section concludes.

2. Mapping of the circulation/diffusion of the virus

Figures 1, 2 and 3 show the cumulative death rate per 10000 inhabitants across European regions.

As it can be observed, in the first months of the pandemic, the first cases were strictly limited to some regions in Italy (5.9 per 10,000 population in Lombardy), France (4.25 per 10,000 population in Haut-Rhin) and Spain (4.15 per 10,000 population in Madrid Community). In the following weeks the Covid-19 epidemic spread out around the continent, and, at the end of May, high levels of death ratio were recorded also in other European countries as United Kingdom (Northern Ireland and North East England), Belgium (Bruxelles region) and Sweden (Stockholm). A similar picture is shown in Figure 3 that presents the spatial diffusion of the Covid-19 epidemic at the end of the first vague (end of July 2020).

Figure 1: Covid-19 death rate per 10.000 Inhabitants, week 14 (end of March)

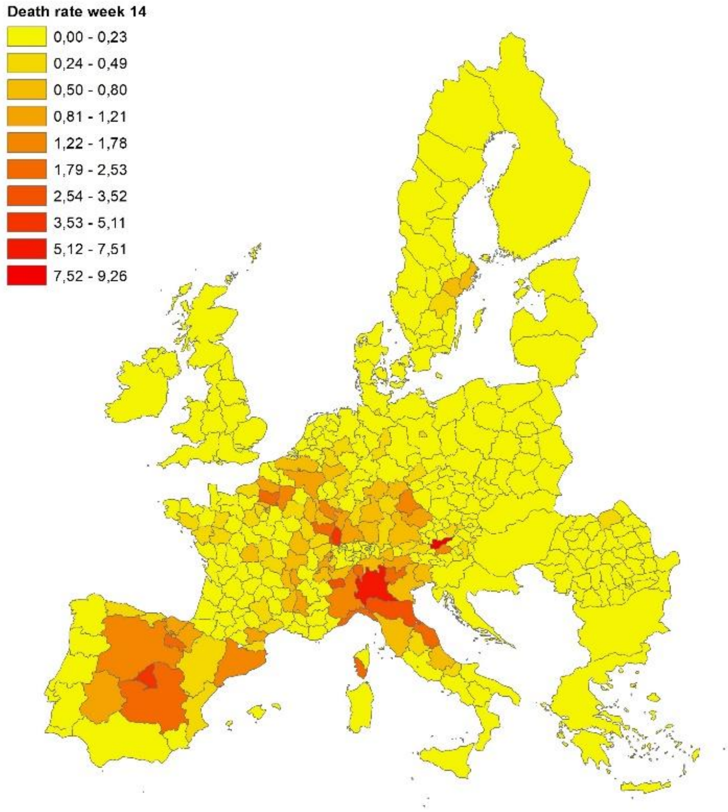


Figure 2: Covid-19 death rate per 10.000 Inhabitants, week 22 (end of May)

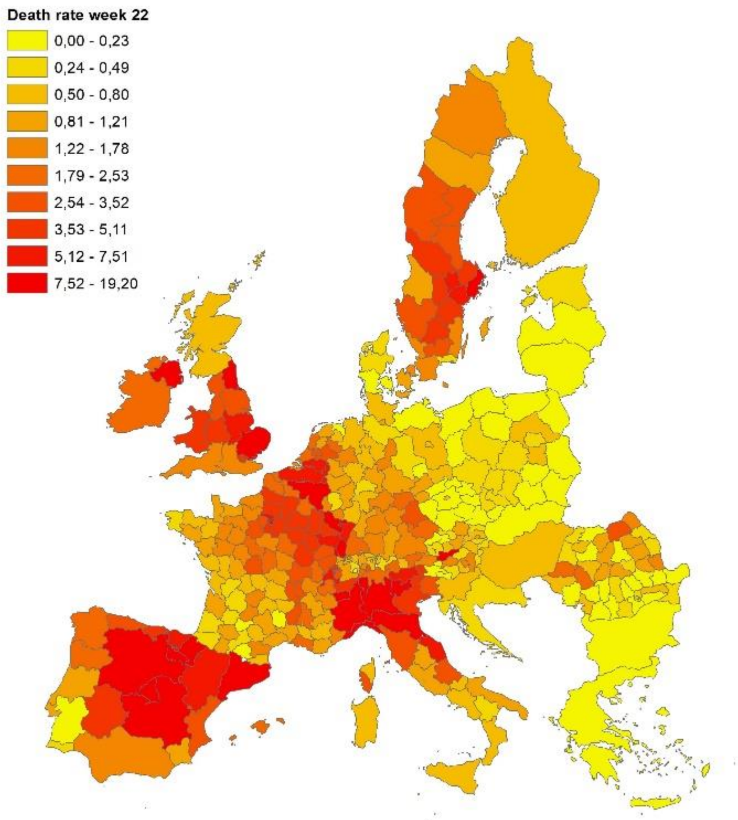
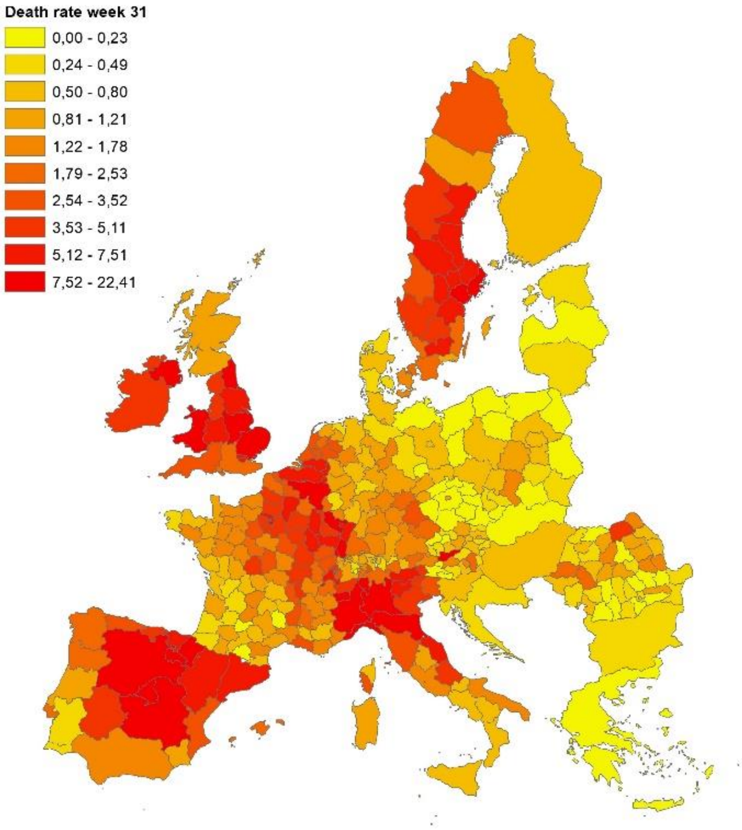


Figure 3: Covid-19 death rate per 10.000 Inhabitants, week 31 (end of July)



Sources: National ministries of health and statistical agencies

After the first cases reported in Europe, some studies pointed out that European regions were not equally hit but that strong differences existed between the peripheral ones where the infection rate remained limited and the core ones where the rates reached high levels (Amdaoud et al. 2020, Bourdin et al. 2020). The regional and local impact of the COVID-19 crisis is highly heterogeneous, with a strong territorial dimension that has important consequences for crisis management and policy responses. Governments at subnational level are responsible for crucial issues of containment measures, health care, social services, economic development, and public investment, putting them at the frontline of crisis management (OECD, 2020).

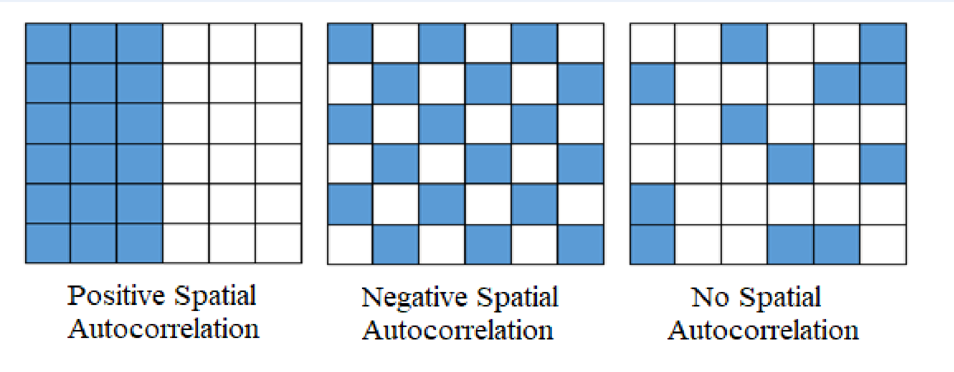
The analysis conducted in this report, is based, on the one hand, on an explanatory analysis of spatial autocorrelation which makes it possible to account for the level of dependence of the death rate linked to Covid-19 at different places in space. On the other hand, we use spatial regression models to capture the diffusion effect of the epidemic between neighbor regions and the role exerted by territorial determinants in the spread of the epidemic.

In order to test the existence of a spatial data clustering phenomenon, we apply the Exploratory Spatial Data Analysis (ESDA) which can provide useful summary information about the spatial arrangement of mortality rate related Covid-19 epidemic.

Exploratory Spatial Data analysis (ESDA)

Spatial autocorrelation is defined as the correlation of a variable with itself due to the spatial location of the observations. It is said to be positive when similar values of the variable to be studied are grouped together geographically: close geographical units are more alike than distant units in accordance with Tobler's first law of geography (Tobler, 1970). Conversely, it is negative, when variables dissimilar to the variable to be studied are grouped together geographically: close geographic units are more different than distant units. Finally, the spatial autocorrelation is equal to zero, when the observations of the variable are randomly distributed in space (see figure below)

Forms of Spatial Autocorrelation



Particularly, the LISA (Local Indicators of Spatial Association; Anselin, 1995) maps provide the identification of clusters or collections of geographical units similar, based on the indicator used. They are used to identify hot spots or cold spots across space. Positive spatial autocorrelation is observed in areas labelled high-high (i.e. high rates death rates in a region surrounded by high values of the weighted average rate of the neighboring regions), and low-low (low rate in a region surrounded by low values of the weighted average rate of the neighboring regions). There are also two forms of negative spatial associations (i.e. association between dissimilar values); high-low (high rate in a region surrounded by low values of the weighted average rate of the neighboring regions), and low-high (low rate in a region surrounded by high values of the weighted average rate of the neighboring regions).

The LISA indicator is expressed as follows;

$$z_i = \sum_{j=1}^{n} w_{ij} z_j \qquad j \neq i$$

where z_i is the difference of the variable y in region i from the global mean $(y_i - \bar{y})$, z_j is the difference of the variable y in region j from the global mean $(y_j - \bar{y})$, and w_{ij} is an element of the Spatial Weight matrix N x N which expresses for each observation (row) those locations (columns) that belong to its neighborhood set as nonzero elements. In this study the specification of which elements are nonzero relies on the inverse of distance weight function such as $w_{ij} = {}^{1}/_{d_{ij}^{\alpha}}$ where the effect of observation j on i is a declining function of the distance between them.

Figures 4, 5 and 6 display the LISA maps for the Covid-19 death rate between March and July 2020 and reveal distinctive geographic patterning of the spreading of the epidemic.

Figure 4: Local Indicator of Spatial Association (LISA). Covid-19 death rate (end of March)

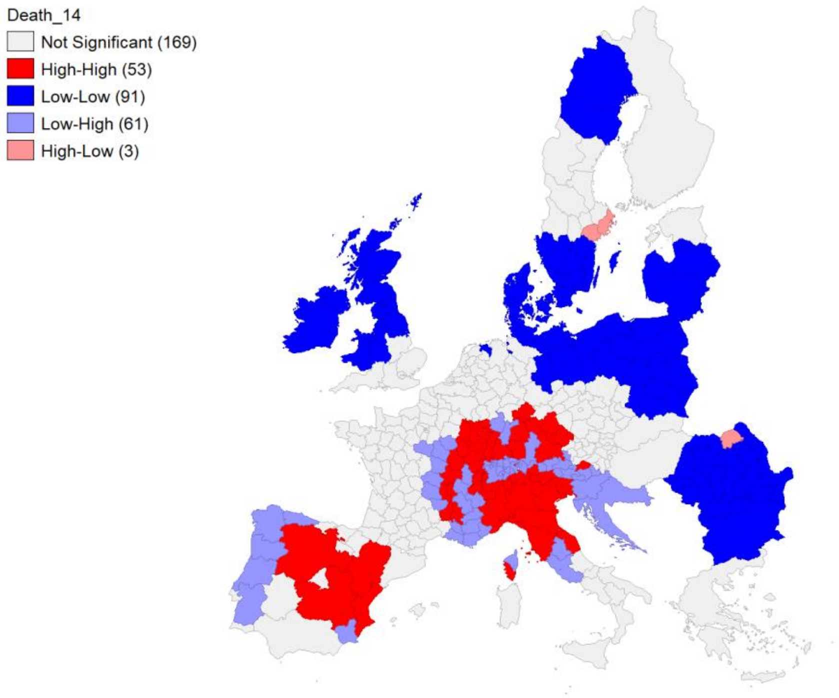


Figure 5: Local Indicator of Spatial Association (LISA). Covid-19 death rate (end of May)

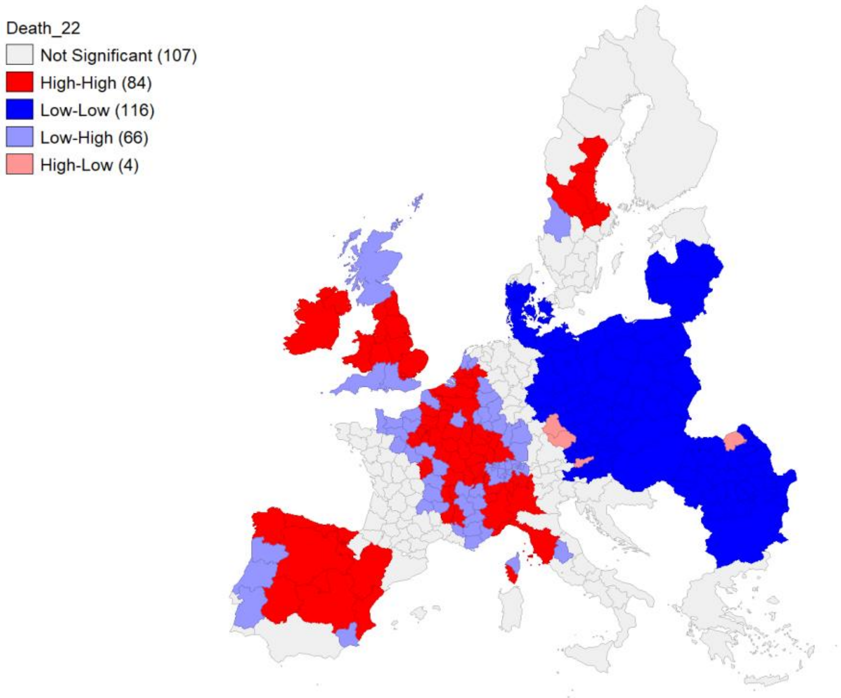
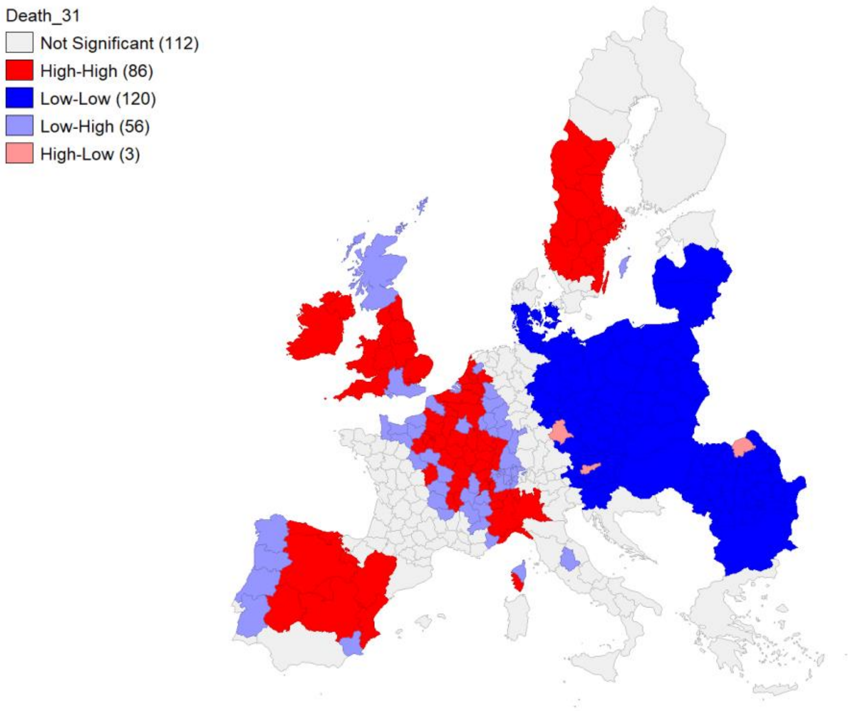


Figure 6: Local Indicator of Spatial Association (LISA). Covid-19 death rate (end of July)



Visually comparing the maps for each individual time point displays some distinctive geographical patterning that remains mainly consistent over time: the north of Italy (with a slight reduction in May and July), and the regions around Madrid have high-high clustering at all three time points. The high-high clustering recorded in France had as starting point the region of east but rapidly spread out into a big cluster from the east to Ile de France (the political and economic center of the country). Other distinctive bands of high-high clustering are also located in the United Kingdom, Ireland, Belgium, Netherlands and Sweden from the month of May.

Geographical patterning of low-low clusters is also broadly consistent over time, with this type of spatial cluster predominantly found in the east of Europe. A complementary perspective can be given observing the LISA maps of the monthly variation of Covid-19 death rate that show the shifting of the Covid-19 epidemic during the first epidemic wave (see Figures 11, 12 and 13 in Appendix).

3. Understand the kinetics of the epidemic across European regions and explain regional disparities

In this section, we apply spatial regression models to our data, with the aim to capture the diffusion effect of the epidemic between neighbor regions and the role exerted by territorial determinants in the spread of Covid-19.

Spatial Econometric Models

The econometric specification considered in this research takes the Ordinary Least Squares (**OLS**) linear regression model as its starting point:

$$\mathrm{Y} = \mathrm{X}\beta + \varepsilon \qquad (1)$$

Y is the dependent variable (Covid-19 death rate). X stands for the explanatory variables used, β is the vector of parameters to assess, and ε is the error term. When a spatial autocorrelation is ignored in the model specification but is present in the data generating process, the OLS estimators are biased and non-convergent.

The spatial autoregressive model (**SAR**) consists in correcting this bias by integrating an "endogenous shifted variable" WY in the model (1) and taking into account the spatial autocorrelation relative to the variable Y. The model is written as follows:

$$\mathrm{Y} = \rho W\mathrm{Y} + \mathrm{X}\beta + \varepsilon \qquad (2)$$

WY is the shifted endogenous variable for the inverse distance matrix **W**, ρ is the autoregressive parameter indicating the intensity of the interaction between the observations of Y. In this model, the observation of Y is partly explained by the values of Y in neighbouring regions.

A second way of incorporating spatial autocorrelation in econometric models is the Spatial Error Model **(SEM)** which consists in specifying a process of spatial dependency of errors in a regression model. The SEM model is defined as follows:

$$\mathrm{Y} = \mathrm{X}\beta + \varepsilon \ \text{ avec } \ \varepsilon = \lambda \mathrm{W}_{\epsilon} + \mathrm{u} \qquad (3)$$

The λ parameter reflects the intensity of the interdependence between the residuals of the regression and u is the error term. Omitting a spatial autocorrelation of errors produces unbiased but inefficient estimators, so that the OLS-based statistical inference will be biased.

These two models can be combined to produce a general model called Spatial Autoregressive Confused (**SAC**). It includes a lagged endogenous variable and a spatial autocorrelation of errors. The model is written as follows:

$$\begin{cases} \mathrm{Y} = \rho W\mathrm{Y} + \mathrm{X}\beta + \varepsilon \\ \varepsilon = \lambda \mathrm{W}_{\epsilon} + \mathrm{u} \end{cases} \qquad (4)$$

There are different approaches that can be used to choose models. We have adopted the so-called bottom-up approach, which consists in starting with the non-spatial model. Tests of the Lagrange multiplier (Anselin et al., 1996) then make it possible to decide between the SAR, SEM, SAC or non-spatial model.

We distinguish different groups of indicators that may explain the spatial heterogeneity in mortality due to the Covid-19 pandemic: demographic & concentration determinants (Population Density, Share of the population aged 65 and over, Life expectancy) , income & wealth determinants (GDP per capita, Poverty Index), health care determinants (hospital beds), an index that proxies the quality of governance in the regions and an indicator describing the region typology (Urban, Intermediate, Rural). Table 1 show the definition and source of the variables. The tables of summary statistics and matrix correlation can be found in the Appendix.

Table 1: Definition and source of the variables

Variable	Definition	Year	Source
Covid death rate	10 000*(cumulative death toll due to Covid-19/Population)	2020	WHO and National Health Ministers
Population density	Total population per km² (log)	2019	Eurostat
Share of the population aged 65 and over	Number of population aged 65 and older over total population	2019	Eurostat
Life expectancy	Life expectancy at birth rate	2019	Eurostat
GDP per capita	Gross domestic product (GDP) per capita at current market prices	2016	Eurostat
Poverty rate	Percentage of person at risk of poverty	2019	Eurostat
Hospital beds	100 000*(number of hospital beds/Population)	2017	Eurostat & NHS
Governance	Index of Good Governance derived from the European Quality of Government Index (University of Gothenburg)	2009	ESPON
Education	Part of population aged 25-64 with tertiary education level (levels 5-8). The variable equals one if the value is greater or equal to the mean	2019	Eurostat
Region typology	Urban/rural typology: Variable that classify regions as predominantly urban, intermediate, or predominantly rural regions.	2020	OECD

This econometric analysis provides spatial dynamic information about the spread of Covid-19 in European region and identifies socioeconomic factors associated with mortality.

Table 2: Empirical results for Covid-19 death rate determinants

	March 31st	May 31st	July 31st
Population density	N.S.	N.S.	N.S.
Share of the population aged 65 and over	N.S.	N.S.	N.S.
Life expectancy	Positive	Positive	Positive
GDP per capita	N.S.	N.S.	Negative
Poverty	N.S.	N.S.	N.S.
Hospital beds	N.S.	Negative	Negative
Governance index	Negative	Negative	Negative
Education	Negative	Negative	N.S.
Intermediate region	N.S.	Positive	Positive
Urban region	N.S.	Positive	Positive
Neighbourood effects	**+++**	**+++**	**+++**

N.S. = Not Significant

Demography is a factor of spatial differentiation in health and, as such, is the subject of frequent analyzes to explain the international (Hu and Goldman, 1990) and regional (Frohlich and Mustard, 1996) differences. Among the demographic variables (Population density, Share of the population and Life expectancy), only one is significant. We observe that a higher proportion of people with high expectancy life causes a higher prevalence of Covid-19. This result confirms the risk factor of age frequently mentioned in the literature (Wilson et al. 2020) and the critical role of demography, particularly, how the age structure of a population may help explain differences in fatality rates across regions and how transmission unfolds. According to WHO Regional Office for Europe (2020), 95% of people who died from Covid-19 in European region are over 60, and more than 50% of all deaths were people aged 80 years or older.

Wealth and income dimension play a major part in driving the pattern of Covid-19 cases and deaths around the world. An important literature points out the responsibility of poverty in the prevalence of epidemics. Low-income are linked to living and housing condition. For example, accommodations that are too small or overpopulated have been related at a high risk of infection from several pathogens, such as tuberculosis or Epstein–Barr virus (Sannigrahi et al., 2020). GDP per capita is too another aspect used in modeling health outcomes, health system performance and mortality trends (Markowitz et al., 2019). Concerning our results, we do not find robust evidence on the effect of wealth and income determinants (GDP per capita and Poverty index) over the period considered in the analysis. Thus, our results do not bring additional evidence about the aggravating role of inequalities and social exclusion in the spreading and intensity of the epidemic.

The quality of the health care system may also explain the differences between regions. For numerous countries in Europe, the local level is the relevant level in public health organization. This reason clearly argues in favor geographic approach of the Covid-19. On this subject too, empirical studies report firstly that well-structured healthcare resources positively affect a government's capacity to deal with Public health emergencies as major epidemics (Gizelis et al., 2017). Secondly, the healthcare infrastructures also have a considerable impact on the government's ability to rapidly detect, diagnose, and report the new infections (Hogan, et al., 2018). Health care determinants reflect the Government's and regional health spending proxied by the number of hospital beds. The variable exerts a negative influence on Covid-19 (after the month of March) prevalence displaying greater susceptibility to the virus infection, confirming that regions in which the quality of the health system is low are more likely to have a more significant mortality associated to Covid-19. With a need for hospitalization in intensive care units for >15% of infected patients (Qiu et al. 2020), the number of available beds has been a critical issue in the management of the Covid-19 emergency and the death rate among areas (Vinci et al. 2020). Adjunctive pharmacologic therapies are, of course, a critical resource to face the pandemic but on the short term and as long as no vaccine is available, supportive care services determine the treatment of infected people. Over the studied period, the capacity of the medical system to treat patients with Covid-19 obviously depends on the number of general and acute on the one hand and critical care beds on the other. At the country level, resources shortening have been shown to be a critical issue when the number of COVID-19 severe cases is higher than the available resources (McCabe et al., 2020). It is also an issue at the regional level as demonstrated by Guzzi et al. (2020) according to the availability of hospital structure resources should be managed to limit the spreading of the disease.

According to different studies (Putnam, 1998; Alesina and Ferrara, 2000), education is one of the most important determinants of social capital. Education reflects an orientation towards the future by strengthening human capital and social capital for economic and social development. Schooling spreads knowledge - the basic component of human capital, and cultivates social norms - the core of social capital. Through civil education from schooling, students learn the basic norms and responsibilities in society and practice in a peer culture that shapes values such as reciprocity, respect and trust. It is for this reason that we introduce in this study, the variable Education (Part of population aged 25-64 with tertiary education level) as a proxy of social capital). Our findings show that death rates due to Covid-19 are negatively correlated with social trust. It is reasonable to consider that social trust functions similarly to institutional trust in that a crisis intensifies the primary trust culture. People with low trust tend, thus, to identify negative aspects of ambiguous situations (, to consider that others do not respect the rules and, thus, to try to bypass them, amplifying the severity of the epidemic. On the contrary, in places where a vast majority of citizens exhibits a high level of confidence in other, rules are expected to be more respected by others and are indeed more respected by everyone, inducing a lower mortality rate. This sort of self-fulfilling process can explain the increasing coefficients over the period under study.

With this finding, we confirm that an essential aspect of epidemic spreading is citizen-to-citizen trust, an intangible asset able to shape the consequences of the Covid-19 phenomenon. Several sort of trust are at stake in such a process. Top-down trust between citizens and authority figures are commonly evocated by the literature. This point has been enhanced by OECD which worries about the decline of confidence in government in member states and underlines that during all stages of the COVID-19 pandemic trust in public institutions is vital for governments' ability to respond rapidly and to secure citizen support. But, beyond trust in institutions which are mostly national, horizontal and local trusts also matter. Social relations more influenced by local culture and habits also shape the spreading of the disease as mentioned by Edelman (2020). Indeed, people willing to engage in protective behaviors and respect lockdown rules depend on beliefs that others act in the same way and, broadly speaking, on social capital, as shown by Chuang et al. (2015). In a paper examining whether each of the social capital dimensions contributes to the intention to adopt any of the health-protective behaviors in an influenza pandemic (wearing a mask or washing hands), those authors show that relational trust (relationships between the trusting person and the other) is a more powerful predictor of compliance with recommended behaviors than calculative trust (past behavior of the other), particularly in an unknown situation. Spreading of the virus could thus be more difficult in places where interpersonal relations and social trust are high than in low social trust regions, as already mentioned by Habibov and al. (2017). Our results are consistent with research concluding that the pandemic tends to shape trust and solidarity between citizens and, by the way, the degree of compliance to the rules enacted by the government such as wearing the mask, maintaining social distance. This is especially true for wearing the mask, which may cause various reactions, including mistrust, even if it is widely agreed that wearing masks is a sensible thing to do (Sunstein, 2020). Knowing that this protection against Covid-19 has been shown to be a critical factor in the control of the epidemic, one can understand that wearing it was more readily accepted in regions where people trust each other more, leading thus to a lower contagion rate and, consequently, to a lower mortality rate. Our finding confirms those of Putnam et al. (1993) who conclude that information and political decisions are not enough to ensure the success of sanitary policies. Instead, they recommend mobilizing `social capital' in the community as an informal mean of action against the epidemic. This background helps to adapt measures to the context and to increase their effectiveness.

The global spread of Coronavirus (COVID-19) has been accompanied by a wave of disinformation that is undermining policy responses and amplifying distrust and concern among citizens. Around the world, governments are leveraging public communication to counteract disinformation and support policy. The efficacy of these actions will depend on grounding them in open government principles, chiefly transparency, to build trust in public institutions. In is in this context that we consider the governance quality at the subnational level as a fundamental indicator that could deeply influence the prevalence of the pandemic. Our findings confirm the hypothesis that a higher level of governance at the subnational level significantly reduced the death rate registered in European regions.

In the context of the Covid-19 pandemic, this type of intervention presents the dual advantage of supporting the effective implementation of emergency measures and satisfying the need for clear and definitive information. Public communication can also be deployed rapidly since virtually all governments have press offices and digital channels in place. These structures are especially important in contexts where pre-existing mechanisms or regulations against disinformation are absent or weak. In order to be effective and foster public trust in government, any activities conducted in this respect must be guided by the principles of transparency, integrity, accountability, and stakeholder participation, set out in the OECD Recommendation of the Council on Open Government (OECD, 2017). These considerations are extremely relevant in the context of the lockdown imposed by several European countries. In response to the pandemic several national governments, during the first wave, implemented a lockdown related to some specific territories or to the entire country Physical crowding is thought to increase the risk of viral transmission and limit the access to care. Lockdown corresponded to a set of measures that implies travel restrictions (national and international traffic) and social distancing requirements, such as closure of schools, public spaces, shops, shopping malls and restaurants. Italy was the first to lockdown the entire country on March 11 followed by Spain on 14 March, France on 17 March, United-Kingdom on 24 march, and many other European countries. These measures are enforced to minimize the spread of transmission of coronavirus disease 2019 and reduce the peak healthcare demand, especially those needing respiratory support with the objective to flatten the infection curve.

We conducted an addition analysis with Ordinary Least Square Regression (OLS) in order to understand if lockdown measures effectively minimize the spread of Covid-19 transmission. On the base of the results obtained with the spatial model, we made the hypothesis that the effectiveness of restrictions measures depends on the governance quality at the local level (government principles, chiefly transparency, to build trust in public institutions).

Ordinary Least Square (OLS) Model

The OLS model we consider is detailed in the following equation

$$Covid\ Death\ rate_i = \alpha_0 + \alpha_1 Lockdown_i + \alpha_2 Gov_i + \alpha_3 Lockdown_i * Gov_i + \alpha_i Control\ Variables + u_i$$

The dependent variable indicates the Cumulative Covid19 death rate in region *i* at week *t* over population, multiplied by 10000, with *i*=1, …, 380 regions and three dates of our analysis.

Lockdown is a dummy variable equal to 1 for European regions where a full lockdown has been adopted by the government, 0 otherwise.

Gov_i is the measure of institutional quality at regional level.

We add the interaction term $Lockdown_i * Gov_i$ to the model since we assume that the effect of lockdown on mortality rate due to Covid19 is different for different values of the regional government quality.

The regression controls for all the other variables considered in the spatial regression (Table 2).

The OLS model considered is detailed in the following equation:

$$Covid\ Death\ rate_i = \alpha_0 + \alpha_1 Lockdown_i + \alpha_2 Gov_i + \alpha_3 Lockdown_i * Gov_i + \alpha_i Control\ Variables + u_i$$

The dependent variable indicates the Cumulative Covid19 death rate in region *i* at week *t* over population, multiplied by 10000, with *i*=1, …, 380 regions and three dates of our analysis. *Lockdown* is a dummy variable equal to 1 for European regions where a full lockdown has been adopted by the government, 0 otherwise. Gov_i is the measure of institutional quality at regional level. We add the interaction term $Lockdown_i * Gov_i$ to the model since we assume that the effect of lockdown on mortality rate due to Covid19 is different for different values of the regional government quality.

The results of this regression are shown in table 3.

Table 3: The effect of Lockdown and government quality on mortality rate due to covid19

	March 31st	May 31st	July 31st
Lockdown	Negative	Negative	Negative
Governance	Negative	Negative	Negative
Lockdown_Governance	Negative	Negative	Negative
Other control variables	Yes	Yes	Yes

The empirical evidence shows that the lockdown measure adopted by several European countries has been significant in reducing cumulated deaths. Indeed, both the coefficient and the level of significance of the variable “Lockdown” increases as time passes since the adoption of the measure, exhibiting its real effectiveness in the medium-long term.

It is interesting to note that the interaction term enters with a negative sign and a high level of significance in all the regressions, with a relatively high coefficient. The econometric findings would indicate that the effect of Lockdown measures on Deaths is different for different values of "government quality", more specifically, for regions with very poor government quality.

Despite the global results obtained with the previous models, it's reasonable to assume that some variable may have a positive effect in some regions, while negative effects are observable in others. The Geographically Weighted Regression (GWR) is a local estimation technique able to cope with the issue of spatial heterogeneity. The GWR relaxes assumption of spatial stationarity supposed in global regression (OLS, SAR, SEM, etc.) in the relationships between explanatory variables and dependent variable. Thus, it allows for the parameters to vary over space.

Geographically Weighted Regression (GWR)

GWR is based on locally linear regressions in order to obtain estimators at each point in space. The estimation procedure is based on a Gaussian principle where the observations closest to the regression point have weights greater than the other observations.
The GWR model is formalized as follows:

$$y_i = \sum_j x_{ij}\, a_j\, (u_i, v_i) + \varepsilon_i$$

where (u_i, v_i) is the location in a geographic space of the i observation. When calibrating the GWR model, it is assumed that the observed data close to an "i" point have more influence in estimating the values of $a_j\,(u_i, v_i)$ than the data located far from i. The equation, therefore, measures the relations inherent to the model around each point i. In GWR, an observation is weighted with respect to its proximity to point i. The choice of weighting scheme is an important step in model specification, since it implies that the observations closest to the location (u_i, v_i) have more influence on the estimated parameters of this location than the observations that are the furthest away. So, weight W_i (u_i, v_i) can be considered as a continuous, ever-decreasing function of distance $d_i\,(u_i, v_i)$. The most used is the Gaussian function:

$$W_i = \left[1 - (d_{ij}/b)^2\right]^2$$

where $b > 0$ and is defined as being the bandwidth of the function or, in other words, the radius of the sphere of influence for point i.

According to the results, four determinants (Life expectancy, Poverty, Hospital Beds, Governance) present an heterogeneous effect on the Covid-19 Death Rate registered in European regions. The results are summarized in the following figures. Generally speaking, we observe an East/West differentiation logic.

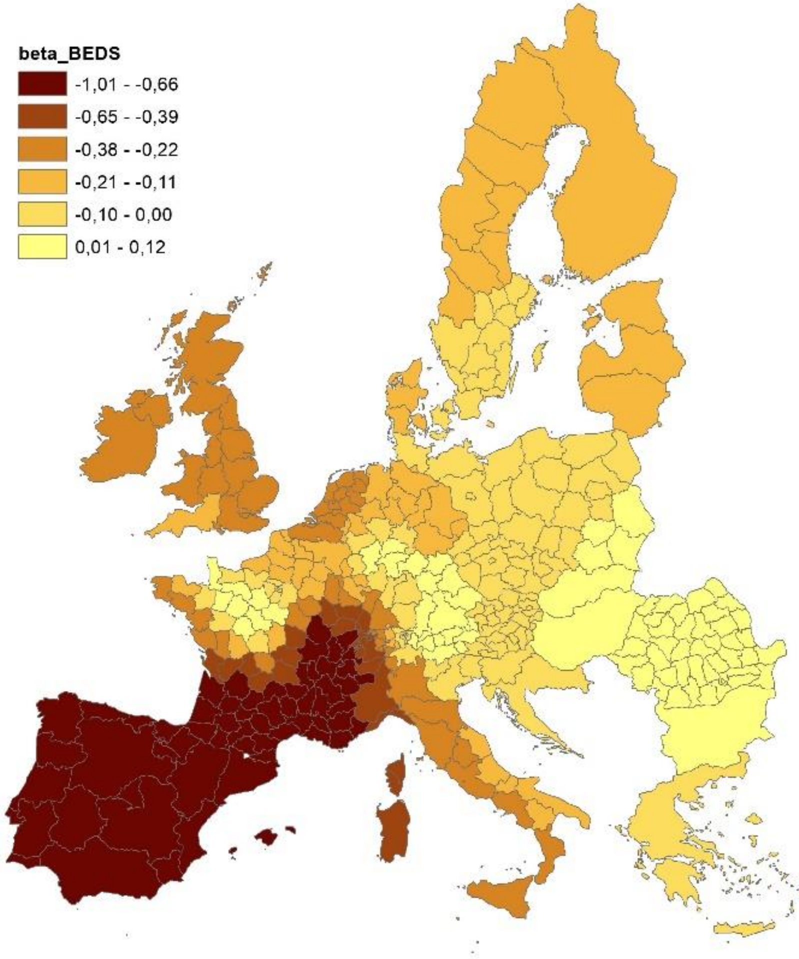
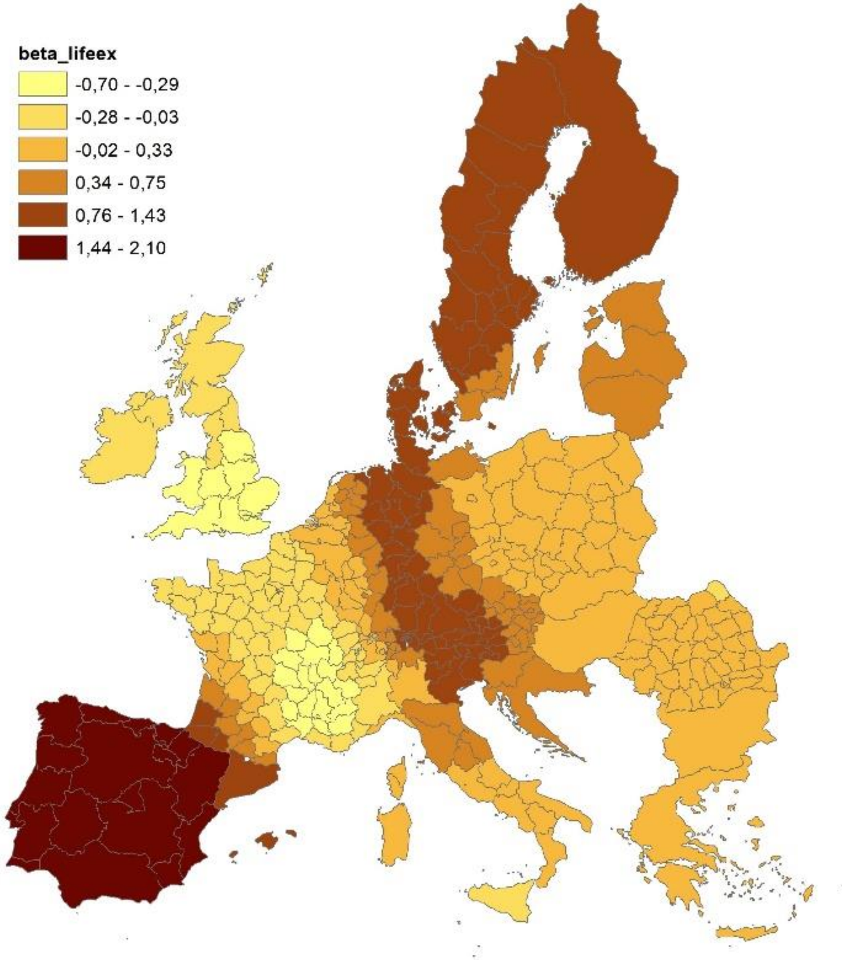
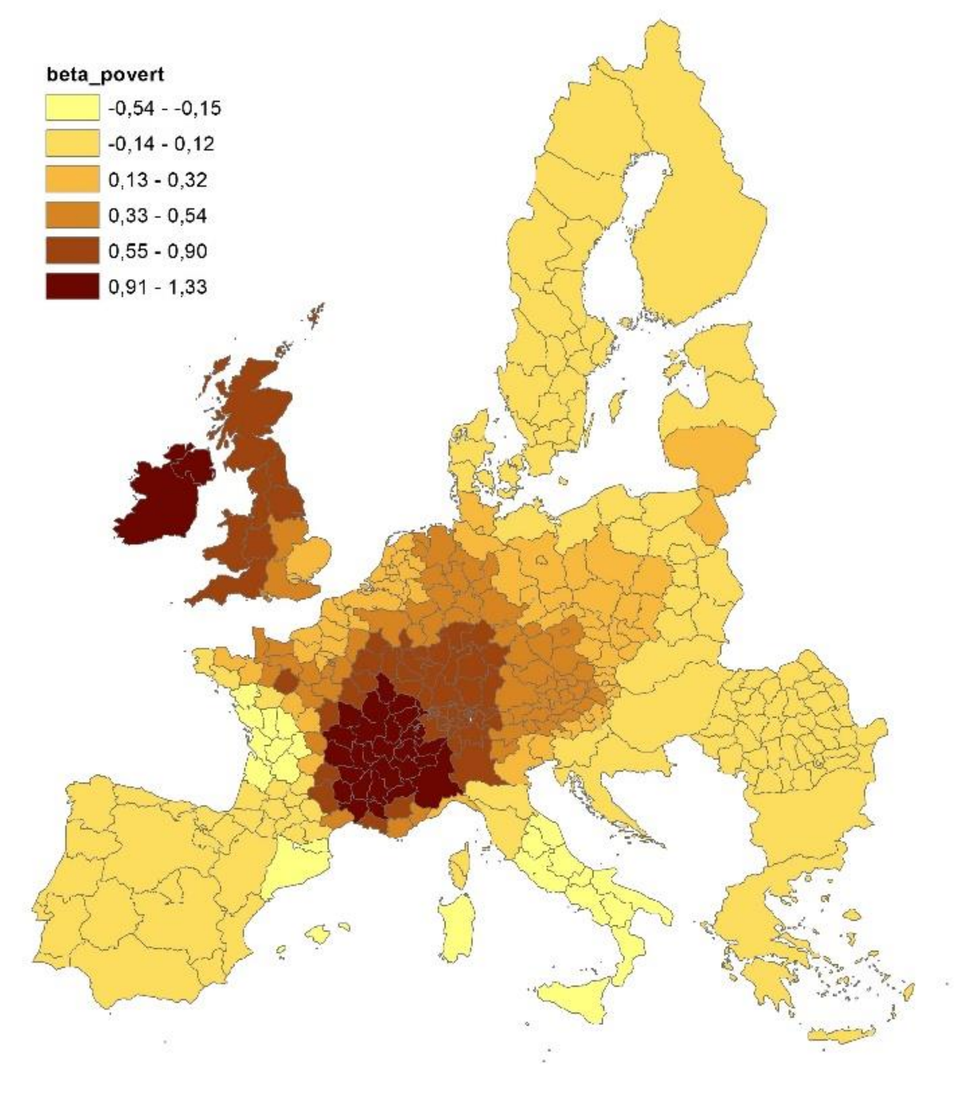
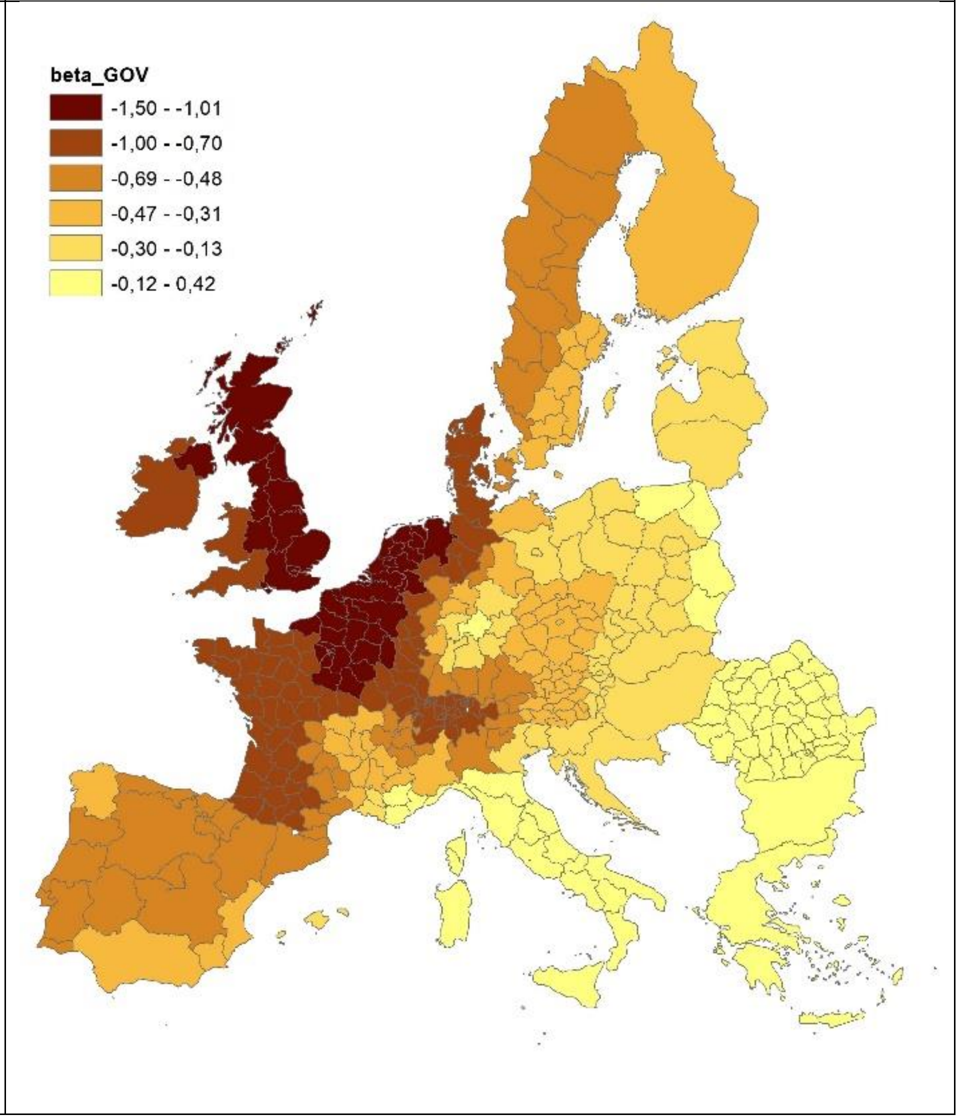
Figure 7: GWR-Hospital beds	*Figure 8: GWR-Life expectancy*
	

Figure 9: GWR-Poverty	Figure 10: GWR-Governance Index
	

The visualization of the GWR model's coefficients made possible by this method highlights the spatial variations of the parameters. GWR enables us to evaluate where and how the relation between selected explanatory variables and the dependent variable. From the figures below, we can observe that the geographic distribution of the estimated coefficients is not random.

The map of the effects of the number of beds per 100 000 people suggests a negative association with the mortality due to the Covid-19 pandemic. The magnitude of the coefficient varies considerably over space. It is strongly high for Portugal, Spain, the south and the east of France. This relationship is not surprising since the number of hospital beds is lower compared to German regions for example. This suggests the importance of accessibility to care beds in the fight against the pandemic. This finding is consistent with that of Bauer et al. (2020).
Life expectancy appears to have a positive influence on the severity of the coronavirus disease 2019 in particularly Spain and Portugal regions (see Figure 8) and in a slightly lesser extent in Germany, Austria, Netherlands and Sweden. It can be assumed that region where life expectancy is higher, the elderly population is more present.
As illustrated in figure 9 poverty is a substantial factor in describing the geographic distribution of COVID-19 incidence rates in a number of regions in France, Italy, Germany, Ireland and UK. People who are living in poverty - not highly educated - are more likely to have low health literacy and therefore are likely to increase the transmission of Covid-19. In effect, understand his responsibility of adhering to recommended measures such as social distancing is crucial to prevent the spread of the virus in the region. This aspect is documented in Singu et al. (2020)
The quality of governance is an influential factor in explaining disease incidence rates across regions in Europe (i.e., France, Germany, Belgium, Netherlands, UK). Local government quality as a proxy of capacity to deal with Public health emergencies as Covid-19 outbreak contributes to reduce Coronavirus's potential mortality. Restrictive measures such as lockdown are one manifestation of the measures taken by regional governments in order to minimize the spread of transmission of the novel coronavirus and to contain the peak healthcare demand

4. Advantages and limitations of spatial technique

The relations between values observed on nearby territories have long been a focus for geographers. Waldo Tobler summed up the problematic in a statement often referred to as the first law of geography: "Everything interacts with everything, but two nearby objects are more likely to do so than two distant objects". The availability of localised data, combined with the spatial statistics procedures now pre-programmed into multiple statistical software tools, raises the question of how this proximity can be modelled into economic studies. The use of spatial econometrics tools has become particularly popular in studies in recent years (Arbia and Paelinck, 2003; Le Gallo *et al.*, 2003).

The motivation for using spatial econometrics tools is obvious: taking regional units as "isolated islands" (e.g. by using non-spatial estimation techniques) may lead to the wrong results, and in the presence of spatial effects in regression analysis the OLS estimations may be biased or inaccurate[2]. Spatial autocorrelations of residuals with spatial data, i.e. dependency between nearby observations are quite common. This dependency in the observations may either impair the OLS method (the estimators will be without bias but less precise, and the tests will no longer have the usual statistical properties), or produce biased estimators. If the model omits an explanatory variable spatially correlated to the variable of interest, then omitted variable bias is said to occur. In addition, comparing multiple spatial econometric models leads to discuss about the uncertainty of the data-generating process, which is never known, and verify the robustness of the results.

As spatial autocorrelation is measured based on a comparison of the value of an individual variable with that of its neighbours, the definition of the neighbourhood will have a significant impact on the measurement of spatial autocorrelation. Codifying the neighbourhood structure, the larger the planned neighbourhood, the greater the number of neighbours considered, and the greater the probability that their average will be closer to the population's average, which may lead to a relatively low value for spatial autocorrelation.

A change in scale can also have implications when measuring spatial autocorrelation. The term MAUP (Modifiable Areal Unit Problem) introduced by Openshaw et al. (1979) is used to describe the influence of spatial breakdown on the results of statistical processing or modelling. Arbia *et al.* (1996) speak of a "second law of geography".

More precisely, the irregular forms and limits of the administrative levels that do not necessarily reflect the reality of the spatial distributions studied are an obstacle to the comparability of the irregularly distributed spatial units[3]. According to Openshaw (1984), MAUP is a combination of two distinct but similar problems:

- The scale problem stems from a change in the information generated when a set of spatial units is aggregated to form smaller and larger units for the needs of an analysis or due to data availability issues;
- The aggregation problem or zoning stems from a change in the diversity of information generated by the various aggregation schemes possible at a same scale. This effect is characteristic of administrative partitioning and adds to the scale effect.

The choice of the level of aggregation is thus of paramount importance in any spatial econometric analysis. Some geographers recommend adopting a multi-scale approach to study the multiplicity of

[2] For example, in the case of European regions we can expect that infection rate of a region will be influenced by those of neighbouring regions. Similarly, a COVID-19 outbreak in one region may be correlated with outbreaks in neighbouring regions if unobserved variables display spatial dependence.

[3] For instance, it is perfectly possible, when analyzing the economic convergence process of a set of regions, to observe convergence at the European NUTS-2 level, and, conversely, divergence at another level (e. g. the NUTS-3 level).

spatial aspects within a single phenomenon. However, in general, there is no solution to the problem of the MAUP. This aspect in some way can limits the analysis.

5. Conclusion

As for any disease, mortality resulting from Covid-19 results from individual characteristics. However, the local economic and social context also matters, as is recalled by the abundant literature (McCoy,2020) which considering the regional characteristics as determinants of the regional mortality may help better understand the regional discrepancies observed from the beginning of the epidemic. This paper sheds light on the spatial heterogeneity between the European region and its persistence during the expansion, peak, and beginning of decrease of the epidemic. It points out that whereas some regions were severely hit by the Covid-19 forming clusters where the mortality rates were significantly higher than on average, some other regions have been spared composing a belt of low mortality rate places mainly located on the east and south fringes of Europe. Our first conclusion is thus that Covid-19 is a global pandemic taking the form of intense local epidemics. In addition to this peculiar spatial distribution of the mortality rates, our results lead us to conclude that if some peculiar events (football matches, meeting of faithful of a church, arrival of infected people coming from already affected non-European countries, etc.) the spreading of epidemic can be explained by a mix of factors describing the socio-economic context. In addition to the classical demographic indicators, we found that degree of urbanization, on the one hand, governance quality and public health policies on the other, were tangible elements enabling us to explain the local differences observed. In addition to these aspects, the introduction of an intangible asset as education (in some extent proxy of social trust) permitted us to enrich the analysis introducing culture and interpersonal relationship. They are showed to influence the mortality rate of Covid-19 and that their role increased over the period. According to our findings, compliance to sanitary rules imposed to control the epidemic and to flatten the peak of infections in order to limit congestion in hospitals depend on trust in respecting them on the part of others. This cultural aspect should thus be considered when deciding on the implementation of sanitary rules because, beyond their theoretical expected effects, their real effect depends on their actual use resulting from social trust.

Our research underlines the importance of regional differences in the mortality rates and their origin along with the epidemic. This contribution can be of interest to policymakers and health agencies. The regional dimension of public health policies, even in centralized countries such as France, requires efforts to disentangle spatial aspects of epidemics to design policies adapted to the context in which they occur. Strengthening this local dimension is all the more essential for two main reasons. First, Covid-19, unlike other epidemics such as flu, does not spread uniformly across regions but tends to remain clustered. Second, the high rate of contagion of this disease requires a rapid detection of zero patients to adopt almost immediately the necessary sanitary rules that help to prevent the spreading of the cases. Moreover, the proximity between policymakers and citizens helps the former better know the culture, social norms, and trust. Consequently, measures adopted to reduce the severity of epidemics could be more effective when defined as closely as possible to the field.

6. References

Alesina A., Ferrara E , 2000. "The Determinants of Trust," NBER Working Papers 7621, National Bureau of Economic Research, Inc

Amdaoud , M., Arcuri, G. Levratto, N. ,2020. Covid-19 : analyse spatiale de l'influence des facteurs socio-économiques sur la prévalence et les conséquences de l'épidémie dans les départements français, EconomiX Working Papers 2020-4, University of Paris Nanterre, EconomiX.

Anselin, L., 1995. Local indicators of spatial association—LISA. Geogr. Anal. 27, 93–115.

Arbia G., Benedetti, R. & Espa, G., 1996. Effects of MAUP on image classification, *Geographical Systems*, 3: 123-141.

Arbia, G. & Paelinck, JHP (2003). Economic convergence or divergence? Modelling the interregional dynamics of EU regions 1985 – 1999, *Geographical Systems*, 5, 1-24, 2003.

Bauer, J. , Brueggmann, D., Klingelhoefer, D.,Maier, W., Schwettmann, L., Weiss, D.& Groneberg, D. (2020). Access to intensive care in 14 European countries: a spatial analysis of intensive care need and capacity in the light of COVID-19. *Intensive care medicine*. https://doi.org/10.1007/s00134-020-06229-6

Bayer, C., Kuhn , M., 2020. Intergenerational ties and case fatality rates: A cross country analysis. CEPR Discussion Paper no. 14519

Bourdin, S., Ludovic, J., Nadou, F., Noiret, G., 2020. Does lockdown work? A spatial analysis of the spread and concentration of Covid-19 in Italy.

Cambois, E., Jusot, F., 2007.Ampleur, tendance et causes des inégalités sociales de santé et de mortalité en Europe : une revue des études comparatives. Bulletin épidémiologique hebdomadaire. 2-3

Chuang, Y-C., Huang, Y-L., Tseng, K-C., Yen, C-H., Yang, L-h., 2015. Social Capital and Health Protective Behavior Intentions in an Influenza Pandemic. PLoS ONE. 10(4): e0122970.

Du, Y., Tu, L., Zhu, P., Mu, M., Wang, R., Yang, P., Wang, X., Hu, C., Ping, R., Hu, P., Li, T., Cao, F., Chang, C., Hu, Q., Jin, Y., Xu, G., 2020. Clinical Features of 85 Fatal Cases of COVID-19 from Wuhan. A Retrospective Observational Study. Am. J. Respir. Crit. Care Med. 201(11), 1372–1379.

Edelman R., 2020, Trust imperative. Finance and Development, 57(2): 30-32 https://www.imf.org/external/pubs/ft/fandd/2020/06/pdf/fd0620.pdf

Eurostat (2020) : https://ec.europa.eu/eurostat/documents/2995521/11156775/2-31072020-BP-EN.pdf/cbe7522c-ebfa-ef08-be60-b1c9d1bd385b

Frohlich, N., Mustard, C., 1996. A regional comparison of socioeconomic and health indices in a Canadian province. Soc. Sci. Med. 42 (9),1273-1281

Geronimus, A.T., Bound, J., Waidmann, T.A., 1999. Poverty, time, and place: variation in excess mortality across selected US populations, 1980-1990. J. Epidemiol. Community Health. 53(6), 325-334

Gizelis, T-I., Karim,S., Østby,G., Urdal, H., 2017. Maternal health care in the time of ebola: a mixedmethod exploration of the impact of the epidemic on delivery services in monrovia. World Dev. 98, 169–178.

Guzzi, PH., Tradigo, G., Veltri, P., 2020. Spatio-Temporal Resource Mapping for Intensive Care Units at Regional Level for COVID-19 Emergency in Italy. Int J Environ Res Public Health. 17(10):3344. doi:10.3390/ijerph17103344

Habibov, N., Cheung, A., Auchynnikava, A., 2017. Does Social Trust Increase Willingness to Pay Taxes to Improve Public Healthcare? Cross-sectional Cross-Country Instrumental Variable Analysis. Soc. Sci. Med. 189, 25–34.

Hu, Y., Goldman, N., 1990.Mortality Differentials by Marital Status: An International Comparison; Demography. 27, 233–250.

Le Gallo, J., Ertur, C. & Baumont, C. (2003). A spatial econometric analysis of convergente across European regions, 1980_1995, in: B. Fingleton (ed.), European regional growth, 99-130, Springer-Verlag, Berlin.

Linard, C., Lamarque, P., Heyman, P., Ducoffre, G., Luyasu, V., Tersago, K., Vanwambeke, S. O., Lambin,E. F., 2007. Determinants of the geographic distribution of Puumala virus and Lyme borreliosis infections in Belgium. Int. J. Health Geogr. 6(1), 15. https://doi.org/10.1186/1476-072X-6-15

Markowitz, S., Nesson, E., Robinson, J. 2019, The effects of employment on influenza rates Eon Hum Biol. 34, 286-295.

McCabe, R., Schmit, N., Christen, P. et al. Adapting hospital capacity to meet changing demands during the COVID-19 pandemic. BMC Med 18, 329 (2020). https://doi.org/10.1186/s12916-020-01781-w).

McCoy, D. 2019, what exactly is the government's coronavirus strategy?, Queen Mary University of London. https://www.qmul.ac.uk/media/news/2020/pr/what-exactly-is-the-governments-coronavirus-strategy.html

(OCDE webinar series Building a New Paradigm for Public Trust https://www.oecd.org/governance/trust-in-government.htm.)

OECD (2017), The OECD Recommendation of the Council on Open Government, https://www.oecd.org/gov/oecd-recommendation-of-the-council-on-open-government-en.pdf.

OECD: The territorial impact of COVID-19: Managing the crisis across levels of government (2020) http://www.oecd.org/coronavirus/policy-responses/the-territorial-impact-of-covid-19-managingthe- crisis-across-levels-of-government-d3e314e1/

OPENSHAW, S. (1984). The modifiable areal unit problem. T. CATMOG 38. GeoBooks, Norwich, England.

OPENSHAW, Stan & Peter TAYLOR (1979). « A million or so correlation coefficients ». Statistical methods in the spatial sciences, 127–144.

Putnam, R.D., Leonardi, R., Nanetti, R.Y., 1993. Making Democracy Work: Civic Traditions in Modern Italy. Princeton University Press, New Jersey

Qiu, Y., Chen, X., Shi, W., 2020a. Impacts of social and economic factors on the transmission of coronavirus disease 2019(COVID-19) in China. J. Popul. Econ.

Sannigrahi, S., Pilla, F., Basu, B., Basu, A.S., 2020. The overall mortality caused by COVID-19 in the European region is highly associated with demographic composition: A spatial regression-based approach. arXiv:2005.04029 [q-bio].

Singu, S., Acharya, A., Challagundla, K., & Byrareddy, S. N. (2020). Impact of Social Determinants of Health on the Emerging COVID-19 Pandemic in the United States. *Frontiers in public health*, 8, 406. https://doi.org/10.3389/fpubh.2020.00406

Stanturf, J. A., Goodrick, S. L., Warren, M. L., Jr, Charnley, S., Stegall, C. M., 2015. Social Vulnerability and Ebola Virus Disease in Rural Liberia. PloS one. 10(9), e0137208.

Sunstein, C.R., 2020. The meaning of masks. Journal of Behavioral Economics for Policy, 4(5-8).

Vinci, DL., Polidori, C., Polidori, P. 2020. The healthcare and pharmaceutical vulnerability emerging from the new Coronavirus outbreak. Eur J Hosp Pharm. 27(3): 129-130.

Wilson N, Kvalsvig A, Barnard LT, Baker MG. Case-Fatality Risk Estimates for COVID-19 Calculated by Using a Lag Time for Fatality. *Emerg Infect Dis*. 2020;26(6):1339-1441. doi:10.3201/eid2606.200320

7. Appendix

Figure 11: LISA Covid-19 death variation rate (February-March)

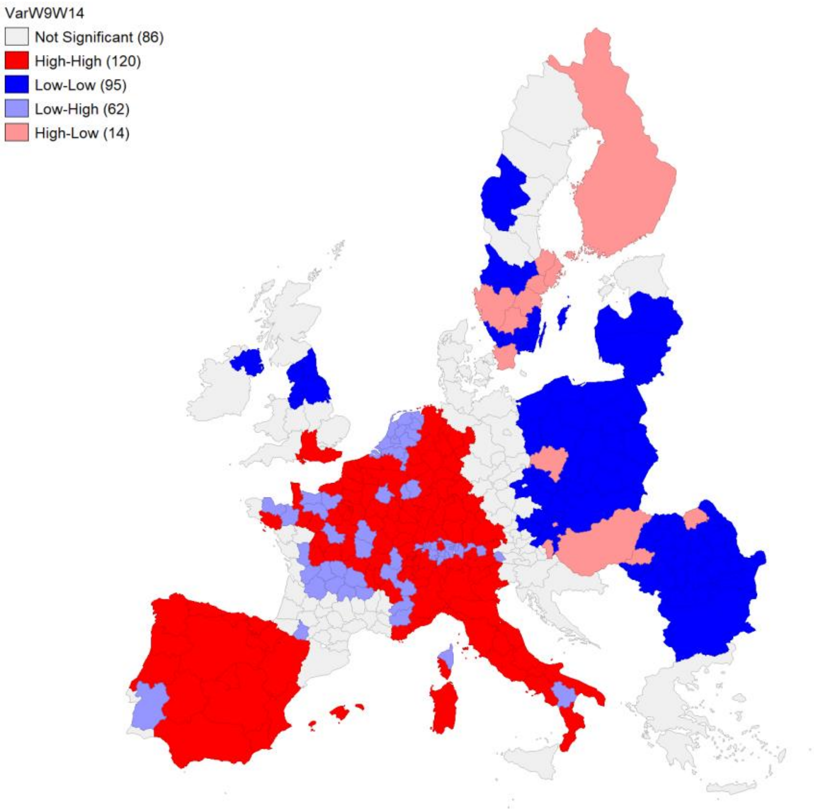


Figure 12: LISA Covid-19 death variation rate (April-May)

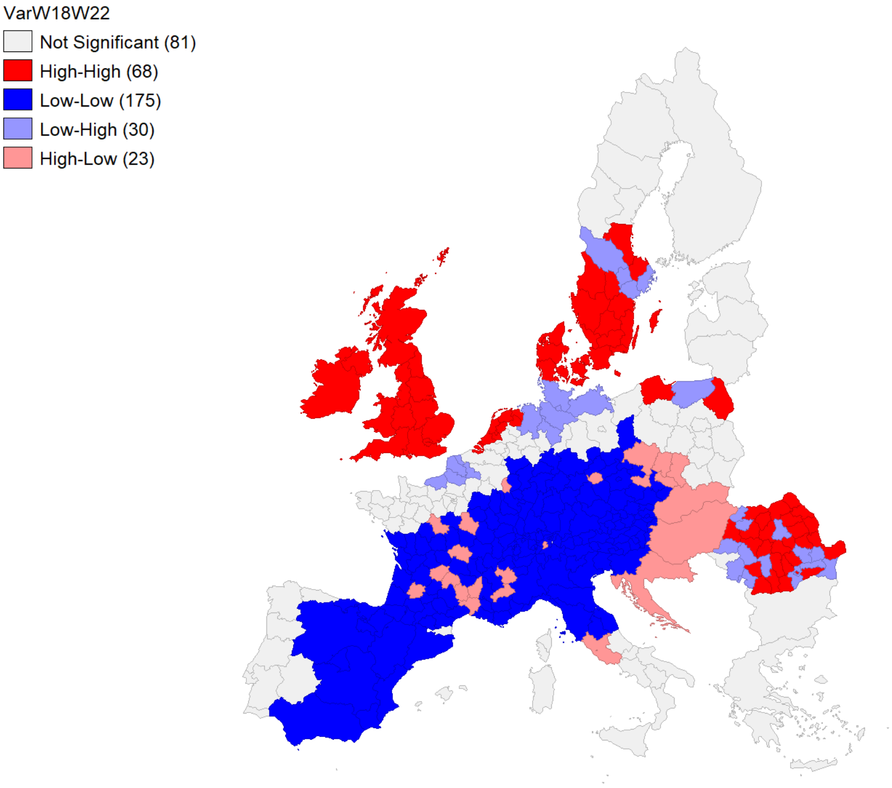


Figure 13: LISA Covid-19 death variation rate (June-July)

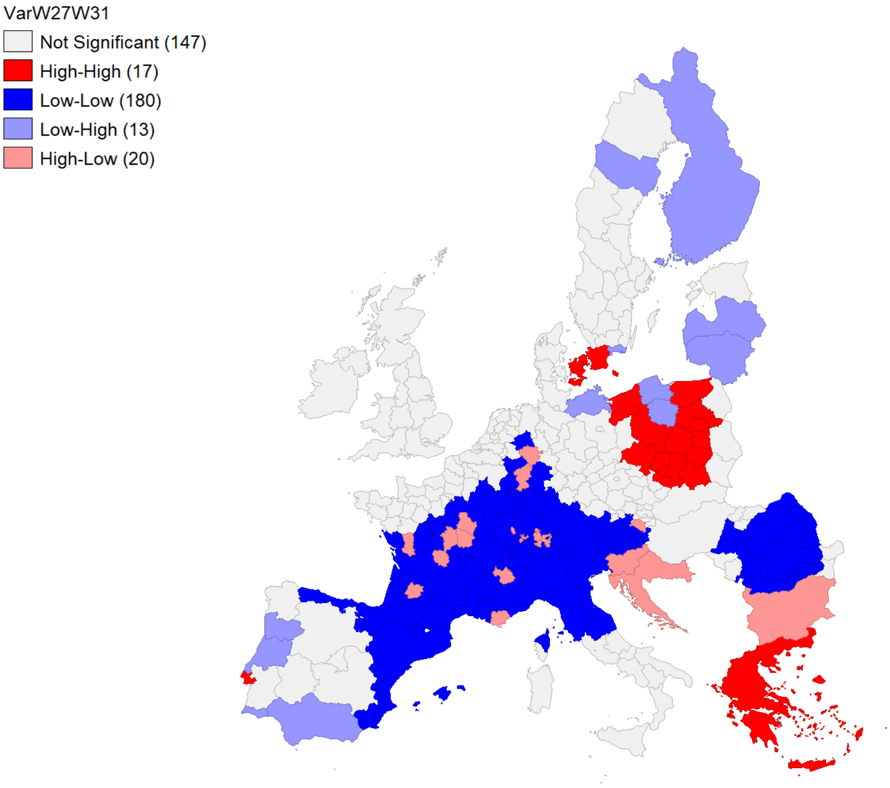


Table 4: Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Covid death rate week 9	377	0,00	0,00	0	0,01
Covid death rate week14	377	0,34	0,79	0	9,26
Covid death rate week18	377	1,46	2,13	0	13,19
Covid death rate week22	377	2,09	2,82	0	19,20
Covid death rate week27	377	2,32	3,07	0	20,52
Covid death rate week31	377	2,37	3,13	0	22,41
Covid death rate week36	377	2,41	3,16	0	22,86
Population density	377	4,82	1,22	0,96	9,95
Share of the population aged 65 and over	377	20,78	3,32	10,72	30,32
Life expectancy	377	81,22	2,76	74,10	85,50
GDP per capita	377	10,14	0,67	8,29	12,05
Poverty	377	20,34	7,69	8,5	53,60
Hospital beds	377	552,82	202,38	138,12	1286,28
Governance	377	1,17	0,21	0,5	1,50
Education	377	0,48	0,50	0	1,00
Intermediate region	377	0,42	0,49	0	1,00
Rural region	377	0,37	0,48	0	1,00
Urban region	377	0,21	0,41	0	1,00

Table 5: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Population density	1.000									
(2) % of pop aged 65 and over	-0.475***	1.000								
(3) Life expectancy	0.120**	0.238***	1.000							
(4) GDP per capita	0.325***	0.027	0.796***	1.000						
(5) Poverty rate	-0.028	-0.105**	-0.496***	-0.547***	1.000					
(6) Hospital beds	-0.005	0.080	-0.321***	-0.208***	-0.098*	1.000				
(7) Governance index	0.012	0.205***	0.651***	0.735***	-0.591***	-0.155***	1.000			
(8) Education	0.173***	-0.081	0.433***	0.455***	-0.278***	-0.320***	0.367***	1.000		
(9) Intermediate region	-0.011	-0.041	0.054	0.079	-0.047	-0.179***	0.004	0.024	1.000	
(10) Urban region	0.584***	-0.289***	0.126**	0.296***	-0.007	-0.053	0.103**	0.207***	-0.435***	1.000

List of figures and tables

List of figures

List of tables