Co-financed by the European Regional Development Fund

Inspire Policy Making with Territorial Evidence

FINAL REPORT //

Territorial impacts of COVID-19 and policy answers in European regions and cities

Methodology

Annex 2 // June 2022

This Final report is conducted within the framework of the ESPON 2020 Cooperation Programme, partly financed by the European Regional Development Fund.

The ESPON EGTC is the Single Beneficiary of the ESPON 2020 Cooperation Programme. The Single Operation within the programme is implemented by the ESPON EGTC and co-financed by the European Regional Development Fund, the EU Member States and the Partner States, Iceland, Liechtenstein, Norway and Switzerland.

Coordination
Michaela Gensheimer, Andreea China, Stefania Rigillo, ESPON EGTC (Luxembourg)
Sebastien Bourdin, Mohamed Hachaichi, EM Normandie Business School (France)

Authors
Sébastien Bourdin, Mohamed Hachaichi, EM Normandie Business School (France)
John Moodie, Nora Sánchez Gassen, Nordregio (Sweden)
András Igari, Hajnalka Lőcsei, HÉTFA Research Institute (Hungary)
Mounir Amdaoud, Giuseppe Arcuri, Nadine Levratto EconomiX (France)

Advisory group
Luisa Pedrazzini, ESPON Monitoring Committee member (Italy), Terézia Somhegyi, ESPON Monitoring Committee member (Hungary), Francesco Molica, Conference of Peripheral Maritime Regions – CPMR, Igor Caldeira, Committee of the Regions – COR, Nicolas Reynes, European Confederation of Local Intermediate Authorities – CEPLI, Quentin Delhaye, CEPLI, Association des Provinces Wallonnes – APW (Belguim), Andreas Listing, CEPLI, Region Hannover (Germany).

Acknowledgments
Durmish Guri and Nathalie Noupadja for promoting this study, EUROCITIES, Council of European Municipalities and Regions (CEMR), European Confederation of Local Intermediate Authorities (CEPLI), ESPON contact points across Europe, European Centre for Disease Prevention and Control (ECDPC)

Information on ESPON and its projects can be found at www.espon.eu.
The website provides the possibility of downloading and examining the most recent documents pertaining to finalised and ongoing ESPON projects.

ISBN: ISBN: 978-2-919816-38-5

Published in June 2022

Graphic design by BGRAPHIC, Denmark

Contact: info@espon.eu

ESPON

EUROPEAN UNION

Co-financed by the European Regional Development Fund

Inspire Policy Making with Territorial Evidence

FINAL REPORT //

Territorial impacts of COVID-19 and policy answers in European regions and cities

Methodology

Annex 2 // June 2022

1 Methodological approach

1.1 The different variables to capture the geography of COVID-19: Strengths and weaknesses

An important issue is the selection of the explained variable – that is the variable that best captures the geography of COVID-19. Several variables can be mobilised (hospitalisations, COVID-19 cases, fatalities due to COVID-19, excess mortality). The two reasons for choosing the variable that best estimates the incidence of the COVID-19 pandemic in Europe are reliability and comparability. First of all, it is noteworthy that there is no scientific consensus on the choice to be made. All the variables have advantages and weaknesses which must be known to analyse the results with full knowledge of the facts.

The **number of reported cases** is the first possibility to capture the geography of COVID-19. A common criticism of the use of this variable is that the number of reported cases depends largely on the testing policy in each country. This policy varies greatly between countries and over time. However, this variable can be used by relating the number of deaths to the number of cases. This ratio makes it possible to assess the efficiency of the health system. For example, if a region has a large number of cases but a low mortality rate, it can be assumed that the health system and its organisation can absorb a pandemic shock. Second, the number of hospitalisations is another option for understanding the spatial diffusion of COVID-19. However, this indicator, by itself, does not indicate whether the hospitalisations are specific for COVID-19 or another health problem. A more refined variable is to consider intensive-care hospitalisations. The problem is that these variables are not readily available for all countries at a local/regional level. We therefore decided to discard this variable.

Another possibility is to consider the reporting of the **number of COVID-19-related deaths**. A criticism often made of this variable is that some deaths may have been counted as COVID-19 related, whereas the people involved died of another disease. Another problem may arise from the inclusion of COVID-19-related deaths in nursing homes and at home. Depending on the country, these deaths are included or in the statistics or they are not included. Furthermore, testing capacity and availability of the testing points/healthcare institutions are key determinants of how many deaths are recorded in an area. Finally, many cases of death by COVID-19 can be hidden by another disease and may not be counted as such. Despite these criticisms, we chose to retain this variable, as this is the commonly accepted WHO measure for estimating the intensity of the pandemic[1]. The datasets are available from various statistical institutes in Europe at the regional or even subregional scale. In this project, data collection was carried out systematically from 5 January 2020, until 28 November 2021[2] each day (or weekly, depending on the availability in some countries) at the regional or infraregional scale.

Finally, the spatial detail of data publication of reported COVID-19 deaths varies from country to country, and it has changed many times over the last year. Conversely, the data publication of **excess mortality** is more timely and spatially consistent (see the appendix - Table 4). Most of the data are available on Eurostat's database at the NUTS 3 level (if not at the NUTS 2 level), except for the United Kingdom. The excess mortality rate is an indicator commonly used in the scientific literature. The collection of data related to deaths is simple (thanks to regular follow-up by EuroMOMO[3]), and European countries are used to it. A recent study by Felix-Cardoso et al. (2020) shows that the use of this indicator is preferable to the use of COVID-19-related mortality because the latter often tends to underestimate the true incidence of COVID-19. However, like other indicators, the excess mortality index is subject to criticism. For example, regarding containment, car use was very limited. As a result, traffic fatalities decreased, thus negatively influencing the excess mortality. Conversely, it was observed that people refused to go to the hospital for treatment of their disease (other than COVID-19) for fear of getting COVID-19. This may have positively influenced the mortality rate. Given the interest of this variable, we chose to keep it. Thus, using econometric models, it was possible to compare whether the determinants influencing the two explanatory variables have similar influences. Data collection was carried out using Eurostat, which collects these data via national statistical institutes. The

[1] https://www.who.int/news-room/commentaries/detail/estimating-mortality-from-covid-19

[2] To create homogeneous datasets, the number of cases and deaths were collected daily and then aggregated weekly to match the excess mortality dataset. High-resolution (daily) datasets are provided as supplementary files.

[3] EuroMOMO is an abbreviation of European mortality monitoring. It is a statistical network that compiles mortality statistics in 24 European countries or federal regions, including France.

estimation of excess deaths is based on the calculation of a standardised indicator – Z-score, which allows the comparison of excesses between different geographical levels. This indicator makes it possible to estimate excess mortality in relation to not only the average mortality of previous years (which would be a percentage) but also the dispersion of the data around the average (i.e., the sometimes strong variations in weekly mortality). The Z-score is calculated using the following formula: (observed number − expected number) / standard deviation of the expected number. The five categories of excess are defined as follows:

-No excess: standardised indicator of death (Z-score) < 2

-Moderate excess of death: standardised indicator of death (Z-score) between 2 and 4.99

-High excess of death: standardised indicator of death (Z-score) between 5 and 6.99

-Very high excess of death: standardised indicator of death (Z-score) between 7 and 11.99

-Exceptional excess of deaths: standardised indicator of death (Z-score) greater than 12.

In our study, we collected data for COVID-19 cases, fatalities due to COVID-19 and excess mortality (based on the Z-score).

1.2 Identifying the determinants of COVID-19 spread and spatial concentration

To describe and understand the spread of COVID-19 patterns and the different waves, we used various potential explanatory variables. We tested the hypothesis that pre-existing spatial characteristics and inequalities impact the spread of the virus and its spatial concentration. To do so, we built a spatial econometric model for exploring the possible factors behind the heterogeneity of mortality indicators. We identified several variables characterising the European regions that may influence the magnitude of the pandemic (Table 1).

To account for factors related to the level of economic development, the first variable we considered is **GDP per capita**. The increase in global connections represented a challenge for spatial approaches at the initial stages of disease management – 'when the cause of a disease is not yet clear but the plane has already taken off' (Zhou and Coleman, 2016). Referring to the previous SARS outbreak, Van Wagner (2008) recounts how Toronto's status as a global city proved to be a vulnerability in this regard. In our case, we considered GDP per capita as a marker of a region's relative position in a network of global cities and as its potential to be further ahead in the pandemic trajectory. On the other hand, we cannot rule out the possibility that less affluent regions have a higher proportion of manual workers who cannot telecommute and thus have more difficulty complying with containment obligations, making them more exposed to COVID-19 (Clouston et al., 2021).

Population density is also relevant because it directly affects the patterns and rates of contact between individuals in a population. Available data suggest a positive relationship between COVID-19 transmission and population density in US counties (Sy et al., 2021), Italian regions (Bourdin et al., 2021) and Indian districts (Bhadra et al., 2021).

We also considered the **percentage of elderly people** (over 65) in a region. Early data for COVID-19 suggest that the mortality rate per case is higher in the elderly (e.g., the Novel Coronavirus Pneumonia Emergency Response Epidemiology Team, 2020[4]). This can be explained by the fact that elderly people are more likely to get sick from COVID-19. However, it is unclear whether a relatively large population of elderly people necessarily translates into higher rates of transmission of infection. Indeed, the tool of choice for containing the spread of the disease has been social distancing. In this regard, studies in the transportation field indicate that older adults tend to travel less frequently and for shorter distances and have higher rates of immobility than most people (Sikder and Pinjari, 2012). In other words, many older adults are already in some form of social isolation. The social distancing associated with confinement during the pandemic may reinforce this condition, as suggested by the age-structured analysis of social contacts conducted in Luxembourg (Latsuzbaia et al., 2020).

[4] https://pesquisa.bvsalud.org/global-literature-on-novel-coronavirus-2019-ncov/resource/en/czh-933

Furthermore, Kaufmann (2009) already highlighted that poverty is an aggravating factor during a pandemic. This has also been indicated by several recent studies on COVID-19. Using the example of New York City, Cordes and Castro (2020) show that households receiving public assistance or those whose rent was higher than 50% of their income were more likely to be infected by the virus. Therefore, we added a variable related to the **level of exposure of the population to the risk of poverty**.

The quality of the healthcare system may also explain differences across regions. First, empirical studies have reported that well-structured health resources positively affect a government's ability to respond to public health emergencies, such as large pandemics (Forster et al., 2018). Second, health infrastructure also has a significant impact on the government's ability to rapidly detect, diagnose and report new infections (Palagyi et al., 2019). The COVID-19 crisis revealed that the number of available beds is a critical issue in managing a health emergency (Holzer and Newbold, 2020). Furthermore, as Gereffi (2020) explains, countries and regions that have problems with the availability of medical equipment (and therefore are not sufficiently prepared for a pandemic) have sometimes experienced serious problems in the supply of medical materials, limiting the ability of medical personnel to properly care for patients. Using the UK example, McCabe et al. (2020) show that a lack of such resources negatively impacts the ability of medical professionals to treat patients. Guzzi et al. (2020) reach similar conclusions at the regional level in Italy. Thus, the determinants of healthcare reflect national and regional healthcare expenditures, and we considered them here through the **number of hospital beds over the total population** and the **number of general practitioners**. Data on the number of critical care hospital beds would have been more appropriate but unfortunately are not available for all European regions.

Another important aspect identified in the literature concerns the level of education. This is traditionally used as a proxy for social capital (Alesina and La Ferrara, 2000; Putnam et al., 1994). It is assumed that a more educated population will tend to comply more with rules (Ferdous et al., 2020). Indeed, educated people have the knowledge to take the necessary measures to avoid the spread of the virus. This is what Zhong et al. (2020) demonstrate using the Chinese example. Furthermore, people with a higher level of education tend to have the opportunity to work from home. This is not the case for workers, for example, who had to travel to their workplace, increasing the possible sources of contamination (Phannajit et al., 2021). Therefore, we included the **share of higher education graduates in the total population** in our study.

The quality of public institutions is also an aspect that has influenced lethality levels. Rodríguez-Pose and Burlina (2021) indicate that the hardest-hit regions were regions where the quality of institutions was declining. This is the case in countries such as Spain, Italy, and Romania and to a lesser extent in France. This decline in national and local institutions may have compromised the credibility of governments to respond to such a crisis. As a result, populations did not necessarily trust policy recommendations to combat the spread of the virus. For these reasons, we included the Quality of Governance Index developed by Charron et al. (2014).

Finally, we examined the impact of geographical characteristics on mortality. Some researchers have investigated the impact of different geographical and environmental characteristics on COVID-19 and have shown that different environmental indicators can influence the spread of the pandemic. Although these studies have predominantly focused on climatic effects, they have also examined characteristics specifically linked to regional typologies: coastal location, urbanisation trends and so forth (Coccia, 2020; Gupta et al., 2020). Therefore, we examined the role of each regional typology in order to answer the question which types of regions are significantly more or less affected by the pandemic. To do so, we used the urban-rural regional types (Eurostat, 2022) available for each NUTS 3 region and considered them as dummy variables. These binary variables indicate whether a certain phenomenon or property is present or not. In the former case, the dummy takes the value 1; in the latter case, the dummy takes the value 0.

Table 1 Definition and source of the variables

Variable	Definition	Year	Source
COVID-19 death rate	10,000*(cumulative death toll due to COVID-19 / Population)	2020–2021	WHO and National Health Ministers
Excess mortality rate	Level of excess mortality (Z-score) Z-score = (number of deaths – baseline over the last 4 years) / standard deviation of the residuals	2020–2021	Eurostat
Population density	Total population per km² (log)	2019	Eurostat
Share of the population aged 65 and over	Number of inhabitants aged 65 and older over total population	2019	Eurostat
GDP per capita (log)	GDP per capita at current market prices	2018	Eurostat
Poverty rate	Percentage of person at risk of poverty	2019	Eurostat
Hospital beds	100,000*(number of hospital beds / Population)	2018	Eurostat & NHS
General practitioners	100 000*(number of medical doctors / Population)	2018	Eurostat & NHS
Governance	Index of Good Governance derived from the European Quality of Government Index	2017	ESPON
Education	Share of population aged 25–64 with tertiary education (Levels 5–8). The variable equals 1 if the value is greater or equal to the mean	2019	Eurostat
Geographical characteristics	Regional typologies (variable that classifies regions as predominantly urban, intermediate or predominantly rural regions) as dummy variables	2021	OECD
Hit (first wave)	Dummy variable that indicates if the territory is a worst-hit region during the first wave. The variable equals 1 if the value of COVID-19 death rate during the first wave is greater or equal to the median	2020	WHO and National Health Ministers

1.3 Analysing the social consequences of COVID-19

The pandemic, which first brought the economy to a halt between March and May 2020 and then held it back for almost a year, also had social consequences, generating inequalities and leading to exclusion and poverty. The health crisis' consequences are far from being uniformly distributed across population and across cities and regions. The pandemic elongated the timeframe of sufferance for households at-risk of poverty (ARoP) and with severe material deprivation, especially for those that are under particular employment agreements, self-employed with a precarious status, part-time or fixed-term workers, and workers in sectors heavily affected by the pandemic, such as tourism. It has also affected profoundly the youth class with perhaps harmful long-term consequences.

National surveys show that the most disadvantaged are disproportionally impacted by illness and job loss. Jobs have diminished, particularly temporary work (Almeida and Santos, 2020). The most disadvantaged households also face greater uncertainty and difficulties regarding their housing situation (e.g. paying rent, mortgage or bills). COVID-19 has led to increased social isolation, especially among single people, the elderly and single-parent households. These groups have been particularly affected by confinement measures

(Clouston et al., 2021). Other factors aggravate the effects of confinement, such as dwelling size (more overcrowding among the least advantaged), the unequal distribution of domestic tasks between men and women (including childcare) and domestic disputes and violence. Home schooling has also generated social inequalities (Warren and Bordoloi, 2020). Students with educational hardships have spent, on average, less time on schoolwork and encountered various difficulties (connection, work organisation, autonomy, a lack of materials, understanding of lessons).

Consequently, we identified several indicators that are able to estimate the social effects of the COVID-19 crisis. We collected data for unemployment (%), youth unemployment (%) and at-risk-of-poverty (ARoP, %) rates. We have collected data on the number of recipients of social assistance/benefits. We do not claim to have exhaustive data at the subregional level for these data, but they can be considered a relevant proxy in portraying the evolution of poverty and social exclusion.

For some indicators, such as unemployment, most of the data was collected at the NUTS 3 or LAU level for 2020 (Annex -)In addition, a survey was conducted with the help of many European organisations, such as the Committee of the Regions, Eurocities, CEPLI[5], CPMR[6] and the European Social Survey. The objective is to have a better understanding of the social impacts of COVID-19 in cities and regions and how elected officials have responded to these consequences. This survey was disseminated in February/March 2022, and the processing of the data collected in the survey took place in April/May 2022.

1.4 Data analysis

1.4.1 Dynamic maps

The first step involves producing maps to provide a spatiotemporal overview of the geography of the COVID-19. The emergency context has highlighted fixed maps, generally weekly, of the situation by territories. However, dynamic mapping makes it possible to observe trends and their changes over time. This will allow us to see the spatial diffusion of the COVID-19 across European regions and draw a geography of the pandemic. With this technique, it is easier to identify the different waves and their spatialities across Europe. In addition, this dynamic cartography will be supplemented by the production of synthetic tables and graphs that will make it possible to understand the geography of COVID-19.

1.4.2 Spatial econometrics

Several researchers have applied mapping and geostatistical methods to analyse disease spread patterns during pandemics involving diseases such as tuberculosis, SARS-CoV, MERS-CoV, H1N1 influenza and dengue. Conducted on different scales and for different diseases, these studies highlight **(i)** a spatial concentration of the diseases and **(ii)** the effects of spatial dependence between regions, partly explaining the spatial heterogeneity of the spread of pandemics. The spatial dependence effects refer directly to the issue of spatial autocorrelation (LeSage and Pace, 2009) – that is, the coincidence of the similarity of values with the similarity of locations (Anselin, 2001).

From a methodological point of view, the first step involves testing the spatial autocorrelation of the data. To do so, an **exploratory spatial data analysis (ESDA)** is required (see Box 1). If there is a spatial autocorrelation, it is important to consider potential spatial spillover effects in the modelling, using spatial econometric techniques (Box 2). The spatial polarisation of COVID-19 incidence can result from a contagion effect spreading the disease from one territory to another. In the presence of this type of spatial grouping of data, the classical methods of analysis are accompanied by a risk of bias. Indeed, if the phenomenon observed in a region is influenced by what is happening in neighbouring territories, the normality of the residuals is no longer respected.

To test the existence of a spatial data clustering phenomenon, we applied ESDA. First, we used Moran's Index and **local indicators of spatial association (LISA)** to assess the level of concentration of COVID-19 across time. This method has been applied in studying geographical patterns of various phenomena (income disparities, homicide rates, urban segregation etc.). Particularly, LISA maps identified clusters or collections of geographical units similar to the pandemic indicator used in statistical terms. LISA maps can be used to identify hot spots or cold spots across space. Hot spots are of particular interest in epidemiological analysis

[5] Confederation of Local Intermediate Authorities

[6] Conference of Peripheral Maritime Regions

of phenomena such as the spread of COVID-19, as they allow the identification of 'hot' groups of areas significantly affected by the virus. It is a group of regions, for instance, with a relatively high indicator which are also surrounded by areas of high indicators.

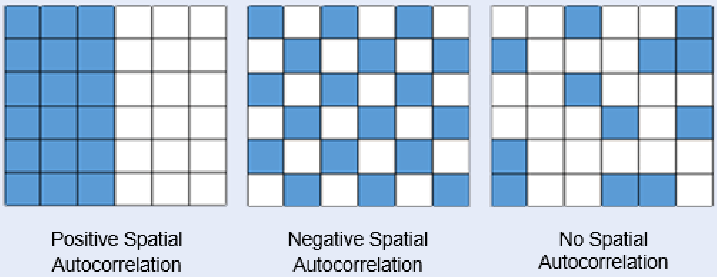
Second, we used spatial econometric models (see

Box 2) to highlight the importance of accounting for spatial interdependencies among the observations. These approaches typically use spatial weight matrices intending to augment standard linear model specifications (ordinary least squares) by allowing for spatial spillovers among the observations. The form of the model depends on whether the spatial interdependencies are thought to derive from omitted variables, motivating a spatially lagged error term (spatial error model), or from the dependent variable, motivating a spatially lagged term for the dependent variable (spatial autoregressive model). A mixed model (spatial autoregressive confused model) assumes both processes. Using spatial models is all the more important, as several researchers in the field of health geography are now calling for the spatial dimension of neighbourhood effects to be taken into account (Baltagi et al., 2018). This recommendation mainly concerns public health policies considering the specific problems of deprived neighbourhoods. However, the effective implementation of policies targeted at disadvantaged areas requires a better knowledge of the mechanisms leading to the conclusion that the 'place' matters independently of the 'individual' to identify the plausible causal pathways by which neighbourhood social and material environment may affect health. Following Flowerdew et al. (2008), we thus explore the idea that people's health in one geographical area may be influenced by the composition of that area's population and the area's geographical context. For that reason, we will explore different kinds of neighbourhoods by using different spatial weight matrices based on either contiguity or distance, on the one hand, and by considering various spatial units, on the other hand. Combining different characteristics enables circumventing the so-called modifiable areal unit problem – which, according to analytical conclusions, may differ substantially according to how data are aggregated.

Box 1 Exploratory spatial data analysis

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 geographically: close geographical units are more alike than distant units, following Tobler's (1970) first law of geography. Conversely, it is negative when variables dissimilar to the variable to be studied are grouped geographically: close geographic units are different from distant units. Finally, the spatial autocorrelation is equal to 0 when the observations of the variable are randomly distributed in space (see the figure below).

Forms of Spatial Autocorrelation



Particularly, regarding local indicators of spatial association, Anselin's (1995) maps provide the identification of clusters or collections of similar geographical units, based on the indicator used. The indicators are used to identify hot spots or cold spots across space. Positive spatial autocorrelation is observed in areas considered high-high (i.e. high death rates in a region surrounded by high values of the weighted average rate in the neighbouring regions) and low-low (low rate in a region surrounded by low values of the weighted average rate in the neighbouring 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 in the neighbouring regions) and low-high (low rate in a region surrounded by high values of the weighted average rate in the neighbouring regions).

The local indicator of spatial association 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 $N \text{ x } N$, which expresses for each observation (row) those locations (columns) that belong to its neighbourhood set as nonzero elements. In this study, the specification of these elements as 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.

Box 2 Spatial econometric models

The econometric specification considered in this research takes the ordinary least squares (OLS) linear regression model as its starting point:

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

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-generation process, the OLS estimators are biased and nonconvergent.

The **spatial autoregressive** model involves correcting this bias by integrating an 'endogenous shifted variable', WY, into the model (1) and taking into account the spatial autocorrelation related to the variable Y. The model is written as follows:

$$Y = \rho WY + X\beta + \varepsilon \qquad (2)$$

WY is the shifted endogenous variable for the inverse distance matrix **W** and 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 the neighbouring regions.

A second way of incorporating spatial autocorrelation in econometric models is the **spatial error** model, which concerns specifying a process of spatial dependency of errors in a regression model. The spatial error model is defined as follows:

$$Y = X\beta + \varepsilon \text{ with } \varepsilon = \lambda W_{\epsilon} + u \qquad (3)$$

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, making the OLS-based statistical inference biased.

These two models can be combined to produce a general model called **spatial autoregressive confused**, which includes a lagged endogenous variable and a spatial autocorrelation of errors. The model is written as follows:

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

Different approaches can be used to choose models. We adopted the so-called bottom-up approach, which involves starting with the nonspatial model. Lagrange multiplier tests (Anselin et al., 1996) then make it possible to decide between the spatial autoregressive, spatial error, spatial autoregressive confused and nonspatial models.

1.4.3 Building a deprivation index to estimate social consequences and propose a regional typology

Traditional indicators such as the unemployment rate or the poverty rate are relevant; however, it is also possible to develop the so-called ecological indices that measure social inequalities. Obtaining an adequate measure of the socioeconomic level is a major and recurrent issue in health research. Motivated by the lack of individual data of the general population routinely measured to inform the social situation, experts in population health research have turned to the use of aggregate or ecological measures. In the absence of measuring the individual's socioeconomic level, the social dimensions of their place of residence are often used. The social situation is multidimensional by definition. To date, there are several ecological indicators in the international literature that have been developed in line with this idea (Pampalon et al., 2010). These indices refer to the concept of 'social disadvantage' or 'deprivation', which generalises the idea that poverty has multiple aspects: income, employment, level of education, housing and so forth (Pampalon et al., 2010). Hence, deprivation indices are built to reduce the complexity of a given phenomenon based on the input matrix (X) (corresponds to socioeconomic features at the regional level – NUTS 3 in this study[7]). However, it is important to highlight that the deprivation indices are not exempt from criticism. First, such indices are built through data amalgamation, resulting in an oversimplification of the studied ecosystem. Hence, indicators must be selected and utilised according to criteria and settings consistent with the expected use and scope; otherwise, they could lead to muddled data interpretations (Vyas and Kumaranayake, 2006).

For our study, to build the deprivation index [DI], we combined the following three indicators: unemployment rates (%), youth unemployment rates (%) and At-Risk of Poverty rates (%). The DI was then calculated using the 'traditional' formula for the Human Development Index (HDI). The formula for calculating the component indicators of the DI is (Actual value − minimum value) / (Maximum value − minimum value). The closer the indicator is to 1, the more social difficulties there are in the region; the closer it is to 0, the less social difficulties there are in the region.

1.5 Examining regional policy responses for tackling the socioeconomic effects of COVID-19: A case study analysis

1.5.1 Aim of the case study analysis

The precursor ESPON study on the geography of the COVID-19[8] outbreak shows that EU cities and regions were hit unevenly by the first wave of the pandemic and that they responded to the crisis by implementing different policy measures. The study highlighted two types of policy responses: 'defensive measures' aimed at mitigating the immediate effects of the virus and 'proactive measures' that used the pandemic as a catalyst for adapting existing regional policies or taking new policy directions, these measures are aimed at the long term. The study demonstrated that policy interventions differed, depending on the type of territory and the mandate of local authorities. Most local/regional policy responses to the first COVID-19 wave were defensive, predominantly focusing on mitigating short-term negative effects rather than laying the foundations for medium- to long-term policy and strategy goals.

This research builds on the precursor study by examining the different policy responses to the crisis within 14 case regions, providing an in-depth assessment of the way in which the health crisis has affected the development of short-, medium- and long-term regional policies and strategies. Case studies provide an important tool for providing detailed empirical evidence on regional policy responses to COVID-19 and assessing their impact. The overall aim of the case studies is to assess whether the COVID-19 pandemic has presented a window of opportunity for regional and local authorities to promote 'proactive' spatial planning and territorial policies. It should be remembered that proactive policies are hereby defined as 'measures that try to make best use of the particular socioeconomic circumstances to further a specific regional policy and

[7] It is noteworthy that not all the indicators were collected at the NUTS 3 level. However, to maintain the spatial resolution of the other indicators collected at the NUTS 3 level, we assumed an equal distribution of values from NUTS 2 to NUTS 3 regions.

[8] https://www.espon.eu/geocov

planning goals, these measures are aimed at the long term'. In meeting this aim, the case studies have been built around six main objectives:

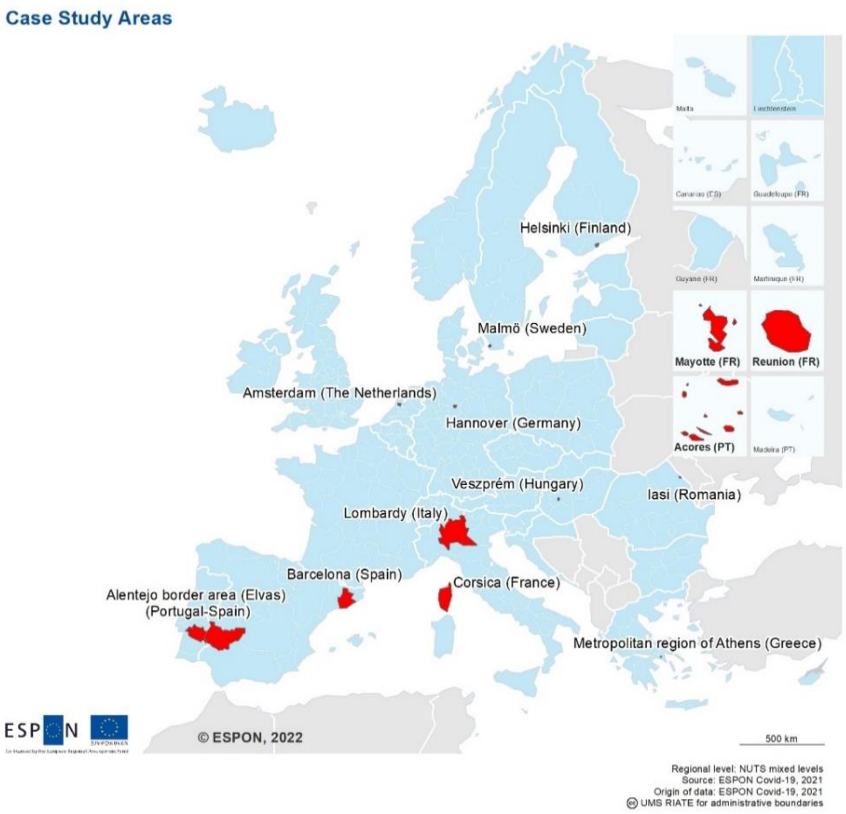
- Identifying regional policies introduced during the course of the pandemic in relation to three core policy thematic areas – just transition, green transition and smart transition
- Assessing the impact and added value of the policy measures introduced
- Exploring the impact of the pandemic on regional policy, governance and financial structures
- Evaluating whether these policies could be transferred to other European cities and regions
- Providing policymakers and practitioners with practical policy, finance and governance recommendations to help build regional resilience and support future crisis periods

1.5.2 Implementation of the analysis, selection and characteristics of the case studies

Fourteen case study regions were selected in discussions between the project management team and the ESPON Steering Committee. The case study regions were selected to reflect a balanced geographical distribution across Europe (based on the United Nations geoscheme: Eastern Europe, Northern Europe, Southern Europe and Western Europe). The regions cover a variety of different territorial contexts (e.g., urban, rural, intermediate, cross-border and island regions) and socioeconomic characteristics. The cases were also selected to include regions in both centralised and decentralised national governance systems and different types of regional- and local-level governance structures where roles and responsibilities are dispersed across multiple local-level authorities (e.g., municipal authorities, metropolitan authorities and regional authorities). Heterogeneity across cases was important to explore how COVID-19 affects regions with different territorial, governance and socioeconomic characteristics. Annex (Table 3) provides a breakdown of the 12 case study regions according to European geographical location, territorial type, economic and social characteristics and governance structures.

The case areas are visualised in Map 1 below: Amsterdam, Athens, the Azores, Barcelona, Corsica, Elvas, Hannover, Helsinki, Iaşi, Malmö, La Réunion, Mayotte, Azores islands, Milan and Veszprém.

Map 1 Case study regions



The case studies are being implemented in two key phases:

1. **Desk-based analysis:** Creating an overview and analysis of regional and local policy documentation and strategies introduced and implemented in the case study area during the first and second waves of the pandemic. This desk research involves identifying the main policy area thematic focus, an overview of the policy proposals and an assessment of the governance structures and stakeholders involved in the process.
2. **Targeted interviews:** Key stakeholders identified in phase one – namely, regional and local public authority representatives – will be invited for targeted online interviews. The interviews will be conducted by the case study partners in each region. The focus will be on the proactive policies, strategies and initiatives developed in the region. Table 2 below presents the key topics and examples of questions that will be investigated in the interviews.

Table 2 Key topics to be investigated in and questions for the interviews

Thematic Interview Topics	Key Interview Questions
Windows of Opportunity and Drivers of Proactive Policies	• To what degree has the pandemic presented a window of opportunity for policymakers and practitioners to advance specific regional and local policy goals and strategies? • To what extent has the pandemic altered existing regional policies/strategies? • To what extent has the pandemic altered regional policies/strategies under construction?
Formulation and Implementation of Proactive Policies	• What are the best examples of proactive policies in your region? • Were proactive policies introduced during the first wave maintained during the second wave? • If proactive policies were not maintained, what were the reasons for this? • How important were multilevel territorial and collaborative cross-sectoral governance in responding to the pandemic? • Which key stakeholders were involved in formulating and implementing these policies? • What have been the main challenges and shortcomings of the proactive policies introduced? • What were the main enablers for implementing these policies? • What are the relative advantages and disadvantages of centralised/decentralised approaches to the crisis?
Impact of Proactive Policies	• What are the main socioeconomic impacts of these policies? • Have these policy measures addressed poverty, inequalities and social exclusion in your region?
Governance Impact	• Has the pandemic affected the existing governance structures in your region? • Has the pandemic affected cooperation at the metropolitan/functional regional level? • Has the pandemic promoted collaboration between regional stakeholders? • Did these policies have an impact beyond your own regional administrative borders?
Future Directions	• Could the policies be upscaled and replicated in other EU regions and cities? • How will the impact of the pandemic inform the future direction of regional and local policies (from the perspective of just, green and smart transitions)? • How can territorial cooperation frameworks, tools and resources for cross-border regions be strengthened in times of crises?

2. References

Alesina, A.F., La Ferrara, E., 2000. The determinants of trust.

Anselin, L., 1995. Local Indicators of Spatial Association—LISA. Geogr. Anal. 27, 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Baltagi, B.H., Moscone, F., Santos, R., 2018. Spatial Health Econometrics, in: Health Econometrics, Contributions to Economic Analysis. Emerald Publishing Limited, pp. 305–326. https://doi.org/10.1108/S0573-855520180000294016

Bhadra, A., Mukherjee, A., Sarkar, K., 2021. Impact of population density on Covid-19 infected and mortality rate in India. Model. Earth Syst. Environ. 7, 623–629. https://doi.org/10.1007/s40808-020-00984-7

Bourdin, S., Jeanne, L., Nadou, F., Noiret, G., 2021. Does lockdown work? A spatial analysis of the spread and concentration of Covid-19 in Italy. Reg. Stud. 55, 1182–1193. https://doi.org/10.1080/00343404.2021.1887471

Charron, N., Dijkstra, L., Lapuente, V., 2014. Regional Governance Matters: Quality of Government within European Union Member States. Reg. Stud. 48, 68–90. https://doi.org/10.1080/00343404.2013.770141

Clouston, S.A.P., Natale, G., Link, B.G., 2021. Socioeconomic inequalities in the spread of coronavirus-19 in the United States: A examination of the emergence of social inequalities. Soc. Sci. Med. 268, 113554. https://doi.org/10.1016/j.socscimed.2020.113554

Coccia, M., 2020. Factors determining the diffusion of COVID-19 and suggested strategy to prevent future accelerated viral infectivity similar to COVID. Sci. Total Environ. 729, 138474. https://doi.org/10.1016/j.scitotenv.2020.138474

Cordes, J., Castro, M.C., 2020. Spatial analysis of COVID-19 clusters and contextual factors in New York City. Spat. Spatio-Temporal Epidemiol. 34, 100355. https://doi.org/10.1016/j.sste.2020.100355

Eurostat, 2022. Archive:Regional typologies overview [WWW Document]. URL https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Regional_typologies_overview (accessed 2.3.22).

Felix-Cardoso, J., Vasconcelos, H., Rodrigues, P.P., Cruz-Correia, R., 2020. Excess mortality during COVID-19 in five European countries and a critique of mortality data analysis. MedRxiv.

Flowerdew, R., Manley, D.J., Sabel, C.E., 2008. Neighbourhood effects on health: Does it matter where you draw the boundaries? Soc. Sci. Med. 66, 1241–1255. https://doi.org/10.1016/j.socscimed.2007.11.042

Forster, T., Kentikelenis, A., Bambra, C., 2018. Health Inequalities in Europe: Setting the Stage for Progressive Policy Action. https://doi.org/10.17169/refubium-1014

Gereffi, G., 2020. What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies. J. Int. Bus. Policy 3, 287–301. https://doi.org/10.1057/s42214-020-00062-w

Gupta, A., Banerjee, S., Das, S., 2020. Significance of geographical factors to the COVID-19 outbreak in India. Model. Earth Syst. Environ. 6, 2645–2653. https://doi.org/10.1007/s40808-020-00838-2

Guzzi, P.H., 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, 3344. https://doi.org/10.3390/ijerph17103344

Holzer, M., Newbold, S.P., 2020. A Call for Action: Public Administration, Public Policy, and Public Health Responses to the COVID-19 Pandemic. Am. Rev. Public Adm. 50, 450–454. https://doi.org/10.1177/0275074020941666

Kaufmann, S., 2009. The New Plagues: Pandemics and Poverty in a Globalized World. Haus Publishing.

Latsuzbaia, A., Herold, M., Bertemes, J.-P., Mossong, J., 2020. Evolving social contact patterns during the COVID-19 crisis in Luxembourg. PLOS ONE 15, e0237128. https://doi.org/10.1371/journal.pone.0237128

LeSage, J., Pace, R.K., 2009. Introduction to spatial econometrics. Chapman and Hall/CRC.

McCabe, R., Schmit, N., Christen, P., D'Aeth, J.C., Løchen, A., Rizmie, D., Nayagam, S., Miraldo, M., Aylin, P., Bottle, A., 2020. Adapting hospital capacity to meet changing demands during the COVID-19 pandemic. BMC Med. 18, 1–12.

Palagyi, A., Marais, B.J., Abimbola, S., Topp, S.M., McBryde, E.S., Negin, J., 2019. Health system preparedness for emerging infectious diseases: A synthesis of the literature. Glob. Public Health 14, 1847–1868. https://doi.org/10.1080/17441692.2019.1614645

Pampalon, R., Hamel, D., Gamache, P., 2010. Health inequalities in urban and rural Canada: Comparing inequalities in survival according to an individual and area-based deprivation index. Health Place 16, 416–420. https://doi.org/10.1016/j.healthplace.2009.11.012

Phannajit, J., Takkavatakarn, K., Katavetin, P., Asawavichienjinda, T., Tungsanga, K., Praditpornsilpa, K., Eiam-Ong, S., Susantitaphong, P., 2021. Factors Associated with the Incidence and Mortality of Coronavirus Disease 2019 (COVID-19) after 126-million Cases: A Meta-analysis. J. Epidemiol. Glob. Health 11, 289–295. https://doi.org/10.2991/jegh.k.210527.001

Putnam, R.D., Leonardi, R., Nanetti, R.Y., 1994. Making Democracy Work: Civic Traditions in Modern Italy, Making Democracy Work. Princeton University Press. https://doi.org/10.1515/9781400820740

Rodríguez-Pose, A., Burlina, C., 2021. Institutions and the uneven geography of the first wave of the COVID-19 pandemic. J. Reg. Sci. 61, 728–752. https://doi.org/10.1111/jors.12541

Sikder, S., Pinjari, A.R., 2012. Immobility Levels and Mobility Preferences of the Elderly in the United States: Evidence from 2009 National Household Travel Survey. Transp. Res. Rec. 2318, 137–147. https://doi.org/10.3141/2318-16

Sy, K.T.L., White, L.F., Nichols, B.E., 2021. Population density and basic reproductive number of COVID-19 across United States counties. PLOS ONE 16, e0249271. https://doi.org/10.1371/journal.pone.0249271

Tobler, W.R., 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. Econ. Geogr. 46, 234–240. https://doi.org/10.2307/143141

Van Wagner, E., 2008. The Practice of Biosecurity in Canada: Public Health Legal Preparedness and Toronto's SARS Crisis. Environ. Plan. Econ. Space 40, 1647–1663. https://doi.org/10.1068/a40281

Vyas, S., Kumaranayake, L., 2006. Constructing socio-economic status indices: how to use principal components analysis. Health Policy Plan. 21, 459–468. https://doi.org/10.1093/heapol/czl029

Warren, M.A., Bordoloi, S., 2020. When COVID-19 exacerbates inequities: The path forward for generating wellbeing. Int. J. Wellbeing 10.

Zhong, B.-L., Luo, W., Li, H.-M., Zhang, Q.-Q., Liu, X.-G., Li, W.-T., Li, Y., 2020. Knowledge, attitudes, and practices towards COVID-19 among Chinese residents during the rapid rise period of the COVID-19 outbreak: a quick online cross-sectional survey. Int. J. Biol. Sci. 16, 1745–1752. https://doi.org/10.7150/ijbs.45221

Zhou, Y.R., Coleman, W.D., 2016. Accelerated Contagion and Response: Understanding the Relationships among Globalization, Time, and Disease. Globalizations 13, 285–299. https://doi.org/10.1080/14747731.2015.1056498

2 Annex

Table 3 Overview of case study region characteristics

Region	European Location	Type of Region	Social Characteristics	Economic Characteristics	Governance Structure
Amsterdam	North	Urban	Growth in population leading to housing challenges and generally high levels of education but growing unemployment amongst lower-educated groups	Highly specialised economy: ICT, commercial services and the culture/tourism sector	Centralised
Athens	South	Urban			Centralised
The Azores	South	Island	High levels of unemployment, poverty and social exclusion, as well as low levels of education compared to the national average	Economy based on public administration, agriculture, fisheries, tourism and retail trade	Centralised
Barcelona	West	Urban	Growing population trend and high levels of employment; children, elderly, women and migrants considered the most vulnerable groups before the pandemic	Diverse economy with a strong industry base and high levels of innovation	Decentralised
Corsica	South	Island	Over the last 10 years, it has recorded a strong demographic increase, twice the national average (due to the migratory surplus); unemployment remains higher than the national rate, and one household in five lives below the poverty line	The tertiary sector (mostly tourism) is the main employer on the island	Centralised
Elvas	West	Rural Cross-border	Population decline and ageing society; high levels of poverty, unemployment and low education levels compared to national averages	Economy based on the tertiary sector and local SMEs working in tourism and retail trade, low levels of innovation and closure of large industries	Decentralised
Hannover	Central	Urban	Ageing population and low birth rates; high levels of immigration and youth unemployment, and mortality rates higher than the national average	Mixed economy based on the tertiary and agriculture sectors, as well as industry	Decentralised
Helsinki	North	Urban	Growing population, high employment and income levels, and high education levels and consistently high scores on quality-of-life indexes	Economy based on the service sector and IT-based industries	Decentralised
Iaşi	East	Intermediate Cross-border	Growing population, as well as high poverty rates and low levels of education	Economy based on the tertiary sector and automobile industry, low innovation levels and labour shortages in the ITC sector	Centralised
Malmö	North	Urban	Growing population, mixed education levels, high	Diverse economy – the chemical industry, ICT,	Decentralised

		Cross-border	unemployment rates among youths and immigrants and lower income levels	life sciences, engineering, food, and construction sectors – and extremely high levels of innovation	
Milan	South	Urban	High levels of employment and education, high population growth and low levels of poverty	Diverse economy, including manufacturing industries, agriculture, fashion and banking, and high levels of innovation, ICT and biotechnology	Decentralized
Veszprem	East	Intermediate	Population decline and ageing society, high education levels and low unemployment, and limited poverty and social exclusion	Economy largely based on the service, culture and tourism sectors, as well as growing R&D infrastructure	Centralized

Co-financed by the European Regional Development Fund

Inspire Policy Making with Territorial Evidence

espon.eu

ESPON 2020

ESPON EGTC
4 rue Erasme, L-1468 Luxembourg
Grand Duchy of Luxembourg
Phone: +352 20 600 280
Email: info@espon.eu
www.espon.eu

The Single Operation within the programme is implemented by the ESPON EGTC and co-financed by the European Regional Development Fund, the EU Member States, the United Kingdom and the Partner States, Iceland, Liechtenstein, Norway and Switzerland.