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Prioritizing investments in public healthcare to address the COVID-19 outbreak: Evidence from Europe and the South Caucasus

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Abstract

This study investigated the association between public healthcare-related features, vaccination rates, and COVID-19 mortality rates in 44 European and South Caucasian nations. COVID-19 mortality rates were averaged for the period from 21 November 2021 to 4 December 2021, i.e., at the peak of the COVID-19 fourth wave. The cross-sectional analysis was performed with the ordinary least squares (OLS) estimator, the spatial autoregressive (SAR) model, and the spatial error (SEM) model. Then, a cluster analysis was conducted to find homogeneous groupings of nations with increasing risk-factors for COVID-19 mortality. The findings revealed that public health expenditure, health personnel, pharmacists, universal health coverage (UHC), and COVID-19 vaccination rates were all significantly and negatively correlated with COVID-19 mortality rates, whereas out-of-pocket expenditure (OOP), and ordinary and intensive care unit (ICU) bed saturation were positively and significantly correlated with COVID-19 mortality rates. Cluster analysis revealed that Eastern European and South Caucasian countries with more decentralized and mostly private insurance-based healthcare systems had the highest risk-factors for COVID-19 mortality, whereas Nordic European countries with universal healthcare systems had the lowest. Thus, countries with publicly financed comprehensive healthcare systems proved to be more effective at lowering COVID-19 mortality rates while easing the burden on national healthcare. These policy recommendations may be beneficial in the event of future such shocks.

Keywords: COVID-19 mortality | public healthcare system | spatial analysis | cluster analysis | Europe

JEL: H50; I18; C21; C38.

1. Introduction

The rapid global spread of the novel COVID-19 disease since December 2019 has highlighted the critical need for an effective package of public health strategies to reduce COVID-19 morbidity and mortality, as well as the burden on the national healthcare system (Ferguson et al. 2020; Chan et al. 2021). Because no vaccines or specific medical treatments were immediately available at the start of the pandemic, most countries had to rely on the healthcare system's resilience along with the implementation of a set of non-pharmacological interventions (NPIs), such as mask-wearing, social distancing, quarantine, mass gathering prohibition, and closures of educational services and non-essential businesses (Bo et al. 2020; Flaxman et al. 2020; Brauner et al. 2021).

However, the latter community mitigation measures were detrimental to the global economy, causing a severe recession and the loss of around 114 million jobs by 2020 (International Labour Organization, 2021). According to a World Bank study (Demirgüç-Kunt et al. 2020), national lockdowns imposed during the pandemic's first peak (between March and April 2020) lowered economic activity in European and Central Asian countries by an average of 10%. This has put significant pressure on national governments to swiftly develop effective COVID-19 vaccines in order to avoid the huge costs associated with statewide lockdowns (Arbel and Pliskin, 2022). Specifically, by the end of 2020 and early 2021, concerted technological and financial collaboration across various international public and private organizations resulted in the US Food and Drug Administration (FDA) authorizing the first COVID-19 vaccines (Bok et al. 2021).

As a result, it has become crucial to evaluate the efficacy of public healthcare-related features and strategies in combating the COVID-19 pandemic. Specifically, the purpose of this study was to contribute to the literature by exploring the cross-sectional relationship between a set of public healthcare system medical resources and characteristics, vaccination rates, and COVID-19 mortality rates at the peak of the pandemic's fourth global wave in 44 European and South Caucasian countries. While medical resources and healthcare system features revealed the strength and resilience of the public healthcare system, COVID-19 vaccination demonstrated national health efficacy in implementing new policies. The empirical approach included a set of econometric techniques, such as the ordinal least squares (OLS) estimator, the spatial models, and the hierarchical cluster analysis.

The paper's primary points of novelty and strength are summarized below: i) first, it used several statistical methods to control for the robustness of the results; ii) second, it controlled for a significant number of cofounders, including demographic factors, freedom degree, income inequality, weather conditions, hazardous health behaviors, and technology; iii) third, it collected data by searching across multiple sources such as national and international statistical databases, scientific papers, government institutions, research centers, and news agencies; and iv) fourth, it enabled the identification of homogeneous groupings of nations sharing comparable risk-factors and healthcare systems.

The remainder of the paper was structured as follows. In section 2, I discussed the relevant literature. In Section 3, I detailed the data utilized in the empirical study. Section 4 discussed the empirical strategy. Section 5 presented and discusses the findings. Finally, in Section 6, I presented my conclusions and policy recommendations.

2. Review of the literature

The relationship between healthcare medical resources/features, vaccination rates, and COVID-19 outcomes has been widely investigated in the literature in both advanced and developing countries (El-Khatib et al. 2020; Kapitsinis, 2020 & 2021; Liang et al., 2020; Cifuentes-Faura, 2021; Coccia, 2021, Meslé et al., 2021; Muthukrishnan et al., 2021; Al-Amin et al., 2022; Arbel and Pliskim, 2022; Chen, 2023; Epané et al., 2023; Almeida, 2024; Gebremariam et al. 2024).

The early part of the literature focused on the effects of healthcare resources on COVID-19 outcomes. Kapitsinis (2020) studied the underlying causes of COVID-19 mortality in 119 European regions from January to May 2020. Using an OLS estimator, he found that regions with fewer hospital beds (465 per 100,000 people) and doctors (413 per 100,000 people) had higher COVID-19 mortality rates than regions with more beds and doctors.

Coccia (2021) utilized Levene's test for equality of variances and a t-test for equality of means and found that a greater level of government health expenditure was linked with reduced COVID-19 mortality as of 14 December 2020 in a sample of 161 countries. In particular, countries with an average health expenditure of 7.6% of GDP and an average health expenditure per capita of 2,300 US dollars had significantly lower COVID-19 fatality rates than those with an average health expenditure of 6% of GDP and an average health expenditure per capita of only 234 US dollars.

Xie et al. (2021) used an ordinary least square estimator, a time-varying effect model, and a regression discontinuity design to examine the influence of medical resources on the COVID-19 mortality rate in China's Hubei area. The findings revealed that a 10-unit increase in hospital beds per capita and medical personnel per capita was associated with a 0.39% and 0.24% drop in COVID-19 mortality rates, respectively.

Janke et al. (2021) examined the relationship between hospital resources and COVID-19 mortality using data from 4,453 hospitals across 306 hospital referral regions (HRR) in the US from March 1, 2020, to July 26, 2020. Using a Poisson distribution regression model, they discovered that an increase in the number of nurses, general medical/surgical beds, and intensive care unit (ICU) beds was associated with a significant decrease in COVID-19-related mortality.

Perone (2021) investigated the relationship between health system indicators and the COVID-19 case fatality rate in Italian regions and provinces during the initial peak of the COVID-19 outbreak in early April 2020. Using the OLS estimator, he discovered that overall healthcare efficiency, government and physician density were negatively correlated with the COVID-19 case fatality rate (CFR), whereas health expenditure and health system ordinary and ICU bed saturation were positively and significantly associated with the COVID-19 CFR, accounting for up to 88% of the COVID-19 (CFR) variability.

Epané et al. (2023) studied the relationship between healthcare resources and COVID-19 mortality in 2,438 US counties. Using a negative binomial regression, they discovered that larger hospital workers were negatively correlated with COVID-19 mortality, whereas increasing healthcare facility resources, such as airborne infection control rooms, the proportion of teaching hospitals, and hospital occupancy rate were positively correlated with COVID-19 death.

Almeida (2024) used Data Envelopment Analysis (DEA), the spatial autoregressive (SAR) model, and the spatial autoregressive model with spatial autoregressive disturbances (SARAR) to study the influence of the health system efficiency index on COVID-19 outcomes across 173 European regions. He found that regions with better health system efficiency in 2017 had higher COVID-19 mortality rates in 2020 and 2021. He interpreted these findings as indicating a trade-off between the economic efficiency and resilience of the health-care system during the COVID-19 pandemic.

Tekerek et al. (2024) used multiple linear regression analysis to investigate the relationship between a set of healthcare-related characteristics and the COVID-19 mortality rate in 37 OECD nations from 2020 to 2022. The researchers discovered that non-communicable diseases mortality was significantly and positively correlated with COVID-19 mortality, whereas nurses and universal health coverage (UHC) were significantly and negatively associated with COVID-19 mortality. Non-communicable diseases mortality was the most important explanatory factor for COVID-19 deaths across the entire study period. In contrast, there was no statistical significance for physicians, ICU beds, out-of-pocket (OOP) expenses, or private health expenditures.

In contrast, another body of research looked into the relationship between mass vaccination programs and COVID-19 outcomes. Jabłońska et al. (2021) utilized non-linear Poisson mixed regression models to study the relationship between vaccinations and COVID-19 mortality rates in Europe and Israel. They discovered that vaccine effectiveness in terms of death prevention was quite satisfactory, at 72%.

Muthukrishnan et al. (2021) utilized logistic regression to investigate the connection between being fully vaccinated and COVID-19 mortality rates in India. They specifically examined 1,168 hospitalized patients with moderate to severe COVID-19 at a designated COVID-19 hospital in New Delhi. The results showed that two doses of the Covishield vaccine were linked with significantly lower mortality rates. For example, fully vaccinated individuals had a mortality rate of 12.5%, whereas unprotected people had nearly three times the likelihood of dying (31.45%).

Arbel and Pliskin (2022) compared the efficacy of vaccination to quarantine measures in preventing COVID-19 mortality in Israel. They discovered that the mass vaccination in 2021 allowed for a large reduction in COVID-19 mortality and avoided strict lockdowns, which would have caused negative further shocks to the economy. Furthermore, the costs of carrying out the mass vaccination campaign through 2021 were far cheaper than those associated with the two lockdowns that happened in 2020. As a result, the mass vaccination plan was substantially more cost-effective than Israel's lockdown strategy.

Chen (2023) studied the effect of COVID-19 cumulative vaccination rates on COVID-19 spread and death in 33 countries. The latter exhibited high cumulative vaccination rates and were classified into three vaccination patterns. Using an analysis of variance (ANOVA) approach, he observed that vaccination patterns dramatically reduced COVID-19 transmission and mortality. Furthermore, when a country's vaccination coverage falls below its herd immunity threshold, non-pharmaceutical interventions (NPIs) like lockdowns, travel restrictions, maintaining social distancing, and mask use must be adopted as part of the COVID-19 mitigation plan.

Gebremariam et al. (2024) used an OLS estimator to assess the relationship between vaccination rates and COVID-19 cases, deaths, and reproduction rates across 49 African nations. The researchers discovered that vaccination rates were negatively and significantly correlated with both COVID-19 cases and deaths, while no stable or consistent statistical relationship was established between vaccination and reproduction rates. Overall, the available research appeared to agree with the premise that healthcare facilities, medical staffing, and COVID-19 vaccination were critical factors in managing and tackling the COVID-19 outbreak around the world.

3. Data

Only the European and Caucasian countries with available observations were considered for the empirical analysis: Albania, Armenia, Austria, Azerbaijan, Belgium, Bosnia Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Faroe Islands, Finland, France, Georgia, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, and the UK.

The independent and dependent variables utilized in this work are discussed in detail below. First, omitting significant explanatory factors from the empirical study might skew the results and make OLS estimates inconsistent, leading to endogeneity issues (Basdcle, 2008). To reduce misspecification, I incorporated a broad set of control variables that account for demographic structure, degree of freedom, economic inequality, tourism, weather characteristics, hazardous health behaviors, and technology:

- ❖ the median age of the population in 2020 (Ritchie and Roser, 2019a);
- ❖ the share of the population who was female in 2020 (Ritchie and Roser, 2019b);[1]
- ❖ the population density in 2020 (Ritchie et al. 2023);
- ❖ the share of the population who lived in urban areas in 2020 (Ritchie et al. 2024);
- ❖ the number of international tourist arrivals per capita in 2021 (Herre et al. 2023);[2]
- ❖ the share of people who live with an income below 50% of the median in 2019 (World Bank Poverty and Inequality Platform, 2023);[3]
- ❖ the electoral democracy index in 2020 (Herre et al. 2024);
- ❖ the overall precipitation, expressed in millimeters (mm), in November 2021 (World Bank, 2023a);
- ❖ the average temperature in November 2021 (World Bank, 2023a);
- ❖ the average long–term humidity over the 1990–2020 period (World Bank, 2023a);[4]
- ❖ the average consumption of pure alcohol in liters per person aged 15 or older in 2015-2018 (Ritchie and Roser, 2022);
- ❖ the share of the population who is obese, measured using the body mass index (BMI), in 2016 (Ritchie and Roser, 2017);[5]
- ❖ the average share of the population aged 15 and older who smoked tobacco products daily (or non–daily) in 2015–2020 (Ritchie and Roser, 2023);[6]

[1] Data were extracted from Ritchie and Roser (2019b), with the exception of the Faroe Islands (Statbank, 2023).
[2] Data were extracted from Herre et al. (2023), with the exception of Azerbaijan (Azerbaijan Tourism Board, 2022), Czech Republic (Czech Statistical Office, 2022), the Faroe Islands (Statistics Faroe Islands, 2023), Ireland (OECD Tourism Statistics, 2023), Romania (Banila, 2022), and the Slovak Republic (OECD Tourism Statistics, 2023).
[3] Data were extracted from the World Bank Poverty and Inequality Platform (2023), with the exception of Azerbaijan (ABC.AZ, 2022), and the Faroe Islands (Statistics Faroe Islands, 2021).
[4] Data were extracted from the World Bank (2023), except for the Faroe Islands (Statbank, 2023).
[5] Data were extracted from Ritchie and Roser (2017), except for the Faroe Islands (Hákun Leo, 2018).
[6] Data were extraced from Ritchie and Roser (2023), except for the Faroe Islands (Frederiksen, 2018), Montenegro (Mugoša et al. 2018), and North Macedonia (Hristovska Mijovic et al., 2020).

- the average gross domestic expenditure on research and development (GERD) as a percentage of GDP over the 2015–2020 period (UNESCO, 2023).[7]

Pearson's correlation coefficients obtained between the control variables also supported the inclusion of all of them. In fact, the pairwise correlations between control variables were always lower than the conventional cutoff of 0.7 proposed by Dorman et al. (2013), and only in five cases out of 101 (i.e., the 4.95%) they were higher than the more restricted threshold of 0.5 established by Donath et al. (2012) (Table A1, Appendix A). As a result, they are not of particular concern.

The inclusion of a control variable for population aging was necessary since it is recognized as one of the most prominent risk factors for COVID-19 mortality (Pijls et al. 2021; Centers for Disease Control and Prevention, 2024). The literature has also established clear sex differences in COVID-19 infection and outcomes. Although women are usually more likely to become infected (Kuehn, 2021; Wu and Qian, 2022), males are at a higher risk of dying from COVID-19 (Bauer et al. 2020; Jin et al. 2020; Nielsen et al. 2021; Geldsetzer, 2022).[8]

Population density may have a direct and indirect impact on COVID-19 outcomes. On the one hand, overcrowding can increase the likelihood of people interacting with each other, potentially accelerating the transmission of the virus. On the other hand, it can influence national governments' containment and mitigation efforts, which may be more difficult to implement in rural regions (Chang et al. 2022; Carozzi et al. 2024). Urbanization was included as a control due to its relatively low association (0.12) with population density in the study sample (Table A1, Appendix A).

Urban areas, in particular, are typically characterized by higher levels of economic development, better access to healthcare resources, and better organization of public space and services, all of which can help to facilitate the implementation and control of mitigation measures such as lockdown and social distancing (Naudé and Nagler, 2022; Shao et al. 2022). However, more economic growth is also coupled with increased industrialization and air pollution emissions, which can be harmful to human health (Shao et al. 2022). Tourism can help spread the COVID-19 illness by increasing people's mobility and concentration as a result of a larger intake of foreign tourists (Farzanegan et al. 2021; Chang et al. 2022). Income inequality may be linked to higher COVID-19 death rates due to its negative influence on social capital, investments, and access to critical healthcare services (Wildman, 2021; Alam et al. 2023).

Countries' levels of democracy can have two opposing effects on COVID-19 outcomes. On the one hand, more democratic states may take longer to deploy containment measures than dictatorial regimes, allowing the illness to spread more rapidly. Countries with high levels of democracy, on the other hand, are more likely to implement timely and effective health measures that reduce the severity of COVID-19 (Karabulut et al. 2021; Sorsa and Kivikoski, 2023).

The research has also highlighted the importance of climatic conditions in explaining COVID-19 mortality. Higher temperatures and humidity can directly reduce COVID-19 mortality (Sarkodie and Owusu, 2020; Wu et al. 2020; Crisstophi et al. 2021; Perone, 2021;

[7] Data were extracted from UNESCO (2023), except for Albania (Government of Albania, 2014, p. 77), and the Faroe Islands (Nordic Council of Ministers, 2017).

[8] I chose to include female share of population over the male share since only the first variable was statistically significant in the multivariate analysis.

Liang and Yauan, 2022). While rain can reduce viral transmission by promoting social distance and preventing individuals from moving (Shenoy et al. 2021; Perone, 2022). Comorbid diseases and high-risk behaviors are also important factors in COVID-19 mortality. Specifically, alcohol use disorder (Bailey et al. 2022), smoking behaviors, and obesity prevalence (Khorrami et al. 2020; Mahamat-Salet et al. 2021) may have a significant and positive impact on COVID-19 mortality.

Finally, innovations and technical equipment, such as ventilators and face mask manufacture, can aid in combating the pandemic's negative effects (Bachmann and Frutos-Bencze, 2022). In this way, GERD may be seen as a trustworthy indicator of domestic innovation success (Omar, 2019). For explanatory variables, I have included the following public health-related factors:

- the number of pharmacists per 10,000 inhabitants in 2020 (or the latest data) (World Health Organization, 2023);[9]
- the health personnel expressed by the total number of medical doctors, generalist medical practitioners, and nurses per 1,000 inhabitants in 2020 (or the latest data) (World Health Organization, 2023);[10]
- the average domestic general government health expenditure (GGHE-D) expressed in international US dollars (PPP) per inhabitant, in the period 2015–2020 (World Health Organization, 2023);[11]
- the average household out-of-pocket expenditure as a percentage of current health expenditure, in the period 2015–2020 (World Health Organization, 2023);
- the average UHC in the period 2015–2019 (UHC) (World Bank, 2023b);
- the saturation of ordinary hospital beds over the period 21 November 2021–4 December 2021, calculated by dividing the number of hospitalized patients with mild symptoms by the number of ordinary hospital beds (Mathieu et al. 2023);[12]
- the saturation of ICU over the period 21 November 2021–4 December 2021, calculated by dividing the number of patients hospitalized in ICU by the number of ICU hospital beds (Mathieu et al. 2023);[13]

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[9] Data were extracted from the World Health Organization (2023), except for the Faroe Islands (Statbank, 2023).

[10] Data were extracted from the World Health Organization (2023), except for the Faroe Islands (Statbank, 2023).

[11] Data were extracted from the World Health Organization (2023), except for the Faroe Islands (Statbank, 2023).

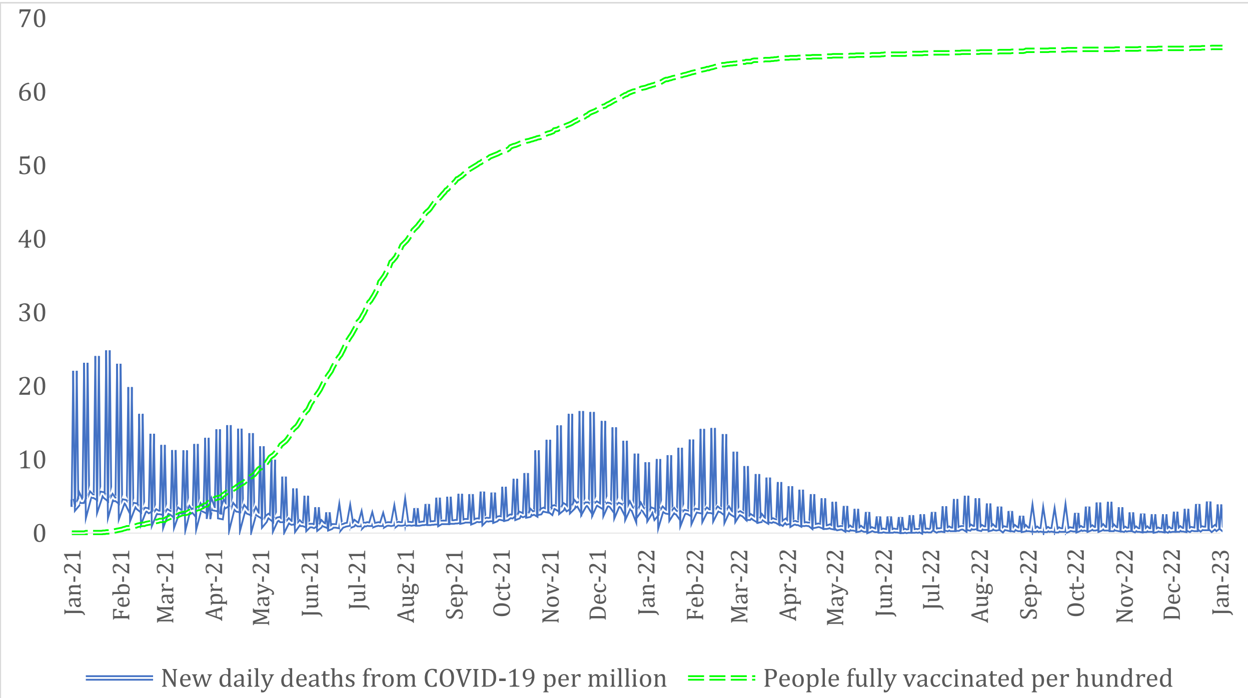
[12] Data for total COVID-19 hospitalizations were extracted from Mathieu et al. (2023), except for the Faroe Islands (The Government of the Faroe Islands, 2021), Georgia (Agenda.Ge, 2021), Germany (Robert Koch Institute, 2023), and Moldova (United Nations Moldova, 2021). While data on the number of hospital beds per 100,000 inhabitants related to 2020 (or the latest) and were extracted from OECD/European Union (2022), except for Albania, Armenia, Azerbaijan, Bosnia and Herzegovina, Georgia, Moldova, Russia, and Ukraine, which came from Our World in Data (2023). Data for the Faroe Islands were gathered from the Faroese Ministry of Health (2023).

[13] Data on COVID-19 hospitalizations in ICU were extracted from Mathieu et al. (2023), with the exception of the Faroe Islands (Landspítali University Hospital, 2022), Georgia (Agenda.Ge, 2021), Hungary (Cabinet Office of the Prime Minister of Hungary, 2021), Latvia (National Health Service - Republic of Latvia, 2021), Lithuania (Lietuvos Nacionalinis Radijas ir Televizija, 2021), and Norway (Government.no, 2021). Data on ICU beds per 100,000 inhabitants related to 2020 (or the latest) and were extracted from OECD (2021), except for Armenia (bne IntelliNews, 2020), Bulgaria (OECD/European Observatory on Health Systems and Policies 2021), the Faroe Islands (Landssjúkrahúsið National Hospital, 2023), Georgia (Tarkhnishvili, 2020), Iceland (Fouda et al., 2020), Malta (Farrugia, 2020), Montenegro (European Observatory on Health Systems and Policies 2020), Slovakia (Bauer et al., 2020), Slovenia (Bauer et al., 2020), the UK (Ewbank et al., 2021), and Ukraine (Shulzhenko, 2020).

- the cumulative number of COVID-19 vaccination doses administered per 100 people on November 21, 2021 (or closer data) (Mathieu et al. 2023);
- the cumulative number of people who received the full protocol of COVID-19 vaccination doses on November 21, 2021 (or closer data) (Mathieu et al. 2023);[14]

In particular, the key factors for healthcare were included one by time in the model to reduce the variance inflation factor (VIF) and avoid misspecification issues. In fact, the pairwise correlation between those variables was generally pretty high and greater than 0.7 in absolute value in 50% of cases (Table A2, Appendix A). These values are commonly problematic and can significantly distort the models' outcomes (Donath et al. 2012; Dorman et al. 2013).
As a dependent variable, I included the number of COVID-19 deaths per 100,000 people, averaged throughout the period 21 November 2021-4 December 2021. This period was chosen because, as shown in Figure 1, it reflected the greatest death rate caused by COVID-19 at the worldwide level, after which a major portion of the world population (about 55%) had full COVID-19 vaccination. As a result, these data should provide a more accurate and trustworthy picture of the initial efficiency of the mass vaccination program in the sample. In Table 1, I summarized the major descriptive data for the regressand and regressors.

Figure 1. COVID-19 mortality rate at the global level over the period 1 January 2021–1 January 2023.



Sources: Mathieu et al. (2023).

Table 1. Main descriptive statistics.

Variables	N	Mean	St. dev.	Min.	Max.
COV-19 mortality	44	6.3658	5.398	0.1915	19.5055
Age	44	40.2068	3.4989	30.6	46.4
Female	44	51.0205	1.3371	48.03	53.91

[14] Data were extracted from Mathieu et al. (2023), with the exception of Luxembourg (The Luxembourg Government, 2021), and Switzerland (Jucker, 2022).

Pop. Density	44	148.2259	245.9009	3.64	1610.51
Urbanization	44	70.5639	14.0865	42.4	98.08
Democracy	44	0.7323	0.1975	0.19	0.91
Poverty	44	10.4261	3.8094	4.49	19.92
Tourism	44	698.3658	677.2403	22.5379	2620.846
Humidity	44	75.1654	4.7564	63.0481	82.929
Rainy	44	76.8839	50.6631	5.08	240.9
Temperature	44	5.71	5.1218	-12.53	18.37
Alcohol	44	10.1594	2.6663	2.085	14.35
Obesity	44	22.4614	3.1461	13	32.1
Smoking	44	28.1591	6.85	13.1	48.4
GERD	44	1.3562	0.9335	0.2036	3.3379
PHAR	43	7.9536	4.8088	0.337	20.269
HPER	43	13.5608	5.3328	5.2216	26.6846
HEXP	44	2314.2	1616.54	184.73	5825.99
OOP	43	27.8115	16.3285	9.4733	82.2583
UHC	42	76.3708	7.917	61.8486	87.1639
OB_S	33	0.0843	0.1316	0.0068	0.6129
ICU_S	30	1.008	2.993	0.0184	16.1306
VR_{doses}	44	119.9445	39.617	39.95	174.47
VR_{fully}	42	56.1759	18.5625	13.38	82.16

Notes: N, observations; St. dev., standard deviation; Min, minimum; Max, maximum.

4. Methodology

4.1 OLS

The primary purpose of this article was to look at the influence of the public health system and COVID-19 vaccination rates on COVID-19 mortality in 44 European countries. First, I employed a multivariate cross-section OLS regression with heteroscedasticity-robust standard errors. The cross-sectional approach was used instead of the panel approach since socioeconomic and healthcare explanatory variables often change slowly, and associated data are only available once a year at most. Furthermore, the regressor and independent variables were log-transformed to make the residuals' normality assumption more plausible and make the findings easier to understand. The final benchmark equation was as follows [1]:

$$lnCovid_{death} = ln\beta_0 + ln\beta_1 AGE_i + ln\beta_2 FEM_i + ln\beta_3 POD_i + ln\beta_4 URB_i + ln\beta_5 DEM_i + ln\beta_6 POV_i + ln\beta_7 TOU_i + ln\beta_8 HUM_i + ln\beta_9 RAIN_i + ln\beta_{10} TEMP_i + ln\beta_{11} ALC_i + ln\beta_{12} OBE_i + ln\beta_{12} SMO_i + ln\beta_{12} GERD_i + ln\beta_{13} Health_i + \varepsilon_i$$

[1]

Where $Covid_{death}$ is the COVID-19 mortality rate, β_0 is the intercept, AGE represents the median age of the population, FEM denotes the female population ratio, POD is the population density, URB is the urbanization rate, DEM is the electoral democracy index, POV denotes the relative poverty rate, TOU depicts international tourist arrivals, HUM is the relative humidity, $RAIN$ depicts the millimeters (mm) of rain, $TEMP$ is the average temperature,[15] ALC represents alcohol consumption, OBE is the obesity prevalence, SMO is the smoking prevalence, $GERD$ refers to the gross domestic expenditure on research and development, $Health$ specifies healthcare-related variables, and ε_i identicates the error term. Specifically, the explanatory variables were included one by one to avoid multicollinearity concerns, which might skew the results and render them incorrect (Kim, 2019).

4.2 Spatial regression models

The presence of spatial dependence in the data can significantly affect standard statistical approaches, such as OLS estimates, leading to biased or inconsistent estimates, inaccurate standard errors, and measures of fit (Anselin, 1988; Kolak and Anselin, 2020). The concept of spatial dependence refers to the possibility that observations from one location are influenced by observations from nearby locations (LeSage and Pace, 2009). In fact, according to Tobler's (1970) first law of geography, although all things are related among them, closer things are definitively more related than distant things. Moreover, this is plausible considering that the countries included in this analysis are spatially close as well as economically, politically, and/or culturally interconnected. As a result, it is unlikely that clinical outcomes of COVID-19 patients were unaffected by the movement of individuals, which is often easier and faster among neighboring countries, requiring that spatial patterns be taken into account.

The feasibility of using the spatial approach was assessed in two steps. To begin, I performed a visual analysis of maps depicting the spatial distribution of COVID-19 mortality and rates in European countries to determine whether there was a spatial association between the neighboring nations. The global Moran's (1948) I statistic, which is a commonly used measure of global spatial autocorrelation (Chen, 2013), was then computed for all the dependent and independent variables included in this investigation. The spatial distribution of the average COVID-19 mortality rate throughout the period 21 November 2021–4 December 2021 in Europe is shown in Figure 2. The Eastern European countries and Caucasian countries clearly showed similar patterns and significantly higher COVID-19 mortality rates than Western and Nordic European countries over the investigated period. Moreover, the global Moran's I index showed that the null hypothesis that the values of the features were spatially uncorrelated was rejected at a 1% level of statistical significance both for regressand and independent variables, except for relative poverty rate, tourism, and obesity prevalence (Table 2). Thus, spatial autocorrelation existed in the sample. The positive sign of Moran's I index indicated that data were spatially clustered, that is that high or low values tended to cluster together.

Based on the evaluation of the aforementioned metrics, SAR and spatial error model (SEM) were employed. In particular, the parameter estimation of SAR and SEM models was done using the generalized spatial two-stage least square (GS2SLS) estimator. This estimator was chosen as a conservative approach because is generally consistent under heteroskedasticity (Drukker et al., 2013). The SAR model equation was obtained by adding an endogenous spatially lagged dependent variable to the basic linear regression equation [1]:

[15] Because negative values exist within the data, a constant is added before performing the log-transformation.

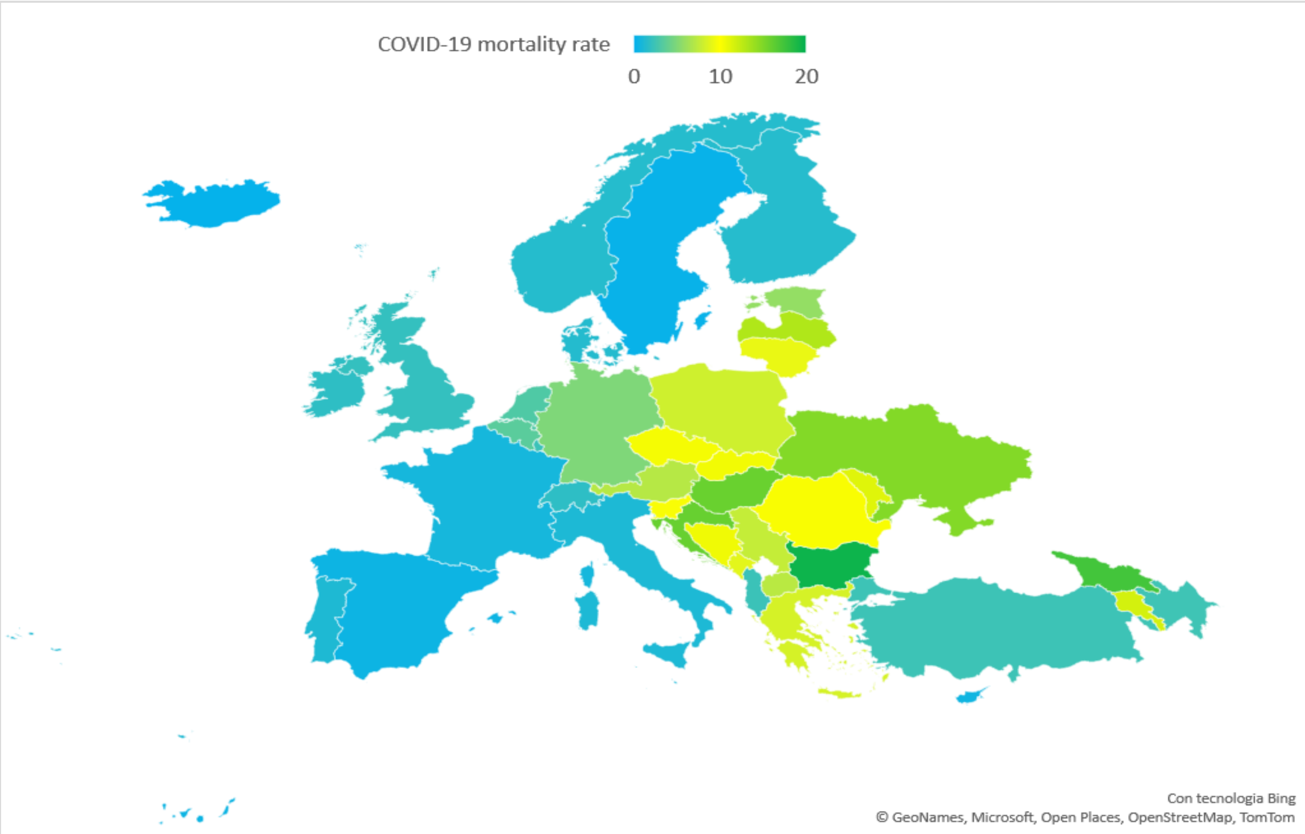
$$lnCovid_{death} = ln\beta_0 + ln\beta_1 AGE_i + ln\beta_2 FEM_i + ln\beta_3 POD_i + ln\beta_4 URB_i + ln\beta_5 DEM_i + ln\beta_6 POV_i + ln\beta_7 TOU_i + ln\beta_8 HUM_i + ln\beta_9 RAIN_i + ln\beta_{10} TEMP_i + ln\beta_{11} ALC_i + ln\beta_{12} OBE_i + ln\beta_{12} SMO_i + ln\beta_{12} GERD_i + ln\beta_{13} Health_i + \rho w_i + \varepsilon_i \quad [2]$$

The SEM model equation was obtained by adding a lagged error term to the basic linear regression equation [1], which allowed to control for spatial autocorrelation in the error:

$$lnCovid_{death} = ln\beta_0 + ln\beta_1 AGE_i + ln\beta_2 FEM_i + ln\beta_3 POD_i + ln\beta_4 URB_i + ln\beta_5 DEM_i + ln\beta_6 POV_i + ln\beta_7 TOU_i + ln\beta_8 HUM_i + ln\beta_9 RAIN_i + ln\beta_{10} TEMP_i + ln\beta_{11} ALC_i + ln\beta_{12} OBE_i + ln\beta_{12} SMO_i + ln\beta_{12} GERD_i + ln\beta_{13} Health_i + \lambda w_i \mu_i + \varepsilon_i \quad [3]$$

Where w_i is a contiguity row normalized spatial–weighting matrix, ρ_i is the spatially lagged dependent variable, λ_i is the spatial error term, and ε_i identifies the error term. The spatial matrix is constructed by using the shapefile from Natural Earth (2009), in which the area of each country is represented by polygons. Specifically, the contiguity matrix is chosen instead of the inverse–distance matrix because the areas of polygons in the shapefile significantly differ in size. In fact, the land area of European countries has a high degree of variability ranging from 2,574.5 and 13,450 square kilometers of Luxembourg and Montenegro (World Bank, 2024), respectively, to the 3,960,000 square kilometers of European Russia (Smirnova et al., 2017). According to Anselin (2020), this can distort the distribution of the neighbor cardinalities. Finally, row normalization in spatial weight matrix has been widely used in the literature (Drukker et al. 2013), and it has the advantage of allowing the comparison of spatial parameters gathered from different models (Perone, 2022).

Figure 2. Spatial distribution of the average COVID-19 mortality rate throughout the period 21 November 2021–4 December 2021.



Notes: own elaboration on Mathieu et al. (2023). Russia was omitted from the chart for clarity reasons.

Table 2. Results of Moran's I for main variables.

Variables	I	E(I)	Sd(I)	Z	p-value
Mortality rate	0.149	-0.023	0.028	6.162	0.000
Age	0.141	-0.023	0.027	6.003	0.000
Female	0.086	-0.023	0.028	3.937	0.000
Pop. Density	0.089	-0.023	0.027	4.129	0.000
Urbanization	0.097	-0.023	0.028	4.304	0.000
Democracy	0.083	-0.023	0.027	3.991	0.000
Poverty	-0.002	-0.023	0.028	0.77	0.441
Tourism	-0.006	-0.023	0.028	1.052	0.293
Humidity	0.172	-0.023	0.028	7.026	0.000
Rain	0.081	-0.023	0.027	3.881	0.000
Temperature	0.054	-0.023	0.027	2.912	0.004
Alcohol	0.072	-0.023	0.025	3.733	0.000
Obesity	-0.041	-0.023	0.027	-0.664	0.507
Smoking	0.116	-0.023	0.028	5.063	0.000
GERD	0.214	-0.023	0.028	8.473	0.000

Notes: I, Global Moran's I; E(I); expected index value; Sd, standard deviation; Z, z-score.

4.3 Cluster analysis

The empirical study concluded with the use of Ward's (Ward, 1963) hierarchical agglomerative clustering approach, which divided the sample into clusters with comparable characteristics and risk variables for COVID-19 mortality rate. The cluster analysis was carried out on variables that possess statistically significant coefficients in the OLS and SAR estimations and allowed for adequate variation across clusters. The process included three subsequent stages (Perone, 2021). First, the variables of interest were standardized to ensure that variables of larger scales did not impact the cluster formation process. The variables were standardized using the following formula:

$$z = \frac{x-\mu}{\sigma}, \quad [4]$$

Where x denotes the observations of each variable from the original dataset, μ is the arithmetic mean obtained by averaging the observations of each variable, and σ represents the standard deviation of the latter. Second, I used the Euclidean distance as a clustering distance metric. It allowed for the calculation of the shortest distance between two points. Specifically, given two points X and Y in a d-dimensional Euclidean space, the Euclidean distance between them was as follows:

$$\|X - Y\| = \sqrt{\sum_{i=1}^{d}(x_i - y_i)^2} \quad [5]$$

Third, I applied Ward's (Ward, 1963) linkage algorithm with the squared Euclidean distance metric (Strauss and Von Maltitz, 2017). Ward's procedure is a variance method that seeks to construct clusters minimizing the within-cluster variance at each merging of the pair of clusters (Murtagh and Legendre, 2014). As a result, the merging cost formula between two clusters, p and q, was given as follows:

$$\Delta(p,q) = \sum_{i\in p \in q}\left\|x_i - m_{p\cup q}\right\|^2 - \sum_{i\in p}\left\|x_i - m_p\right\|^2 - \sum_{i\in q}\left\|x_i - m_q\right\|^2, \quad [6]$$

from which, it was obtained the final formula:

$$\Delta(p,q) = \frac{n_p n_q}{n_p + n_q} \left\| m_p - m_q \right\|^2, \qquad [7]$$

Where m_j represents the center of cluster j, and n_j denotes the total number of points included in cluster j.

5. Results and discussion

5.1 OLS estimates

Table 3 (parts A and B) showed the OLS estimates for the COVID-19 mortality rate after adding critical health-related factors one at a time. Specifically, in model 1, I showed the regression with only the control variables, whereas models 2–10 incorporated the explanatory factors for healthcare. The overall F-test for joint statistical significance demonstrated that the null hypothesis that none of the regressors were significant was always rejected at a statistical significance level of 1% in all regressions. Thus, a significant relationship was shown between the COVID-19 mortality rate and the identified vector of regressors. The VIF calculated for each independent variable spanned from 1.26 to 4.72. Because the VIF was strictly lower than the crucial threshold of 5, I inferred that the regressors were not significantly correlated, and no major multicollinearity concerns were found in the estimates (Menard, 2001; Hair et al., 2017). The Shapiro-Wilk's (1965) test demonstrated that the null hypothesis that data were normally distributed, was always accepted. Similarly, Cameron and Trivedi's (1990) decomposition of the Information Matrix (IM) test showed that the null hypothesis that the error term's variance was constant was always accepted. Thus, both the normality and homoscedasticity conditions were satisfied, indicating that OLS estimates were consistent and unbiased. However, due to the sample's small size, I used the HC2 variance estimator as a conservative approach. It employs a robust small sample correction to increase the precision and accuracy of standard errors (MacKinnon and White, 1985). Furthermore, adjusted R^2 values ranged from 0.6 for model 3 to 0.81 for model 8, implying that the OLS regression equations could explain 60% to 81% of the variance in COVID-19 mortality rates. Notably, including healthcare-related variables increased explanatory power by up to 18% in absolute terms.

The COVID-19 mortality rate was both positively and significantly associated with the following control variables: median age, female share, population density, tourism, humidity, obesity prevalence, smoking prevalence, and GERD. On the other hand, urbanization and temperature have a negative and significant relationship with COVID-19 mortality. Even though it was negative, the electoral democracy index was only statistically significant at 10% in models 8–10. The positive impact of median age on COVID-19 mortality supported the assumption that an older population was more likely to suffer from severe symptoms (Sasson, 2021; Krause and Smolle, 2022; Sorensen et al. 2022; Isath et al. 2023)

The greater mortality rate in the female population contradicted previous literature (Jin et al. 2020; Nielsen et al. 2021; Geldsetzer, 2022). This conclusion may be bolstered by the fact that the majority of studies conducted throughout the world found that women were more likely to display hesitancy about COVID-19 vaccination than males (Agouridis et al. 2023; Zintel et al. 2023). Urbanization and population density had opposing effects on COVID-19 morality. Increased population density raised the possibility of individuals interacting and transmitting the virus, resulting in higher COVID-19 mortality. This was similar to prior findings (Bray et al., 2020; Chang et al., 2022; Perone, 2022).

Part of the literature, however, did not support the favorable impact of increased urbanization on COVID-19 mortality (Viezzer and Biondi, 2021; Chang et al. 2022; Upadhyaya et al. 2022). The negative sign of the urbanization coefficient might be explained by the fact that urbanized regions usually have better access to population health infrastructure and services than rural areas (European Commission, 2019). The positive effect of tourism on COVID-19 mortality was consistent with the sign of the population density coefficient, highlighting the fact that higher movement of people produced by a larger intake of visitors can promote viral transmission among the population. Other studies, such as Farzanegan et al. (2021), Chang et al. (2022), and Naudé and Nagler (2022), were in line with this finding.

The research has largely confirmed that higher temperatures protect against COVID-19 mortality (Perone, 2021 & 2022; Christophi et al. 2021; Liang and Yuan, 2022). The adverse impact of humidity on COVID-19 mortality discovered in this work may be affected by the fact that some studies identified a non-linear association between these variables (Chien and Chen, 2020; Liang et al. 2022; Ismail et al. 2022). Obesity and smoking had a negative influence on COVID-19 mortality, which was consistent with prior research (Khorrami et al. 2020; Tartof et al. 2020; Mahamat-Salet et al. 2021). The beneficial effect of GERD on COVID-19 mortality showed that the country's degree of technical innovation played a role in its ability to cope better with the COVID-19 epidemic.

In terms of explanatory healthcare-related variables, pharmacists, health personnel, healthcare expenditure, UHC, and vaccination rates were all negatively and significantly correlated with COVID-19 mortality, whereas ordinary and ICU hospital bed saturation was positively and significantly associated with COVID-19 mortality. Interestingly, healthcare-related variables were statistically significant at the 1% level, except for health personnel and ordinary hospital bed saturation, which were statistically significant at the 5% level.

A 1% increase in pharmacists, health staff, and public health spending was correlated with a decrease of 0.63%, 1.12%, and 0.85% in COVID-19 mortality rates, respectively. These findings were consistent with the literature (Kapitsinis, 2020 & 2021; Alwhaibi et al. 2021; Coccia, 2021; Perone, 2021; Epané et al. 2023) and highlighted that strengthening health systems by allocating more financial resources to healthcare facilities and hiring enough health workers can make them more resilient to face, absorb, and recover from unexpected health shocks such as the COVID-19 pandemic. Interestingly, pharmacists appeared to play an important supporting role in addressing the COVID-19 pandemic by ensuring a sufficient supply of relevant medicines, collaborating with other healthcare personnel to provide patient care, and educating the community about infection prevention and control (IPC) key practices (Hess et al. 2020; Damdar, 2021). In addition, pharmacists were actively involved in administering COVID-19 vaccines in various European countries (Turcu-Stiolica, 2021; Costa et al. 2022).

The signs of the coefficients of UHC and OOP variables were consistent with the literature (El-Khatib et al. 2020; Tekerek et al. 2024), emphasizing the importance of providing people with timely and high-quality essential healthcare services that do not burden them financially.[16]

A 1% increase in ordinary and ICU hospital bed saturation was positively and significantly

[16] Although OOP was not significant in OLS estimates, it became statistically significant in the spatial analysis (Section 5.2).

associated with a 0.7% and 0.48% rise in COVID-19 mortality, respectively. This was congruent with Perone (2021) and Epané et al. (2023). Thus, providing a sufficient number of hospital beds for COVID-19 patients with mild and severe symptoms was critical for properly controlling the pandemic.

In terms of vaccination policy, a 1% increase in the cumulative number of vaccination doses delivered per 100 people, as well as the prevalence of fully vaccinated people, was associated with a 1.53% and 1.43% drop in COVID-19 mortality rates, respectively. Several studies (Jabłońska et al. 2021; Muthukrishnan et al. 2021; Arbel and Pliskin, 2022; Chen, 2023) supported the beneficial effect of vaccination on COVID-19 outcomes. Thus, the mass vaccination program was effective in combating the COVID-19 pandemic, at least as much as other healthcare-related factors. In this view, interventions that promoted vaccination against COVID-19 by enhancing people's vaccine rational understanding and knowledge significantly contributed to lowering the detrimental impacts of these shocks while also lessening the load on the healthcare system (Omer et al. 2021).

Table 3 (part A). Results from OLS estimator.

OLS	(1)	(2)	(3)	(4)	(5)
Age	4.2701*	4.9141*	8.3820	4.2831**	2.5514
	(2.4191)	(2.5556)	(6.8816)	(2.0897)	(2.3811)
Female	8.2323	-2.3925	1.9454	1.0357	7.6309
	(5.1991)	(6.7976)	(2.7151)	(6.1951)	(5.9512)
Pop. Density	0.4968***	0.1042	0.4804***	0.4852***	0.5064**
	(0.1780)	(0.1405)	(0.1704)	(0.1544)	(0.2029)
URB	-2.6907***	-3.5342***	-2.8489***	-2.7796***	-3.7073***
	(0.8727)	(1.0578)	(0.8507)	(0.7358)	(0.8674)
Democracy	-0.3019	-0.2395	-0.1616	0.0950	-0.2128
	(0.4348)	(0.4618)	(0.4692)	(0.4110)	(0.4891)
Poverty	-0.3278	-0.0567	-0.4149	-0.0148	-0.1608
	(0.3004)	(0.2711)	(0.3512)	(0.2602)	(0.2997)
Tourism	0.1569	0.0669	0.0411	0.1506	0.1588
	(0.0967)	(0.1304)	(0.1144)	(0.1060)	(0.1069)
Humidity	3.6021	7.0179**	3.8219	6.0397**	4.8619
	(3.1759)	(2.9654)	(3.4293)	(2.8294)	(3.2245)
Rain	-0.0591	-0.1850	0.0916	-0.0084	0.0093
	(0.1788)	(0.1945)	(0.3019)	(0.1772)	(0.1802)
Temperature	-0.1381***		-0.1193***	-0.1268***	-0.1241***
	(0.0393)		(0.0416)	(0.0324)	(0.0440)
Alcohol	-0.1819	-0.0400	0.2273	-0.0120	-0.2187
	(0.4995)	(0.4950)	(0.5974)	(0.4971)	(0.5266)
Obesity	3.3771***	3.9758***	2.9027***	3.5533***	3.3938**
	(1.0407)	(1.4084)	(1.0503)	(0.9494)	(1.3869)
Smoking	1.4317**	1.6997***	1.4161**	1.2828**	1.5253**
	(0.6032)	(0.5848)	(0.6512)	(0.5358)	(0.6069)
GERD	-0.5405**				
	(0.2371)				
PHAR		-0.6339***			
		(0.1934)			
HPER			-1.1152**		
			(0.5288)		
HEXP				-0.8508***	
				(0.2749)	

OOP					0.5408
					(0.3789)
Constant	-53.4269**	-39.5139	-43.8856	-31.3396	-49.9945*
	(24.7382)	(26.2787)	(27.7500)	(26.3528)	(24.8750)
Observations	44	43	43	44	43
F-test	18.48***	9.51***	20.35***	18.4***	13.93***
IM-test (P)	0.429	0.4282	0.4282	0.429	0.4282
Shapiro-W. (P)	0.9548	0.9817	0.7173	0.9753	0.9848
VIF	1.73–4.35	1.26–3.57	1.9–3.77	1.71–4.72	1.67–4.05
Adjusted R^2	0.6277	0.6636	0.6064	0.6947	0.5963

Notes: p-value < 0.01***, p-value < 0.05**, p-value < 0.1*. Notes: p-value < 0.01***; p-value < 0.05**; p-value < 0.1*. Robust standard errors in brackets. The OLS estimated were obtained by using the STATA command "regress" (https://www.stata.com/manuals/rregress.pdf).

Table 3 (part B). Results from OLS estimator.

OLS	(6)	(7)	(8)	(9)	(10)
Age	3.8393**	5.4532*	6.0666**	4.2176**	3.9390**
	(1.8529)	(2.8655)	(2.5803)	(1.5454)	(1.6955)
Female	4.8523	1.0060	8.5646	6.1144*	5.0187
	(5.3259)	(7.6468)	(5.5000)	(3.3913)	(3.6739)
Pop. Density	0.5225***	0.3987**	0.3989**	0.3905***	0.3756***
	(0.1459)	(0.1762)	(0.1401)	(0.1316)	(0.1317)
URB	-2.0677**	-2.1437***	-1.6231	-2.5276***	-2.5973***
	(0.8217)	(0.7413)	(0.9441)	(0.6746)	(0.7166)
Democracy	0.2074	-0.4691	-2.7892*	-0.5208*	-0.5103*
	(0.4296)	(0.7370)	(1.4310)	(0.2577)	(0.2835)
Poverty	-0.1394	-0.0199	-0.2346	-0.1973	-0.1465
	(0.2428)	(0.4607)	(0.3691)	(0.2053)	(0.2147)
Tourism	0.1028	0.1515	0.2038	0.1931**	0.1732*
	(0.0757)	(0.1887)	(0.1771)	(0.0830)	(0.0945)
Humidity	2.1390	5.8477**	9.4781***	5.3296***	5.5403**
	(2.8127)	(2.7771)	(2.7316)	(1.9177)	(2.0463)
Rain	-0.1339	-0.1765	-0.2979	-0.0558	-0.0617
	(0.1566)	(0.2270)	(0.2219)	(0.1309)	(0.1375)
Temperature	-0.1263***	-0.0855*	-0.0655	-0.0798***	-0.0742***
	(0.0297)	(0.0466)	(0.0411)	(0.0259)	(0.0261)
Alcohol	-0.2197	-0.6046	-0.2108	-0.2887	-0.0526
	(0.4133)	(0.7394)	(0.5617)	(0.3356)	(0.3956)
Obesity	2.9616***	2.7168**	1.7535*	3.5220***	3.4737***
	(1.0045)	(0.9512)	(0.9027)	(0.7641)	(0.8143)
Smoking	0.7012	0.7998	0.7877	1.0667**	1.1934**
	(0.6803)	(0.6222)	(0.6758)	(0.4910)	(0.4998)
UHC	-7.1078***				
	(2.4993)				
OB_S		0.6991**			
		(0.2614)			
ICU_S			0.4822***		
			(0.1526)		
VR_{doses}				-1.5331***	
				(0.2155)	
VR_{fully}					-1.4554***
					(0.2068)

Constant	-1.2873	-39.7476*	-91.0350***	-51.1308***	-49.1747**
	(32.5864)	(21.3248)	(21.4940)	(17.8008)	(18.9461)
Observations	42	33	30	44	44
F-test	36.9***	30.02***	43.02***	37.38***	41.01***
IM-test (P)	0.4274	0.418	0.414	0.429	0.429
Shapiro-W. (P)	0.9719	0.3856	0.8088	0.673	0.9735
VIF	1.62–4.31	1.66–3.62	1.52–4.01	1.68–3.63	1.68–3.68
Adjusted R^2	0.6967	0.7556	0.8094	0.7641	0.7503

Notes: p-value < 0.01***, p-value < 0.05**, p-value < 0.1*. Notes: p-value < 0.01***; p-value < 0.05**; p-value < 0.1*. Robust standard errors in brackets. The OLS estimated were obtained by using the STATA command "regress" (https://www.stata.com/manuals/rregress.pdf).

5.2 Robustness checks: spatial analysis

As a robustness check, I explored SAR and SEM models fitted with the GS2SLS estimator. Tables 7 and 8 (parts A and B) showed the results. The spatial models fitted the data quite well since their pseudo-R^2 was significantly higher than 0.2 (McFadden, 1977, p. 35). Pseudo-R^2 varied from 0.69 to 0.93 for SAR specifications and from 0.71 to 0.86 in SEM specifications. Furthermore, the Wald test rejected the null hypothesis that regressor coefficients were equal to zero, indicating a significant link between the COVID-19 mortality rate and the independent factors. Thus, spatial models were unaffected by relevant misspecification concerns.

The results showed that the spatially lagged dependent variable (ρ) was always positive and statistically significant at the 1% level of significance (except for model 7), with spatial autoregressive parameters ranging from 0.4 to 0.8 (Table 6). While the spatially lagged error term (λ) was positive and statistically significant in models 1, 3, and 5, but negative and not statistically significant in the other models (Table 7). The positive value of ρ implied a strong positive spatial dependence across European countries. Thus, observed COVID-19 mortality rates were not randomly distributed but were impacted by country proximity. This can be explained by the fact that people interact with each other spreading the infection, as well they may cross borders more easily than distant countries. This was especially true during the COVID-19 waves, which resulted in draconian travel restrictions that severely limited global movement. The statistical insignificance of ρ showed that no significant explanatory factors with spatial patterns were omitted from the model (Rüttenauer, 2022). The inclusion of healthcare factors and vaccination rates raised the pseudo-R^2 from 0.74 to 0.93, validating the worth of the empirical analysis.

The SAR and SEM models mostly confirmed the results obtained using the OLS estimator, except for OOP expenditure, which became statistically significant at the 5% level. In fact, the signs and statistical significance of the control and explanatory variables were unchanged, demonstrating the robustness of the results (Table 8).

Table 4 (part A). Results from SAR models.

SAR	(1)	(2)	(3)	(4)	(5)
Spatial lag (ρ)	0.6281***	0.7409***	0.6454***	0.5253***	0.797***
	(0.1231)	(0.1324)	(0.1219)	(0.1109)	(0.1475)
Age	2.0811	2.3376	0.5755	2.3109	0.7772
	(1.7293)	(1.6252)	(1.9410)	(1.4316)	(1.4904)

Female	5.6537	-2.2547	6.3870	1.4284	4.4014
	(4.5359)	(4.8550)	(5.2762)	(4.7990)	(4.4789)
Pop. Density	0.3221***	0.0862	0.3021**	0.3412***	0.3271***
	(0.1211)	(0.0832)	(0.1280)	(0.1139)	(0.1124)
URB	-1.4306**	-1.5810*	-1.7685***	-1.7288***	-1.4951**
	(0.6257)	(0.8251)	(0.6230)	(0.5857)	(0.6470)
Democracy	0.1860	0.3798	0.1988	0.3674	0.4285
	(0.2705)	(0.2674)	(0.3018)	(0.2793)	(0.2785)
Poverty	-0.1277	0.0125	-0.0980	0.0584	-0.0256
	(0.2156)	(0.1870)	(0.2649)	(0.1973)	(0.2083)
Tourism	0.0568	-0.0363	0.0162	0.0657	0.0151
	(0.0727)	(0.0792)	(0.0696)	(0.0706)	(0.0746)
Humidity	1.3248	1.5626	1.5179	3.3212*	0.4541
	(2.0458)	(1.8702)	(2.0744)	(1.8909)	(2.1443)
Rain	0.0093	-0.0553	0.0272	0.0389	0.0619
	(0.1364)	(0.1236)	(0.2194)	(0.1183)	(0.1210)
Temperature	-0.0839***		-0.0673**	-0.0834***	-0.0743***
	(0.0291)		(0.0289)	(0.0259)	(0.0268)
Alcohol	0.2096	0.5615*	0.3957	0.2712	0.4440
	(0.3024)	(0.2881)	(0.3453)	(0.2776)	(0.3413)
Obesity	1.8286***	2.7989***	1.5787**	2.1819***	2.2846***
	(0.6520)	(0.9063)	(0.6901)	(0.6153)	(0.7211)
Smoking	0.8733*	0.8645**	0.8983*	0.8696*	0.6148
	(0.5004)	(0.3902)	(0.4841)	(0.4742)	(0.4612)
GERD	-0.3616**				
	(0.1673)				
PHAR		-0.4778***			
		(0.1380)			
HPER			-0.4216		
			(0.3971)		
HEXP				-0.5755***	
				(0.2060)	
OOP					0.5128**
					(0.2133)
Constant	-30.7641	-11.3678	-27.7319	-19.8342	-21.1353
	(19.5827)	(17.4069)	(19.7006)	(20.3819)	(21.0001)
Observations	44	43	43	44	43
Wald test	26.04***	31.32***	28.03***	22.45***	29.21***
Pseudo- R^2	0.7578	0.7588	0.7198	0.8175	0.6917

Notes: p-value < 0.01***, p-value < 0.05**, p-value < 0.1*. Notes: p-value < 0.01***; p-value < 0.05**; p-value < 0.1*. Standard errors in brackets. The SAR models were estimated by using the STATA command "spxtregress" (https://www.stata.com/manuals/spspxtregress.pdf).

Table 4 (part B). Results from SAR models.

SAR	(4)	(5)	(6)	(7)	(8)
Spatial lag (ρ)	0.5634***	0.2251	0.4002***	0.3989***	0.4497***
	(0.1533)	(0.2334)	(0.137)	(0.136)	(0.1292)
Age	1.7724	4.8096**	5.2521***	2.7358**	2.4159**
	(1.4247)	(2.2015)	(1.8622)	(1.1471)	(1.1829)
Female	4.9369	-1.5285	2.4886	5.1773	4.0441
	(4.2869)	(5.5828)	(4.6949)	(3.2895)	(3.4539)
Pop. Density	0.3697***	0.3260***	0.2773***	0.3044***	0.2804***
	(0.1102)	(0.1226)	(0.0948)	(0.1063)	(0.0997)

URB	-0.9529	-2.0279***	-1.0467*	-1.7913***	-1.7275***
	(0.6486)	(0.5407)	(0.5830)	(0.6051)	(0.6103)
Democracy	0.4264	-0.1537	-1.9953***	-0.1628	-0.1110
	(0.3113)	(0.5696)	(0.6604)	(0.2049)	(0.2013)
Poverty	-0.0631	-0.0004	-0.3661	-0.0968	-0.0465
	(0.2056)	(0.3156)	(0.2572)	(0.1759)	(0.1737)
Tourism	-0.0004	0.0917	0.0240	0.1182*	0.0965
	(0.0727)	(0.1710)	(0.1519)	(0.0688)	(0.0633)
Humidity	-0.3792	4.5404*	5.5419***	3.4432**	3.4194**
	(2.2693)	(2.6598)	(1.7276)	(1.6804)	(1.6040)
Rain	-0.0264	-0.1341	-0.1480	-0.0082	-0.0102
	(0.1227)	(0.1707)	(0.1535)	(0.1063)	(0.1086)
Temperature	-0.0815***	-0.0700**	-0.0400	-0.0584***	-0.0509**
	(0.0271)	(0.0352)	(0.0254)	(0.0215)	(0.0202)
Alcohol	0.3122	-0.4645	0.0849	-0.0059	0.1982
	(0.3236)	(0.5887)	(0.4125)	(0.2572)	(0.2458)
Obesity	2.0970***	2.6708***	1.8248***	2.4874***	2.3353***
	(0.6620)	(0.7412)	(0.7080)	(0.6262)	(0.5919)
Smoking	0.3949	0.6858	0.4531	0.8061*	0.8548*
	(0.5386)	(0.5197)	(0.4253)	(0.4576)	(0.4664)
UHC	-4.6177**				
	(2.0055)				
OB_S		0.5825**			
		(0.2648)			
ICU_S			0.3990***		
			(0.1106)		
VR_{doses}				-1.1559***	
				(0.2055)	
VR_{fully}					-1.0912***
					(0.1789)
Constant	-0.9384	-23.7521	-51.1534**	-37.5989**	-34.1264**
	(24.3353)	(23.7716)	(21.2336)	(16.0571)	(16.2137)
Observations	42	33	30	44	44
Wald test	13.5***	0.93	8.54***	8.61***	12.11***
Pseudo-R^2	0.7995	0.8696	0.9267	0.8622	0.8591

Notes: p-value < 0.01***, p-value < 0.05**, p-value < 0.1*. Notes: p-value < 0.01***; p-value < 0.05**; p-value < 0.1*. Standard errors in brackets. The SAR models were estimated by using the STATA command "spxtregress" (https://www.stata.com/manuals/spspxtregress.pdf).

Table 5 (part A). Results from SEM models.

SEM	(1)	(2)	(3)	(4)	(5)
Spatial error (λ)	0.4597**	0.2796	0.4015**	0.4424	0.6122***
	(0.2008)	(0.2283)	(0.1836)	(0.302)	(0.2147)
Age	3.9634**	4.6524**	1.9382	3.9375**	2.7357
	(1.9943)	(2.0558)	(2.1954)	(1.6914)	(1.8137)
Female	9.6452**	-1.2948	10.2665*	2.6049	8.5893*
	(4.3993)	(5.9455)	(5.6900)	(4.9206)	(4.7182)
Pop. Density	0.4341***	0.1101	0.4421***	0.4283***	0.4367***
	(0.1410)	(0.1176)	(0.1384)	(0.1313)	(0.1539)
URB	-2.7219***	-3.6050***	-2.9234***	-2.8385***	-3.7092***
	(0.7650)	(0.9275)	(0.7227)	(0.6808)	(0.7994)
Democracy	-0.1273	-0.1709	-0.0413	0.1873	0.0600

	(0.2930)	(0.3359)	(0.3327)	(0.2681)	(0.2916)
Poverty	-0.2702	-0.0371	-0.3845	0.0195	-0.1186
	(0.2229)	(0.1973)	(0.2645)	(0.2058)	(0.2229)
Tourism	0.0974	0.0338	0.0163	0.1094	0.0954
	(0.0746)	(0.0987)	(0.0837)	(0.0849)	(0.0785)
Humidity	3.0783	6.3563***	3.7610	5.3189**	4.0868*
	(2.5299)	(2.3942)	(2.6200)	(2.1442)	(2.4227)
Rain	0.0087	-0.1389	0.1306	0.0370	0.0598
	(0.1345)	(0.1506)	(0.2392)	(0.1334)	(0.1359)
Temperature	-0.1262***		-0.1089***	-0.1189***	-0.1186***
	(0.0283)		(0.0305)	(0.0245)	(0.0300)
Alcohol	0.0545	0.1007	0.3816	0.1157	0.0214
	(0.3595)	(0.3640)	(0.4036)	(0.3338)	(0.3686)
Obesity	3.3132***	4.0439***	2.9454***	3.5348***	3.6696***
	(0.8799)	(1.1990)	(0.8402)	(0.7945)	(1.2013)
Smoking	1.1829**	1.4709***	1.2143**	1.1329**	1.1195**
	(0.5078)	(0.4845)	(0.5352)	(0.4653)	(0.4880)
GERD	-0.4935***				
	(0.1753)				
PHAR		-0.6003***			
		(0.1555)			
HPER			-1.0123**		
			(0.4174)		
HEXP				-0.7873***	
				(0.2016)	
OOP					0.5695**
					(0.2774)
Constant	-55.9655***	-39.5941*	-51.7588**	-33.6578	-51.3811**
	(20.9427)	(22.7903)	(22.7215)	(21.6097)	(20.7793)
Observations	44	43	43	44	43
Wald test	5.24**	1.5	4.78**	2.15	8.13***
Pseudo-R^2	0.7374	0.7648	0.7279	0.7893	0.7103

Notes: p-value < 0.01***, p-value < 0.05**, p-value < 0.1*. Notes: p-value < 0.01***; p-value < 0.05**; p-value < 0.1*. Standard errors in brackets. The SEM models were estimated by using the STATA command "spxtregress" (https://www.stata.com/manuals/spspxtregress.pdf).

Table 5 (part B). Results from SEM models.

SEM	(4)	(5)	(6)	(7)	(8)
Spatial error (λ)	0.3407	-0.0842	-0.3932	-0.0559	0.0534
	(0.2773)	(0.2283)	(0.2895)	(0.2486)	(0.2486)
Age	3.7377**	5.2860**	6.7476***	4.2584***	3.9466***
	(1.5733)	(2.1022)	(1.8599)	(1.3084)	(1.4236)
Female	5.6792	1.9877	9.5776***	6.0505**	5.0223
	(4.2614)	(5.6147)	(3.3181)	(2.8665)	(3.1543)
Pop. Density	0.4875***	0.4165***	0.3710***	0.3993***	0.3771***
	(0.1185)	(0.1298)	(0.0928)	(0.1115)	(0.1122)
URB	-2.0839***	-1.8750***	-1.3959**	-2.4863***	-2.5872***
	(0.6931)	(0.5340)	(0.6149)	(0.5728)	(0.6195)
Democracy	0.2491	-0.6114	-2.6731***	-0.5467***	-0.5152**
	(0.2780)	(0.4810)	(0.7524)	(0.2079)	(0.2268)
Poverty	-0.1357	-0.0943	-0.2593	-0.2078	-0.1485
	(0.1962)	(0.3414)	(0.2633)	(0.1693)	(0.1736)

Tourism	0.0804	0.1564	0.2961**	0.2044***	0.1752**
	(0.0634)	(0.1427)	(0.1254)	(0.0691)	(0.0753)
Humidity	1.7182	6.1930***	11.0017***	5.5044***	5.5675***
	(2.2526)	(1.9408)	(1.9133)	(1.5327)	(1.6172)
Rain	-0.1027	-0.1738	-0.3776***	-0.0655	-0.0636
	(0.1241)	(0.1549)	(0.1399)	(0.1107)	(0.1136)
Temperature	-0.1231***	-0.0862**	-0.0547**	-0.0808***	-0.0744***
	(0.0222)	(0.0345)	(0.0279)	(0.0220)	(0.0216)
Alcohol	-0.0983	-0.5963	-0.3364	-0.3221	-0.0580
	(0.3051)	(0.5463)	(0.4147)	(0.2626)	(0.2913)
Obesity	2.9605***	2.3272***	1.6116**	3.5106***	3.4671***
	(0.8336)	(0.6894)	(0.6868)	(0.6243)	(0.6666)
Smoking	0.6402	0.9044**	0.8798**	1.0953***	1.2003***
	(0.5568)	(0.4457)	(0.4339)	(0.4179)	(0.4338)
UHC	-6.7658***				
	(1.9260)				
OB_S		0.7045***			
		(0.2045)			
ICU_S			0.5418***		
			(0.1006)		
VR_{doses}				-1.5618***	
				(0.1751)	
VR_{fully}					-1.4604***
					(0.1626)
Constant	-4.0064	-44.6799***	-105.79***	-51.7513***	-49.3340***
	(25.9504)	(15.5541)	(14.6325)	(14.9284)	(15.8165)
Observations	42	33	30	44	44
Wald test	1.51	0.14	1.84	0.05	0.05
Pseudo-R^2	0.7977	0.8371	0.8607	0.8407	0.8316

Notes: p-value < 0.01***, p-value < 0.05**, p-value < 0.1*. Notes: p-value < 0.01***; p-value < 0.05**; p-value < 0.1*. Standard errors in brackets. The SEM models were estimated by using the STATA command "spxtregress" (https://www.stata.com/manuals/spspxtregress.pdf).

5.3 Hierarchical cluster analysis

Ward's (1963) minimum-variance method was used to perform hierarchical cluster analysis. Figure 3 displayed the distance matrix calculated using Euclidean distance as a dissimilarity metric. In Figure 4, I showed the dendrogram, which is a tree-like figure that represents the groups created by applying Ward's hierarchical approach to the aforementioned distance matrix. Specifically, each branch of the dendrogram terminated in nodes from which smaller branches emerged, ultimately collapsing in the leaves, which were the nations. The height (y-axis) represented the cophenetic distance at which clusters coalesced into a single branch. The variables included in the cluster analysis were Covid-19 mortality, females, urbanization, humidity, temperature, smoking, and vaccination rate (doses per 100 people). They were chosen because they proved to be statistically significant in the cross-sectional analysis (Section 4) and allowed for significant variation between clusters.

Regarding healthcare-related factors, I only chose the vaccination rate because the high pairwise correlation between healthcare features could distort the clustering procedure by giving too much weight to the highly correlated attributes. Moreover, vaccination against COVID-19 was the most interesting parameter because mass vaccination has been from 2021 the leading strategy in fighting the pandemic across the world (Agrawal et al. 2023).

I used the "NbClust" package developed by Charrad et al. (2014) in the R environment to figure out the appropriate number of clusters to divide the dendrogram into. The findings showed that five indices advocated two clusters, 12 indices favored three clusters, one index favored five clusters, one index picked seven clusters, and eight indices favored 15 clusters (Table B1, Appendix B). Thus, the majority rule selected three clusters as the ideal partition size. Cutting the dendrogram at an estimated height of 8.5 revealed three homogeneous groups of nations with progressively increased risk factors for COVID-19 mortality (Figure 4).

Cluster 1 (green-colored) highlighted nations with lower risk-factors, most of which were in Nordic Europe. They had an average COVID-19 mortality rate of 1.67%, a vaccination rate of 154.85, a female share of 49.93, an urbanization rate of 89.89, a humidity of 79.84, a temperature of 4.14, and a smoking rate of 20.82. Cluster 3 (red-colored) highlighted nations with higher risk-factors, the majority of which were in Eastern Europe and the South Caucasus. They had an average COVID-19 mortality rate of 12.46%, a vaccination rate of 81.93, a female share of 52.45, an urbanization rate of 62.69, a humidity of 74.48, a temperature of 4.05, and a smoking rate of 31.86 percent. Cluster 2 (blue-colored) lied in the middle and contained nations with medium-risk factors, primarily from Western Europe, Southern Europe, and the Balkans.[17]

Moreover, Cluster 1 had a vaccination rate of 72.92 and 25.74 doses per 100 inhabitants higher than Cluster 3 and Cluster 2. Whereas Cluster 1 had a COVID-19 mortality rate (in absolute value) lower than Clusters 3 and 2 by 10.79% and 2.77%, respectively.

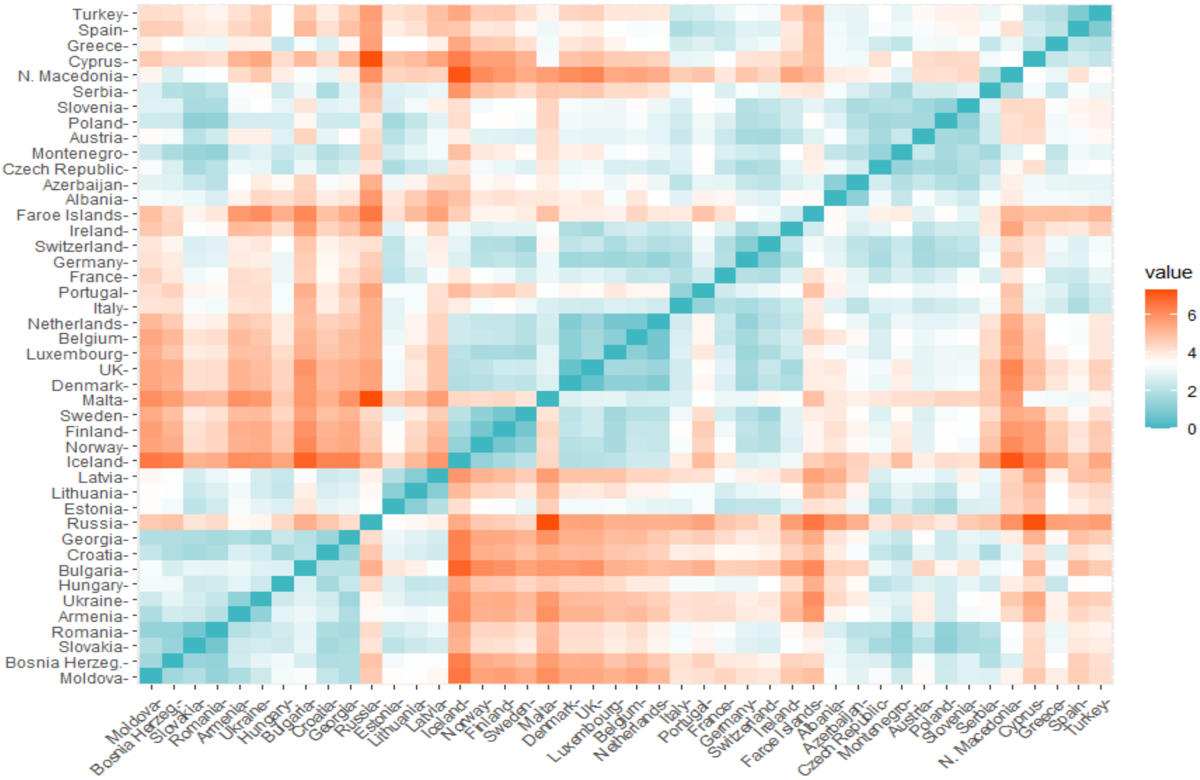
Furthermore, Cluster 1 had a greater vaccination rate than Cluster 3 of 72.95 doses per 100 inhabitants, in the face of a COVID-19 mortality rate that was less than 10.79% of Cluster 3 (in absolute terms).

Several factors might be given to support these findings. The Nordic nations' healthcare system is built on three pillars: a universal public healthcare system, quick access to quality healthcare services, and advanced therapies (Einhorn, 2019). While Central and Eastern European countries struggle to deliver universal, egalitarian, and high-quality healthcare. There is insufficient integration between the health and social care sectors, a scarcity of medical personnel, and patients having limited access to newly authorized drugs (Kurpas et al. 2021; Kyriakides, 2023). The post-communist welfare state in these nations has been distinguished by progressive healthcare system decentralization and market-oriented health care reforms (Forster et al., 2018).

For example, in 2019, the Nordic countries had an average UHC of 85.54% of the population, whereas CEEC countries had an average UHC of 72.28%, more than 13% lower (World Bank, 2022). In comparison, CEEC countries had an average OOP spending of 28.34%, over twice that of Nordic countries (14.88%) (World Health Organization, 2023). In other words, CEEC countries impose a far higher burden of healthcare spending on families and households than Nordic countries, which might have serious consequences for access to essential healthcare services. In this sense, the groups found using cluster analysis appear to also have similar healthcare systems.

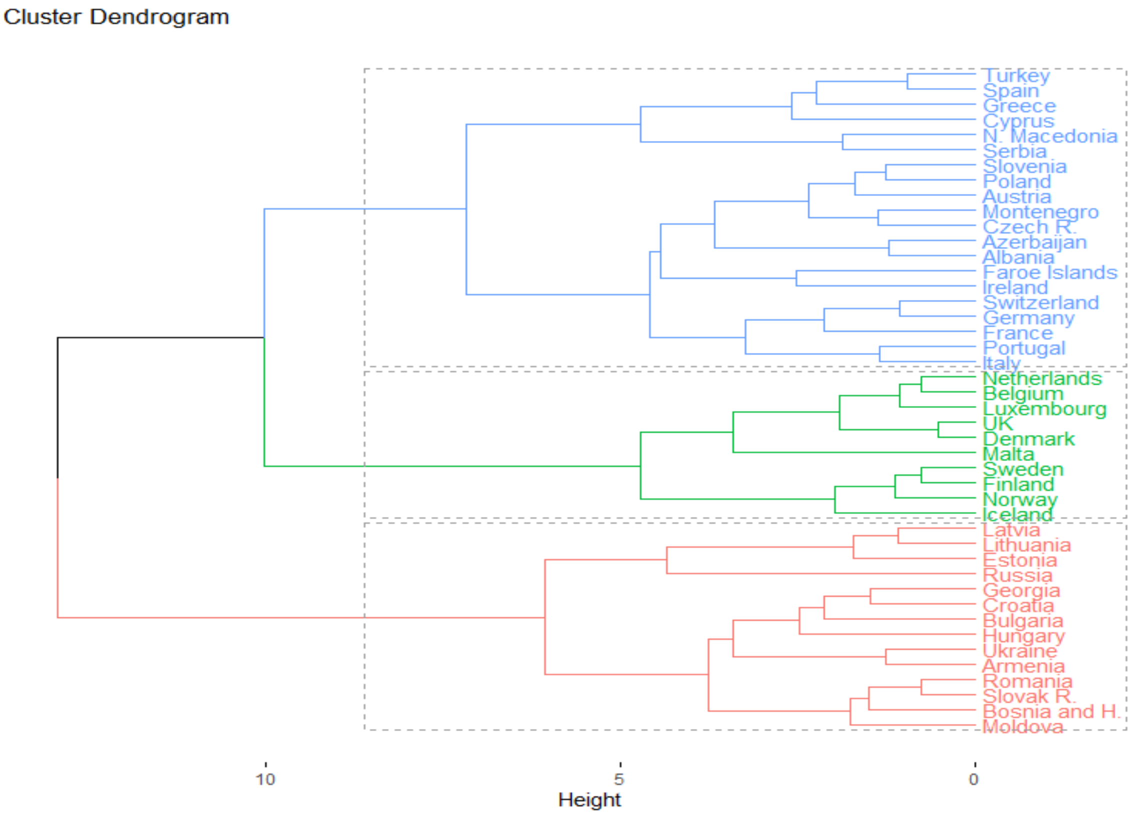
[17] The three increasing risk clusters for COVID-19 mortality were mapped in Figure 5.

Figure 3. Distance matrix obtained using Euclidean distance.



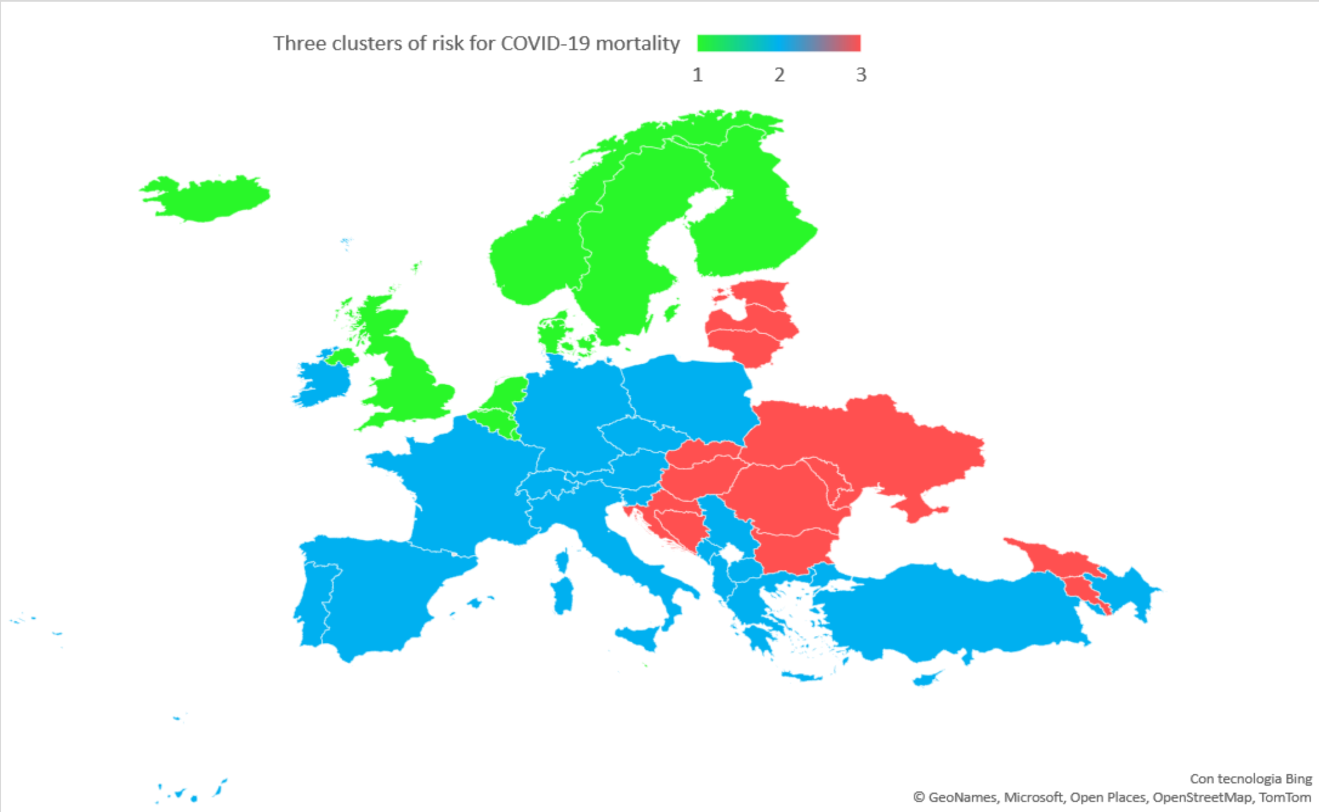
Notes: the distance matrix was obtained using the package "factoextra" in the R environment (Kassambara and Mundt, 2020).

Figure 4. Dendrogram obtained using Ward's hierarchical clustering method.



Notes: the dendrogram was obtained using the package "factoextra" in the R environment (Kassambara and Mundt, 2020).

Figure 5. Map of the three increasing risk clusters for COVID-19 mortality in Europe.



Notes: Russia was omitted from the chart for clarity reasons.

Table 6. Clusters of countries with increasing risk-factors for COVID-19 mortality.

	Cluster 1 (red) Low risk	Cluster 2 (blue) Medium risk	Cluster 3 (green) High risk
Mortality rate	1.67	4.44	12.46
Female	49.93	50.57	52.45
Urbanization	89.89	66.41	62.69
Humidity	79.84	73.31	74.48
Temperature	4.14	7.66	4.049
Smoking	20.82	29.23	31.86
Vaccination (doses)	154.85	129.11	81.93

6. Conclusions

The main objective of this article was to look at the link between a wide range of healthcare-related variables and COVID-19 mortality rates in 44 European and Caucasian countries. The cross-sectional linear regression and spatial analysis revealed that, while pharmacists, health personnel, health expenditure, and COVID-19 vaccination rates were all negatively associated with COVID-19 mortality rates, saturation of ordinary and ICU hospital beds was positively associated with COVID-19 mortality rates. The cluster analysis revealed that the sample had three homogeneous clusters with higher risk factors for COVID-19 mortality. European Nordic nations exhibited much-reduced risk factors compared to CEEC and South Caucasian countries, showing the existence of a strong spatial pattern for healthcare factors and COVID-19 mortality in Europe. Overall, the results were consistent and robust across several alternative model specifications.

However, considerable disparities were found among the nations studied. In particular, the findings indicate that large-scale reforms to the healthcare system in post-communist nations have harmed their ability to respond to acute shocks as well as their effective coordination. This was especially important during the COVID-19 pandemic, as the public healthcare system and institutions were primarily responsible for managing the outbreak, as well as planning and coordinating the COVID-19 mass vaccination campaign.

As a result, shifting from a decentralized and health insurance-based healthcare system to a more centralized healthcare system may enable the aforementioned nations to better deal with exogenous shocks like as the COVID-19 epidemic. Interestingly, the strategic pillars of the COVID-19 response would also benefit from community pharmacists' active participation in controlling the pandemic and administering the vaccine procedure. Finally, prioritizing investments in public health resources and services can considerably reduce the negative health effects of COVID-19 while also preparing the national response to future akin public health emergencies.

References

ABC.AZ (2022), Number of Azerbaijani citizens living below poverty line unveiled, Abc.az news, October 10, 2022. Retrieved from: https://abc.az/en/news/105090.

Agenda.Ge (2021). News. Retrieved from: https://agenda.ge/en/news/news.

Agouridis, A. P., Karageorgos, S. A., & Tsioutis, C. (2023). Role of gender in hesitancy toward the COVID-19 vaccine beyond medical students: Reply to Rujittika Mungmunpuntipantip and Viroj Wiwanitkit. Germs, 13(4), 385-387.

Agrawal, V., Sood, N., & Whaley, C. M. (2023). The impact of the global COVID-19 vaccination campaign on all-cause mortality (No. w31812). National Bureau of Economic Research. Retrieved from: https://www.nber.org/papers/w31812.

Alam, M. F., Wildman, J., & Rahim, H. A. (2023). Income inequality and its association with COVID-19 cases and deaths: a cross-country analysis in the Eastern Mediterranean region. BMJ Global Health, 8(11), e012271.

Al-Amin, M., Islam, M. N., Li, K., Shiels, N., & Buresh, J. (2022). Is there an association between hospital staffing levels and inpatient-COVID-19 mortality rates?. Plos one, 17(10), e0275500.

Alwhaibi, A., Alrwaished, A., Binobydaan, S. M., Alawwad, S., Wajid, S., Bablghaith, S., Alghadeer, S., & Al Arifi, M. N. (2021). Role of pharmacist during COVID-19 pandemic: A retrospective study focused on critically ill COVID-19 patients. Saudi Pharmaceutical Journal, 29(9), 1050-1055.

Anselin L. (2020). Distance-Band Spatial Weights, GeoDa, 10 August 2020 (updated). Retrieved from: https://geodacenter.github.io/workbook/4b_dist_weights/lab4b.html.

Anselin, L. (1998). *Spatial Econometrics: Methods and Models.* London: Kluwer.

Arbel, R., & Pliskin, J. (2022). Vaccinations versus Lockdowns to Prevent COVID-19 Mortality. Vaccines, 10(8), 1347.

Azerbaijan Tourism Board (2022). A look back at the tourism industry achievements of Azerbaijan in the 'new normal', January 18, 2022. Retrieved from: https://www.tourismboard.az/news/688-a-look-back-at-the-tourism-industry-achievements-of-azerbaijan-in-the-new-normal.

Bachmann, P., & Frutos-Bencze, D. (2022). R&D and innovation efforts during the COVID-19 pandemic: The role of universities. Journal of Innovation & Knowledge, 7(4), 100238.

Bailey, K. L., Sayles, H., Campbell, J., Khalid, N., Anglim, M., Ponce, J., ... & Hanson, C. (2022). COVID-19 patients with documented alcohol use disorder or alcohol-related complications are more likely to be hospitalized and have higher all-cause mortality. Alcoholism: Clinical and Experimental Research, 46(6), 1023-1035.

Banila N. (2022). Romania's tourist numbers up 46% y/y in 2021 – table, SeeNews in Brief, Bucharest, February 3, 2022. Retrieved from: https://seenews.com/news/romanias-tourist-numbers-up-46-yy-in-2021-table-771878.

Bascle, G. (2008). Controlling for endogeneity with instrumental variables in strategic management research. Strategic organization, 6(3), 285-327.

Bauer, J., Brüggmann, D., Klingelhöfer, D., Maier, W., Schwettmann, L., Weiss, D. J., & Groneberg, D. A. (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, 46(11), 2026-2034.

Bauer, P., Brugger, J., König, F., & Posch, M. (2021). An international comparison of age and sex dependency of COVID-19 deaths in 2020: A descriptive analysis. Scientific Reports, 11(1), 1-11.

bne IntelIiNews (2020). Armenia 'has just 26 intensive care beds left for COVID-19 patients', May 25, 2020. Retrieved from: https://www.intellinews.com/armenia-has-just-26-intensive-care-beds-left-for-covid-19-patients-183939/.

Bo, Y., Guo, C., Lin, C., Zeng, Y., Li, H. B., Zhang, Y., Hossain, M. S., Chan, J. W., Yeung, D. W., Kwok, K. O., Wong, S. Y., Lau, A. K., & Lao, X. Q. (2020). Effectiveness of non-pharmaceutical interventions on COVID-19 transmission in 190 countries from 23 January to 13 April 2020. International Journal of Infectious Diseases, 102, 247-253.

Bok, K., Sitar, S., Graham, B. S., & Mascola, J. R. (2021). Accelerated COVID-19 vaccine development: milestones, lessons, and prospects. Immunity, 54(8), 1636-1651.

Borghi-Silva, A., Back, G. D., de Araújo, A. S. G., Oliveira, M. R., da Luz Goulart, C., Silva, R. N., ... & Arena, R. (2022). COVID-19 seen from a syndemic perspective: Impact of unhealthy habits and future perspectives to combat these negative interactions in Latin America. Progress in cardiovascular Diseases, 71, 72-78.

Brauner, J. M., Mindermann, S., Sharma, M., Johnston, D., Salvatier, J., Gavenčiak, T., Stephenson, A. B., Leech, G., Altman, G., Mikulik, V., Norman, A. J., Monrad, J. T., Besiroglu, T., Ge, H., Hartwick, M. A., Teh, Y. W., Chindelevitch, L., Gal, Y., & Kulveit, J. (2021). Inferring the effectiveness of government interventions against COVID-19. Science.

Bray, I., Gibson, A., & White, J. (2020). Coronavirus disease 2019 mortality: a multivariate ecological analysis in relation to ethnicity, population density, obesity, deprivation and pollution. Public health, 185, 261-263.

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica: Journal of the econometric society, 1287-1294.

Cabinet Office of the Prime Minister of Hungary (2021). About Hungary: News in Brief. Retrieved from: https://abouthungary.hu/.

Cameron, A. C., and P. K. Trivedi. 1990. The information matrix test and its applied alternative hypotheses. Working paper 372, University of California–Davis, Institute of Governmental Affairs. Retrieved from: https://cameron.econ.ucdavis.edu/research/imtest_impliedalternatives_ucdwp372.pdf.

Carozzi, F., Provenzano, S., & Roth, S. (2024). Urban density and COVID-19: understanding the US experience. The Annals of regional science, 72(1), 163-194.

Centers for Disease Control and Prevention (2024). COVID-19: Underlying Medical Conditions, 12 April 2024. Retrieved from: https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-care/underlyingconditions.html.

Chan, L. Y., Yuan, B., & Convertino, M. (2021). COVID-19 non-pharmaceutical intervention portfolio effectiveness and risk communication predominance. Scientific Reports, 11(1), 1-17.

Chang, D., Chang, X., He, Y., & Tan, K. J. K. (2022). The determinants of COVID-19 morbidity and mortality across countries. Scientific reports, 12(1), 5888.

Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust: an R package for determining the relevant number of clusters in a data set. Journal of statistical software, 61, 1-36.

Chen, Y. (2013). New approaches for calculating Moran's index of spatial autocorrelation. PloS one, 8(7), e68336.

Chen, Y. T. (2023). Effect of vaccination patterns and vaccination rates on the spread and mortality of the COVID-19 pandemic. Health Policy and Technology, 12(1), 100699.

Chien, C., & Chen, W. (2020). Meteorological impacts on the incidence of COVID-19 in the U.S. Stochastic Environmental Research and Risk Assessment, 34(10), 1675-1680.

Christophi, C. A., Sotos-Prieto, M., Lan, F. Y., Delgado-Velandia, M., Efthymiou, V., Gaviola, G. C., ... & Kales, S. N. (2021). Ambient temperature and subsequent COVID-19 mortality in the OECD countries and individual United States. Scientific reports, 11(1), 8710.

Coccia, M. (2021). High health expenditures and low exposure of population to air pollution as critical factors that can reduce fatality rate in COVID-19 pandemic crisis: a global analysis. Environmental Research, 199, 111339.

Costa, S., Romão, M., Mendes, M., Horta, M. R., Rodrigues, A. T., Carneiro, A. V., Martins, A. P., Mallarini, E., Naci, H., & Babar, Z. (2022). Pharmacy interventions on COVID-19 in Europe: Mapping current practices and a scoping review. Research in Social and Administrative Pharmacy, 18(8), 3338-3349.

Czech Statistical Office (2022). Tourism - 4. quarter of 2021, February 9, 2022. Retrieved from: https://www.czso.cz/csu/czso/ari/tourism-4-quarter-of-2021.

Damdar, G. T. (2022). Role of clinical pharmacist in COVID-19 crisis. Hospital Pharmacy, 57(1), 7-10.

Donath, C., E. Gr¨aßel, D. Baier, C. Pfeiffer, S. Bleich and T. Hillemacher (2012), 'Predictors of binge drinking in adolescents: ultimate and distal factors-a representative study,' BMC Public Health, 12(1), 263.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., ... & Lautenbach, S. (2013). Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography, 36(1), 27-46.

Einhorn E. (2019), Healthcare in the Nordics, Nordics Info (Aarhus University), 25 February 2019. Retrieved from: https://nordics.info/show/artikel/healthcare-in-the-nordic-region.

El-Khatib, Z., Otu, A., Neogi, U., & Yaya, S. (2020). The association between out-of-pocket expenditure and COVID-19 mortality globally. Journal of epidemiology and global health, 10(3), 192.

Epané, J. P., Zengul, F., Ramamonjiarivelo, Z., McRoy, L., & Weech-Maldonado, R. (2023). Resources availability and COVID-19 mortality among US counties. Frontiers in Public Health, 11, 1098571.

European Centre for Disease Prevention and Control (2021). Rollout of COVID-19 vaccines in the EU/EEA: challenges and good practice, 29 March 2021. Retrieved from: https://www.ecdc.europa.eu/en/publications-data/rollout-covid-19-vaccines-eueea-challenges-and-good-practice.

European Commission (2019). https://urban.jrc.ec.europa.eu/thefutureofcities/urban-health#ensuring-general-well-being-in-cities. Accessed 24 November 2023.

European Observatory on Health Systems and Policies (2020). COVID-19 Health System Response Monitor (HSRM): Montenegro, June 1, 2020. Retrieved from: https://eurohealthobservatory.who.int/monitors/hsrm/all-updates/hsrm/montenegro/planning-services.

Ewbank L., Thompson J., McKenna H., Anandaciva S., and Ward D. (2021). NHS hospital bed numbers, The King's Fund, September 2021. Retrieved from: https://www.kingsfund.org.uk/insight-and-analysis/long-reads/nhs-hospital-bed-numbers.

Faroese Ministry of Health (2023). The hospital service. Retrieved from: https://www.hmr.fo/en/what-we-do/health-and-prevention/hospitals/three-hospitals/.

Farrugia C. (2020). 100 ICU beds available for COVID-19 patients, 120 ventilators, Times of Malta, October 14, 2020. Retrieved from: https://timesofmalta.com/article/100-icu-beds-available-for-covid-19-patients-120-ventilators.824584.

Farzanegan, M. R., Gholipour, H. F., Feizi, M., Nunkoo, R., & Andargoli, A. E. (2021). International tourism and outbreak of coronavirus (COVID-19): A cross-country analysis. Journal of travel research, 60(3), 687-692.

Ferguson, N. M., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., ... & Ghani, A. C. (2020). Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand (Vol. 16). London: Imperial College London. Retrieved from: https://doi.org/10.25561/77482.

Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J., Mellan, T. A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J. W., Monod, M., Ghani, A. C., Donnelly, C. A., Riley, S., Vollmer, M. A., Ferguson, N. M., Okell, L. C., & Bhatt, S. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature, 584(7820), 257-261.

Forster, T., Kentikelenis, A., & Bambra, C. (2018). Health inequalities in Europe: setting the stage for progressive policy action, Think-tank for Action on Social Change (TASC): Dublin. Retrieved from: https://refubium.fu-berlin.de/handle/fub188/23222.

Fouda, A., Mahmoudi, N., Moy, N., & Paolucci, F. (2020). The COVID-19 pandemic in Greece, Iceland, New Zealand, and Singapore: Health policies and lessons learned. Health Policy and Technology, 9(4), 510-524.

Frederiksen N. (2018). Smoking cessation in the Nordic region, Nordic Welfare Centre, February 2018. Retrieved from: https://nordicwelfare.org/wp-content/uploads/2018/03/eng-180307_lankar.pdf.

Gebremariam, A. G., Abegaz, D., Nigus, H. Y., Argaw, T. L., Gerbaba, M., Genie, M. G., & Paolucci, F. (2024). Vaccine uptake and effectiveness: Why some African countries performed better than the others?. Health Policy and Technology, 13(1), 100820.

Geldsetzer, P., Mukama, T., Jawad, N. K., Riffe, T., Rogers, A., & Sudharsanan, N. (2022). Sex differences in the mortality rate for coronavirus disease 2019 compared to other causes of death: an analysis of population-wide data from 63 countries. European journal of epidemiology, 37(8), 797-806.

Government of Albania (2014). Albania's Economic Reform Programme 2016–2018. Retrieved from: https://shtetiweb.org/wp-content/uploads/2016/02/Albanias-Economic-Reform-Programme-2016-2018.pdf.

Government.no (2021). Prime Minister's address to the Storting on the coronavirus pandemic, 30 November 2021. Retrieved from: https://www.regjeringen.no/en/aktuelt/prime-ministers-address-to-the-storting-on-the-coronavirus-pandemic/id2890249/.

Hair, J.F., G.T.M. Hult, C.M. Ringle, and M. Sarstedt. (2017). A primer on partial least squares structural equation modeling (PLS-SEM). Thousand Oaks, CA: Sage Publications.

Hákun Leo J. (2018). 56% of Faroe Islanders classed as overweight or obese, Local.fo, November 2, 2018. Retrieved from: https://local.fo/56-of-faroe-islanders-classed-as-overweight-or-obese/.

Herre B., Ortiz-Ospina E., and Roser M. (2024) - "Democracy" Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/democracy.

Herre B., Samborska V., and Roser M. (2023) - "Tourism" Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/tourism.

Hess, K., Bach, A., Won, K., & Seed, S. M. (2020). Community Pharmacists Roles During the COVID-19 Pandemic. Journal of Pharmacy Practice. https://doi.org/10.1177/0897190020980626.

Hristovska Mijovic, B., Spasova Mijovic, T., Trenovski, B., Kozeski, K., Trpkova-Nestorovska, M., & Trajkova-Najdovska, N. (2020). Tobacco consumption in North Macedonia. Analytica, Skopje, North Macedonia. Retrieved from: https://repository.ukim.mk/handle/20.500.12188/25836.

Isath, A., Malik, A. H., Goel, A., Gupta, R., Shrivastav, R., & Bandyopadhyay, D. (2023). Nationwide Analysis of the Outcomes and Mortality of Hospitalized COVID-19 Patients. Current Problems in Cardiology, 48(2), 101440.

Ismail, I. M., Rashid, M. I., Ali, N., Altaf, B. A. S., & Munir, M. (2022). Temperature, humidity and outdoor air quality indicators influence COVID-19 spread rate and mortality in major cities of Saudi Arabia. Environmental Research, 204, 112071.

Jabłońska, K., Aballéa, S., & Toumi, M. (2021). The real-life impact of vaccination on COVID-19 mortality in Europe and Israel. Public Health, 198, 230-237.

Janke, A. T., Mei, H., Rothenberg, C., Becher, R. D., Lin, Z., & Venkatesh, A. K. (2021). Analysis of hospital resource availability and COVID-19 mortality across the United States. Journal of hospital medicine, 16(4), 211-214.

Jin, J. M., Bai, P., He, W., Wu, F., Liu, X. F., Han, D. M., ... & Yang, J. K. (2020). Gender differences in patients with COVID-19: focus on severity and mortality. Frontiers in public health, 8, 545030.

Jucker, J. (2022). Popular approval of Covid-19 restrictions is strongly correlated with vaccination rate, Swiss Medical Weekly. Retrieved from: https://smw.ch/index.php/smw/announcement/view/52.

Kapitsinis, N. (2020). The underlying factors of the COVID-19 spatially uneven spread. Initial evidence from regions in nine EU countries. Regional Science Policy & Practice, 12(6), 1027-1046.

Kapitsinis, N. (2021). The underlying factors of excess mortality in 2020: a cross-country analysis of pre-pandemic healthcare conditions and strategies to cope with Covid-19. BMC health services research, 21, 1-19.

Karabulut, G., Zimmermann, K. F., Bilgin, M. H., & Doker, A. C. (2021). Democracy and COVID-19 outcomes. Economics Letters, 203, 109840.

Kassambara, A. and Mundt, F. (2020) Factoextra: Extract and Visualize the Results of Multivariate Data Analyses. R Package Version 1.0.7. Retrieved from: https://CRAN.R-project.org/package=factoextra.

Khorrami, Z., Nili, S., Sharifi, H., Eybpoosh, S., & Shokoohi, M. (2020). Association of cigarette smoking, obesity, and underlying medical conditions with COVID-19 hospitalization and mortality in Iran: A nationwide retrospective ecological study. Medical journal of the Islamic Republic of Iran, 34, 133.

Kim, J. H. (2019). Multicollinearity and misleading statistical results. Korean Journal of Anesthesiology, 72(6), 558-569. https://doi.org/10.4097/kja.19087.

Kolak, M., & Anselin, L. (2020). A spatial perspective on the econometrics of program evaluation. International Regional Science Review, 43(1-2), 128-153.
Krause, R., & Smolle, J. (2022). Covid-19 mortality and local burden of infectious diseases: A worldwide country-by-country analysis. Journal of Infection and Public Health, 15(12), 1370-1375.
Kuehn, B. M. (2021). COVID-19 in Clinicians—More Cases in Women, More Deaths in Men. Jama, 325(15), 1498-1498.
Kurpas, D., Stefanicka-Wojtas, D., Shpakou, A., Halata, D., Mohos, A., Skarbaliene, A., ... & Tkachenko, V. (2021). The advantages and disadvantages of integrated care implementation in Central and Eastern Europe–perspective from 9 CEE countries. International journal of integrated care, 21(4).
Kyriakides S. (2023). Keynote speech by Commissioner Stella Kyriakides to the conference "At a turning point: Healthcare systems in Central and Eastern Europe" organized by the American Chamber of Commerce to the EU, European Commission, Brussels, 21 April 2023. Retrieved from: https://ec.europa.eu/commission/presscorner/detail/en/speech_23_2409.
Landspítali University Hospital (2021). COVID-19 á Landspítala. https://www.landspitali.is/um-landspitala/spitalinn-i-tolum/-covid-19-a-landspitala/.
Landssjúkrahúsið National Hospital (2023), Facts about Landssjúkrahúsið. Retrieved from: https://sv.ls.fo/um-okkum.
LeSage, J. and Pace, K.R. (2009) Introduction to Spatial Econometrics. Chapman and Hall/CRC, London.
LeSage, J. P., & Pace, R. K. (2014). The biggest myth in spatial econometrics. Econometrics, 2(4), 217-249.
Liang, J., & Yuan, H. Y. (2022). Assessing the impact of temperature and humidity exposures during early infection stages on case-fatality of COVID-19: A modelling study in Europe. Environmental Research, 211, 112931.
Liang, L. L., Tseng, C. H., Ho, H. J., & Wu, C. Y. (2020). Covid-19 mortality is negatively associated with test number and government effectiveness. Scientific reports, 10(1), 12567.
Lietuvos Nacionalinis Radijas ir Televizija (LRT) (2022). News. Retrieved from: https://www.lrt.lt/en/news-in-english.
MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. Journal of econometrics, 29(3), 305-325.
Mahamat-Saleh, Y., Fiolet, T., Rebeaud, M. E., Mulot, M., Guihur, A., El Fatouhi, D., ... & Severi, G. (2021). Diabetes, hypertension, body mass index, smoking and COVID-19-related mortality: a systematic review and meta-analysis of observational studies. BMJ open, 11(10), e052777.
Mathieu E., Ritchie H., Rodés-Guirao L., Appel C., Giattino C., Hasell J., Macdonald B., Dattani S., Beltekian D., Ortiz-Ospina E., and Roser M. (2023) - "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/coronavirus.
McFadden D., "Quantitative Methods for Analyzing Travel Behaviour of Individuals: some recent developments" (1977). Cowles Foundation Discussion Papers. 707. Retrieved from: https://elischolar.library.yale.edu/cowles-discussion-paper-series/707.
Menard, S. (2001). Applied Logistic Regression Analysis (2nd ed.). London: Sage Publications.
Meslé, M. M., Brown, J., Mook, P., Hagan, J., Pastore, R., Bundle, N., ... & Pebody, R. G. (2021). Estimated number of deaths directly averted in people 60 years and older as a result of COVID-19 vaccination in the WHO European Region, December 2020 to November 2021. Eurosurveillance, 26(47), 2101021.
Moran, P. A. (1948). The interpretation of statistical maps. Journal of the Royal Statistical Society. Series B (Methodological), 10(2), 243-251.
Mugoša A., Popović M., Laković T., & Čizmović M. (2018). Accelerating Progress on Effective Tobacco Tax
Murtagh, F., & Legendre, P. (2014). Ward's hierarchical agglomerative clustering method: which algorithms implement Ward's criterion?. Journal of classification, 31, 274-295.
Muthukrishnan, J., Vardhan, V., Mangalesh, S., Koley, M., Shankar, S., Yadav, A. K., & Khera, A. (2021). Vaccination status and COVID-19 related mortality: A hospital based cross sectional study. medical journal armed forces india, 77, S278-S282.
National Health Service – Republic of Latvia (2021). News. Retrieved from: https://www.vmnvd.gov.lv/en.
Natural Earth (2009). Admin 0 – Countries, Version 5.1.1. Retrieved from: https://www.naturalearthdata.com/downloads/10m-cultural-vectors/10m-admin-0-countries/.
Naudé, W., & Nagler, P. (2022). COVID-19 and the city: Did urbanized countries suffer more fatalities? Cities (London, England), 131, 103909.
Nielsen, J., Nørgaard, S. K., Lanzieri, G., Vestergaard, L. S., & Moelbak, K. (2021). Sex-differences in COVID-19 associated excess mortality is not exceptional for the COVID-19 pandemic. Scientific Reports, 11(1), 1-9.

Nordic Council of Ministers (2017). Nordic Statistics 2017. http://dx.doi.org/10.6027/ANP2017-748.
OECD (2021), Health at a Glance 2021: OECD Indicators, OECD Publishing, Paris. Retrieved from: https://doi.org/10.1787/ae3016b9-en.
OECD (2023). OECD Tourism Statistics Database. Retrieved from: https://www.oecd-ilibrary.org/industry-and-services/data/oecd-tourism-statistics_2b45a380-en.
OECD/European Observatory on Health Systems and Policies (2021), Bulgaria: Country Health Profile 2021, State of Health in the EU, OECD Publishing, Paris. https://doi.org/10.1787/c1a721b0-en.
Omar, N. S. (2019). Innovation and economic performance in MENA region. Review of Economics and Political Science, 4(2), 158-175.
Omer, S. B., Benjamin, R. M., Brewer, N. T., Buttenheim, A. M., Callaghan, T., Caplan, A., ... & Hotez, P. J. (2021). Promoting COVID-19 vaccine acceptance: recommendations from the Lancet Commission on Vaccine Refusal, Acceptance, and Demand in the USA. The Lancet, 398(10317), 2186-2192.
Our World in Data (2023). “Hospital beds (per 1,000 people)” [dataset]. Retrieved from: https://ourworldindata.org/grapher/hospital-beds-per-1000-people.
Perone, G. (2021). The determinants of COVID-19 case fatality rate (CFR) in the Italian regions and provinces: An analysis of environmental, demographic, and healthcare factors. Science of the total environment, 755, 142523.
Perone, G. (2022). Assessing the impact of long-term exposure to nine outdoor air pollutants on COVID-19 spatial spread and related mortality in 107 Italian provinces. Scientific Reports, 12(1), 13317.
Pijls, B. G., Jolani, S., Atherley, A., Derckx, R. T., Dijkstra, J. I., Franssen, G. H., ... & Zeegers, M. P. (2021). Demographic risk factors for COVID-19 infection, severity, ICU admission and death: a meta-analysis of 59 studies. BMJ open, 11(1), e044640.
Policies in Low- and Middle-Income Countries: National Study – Montenegro, Institute of Socio-Economic Analysis (ISEA), Podgorica, Montenegro. Retrieved from: https://tobaccotaxation.org/cms_upload/pages/files/National-study-Montenegro-1.pdf.
Ritchie H. and Roser M. (2017). “Obesity” Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/obesity.
Ritchie H. and Roser M. (2019a). “Age Structure” Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/age-structure.
Ritchie H. and Roser M. (2019b). “Gender Ratio” Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/gender-ratio.
Ritchie H. and Roser M. (2022) - “Alcohol Consumption” Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/alcohol-consumption.
Ritchie H. and Roser M. (2023). “Smoking” Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/smoking.
Ritchie H., Rodés-Guirao L., Mathieu E., Gerber M., Ortiz-Ospina E., Hasell J., and Roser M. (2023). “Population Growth”. Data adapted from Gapminder, PBL Netherlands Environmental Assessment Agency, United Nations, Food and Agriculture Organization of the United Nations. Retrieved from https://ourworldindata.org/grapher/population-density.
Ritchie H., Samborska V., and Roser M. (2024). “Urbanization” Published online at OurWorldInData.org. Retrieved from: https://ourworldindata.org/urbanization.
Robert Koch Institute (2023). Covid-19 outbreak: Situationsberichte. Retrieved from: https://www.rki.de/EN/Content/infections/epidemiology/outbreaks/COVID-19/Situationsberichte_Tab.html. Accessed on May 22, 2023.
Rüttenauer, T. (2022). Spatial regression models: a systematic comparison of different model specifications using Monte Carlo experiments. Sociological Methods & Research, 51(2), 728-759.
Sarkodie, S. A., & Owusu, P. A. (2020). Impact of meteorological factors on COVID-19 pandemic: Evidence from top 20 countries with confirmed cases. Environmental Research, 191, 110101.
Sasson, I. (2021). Age and COVID-19 mortality. Demographic Research, 44, 379-396.
Shao, Q., Tao, R., & Luca, M. M. (2022). The Effect of Urbanization on Health Care Expenditure: Evidence From China. Frontiers in Public Health, 10.
Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). Biometrika, 52(3/4), 591-611.
Shenoy, A., Sharma, B., Xu, G., Kapoor, R., Rho, H. A., & Sangha, K. (2021). God is in the rain: The impact of rainfall-induced early social distancing on COVID-19 outbreaks. Journal of Health Economics, 81, 102575.

Shulzhenko D. (2020). Ukraine's top sanitary doctor: 240 hospitals, 67,000 beds ready for COVID-19 patients, Kyiv Post, March 31, 2020. Retrieved from: https://archive.kyivpost.com/ukraine-politics/ukraines-top-sanitary-doctor-240-hospitals-67000-beds-ready-for-covid-19-patients.html.

Smirnova, O. V., Bobrovsky, M. V., Khanina, L. G., Voskresensky, I. S., Zukert, N. V., Bykhovets, S. S., ... & Turubanova, S. A. (2017). Natural Conditions and General Descriptions of Forest Vegetation and Forest Soils. In: Smirnova, O., Bobrovsky, M., Khanina, L. (eds) European Russian Forests. Plant and Vegetation, vol 15. Springer, Dordrecht.

Sorensen, R. J. D., Barber, R. M., Pigott, D. M., Carter, A., Spencer, C. N., Ostroff, S. M., ... & Murray, C. (2022). Variation in the COVID-19 infection-fatality ratio by age, time, and geography during the pre-vaccine era: A systematic analysis. The Lancet, 399(10334), 1469-1488.

Sorsa, V. P., & Kivikoski, K. (2023). COVID-19 and democracy: a scoping review. BMC Public Health, 23(1), 1668.

Statbank (2023). Statistical Database. Retrieved from: https://statbank.hagstova.fo/pxweb/en/H2/.

Statistics Faroe Islands (2021). A more equal income distribution and fewer people at risk of poverty in 2019, November 12, 2021. Retrieved from: https://hagstova.fo/en/news/more-equal-income-distribution-and-fewer-people-risk-poverty-2019.

Statistics Faroe Islands (2023). Accomodation: stays and tourists by country of residence. Retrieved from: https://hagstova.fo/en/business/i-accommodation-and-food-service-activities/accomodation.

Strauss, T., & Von Maltitz, M. J. (2017). Generalising Ward's method for use with Manhattan distances. PloS one, 12(1), e0168288.

Tarkhnishvili N. (2020). How Prepared is Georgian Healthcare System for COVID-19 Pandemic?, Civil.ge, March 13, 2020. Retrieved from: https://civil.ge/archives/342281.

Tartof, S. Y., Qian, L., Hong, V., Wei, R., Nadjafi, R. F., Fischer, H., ... & Murali, S. B. (2020). Obesity and mortality among patients diagnosed with COVID-19: results from an integrated health care organization. Annals of internal medicine, 173(10), 773-781.

Tekerek, B., Günaltay, M. M., Ozler, G., & Turgut, M. (2024). Determinants of COVID-19 cases and deaths in OECD countries. Journal of Public Health, 32(3), 473-484.

Tekerek, B., Günaltay, M. M., Ozler, G., & Turgut, M. (2024). Determinants of COVID-19 cases and deaths in OECD countries. Journal of Public Health, 32(3), 473-484.

The Government of the Faroe Islands (2021). Korona í Føroyum. Retrieved from: https://korona.fo/news.

The Luxembourg Government (2021). Ministry of Health and Social Security: New COVID-19 cases – Weekly review: 8–14 November, 18 November 2021. Retrieved from: https://m3s.gouvernement.lu/en/actualites.gouvernement%2Ben%2Bactualites%2Btoutes_actualites%2Bcommuniques%2B2021%2B11-novembre%2B17-retrospective.html.

Turcu-Stiolica, A., Kamusheva, M., Bogdan, M., Tadic, I., Harasani, K., Subtirelu, M. S., ... & Petrova, G. (2021). Pharmacist's perspectives on administering a COVID-19 vaccine in community pharmacies in four balkan countries. Frontiers in public health, 9, 766146.

UNESCO (2023). UNESCO Institute for Statistics. Retrieved from: http://data.uis.unesco.org/.

United Nations Moldova (2021). COVID-19 Response and Recovery Monthly Bulletin – November 2021. Retrieved from: https://moldova.un.org/sites/default/files/2021-12/UN%20Moldova%20Covid-19%20Response%20and%20Recovery%20Monlthy%20Update-%20November_2021.pdf.

Upadhyaya, A., Koirala, S., Ressler, R., & Upadhyaya, K. (2022). Factors affecting COVID-19 mortality: an exploratory study. Journal of Health Research, 36(1), 166-175.

Viezzer, J., & Biondi, D. (2021). The influence of urban, socio-economic, and eco-environmental aspects on COVID-19 cases, deaths and mortality: A multi-city case in the Atlantic Forest, Brazil. Sustainable Cities and Society, 69, 102859.

Ward Jr, J. H. (1963). Hierarchical grouping to optimize an objective function. Journal of the American statistical association, 58(301), 236-244.

Wildman, J. (2021). COVID-19 and income inequality in OECD countries. The European Journal of Health Economics, 22, 455-462.

World Bank (2022). Universal Health Coverage Global Monitoring Data – 2021. Retrieved from: https://datacatalog.worldbank.org/search/dataset/0060802.

World Bank (2023a). Climate Change Knowledge Portal. Retrieved from: https://climateknowledgeportal.worldbank.org/. Accessed on 2 November 2023.

World Bank (2023b). Universal Health Coverage Global Monitoring Data – 2021 (updated 18 January 2023). Retrieved from: https://datacatalog.worldbank.org/search/dataset/0060802/Universal-Health-Coverage-Global-Monitoring-Data---2021.

World Bank (2024). World Bank Open Data. Retrieved from: https://data.worldbank.org/.

World Bank Poverty and Inequality Platform (2023) – with major processing by Our World in Data. “Share of population below 50% of median income or consumption – World Bank”. Retrieved from: https://ourworldindata.org/grapher/relative-poverty-share-of-people-below-50-of-the-median.

World Health Organization (2023). The Global Health Observatory. Retrieved from: https://www.who.int/data/gho/data/indicators.

Wu, C., & Qian, Y. (2022). The gender peak effect: Women are most vulnerable to infections during COVID-19 peaks. Frontiers in public health, 10, 937179.

Wu, Y., Jing, W., Liu, J., Ma, Q., Yuan, J., Wang, Y., Du, M., & Liu, M. (2020). Effects of temperature and humidity on the daily new cases and new deaths of COVID-19 in 166 countries. Science of The Total Environment, 729, 139051.

Xie, L., Yang, H., Zheng, X., Wu, Y., Lin, X., & Shen, Z. Medical resources and coronavirus disease (COVID-19) mortality rate: Evidence and implications from Hubei province in China. PLOS ONE, 16(1), e0244867.

Xu, S., Huang, R., Sy, L. S., Glenn, S. C., Ryan, D. S., Morrissette, K., ... & Qian, L. (2021). COVID-19 vaccination and non–COVID-19 mortality risk—seven integrated health care organizations, United States, December 14, 2020–July 31, 2021. Morbidity and Mortality Weekly Report, 70(43), 1520.

Zintel, S., Flock, C., Arbogast, A. L., Forster, A., von Wagner, C., & Sieverding, M. (2023). Gender differences in the intention to get vaccinated against COVID-19: a systematic review and meta-analysis. Journal of Public Health, 31(8), 1303-1327.

Appendix A

Table A1. Pairwise correlations matrix between control variables.

	AGE	FEM	PD	URB	DEM	POV	TOUR	HUM	RAIN	TEMP	ALC	OBES	SMOK	GERD
AGE	1													
FEM	0.2237	1												
PD	-0.1485	0.1177	1											
URB	-0.1353	0.1389	0.1175	1										
DEM	-0.1581	0.5	0.1215	0.2578	1									
POV	0.1036	0.2189	0.0457	0.1181	0.0023	1								
TOUR	-0.328	0.1463	0.1017	0.2062	0.3595	0.1521	1							
HUM	-0.2019	0.1757	-0.1435	0.2372	0.4485	-0.3235	0.0162	1						
RAIN	-0.3292	0.2017	-0.1271	0.0914	0.1	0.246	**0.5367**	0.1704	1					
TEMP	-0.1732	-0.0058	**0.6715**	-0.0903	0.0598	0.1293	0.3544	-0.4316	0.0689	1				
ALC	0.2519	**0.6723**	0.0018	0.1392	**0.5068**	-0.0741	0.0749	0.4053	-0.0633	-0.1632	1			
OBES	0.2588	-0.0191	0.1409	0.4825	-0.1674	0.2947	0.0434	-0.2262	-0.0545	0.1591	0.0023	1		
SMOK	0.3657	0.1734	0.0496	-0.4201	-0.2577	0.372	-0.0551	**-0.5419**	-0.0826	0.2505	-0.0282	0.0702	1	
GERD	-0.1931	0.4709	0.0031	0.58	0.4954	-0.0611	0.1696	0.4693	0.0749	-0.3086	0.3868	0.0801	-0.3838	1

Notes: Correlations higher than 0.5 (in absolute value) were made bold. Before carrying on correlations, the variables were log-transformed.

Table A2. Pairwise correlations matrix between explanatory variables.

	PHARM	HPER	HEXP	OOP	UHC	VR_{doses}	VR_{fully}	OB_S	ICUs_S
PHAR	1								
HPER	0.3919	1							
HEXP	0.5819	**0.7089**	1						
OOP	-0.4386	-0.5628	**-0.8578**	1					
UHC	0.4822	0.6885	**0.8851**	**-0.7515**	1				
VR_{dose}	0.6417	0.5302	**0.7835**	-0.6051	**0.8119**	1			
VR_{fully}	0.6947	0.5442	**0.8097**	-0.6393	**0.7915**	**0.9766**	1		
OB_S	-0.5787	-0.5806	**-0.8175**	0.4969	**-0.8023**	**-0.7928**	**-0.7967**	1	
ICUs_S	-0.625	-0.4306	**-0.7116**	0.4659	-0.6276	**-0.7394**	**-0.7718**	**0.7728**	1

Notes: Correlations higher than 0.7 (in absolute value) were made bold. Before carrying on correlations, the variables were log-transformed.

Appendix B

Table B1. The optimal number of clusters obtained using the "NbClust" package.

	Index	Index	Index	Index	Index	Index
	KL	CH	Hartigan	CC	Scott	Marriot
Value	1.936	16.46	5.166	1.229	63.61	3775308944
Clusters (N)	3	3	3	15	3	3
	TrCovW	TraceW	Friedman	Rubin	Cindex	DB
Value	963.5	24.53	9.675	-0.0879	0.3871	0.8894
Clusters (N)	3	3	15	3	2	15
	Silhouette	Duda	PseudoT2	Beale	Ratkowsky	Ball
Value	0.3025	0.6932	12.39	1.711	0.3756	53
Clusters (N)	15	2	2	3	3	3
	PtBiserial	Gap	McClain	Gamma	Gplus	Tau
Value	0.5078	-0.4624	0.6043	0.9298	1.818	122.5
Clusters (N)	5	2	2	15	15	3
	Dunn	SDindex	SDbw			
Value	0.446	1.29	0.1607			
Clusters (N)	15	7	15			