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A beta mixed model approach for analyzing country-level risk and protective factors of COVID-19 death rates in Europe

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ABSTRACT

Although personal health and demographic factors affect COVID-19 death rates, it is also important to examine country-level factors such as healthcare capacity, vaccination coverage, and economic conditions. This study investigates COVID-19 death rates in European countries from January 2020 to August 2023 using a beta mixed-effects model. The main predictors are vaccination rate, gross domestic product (GDP), number of hospital beds, and the share of the population aged 65 and above. The results show that mortality first increases in a linear pattern and then decreases in a quadratic pattern over time. Higher vaccination rates and stronger economies are linked to lower death rates, while a larger elderly population is linked to higher death rates. These findings highlight important national-level risk and protective factors for COVID-19 and offer useful guidance for public health planning and policy decisions.

1. Introduction

The Novel Coronavirus, which originated in December 2019 in Wuhan, China, is one of the most dangerous viruses in human history. This deadly virus, known as COVID-19, affected almost every country in the world. More than 500 million people have been infected with this deadly virus that has killed more than 600 million people until the end of 2022 (WHO, 2023). The public health emergency created by this terrible virus was unparalleled compared to other viruses in human history, raising global concern to minimize the infectious and death rates of COVID-19 (Wu et al., 2020). Researchers and scientists have been continuously working to find ways to minimize the infection and death rates of COVID-19. Despite ongoing efforts, persistent infection underscores the crucial need to understand the risk and protective factors of COVID-19 for effective prevention and management in infected individuals (Zhang et al., 2023). In light of current evidence, the development of vaccines is a crucial step toward preventing both COVID-19 infections and deaths (Mohammed et al., 2022). However, pre-existing health conditions such as diabetes, high blood pressure, and obesity make the situation riskier, amplifying the likelihood of both infection and death (Zhou et al., 2020). Although understanding individual-level risk factors of COVID-19 infection and death is crucial to planning interventions, it is equally important to explore country-level factors, including the economy, healthcare facilities, and population structure, to effectively address and control COVID-19 infection and death rates (Allel et al., 2020; Bam, 2023). Identifying and systematically examining the association of country-level factors with COVID-19 infection and fatality rates is crucial to developing strategies to prevent and mitigate adverse outcomes of COVID-19.

Although COVID-19 has affected countries worldwide and resulted in millions of fatalities, Europe has been among the hardest-hit regions (Pillai et al., 2020). Despite relatively strong healthcare systems and economic resources, European countries have faced significant challenges, experiencing particularly high rates of infection and death. As of January 1, 2024, approximately 253 million people in Europe had tested positive for COVID-19, with about 2 million deaths attributed to the virus (WHO, 2023). In Asia, where the pandemic first emerged, around 221 million people were infected, and roughly 1.6 million lives were lost (WHO, 2023). When comparing infection and fatality rates relative to population

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size, Europe has been the region most severely affected. Thus, Europe is a critical region to study because, despite advanced healthcare and resources, it experienced some of the highest COVID-19 infection and death rates worldwide.

Several previous studies have analyzed country-level risk factors of COVID-19 deaths across Europe (Aboelnaga et al., 2023; Allel et al., 2020; Jabłońska et al., 2021; Lupu and Tiganasu, 2022). However, despite COVID-19 death rates being fractional and naturally bounded between 0 and 1, existing research has not employed models specifically designed to handle bounded outcomes while accounting for the correlated structure of the data. Recognizing the bounded and correlated nature of COVID-19 death rates, as well as the importance of examining country-level risk and protective factors in a region with high mortality, this study investigates the determinants of COVID-19 death rates using a beta mixed-effects model, a widely applicable approach for analyzing bounded and correlated outcomes.

1.1. Risk factors of COVID-19 deaths

COVID-19 mortality is influenced by both individual- and country-level risk factors. Individual-level factors, such as older age, male gender, and comorbidities (e.g., cardiovascular disease, obesity, diabetes, and hypertension), are associated with an increased risk of COVID-19 death, whereas vaccination and adequate nutrition serve as protective factors (Cai et al., 2020; Liu et al., 2020; Zhou et al., 2020; Zhang et al., 2023). At the country level, favorable conditions—including stronger economies, higher-quality healthcare systems, and broader vaccination coverage—contribute to reducing death rates, while a larger share of elderly populations and adverse environmental conditions are linked to elevated fatality rates (Hamidi et al., 2020; Jabłońska et al., 2021; Liang et al., 2021; Lupu and Tiganasu, 2022; Sobczak and Pawliczak, 2022). These findings underscore the multi-layered nature of COVID-19 risk and highlight the importance of examining country-level determinants along with individual-level factors.

Age is a key determinant of COVID-19 outcomes at both the individual and country levels, as consistently demonstrated in previous studies (Liu et al., 2020; Masrizal et al., 2023; Zhang et al., 2023). At the individual level, older adults face a substantially higher risk of death compared to younger individuals (Liang et al., 2021; Zhang et al., 2023). At the country level, studies focusing on Europe have reported a positive association between the proportion of elderly individuals and COVID-19 death rates (Lupu and Tiganasu, 2022; Moustakidis et al., 2022), whereas research outside Europe, such as in the United States, has not found a significant association (Hamidi et al., 2020). Taken together, these findings underscore age as a critical risk factor for COVID-19 mortality at both the individual and country levels, although some variation across studies suggests that contextual factors may influence this relationship.

Economic indicators, particularly GDP, have been examined in numerous studies as predictors of COVID-19 death rates, yet the findings remain inconsistent (Abbasi et al., 2025). In studies focusing on European Union nations, some reported no significant association between GDP and death rates (Mattiuzzi et al., 2021; Lupu and Tiganasu, 2022), whereas others observed positive (Wildman, 2021) or negative associations (Pizzato et al., 2024). These discrepancies may reflect differences in statistical approaches, study design, data quality, and contextual factors. On the one hand, higher GDP can strengthen healthcare infrastructure, education, and public health systems, potentially lowering mortality (Rahman, 2011); on the other hand, it may drive urbanization and population density, facilitating disease transmission (Glaeser, 2011). Although opinions differ on the role of GDP in death rates, stronger economic systems are generally preferable for controlling the spread and fatality of infectious diseases (Rahman, 2011). Taken together, these findings suggest that GDP is a potentially important country-level determinant of COVID-19 mortality, though its effect may vary depending on contextual factors and the choice of statistical models.

Healthcare capacity is a key protective factor in infectious disease outbreaks, commonly measured by hospital bed availability. Existing research examining hospital beds as a predictor of COVID-19 death rates has produced mixed results. Within Europe, some studies reported no significant association between hospital bed availability and COVID-19 death rates (Mattiuzzi et al., 2021), whereas others found a positive association (Ferrara et al., 2022). Outside Europe, analyses across 168 countries observed no significant association (Canatay et al., 2021), while research in U.S. metropolitan counties found that greater hospital and ICU bed availability was linked to lower death rates (Hamidi et al., 2020). Despite mixed findings, adequate hospital bed capacity is preferable to shortages, and hospital bed availability should not be considered a risk factor; it is, without a doubt, a protective factor for COVID-19 and other infectious diseases.

The development of COVID-19 vaccines represents a critical milestone in controlling both infection and death rates. Recent studies have examined the relationship between overall vaccination coverage and COVID-19 fatality (Hoxha et al., 2023; Jabłońska et al., 2021; Liang et al., 2021; Mattiuzzi et al., 2021). The findings of Hoxha et al. (2023) and Mattiuzzi et al. (2021) indicated that higher vaccination rates are linked to marked reductions in both COVID-19 transmission and deaths. Nonetheless, disparities in vaccination coverage exist across countries and between rural and urban areas (Wang et al., 2023). While individuals who receive booster doses typically do not require additional vaccination in the short term (Kirsebom et al., 2022), vaccine effectiveness is

lower against emerging variants such as Omicron compared to earlier strains (Barouch, 2022). Together, these findings underscore vaccination as a key protective factor against COVID-19 mortality, highlighting the importance of monitoring coverage and effectiveness across populations and variants.

1.2. Rationale and objectives of the study

Europe has been one of the continents most severely affected by COVID-19 mortality. Several studies have investigated the association between individual- and country-level risk factors and COVID-19 fatalities both within and outside Europe. However, many of these studies have not accounted for the proportional nature of death rates, which are restricted to the unit interval (0, 1), or for their correlated structure. Existing studies within and outside Europe have used a variety of approaches, including linear mixed models (Hamidi et al., 2020; Verbeeck et al., 2023; Yanez et al., 2020), negative binomial regression (Allel et al., 2020; Chaudhry et al., 2020), and multiple linear regression (Mattiuzzi et al., 2021). When outcomes are proportions bounded within (0, 1), normal linear models are not appropriate, as they may violate key assumptions or ignore the scale restrictions, leading to biased estimates (Ferrari and Cribari-Neto, 2004). To address this issue, Ferrari and Cribari-Neto (2004) proposed beta regression, which is specifically designed for unit-interval outcomes. Nonetheless, studies of COVID-19 mortality have rarely adopted models that properly account for this structure.

In addition, research focusing on European countries has often overlooked the longitudinal nature of mortality data (Mattiuzzi et al., 2021). Ignoring time dependence can bias estimates and reduce statistical power. Although some studies, both within and outside Europe, have incorporated random effects, they have typically relied on general linear mixed models with transformations of death rates (Hamidi et al., 2020; McCann et al., 2022), which disregarded the bounded outcome scale.

Thus, this study investigates the association between COVID-19 death rates and country-level risk and protective factors in European countries by employing a beta mixed-effects model that accounts for both the longitudinal and bounded nature of the data. Specifically, the study seeks to answer the following questions:

- Research question 1: Does the trend in COVID-19 death rates change over time across European countries?
- Research question 2: Are hospital bed availability, GDP, the proportion of the population aged 65 and older, and vaccination rates associated with COVID-19 death rates in Europe?

Although several models have been developed for analyzing bounded outcome measures, only a few can simultaneously account for both the bounded nature and the correlated structure of the data. The unit-Lindley mixed-effects model is one of such approaches. In this study, we employ a beta mixed-effects model and compare its performance with the unit-Lindley mixed-effects model.

2. Methods

2.1. Source of data

The data used in this study were accessed through Our World in Data. These data were compiled by Our World in Data (Mathieu et al., 2020) with the collaboration of the COVID-19 data repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU), the World Health Organization (WHO), the United Nations (UNO), and other country-level data centers. The participants (subjects) of the study are all countries in Europe that have at least one mortality case from January 1, 2020, to August 31, 2023, and for which complete data are available on death rates and other predictor variables, including gross domestic product, hospital bed count, and the proportion of the population aged 65 years and older. Based on the specified inclusion and exclusion criteria, 38 countries in Europe are considered for this study.

2.2. Variables

Death rates of COVID-19 were measured as deaths per 10,000 people. The variable 'Months' is the number of months between January 1, 2020, and August 31, 2023. There are 0 to 45 months (0 is the baseline time). The hospital beds per 1,000 were considered as a potential predictor variable of COVID-19 death rates. Another potential predictor of death rates considered in this study was the percentage of people 65 years and older within the country. This study also includes the GDP as a predictor variable of death rates due to COVID-19 to investigate how a nation's economy influences death rates. Another crucial predictor variable considered for COVID-19 death rates was the vaccination rate per 100 individuals, representing the percentage of fully vaccinated people in each country.

2.3. Statistical models

If the response variable is constrained between 0 and 1, beta regression, introduced by Ferrari and Cribari-Neto (2004), is commonly employed as a suitable method. Although COVID-19 death rates fall within the range of 0 and 1, their correlation poses a challenge, as beta regression is typically designed for analyzing independent responses. Thus, there is a need for generalized linear models tailored to accommodate bounded and correlated observations of response variables. Several viable options exist for modeling correlated and bounded response variables, including the beta mixed model (Bonat et al., 2015), the unit-gamma mixed model (Petterle et

al., 2023), and the unit-Lindley mixed model (Akdur, 2021). The unit-Lindley mixed model has only one parameter, making it less suitable for handling complex data structures such as COVID-19 mortality. The unit-gamma mixed model, which models both the mean and precision as outcomes, can be overly complex for such applications. In addition, the original unit-gamma model paper contained errors that were later corrected, which reduces our motivation to apply this model. By contrast, the beta mixed model is widely used, modeling the mean as the outcome and treating precision as a nuisance parameter. It effectively handles complex data while remaining relatively simple to implement using packages such as glmmTMB. Therefore, for this study, we propose the beta mixed-effects model and compare its performance with the unit-Lindley mixed model.

2.4. The beta mixed model

The beta regression model provides an appropriate statistical approach for continuous outcomes bounded between 0 and 1, such as proportional measures. Let $Y \sim B(\mu\phi, (1-\mu)\phi)$ represent a random variable that follows a beta distribution, with its probability density function expressed in terms of the mean μ and the precision parameter ϕ, as follows:

$$f(y;\mu,\phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} \times y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1}, \quad 0<y<1, \quad \phi>0, \quad 0<\mu<1. \tag{1}$$

The mean of the distribution is $E(Y) = \mu$ and the variance is $Var(Y) = \frac{\mu(1-\mu)}{1+\phi}$. If $Y_i \sim B(\mu_i\phi, (1-\mu_i)\phi)$, the following beta regression model was presented by Ferrari and Cribari-Neto (2004) by applying a suitable link function.

$$g(\mu_i) = x_i^T \beta, \tag{2}$$

where, β denotes a vector of regression coefficients and x_i is a vector of covariates.

For the link function $g(\cdot): (0,1) \to \Re$, we applied the logit link function $\text{logit}(\mu_i) = g(\mu_i) = \log\frac{(\mu_i)}{1-\mu_i}$. The regression model described in Eq. 2 required independent observations, but COVID-19 death rates are not independent. Therefore, it is necessary to add a latent random effects term to the fixed effects model $g(\mu_i) = x_i^T\beta$ to properly account for the dependency structure of the data. Denote y_{it} as the observed death rates from COVID-19 in the country i at time t, where $t = 1,2,\ldots,n_i$ and $i = 1,\ldots,q$. In this case, y_i denotes an n_i dimensional vector of the death rates from COVID-19 from the ith country. Let b_i be a q-dimensional random effect. By adding the random effect to the model $g(\mu_i) = x_i^T\beta$, the mixed beta model given by Bonat et al. (2015) is:

$$g(\mu_{ij}) = \log\left(\frac{\mu_{ij}}{1-\mu_{ij}}\right) = x_{ij}^T\beta + z_{ij}^T b_i. \tag{3}$$

In Eq. 3, x_{ij} is the design vector of fixed effects, z_{ij} is the design vector of random effects, and β is the vector of regression coefficients of fixed effects. The model specification assumes the distribution of random effects should be multivariate normal, $b_i \sim N(0,\Sigma)$. Parameter estimation of the beta mixed model was performed in R using the 'glmmTMB' package (Brooks et al., 2017). Because $\text{logit}(\mu_{ij}) \neq x_{ij}^T\beta$, marginal effects are estimated by integrating the joint distribution of $[Y, b]$ over the random effect. The log-likelihood of the ith country is given by:

$$f_i(y_i|\beta,\Sigma,\phi) = \int \prod_{j=1}^{n_i} f_{ij}(y_{ij}|b_i,\beta,\phi) f(b_i|\Sigma)\, db_i. \tag{4}$$

Assuming the independence among countries, the full likelihood is:

$$L(\beta,\Sigma,\phi) = \prod_j^q f_i(y_i|\beta,\Sigma,\phi). \tag{5}$$

Evaluating Eq. 5 requires solving the integral q times. Since a manual solution is not feasible, the mfx package in R was used to perform the calculations.

In the following section, we present a mixed beat model utilized to explore the association between explanatory variables (including time, vaccination rate, hospital bed count, the proportion of elderly people, and GDP) and COVID-19 death rates.

2.4.1. Time-only model

In this model, we only add the time as an independent variable to know the time effect on the COVID-19 death rates. The model is specified as follows:

$$g(\mu_{ij}) = (\beta_0 + b_{i0}) + (\beta_1 + b_{i1}) \cdot \text{Months}_{ij} + \beta_2 \cdot \text{Months}_{ij}^2, \tag{6}$$

In Eq. 6, $b_i = \begin{bmatrix} b_{i0} \\ b_{i1} \end{bmatrix} \sim N(0,\Sigma), \Sigma = \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{01} & \sigma_1^2 \end{bmatrix}$,

$g(\mu_{ij})$ is a function of the fixed effects β_0 and β_1, β_2 and the random effects b_{i0} and b_{i1}.

2.4.2. Random intercept model

In this model, a random intercept was included alongside the fixed effects, specified as follows:

$$g(\mu_{ij}) = (\beta_0 + b_{i0}) + \beta_1 \cdot \text{Months}_{ij} + \beta_2 \cdot \text{Months}_{ij}^2 + \beta_3 \cdot \text{Vaccine}_{ij} + \beta_4 \cdot \text{HS}_i + \beta_5 \cdot \text{GDP}_i + \beta_6 \cdot \text{Age}_i + \beta_7 \cdot \text{Vaccine}_{ij} : \text{Months}_{ij} + \beta_8 \cdot \text{Vaccine}_{ij} : \text{Months}_{ij}^2. \tag{7}$$

In Eq. 7, $b_{i0} \sim N(0,\sigma_0^2)$, $g(\mu_{ij})$ is a function of the fixed effects $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$, and the random effect b_{i0}. In this context, "Months" represents the number of months, "Vaccine" denotes the proportion of fully vaccinated individuals in the country, "HS" corresponds to the hospital bed count per 1000, "GDP" signifies the gross domestic product, and "Age" indicates the proportion of elderly individuals aged 65 and over within the

country, Vaccine_{ij}: Months_{ij}, and Vaccine_{ij}: Months_{ij}^2 are interaction effects of linear and quadratic effect of time with vaccination rate.

2.4.3. Random slope model 1

In this model, we have incorporated a random slope, capturing individual variability in the rate of change over time, as presented below:

$$g(\mu_{ij}) = (\beta_0 + b_{i0}) + (\beta_1 + b_{i1}) \cdot \text{Months}_{ij} + (\beta_2 + b_{i2}) \cdot \text{Vaccine}_{ij} + \beta_3 \cdot \text{Months}_{ij}^2 + \beta_4 \cdot \text{HS}_i + \beta_5 \cdot \text{GDP}_i + \beta_6 \cdot \text{Age}_i + \beta_7 \cdot \text{Vaccine}_{ij}: \text{Months}_{ij} + \beta_8 \cdot \text{Vaccine}_{ij}: \text{Months}_{ij}^2. \quad (8)$$

In Eq. 8, $b_i = \begin{bmatrix} b_{i0} \\ b_{i1} \end{bmatrix} \sim N(0, \Sigma), \Sigma = \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{01} & \sigma_1^2 \end{bmatrix}$, $g(\mu_{ij})$ is a function of the fixed effects $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$, and the random effects b_{i0}, b_{i1}.

2.4.4. Random slope model 2

In this model, we have incorporated a random slope, capturing individual variability in the rate of change over time, along with a random vaccine effect, accounting for subject-specific responses to the time-dependent covariate 'vaccine,' as presented below:

$$g(\mu_{ij}) = (\beta_0 + b_{i0}) + (\beta_1 + b_{i1}) \cdot \text{Months}_{ij} + (\beta_2 + b_{i2}) \cdot \text{Vaccine}_{ij} + \beta_3 \cdot \text{HS}_i + \beta_4 \cdot \text{GDP}_i + \beta_5 \cdot \text{Age}_i. \quad (9)$$

here, $b_i = \begin{bmatrix} b_{i0} \\ b_{i1} \\ b_{i2} \end{bmatrix} \sim N(0, \Sigma), \Sigma = \begin{bmatrix} \sigma_0^2 & \sigma_{01} & \sigma_{02} \\ \sigma_{01} & \sigma_1^2 & \sigma_{12} \\ \sigma_{02} & \sigma_{12} & \sigma_2^2 \end{bmatrix}$, $g(\mu_{ij})$ is a function of the fixed effects $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$, and the random effects b_{i0}, b_{i1}, b_{i2}.

2.5. Data analysis plan

The data analysis commenced with meticulous data management. Due to data unavailability, certain countries such as Vatican City, Jersey, Monaco, Liechtenstein, Andorra, etc., were excluded. Consequently, a total of 38 countries were considered for this study. After the exclusion of certain countries, we transformed daily death rates into monthly death rates using the dplyr package in R programming. Since the beta mixed model requires a response variable strictly confined within the interval of 0 and 1. There are some 0s in the response variable. Therefore, we employed the corrections proposed by Verkuilen and Smithson (2012). According to their recommendations, when the response variable does not fall within the closed interval of 0 and 1, it should be adjusted using the following relationship:

$$Y_{\text{new}} = \frac{Y_{\text{old}}(N-1) + 0.5}{N},$$

where, Y_{new} is the transferred response variable, Y_{old} is the old response variable, and N is the sample size. After finalizing data management, data analysis began by exploring descriptive summary measures for each variable and visualizing response variables and vaccination rates over time, to provide a comprehensive overview. These visuals provide some guidelines for deciding on a suitable model.

In this study, we employed the beta-mixed model, as outlined in the model section. Our analysis of visualizations revealed a discernible non-linear trend in mortality rates. To capture this complexity, we integrated both linear and non-linear temporal elements into the model, alongside various fixed and random effects. Our modeling process unfolded in stages: We began with a time-only model, progressively incorporating a random intercept model, a random slope model featuring a random slope, and ultimately integrating vaccination rate as a time-dependent variable into the model. Parameter estimation for all models was conducted using the 'glmmTMB' package in R. To assess model performance, we considered both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), with lower values indicating better-fitting models. The proposed beta mixed-effects model was then compared to a unit-Lindley mixed model. Model adequacy was further evaluated through residual analysis using the DHARMa package (Hartig, 2020) in R. The package simulates scaled residuals, which are expected to follow a uniform distribution between 0 and 1. We produced both a QQ plot and a plot of scaled residuals versus fitted values. The QQ plot closely follows the central diagonal line, and the absence of patterns in the residuals versus fitted values plot indicates an adequate model fit.

3. Results

Table 1 summarizes the descriptive statistics of key variables. On average, the monthly death rate was 0.24 per 10,000 (SD=0.0759), the infectious rate was 2.77 per 10,000 (SD=5.81), the vaccination rate was 18.02% (SD=26.41), the hospital bed count was 4.91 per 1,000 (SD=1.79), the proportion aged 65 and older was 17.78% (SD=2.82), and GDP was USD 33,156 (SD=17,309).

Figs. 1 and 2 and Table 2 illustrate spaghetti plots showing COVID-19 death rates and infection rates per 10,000 people in Europe, respectively. According to the plots, Bosnia and Herzegovina, Slovenia, Romania, Bulgaria, and Hungary exhibit higher death rates, while the Netherlands, Iceland, Latvia, and Denmark show higher infection rates. For visualization purposes, we classified hospital bed counts into three categories based on quartiles. Countries with a hospital bed count per 1000 below the first quartile were labeled as "lower," those between the first and third quartiles were classified

as "middle," and those above the third quartile were designated as "upper." Figs. 3 and 4 present the interaction plot of death rates across hospital bed count quartiles and the spaghetti plot of vaccination rates, respectively. Fig. 3 indicates that countries in the upper quartile of hospital bed availability experienced higher death rates compared with those in the middle and lower quartiles. Fig. 4 highlights that Malta, Italy, Belgium, Ireland, and France have comparatively higher vaccination rates.

Table 1: Summary statistics

Variables	Sample size	Mean	Median	Min	Max	SD
Death rate	1710	0.022	0.008	0.00	0.24	0.076
Infectious rate	1710	2.77	0.810	0.00	73.09	5.81
Vaccination rate	1710	18.02	2.400	0.00	88.18	26.41
Hospital beds count	1710	4.90	4.505	2.22	8.80	1.79
Age	1710	17.78	18.680	10.86	23.02	2.82
GDP	1710	33156	30778	5190	94278	17309

Table 2: Marginal effects

Parameters	Estimate (df/dx)	SE B	z	p
Month 1	0.0027	0.0004	17.9600	0.0000***
Month 2	-0.00006	0.000003	-19.3900	0.0000***
Hospital beds count	0.0006	0.0002	2.6600	0.0077*
Age	0.0006	0.0001	3.9900	0.0000***
GDP	-0.00001	0.000002	-5.5500	0.0000***
Vaccine	-0.0008	0.00002	-3.7100	0.0002***
Time1: Vaccine	0.00004	0.00001	3.1300	0.0017***
Time2: Vaccine	-0.000006	0.0000007	-2.5200	0.0116*

*: $p < 0.05$; ***: $p < 0.001$

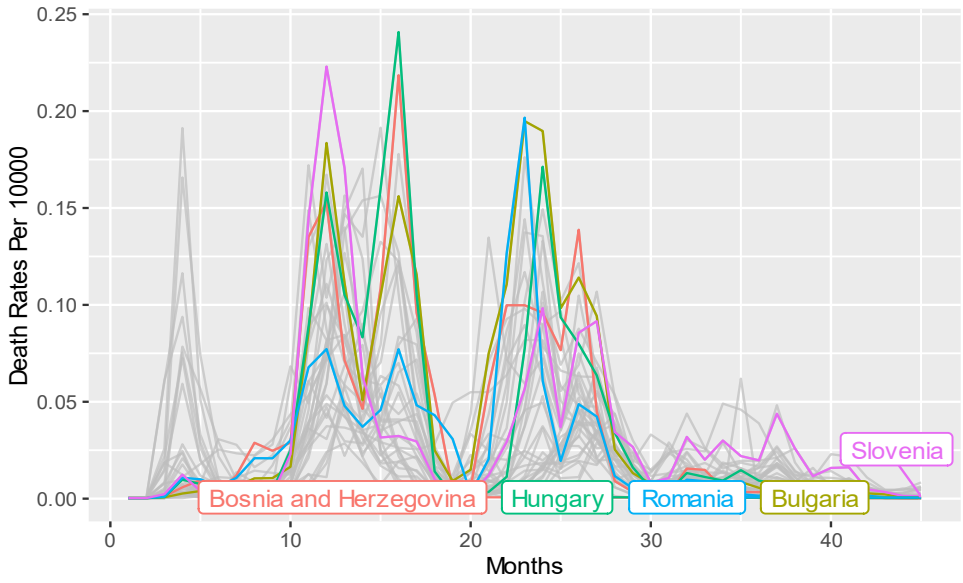

Fig. 1: Spaghetti plot of death rates

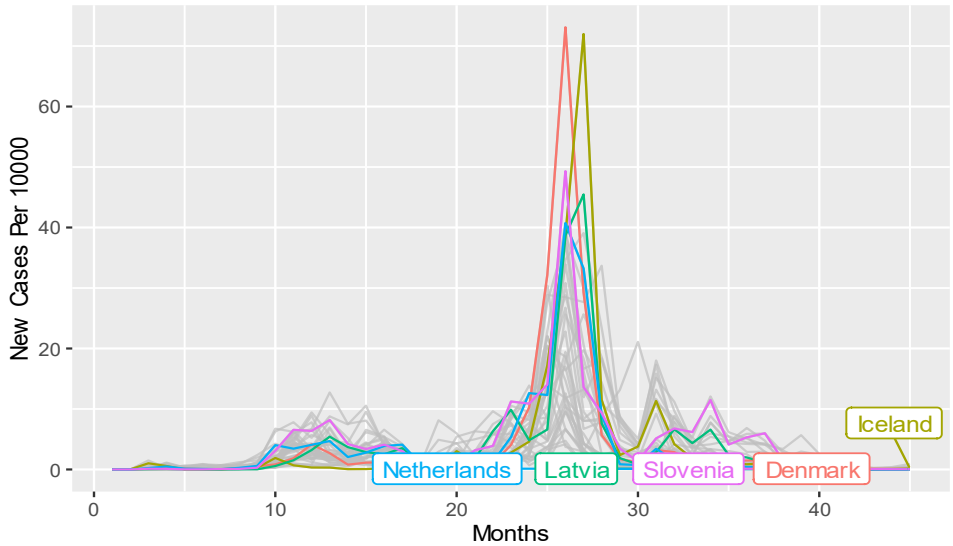

Fig. 2: Spaghetti plot of infectious rates

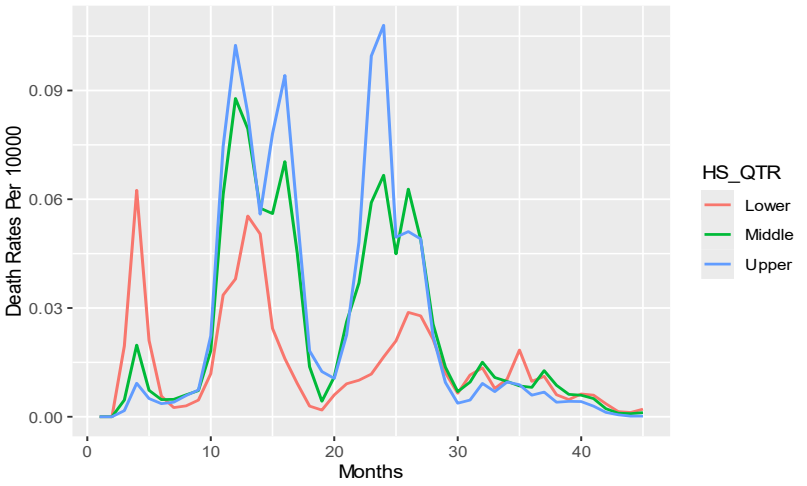

Fig. 3: Interaction plot of death rates across hospital bed count quartiles

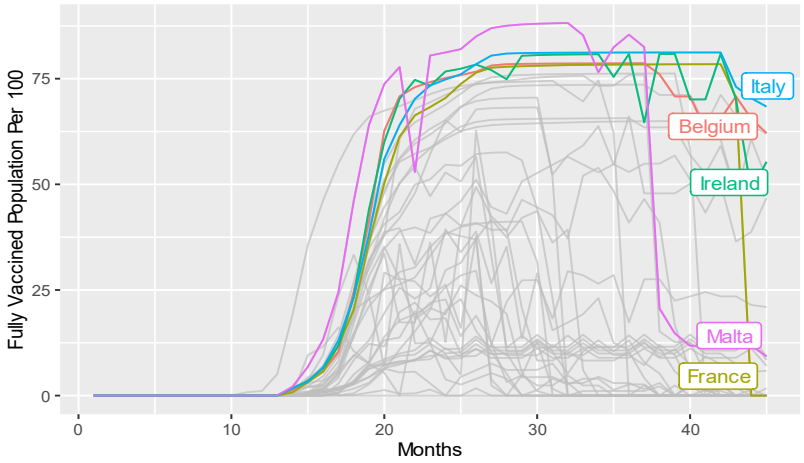

Fig. 4: Spaghetti plot of vaccination rates

Because of the nonlinear trend observed in COVID-19 death rates (Fig. 1), a quadratic beta mixed model was utilized to analyze death rates. Table 3 presents the results of the parameter estimation of all proposed models. Model 1 (time-only model) shows that linear and quadratic time trends are statistically significant. To better explain variation in death rates, the model was expanded to include hospital bed count per 1,000, the proportion of people aged 65 and older, GDP, vaccination rate, and the interaction between time and vaccination rate. To address the research questions, AIC and BIC criteria were used for model selection. Of the four models evaluated, Model 3—a random slope model incorporating time-independent vaccination rates—demonstrated the best fit (Table 3) and was subsequently used for analysis. Model adequacy was assessed using residual diagnostics. Quantile–quantile plots of scaled residuals (Fig. 5) and plots of scaled residuals versus predicted values (Fig. 6) revealed no substantial departures from the model assumptions. To further support the results of Tables 2 and 3, predicted plots are presented in Fig. 7.

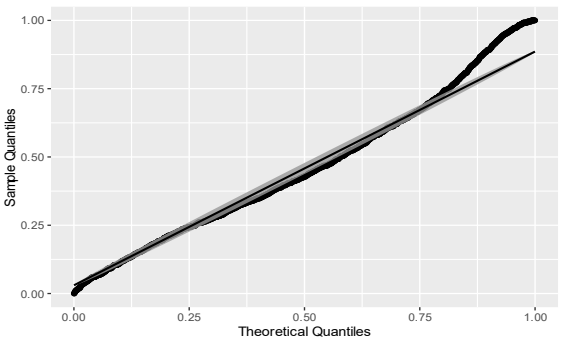

Fig. 5: QQ plot of scaled residuals

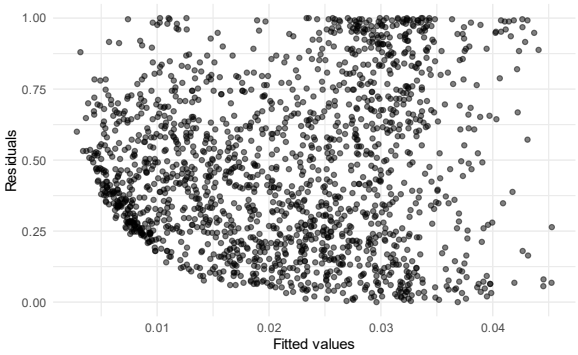

Fig. 6: Plot of scaled residuals vs. fitted values

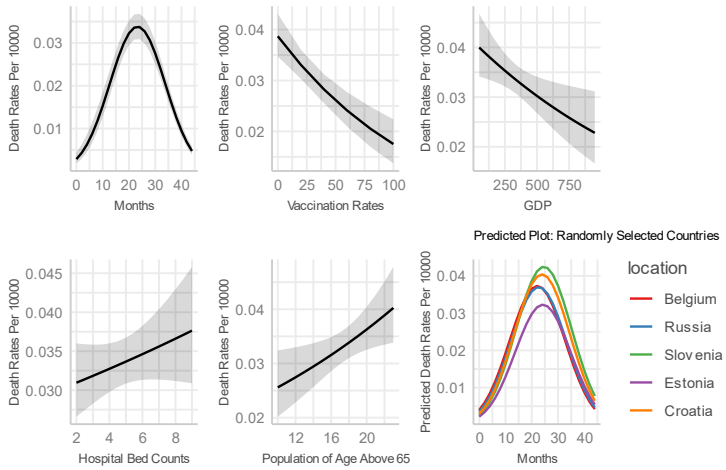

Fig. 7: Predicted plots: Death rates vs. predictors (first five) and death rates vs. months for selected countries (bottom right)

Table 3: Results of parameter estimation of all models

Models	Parameters	Estimate	SE B	95% CI		t-value	p
				LL	UL		
Model 1	Intercept	-4.8200	0.0930	-5.0100	-4.9700	-51.5100	0.0000***
	Month 1	0.1370	0.0068	0.1200	0.1500	20.2000	0.0000***
	Month 2	-0.0030	0.0001	-0.0040	-0.0030	-22.7300	0.0000***
	σ_0^2	0.1540					
	σ_1^2	0.00015					
	ρ_{01}	-0.8200					
	φ	37.8000					
	AIC	-10695.1					
	BIC	-10657.0					
Model 2	Intercept	-5.3500	0.2860	-5.9100	-4.7900	-18.6900	0.0000***
	Month	0.1420	0.0080	0.1420	0.1740	18.8800	0.0000***
	Month 2	-0.0038	0.0002	-0.0042	-0.0034	-19.6900	0.0000***
	Hospital beds count	0.0320	0.0216	-0.0100	0.0740	1.4900	0.1361
	Age	0.0300	0.0135	0.0043	0.0570	2.2800	0.0226*
	GDP	-0.0007	0.00023	-0.0011	-0.0002	-2.9200	0.0034**
	Vaccine	-0.0480	0.0109	-0.0690	-0.0260	-4.3900	0.0000***
	Month 1: Vaccine	0.0026	0.0008	0.0011	0.0040	3.4800	0.0005***
	Month 2: Vaccine	-0.000034	0.00001	-0.00006	-0.000009	-2.6600	0.0077**
	σ_0^2	0.03645					
	φ	37.9000					
	AIC	-10723.6					
	BIC	-10663.8					
Model 3	Intercept	-5.5100	0.3200	-6.4100	-4.8900	-17.2470	0.0000***
	Month 1	0.1670	0.0089	0.1490	0.1842	18.7500	0.0000***
	Month 2	-0.0040	0.0002	-0.0043	-0.0036	-20.2300	0.0000***
	Hospital beds count	0.0290	0.0220	-0.0160	0.0730	1.2700	0.2028
	Age	0.0360	0.0150	0.0066	0.0650	2.4060	0.0160*
	GDP	-0.0006	0.00025	-0.0011	-0.00015	-2.5470	0.0108*
	Vaccine	-0.0501	0.0110	-0.0700	-0.0280	-4.5600	0.0000***
	Month 1: Vaccine	0.0027	0.0007	0.0012	0.0041	3.5300	0.00041***
	Month 2: Vaccine	-0.000035	0.00001	-0.00006	-0.00001	-2.6610	0.0077**
	σ_0^2	0.1447					
	σ_1^2	0.00018					
	ρ_{01}	-0.8500					
	φ	39.8000					
	AIC	-10744.0					
	BIC	-10673.2					
Model 4	Intercept	-5.4000	0.3470	-6.4100	-4.8900	-15.5300	0.0000***
	Month 1	0.1660	0.0090	0.1490	0.1842	18.7500	0.0000***
	Month 2	-0.0040	0.0002	-0.0043	-0.0036	-20.0800	0.0000***
	Hospital beds count	0.0280	0.0237	-0.0160	0.0730	1.1800	0.2366
	Age	0.0310	0.0155	-0.0066	0.0650	2.0280	0.0426*
	GDP	-0.0007	0.00027	-0.0011	-0.00015	-2.7600	0.0057**
	Vaccine	-0.0490	0.0110	-0.0700	-0.0280	-4.4100	0.0000***
	Month 1: Vaccine	0.0027	0.00077	0.0012	0.0041	3.5200	0.0004***
	Month 2: Vaccine	-0.00004	0.00001	-0.00006	-0.00001	-2.6750	0.0074**
	σ_0^2	0.1380					
	σ_1^2	0.00017					
	σ_2^2	0.00002					
	ρ_{01}	-0.7600					
	ρ_{02}	-0.3600					
	ρ_{12}	-0.1700					
	φ	40.2000					
	AIC	-10741.5					
	BIC	-10654.5					

***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$

Based on the output of the random slope model, linear time is positively related to death rates, whereas the quadratic time effect is negatively related. In summary, the positive linear effect indicates that death rates increased over time, while the negative quadratic effect reflects a deceleration in this increase, leading to a peak followed by a decline. This pattern was also corroborated by the spaghetti plot of death rates over time (Fig. 1). The results presented in Table 3 show that age is positively associated with death rates, whereas GDP and vaccination rates are negatively associated. This indicates that a higher proportion of elderly individuals within a country is a risk factor for increased COVID-19 death rates. Conversely, better economic conditions and higher vaccination coverage serve as protective factors.

Furthermore, there is a significant interaction effect of time and vaccination rates on death rates. The results of parameter estimation presented in Table 3 are a combination of fixed and random effects; therefore, it is necessary to separate the fixed effects. To marginalize fixed effects from random effects, we utilized the "mfx" package in R. The resulting output is shown in Table 2. Based on the marginal effects, linear time, hospital bed count per 1,000, and age are positively associated with death rates, whereas the quadratic time effect, GDP, vaccination rate, and the interaction between quadratic time and vaccination rate are negatively associated with death rates. Only the marginal effect of hospital bed count is statistically significant, whereas the combined marginal and random effects are not. Although the marginal effect of hospital bed count is positively associated with COVID-19 mortality, this does not imply that hospital bed availability is a risk factor. The observed association may instead reflect the influence of other contextual factors. Finally, to corroborate the results of inferential findings, Fig. 7 presents predicted death rates for each predictor variable, alongside predicted random effects for selected countries.

To answer the research question of this study, we have selected the most appropriate model, Model 3. Regarding Research Question 1, the findings suggested that there is a significant change in the trend of death rates due to COVID-19 over time. This trend shows a quadratic pattern. Similarly, about Research Question 2, the country's GDP, the proportion of people 65 years and older, the vaccination rate, and the interaction effect of time and vaccination rates were identified as significant predictors of death rates due to COVID-19. The hospital bed count was only significant when considering the marginal effect. The direction of all the associations was discussed above.

Finally, the beta mixed model is further compared with the unit-Lindley mixed-effects model, which was introduced by Akdur (2021) for analyzing bounded data with correlated outcomes. The model is based on the unit-Lindley distribution proposed by Mazucheli et al. (2019) and was found to outperform the beta mixed model in some settings. However, for COVID-19 data, which are large and complex, the unit-Lindley model is not suitable and performs worse than the beta mixed model based on AIC and BIC criteria. Specifically, the AIC and BIC for the unit-Lindley mixed model were -10,249.2 and -10,231.18, respectively, whereas for the beta mixed model, they were -10,744 and -10,673.2. Overall, the unit-Lindley model is weaker than all four beta mixed models, indicating that the beta mixed model is more suitable for analyzing the COVID-19 death rate.

4. Discussion

This study provides evidence on country-level factors influencing COVID-19 fatality across Europe using a beta mixed-effects model. In contrast to previous studies that primarily relied on linear mixed models or other regression approaches (as discussed in Section 1.2.2), this study employed a model specifically designed to handle the bounded nature and correlated nature of death rates. This approach allowed us to gain clearer insights into how country-level factors affect COVID-19 outcomes across Europe.

The associations observed between the predictors and COVID-19 death rates are largely consistent with findings reported in existing research. Our results indicate that GDP serves as a potential protective factor against COVID-19 mortality, in line with the findings of Pizzato et al. (2024). In contrast, Mattiuzzi et al. (2021) and Lupu and Tiganasu (2022) did not find a significant association across European countries, likely because their models did not account for the correlated outcomes and the bounded nature of death rates. Similarly, our finding shows that the vaccination rate emerges as another potential protective factor against COVID-19 deaths, consistent with the findings of several other studies (Hoxha et al., 2023; Mattiuzzi et al., 2021). Our study also identified the proportion of elderly people as a risk factor for COVID-19 deaths, aligning with similar results explored by several other studies (Canatay et al., 2021; Moustakidis et al., 2022). While our study did not identify hospital bed count as a significant predictor of COVID-19 death rates when considering both marginal and random effects, the marginal effect alone was significant. Similarly, Mattiuzzi et al. (2021) did not find a significant association between hospital bed count and death rates in European countries, whereas Ferrara et al. (2022) reported a positive association. Outside of Europe, Canatay et al. (2021) also found no significant relationship between hospital bed count and death rates. Although previous studies and our analysis did not find a significant association between hospital bed availability and COVID-19 death rates, maintaining a higher number of hospital beds remains important to prevent shortages and ensure adequate healthcare capacity. This study identified key country-level risk and protective factors for COVID-19 outcomes, providing valuable insights for

healthcare policymakers, researchers, and academics.

5. Conclusion

This extensive analysis investigated and explored potential country-level risk factors and protective factors of COVID-19 death rates, focusing on countries on the European continent. This study concludes that death rates increase linearly and, at a certain point, begin to decrease quadratically. The study identified the vaccination rate and economic status (GDP) as potential protective factors against COVID-19, while the proportion of elderly people emerged as a risk factor for COVID-19 mortality. As other studies emphasized the amplification of vaccinations, the finding of this study also supports their conclusions by advocating for the intensification of vaccination efforts. Countries with a higher proportion of elderly people and a lower GDP are more vulnerable to COVID-19 deaths, which requires greater caution. Countries with lower GDP and larger elderly populations should prioritize and sustain vaccination efforts to reduce the risk of higher COVID-19 fatality.

5.1. Limitations

Although the study is methodologically sound and provides robust inferences, it is not without limitations. As the analysis is based on observational data, unrecognized and unmeasured confounders may still be present, and future research is needed to identify and account for them. Furthermore, due to data constraints, the analysis was limited to variables such as hospital bed count, age, GDP, and vaccination rate. Expanding the scope to include a wider range of healthcare infrastructure measures and other potentially influential country-level characteristics would provide a more comprehensive understanding.

List of abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CI	Confidence interval
CSSE	Center for Systems Science and Engineering
GDP	Gross domestic product
HS	Hospital bed count
ICU	Intensive care unit
JHU	Johns Hopkins University
LL	Lower limit
QQ	Quantile–quantile plot
SD	Standard deviation
SE B	Standard error of coefficient
UL	Upper limit
UNO	United Nations Organization
WHO	World Health Organization
ρ_{01}	Correlation between intercept and slope(time)
ρ_{02}	Correlation between intercept and slope(vaccine)
ρ_{12}	Correlation between slopes
${\sigma_0}^2$	Variance of random intercept
${\sigma_1}^2$	Variance of random slope (time)
${\sigma_2}^2$	Variance of random slope (vaccine)
φ	Precision parameter

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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