Spatial Variation of The Delay and Long-Run Effects In The Occurrence of Covid-19 Deaths Among European Countries

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Abstract

Background: Over the past two years, the COVID-19 disease has become a global problem, affecting the health systems and economies of countries throughout the world. New cases and hospitalizations associated with the disease appear to affect the number of deaths caused by coronavirus infection. COVID-19 causes a variable number of hospital deaths each day, and the projected mortality rate fluctuates according to the daily tally of new cases. Using a distributed-lag model, this study tries to quantify the influence of COVID-19 new cases on death rates in Europe.

Material and method: The "European Centre for Disease Prevention and Control" database was used to gather information on daily Covid-19 cases and deaths in 49 European nations. In the first half and second half of 2020, each of the 49 countries was fitted with the Distributed Lag Model (DLM).

Results: The European continent saw an average of 13.5 days between daily Covid-19 new cases and mortality. For the first half and second half of 2020, results from the fitting of the Distributed Lag Model showed that there was a wide range of values for mean delay and long-term effects in Europe.

Conclusion: European countries differ in terms of the mean delay and long-term impacts for the first and second half of 2020, according to the findings of the study. Understanding the time lag between new cases and deaths in the COVID-19 pandemic will help policymakers and governments use medical resources more effectively and provide better healthcare interventions that are more impactful.

Introduction

A global pandemic of COVID-19 disease began in Wuhan, China, towards the end of December of 2019 and was declared ongoing by March of the following year[1]. Over the past two years, this virus has become a global problem, harming healthcare systems and economies in a variety of countries. Early in 2020, the pandemic began to spread in Europe. When it was first discovered in the north of Italy and Spain, it quickly spread across the continent. The WHO estimates that 48,532,101 cases of coronavirus infection and 1,109,400 fatalities associated with the disease had been reported in Europe as of July 8, 2021. As a result of the high incidence of this disease, Europe has become the deadliest continent. [4, 5]

An accurate diagnosis of COVID-19 is sometimes delayed by many months, making early detection a challenge[6]. There has been a great deal of research done on the consequences of delaying the diagnosis of infectious diseases[7, 8]. Research shows that infections and the economic losses they cause might be increased by a delay in diagnosis. In addition, delays in diagnosis have been linked to a significant number of deaths. One of the most essential methods to manage COVID-19 and prevent transmission in the community and reduce mortality is to investigate the effect of delayed diagnosis [9].

It is well established that the onset of COVID-19 disease is preceded by a period of morbidity [10]. There is an incubation period associated with infectious diseases, which is the time it takes for the disease to begin to manifest itself after the initial infection has occurred. For this reason, it is important to know when a disease

is detected in an infected person, as a delay in diagnosis can directly affect the patient's death and hence the overall mortality rate [11].

There is a distinct delay between the maximum number of daily COVID-19 infections and the maximum number of daily deaths seen in several linked time-series investigations. This delay may be related to the amount of days between infection and mortality in the individuals. As infections spread, people die more slowly, and the level of care they receive can have an impact on how long it takes for them to succumb. A greater lag time is expected in nations with superior health care [12–14].

People who have been infected for a long time are recruited to die on a specific day. Therefore, comparing the number of deaths and those affected on a single day is not sufficient. Depending on the length of the lag time between diagnosis and death, the bias is minimal or large (as in COVID-19) [15].

According to research [10, 16], when a new wave of COVID-19 cases appears, hospitalizations and deaths increase, but the timing of these increases varies by nation. According to the World Health Organization (WHO), it takes between 2 and 8 weeks for a person to develop symptoms and die from an infection like Ebola. According to numerous studies, the median time between the onset of symptoms and death is either 16 or 19 days. The median time between admission and mortality in the intensive care unit was discovered to be between 7 and 12.5 days (ICU). As a result, the impact of new cases on COVID-19 deaths must be considered.

However, it is too early to tell. Only a few studies have looked at COVID-19 infections in people with various underlying illnesses, and only a few have looked at the time lag between daily COVID-19 cases and mortality. Because the daily death toll from COVID-19 changes, conventional methodologies for estimating the risk of hospital mortality are inapplicable because the daily number of new COVID-19 cases is a significant determinant. As a result, the distributed lag model is being used to anticipate the delay effect of the number of COVID-19 hospitalizations on European death rates.

Methods

Data

Data on the daily COVID-19 cases and deaths in European countries was obtained from the "**European Centre for Disease Prevention and Control**" database [20]. We used data from February 1, 2020 to December 31, 2020 since some nations began vaccination campaigns against Covid-19 in 2021. New cases of COVID-19 in European countries peaked in the first half of 2020 and then again in the second half of the year, according to a time-series analysis. The first half of 2020 and the second half of 2020 were chosen because we wanted to evaluate the healthcare systems of European countries following the first peak of the epidemic.

Data analysis

Distributed Lag Models (DLMs)

Several research in environmental health and epidemiology have examined the possibility of delayed impacts. A tool originally developed for economic modeling, Distributed Lag Models (DLMs), is commonly used to explain delayed effects. In environmental epidemiology, these models have been used widely [22–24].

In a distributed lag model, the effect of an explanatory variable X on Y appear with a delay and is distributed over time. Let Y_t be the number of COVID-19 deaths at day t ; $t = 1, \dots, T$ and X_{t-l} be the number of COVID-19 cases at day $t - l$; $l = 0, 1, \dots$, the infinite DLM can be written as follow:

$$Y_t = \alpha + \sum_{l=0}^{\infty} \beta_l X_{t-l} + \epsilon_t \quad (1)$$

Where $E(\epsilon_t) = 0$ and $\text{var}(\epsilon_t) = c$, α is intercept, β -parameters are the impacts of the changes in X_t on the expected value of Y_t . Estimation of an infinite number of β coefficients is impossible, and it is usually assumed that $\lim_{i \rightarrow \infty} \beta_i = 0$ and $\sum_{i=0}^{\infty} \beta_i = \beta < \infty$. Now assume that the changes in X_t do not have much effect after a certain times, for example, after L number of days. In this case, the model reduces to a finite distributed lag model as follows:

$$Y_t = \alpha + \sum_{l=0}^L \beta_l X_{t-l} + \epsilon_t \quad (1)$$

Bounded summing of finite length L yields a finite linear DLM of order L , which is the only solution. Keep in mind that $n-l$ pairings of $[y_t, x_t]$ are used to estimate model parameters. The fact that these distributed delay models incorporate so many parameters should not be overlooked. A conservative assumption is that the delayed variable coefficients are not all independent, but rather functionally connected. According to the Akaike information criterion (AIC), the ideal number of parameters for each country was selected in this study. In this situation, the number of COVID-19 deaths at a given time t may be explained in terms of past number of new cases X_{t-l} with l as the lag, representing the period elapsed between the independent variable and the response. For statistical computation we employ the “*dLagM*” R package to carry on modeling and ArcMap in order mapping the result of model.

Results

Results from the fitting of the distributed lag model to data on the daily number of newly reported COVID-19 cases and deaths in 49 European countries revealed that there was heterogeneity among countries in respect of the values of the mean delay and long-run effects in both the first and the second half of 2020. The results of the fitted models are shown in Table 1. As we can see, in most countries, the values of R^2 are more than 60%, which indicates a suitable fit of the models for this data. The results of these models showed that the mean delay between the number of new cases and the daily death of COVID-19 among European countries in the first six months of 2020 varied between 0 and 24 days. The lowest average delays were in Belarus, Liechtenstein, San Marino and Serbia with the number of days of delay being zero. The highest average delays were found in Sweden, Latvia, Russia, and Croatia and their respective delays were 24, 23.2,

21.2 and 19.7 days. The average delay time of all European countries during this period was 9.1 days, which means that the effect of any decrease or increase in the number of new cases would affect the number of daily deaths by an average delay of 9.1 days.

Furthermore, results from the fitting of models to data from the second half of 2020 showed that the mean delay had increased in all European countries in this period, such that the overall mean delay was observed to be 13.5 days and it varied between 0 and 27.3 days. Also, in these six months, the lowest mean delay was seen in Andorra, Belarus, and Ukraine with the average delay being zero days, and the highest delay was noted in Malta, Germany, and Iceland at 25.7, 26.1, and 27.3 days, respectively.

In addition, there is a considerable variation among different countries regarding the long-run effect which shows the adjusted mortality rate based on new cases identified in the previous days. Thus, in the first six months of 2020, the highest values of this index belonged to three countries, namely, France, England and Belgium. They had long-term effect rates of 0.27, 0.27 and 0.2 respectively. The lowest value was observed in Belarus (zero). Furthermore, our findings show that this index decreased in majority of the countries in the second half of 2020, indicating a decrease in mortality in these countries. For example, in case of Britain and France, this index decreased to 0.015 and 0.008, respectively.

Table 1

Mean Delay, Long Run Effect and Coefficient of determination Estimated by Distributed Lag Models in European countries in the first and second halves of 2020.

Country	Feb1,2020 to Jul 30, 2020			Jun1, 2020 to Dec 31, 2020		
	Mean Delay (day)	Long run effect	R ²	Mean Delay(day)	Long run effect	R ²
Sweden	24	0.097	0.99	15.6	0.008	0.98
Latvia	23.2	0.016	0.4	25.2	0.01	0.88
Croatia	21.2	0.094	0.71	7.8	0.02	0.95
Russia	19.7	0.043	0.81	9.1	0.022	0.98
Isle of Man	18.6	0.064	0.81	14.3	0.068	0.39
Bulgaria	16.1	0.058	0.68	17.2	0.052	0.97
Norway	15.8	0.051	0.78	22.9	0.002	0.53
Bosnia and Herzegovina	15.4	0.055	0.47	13.6	0.037	0.85
Estonia	14.2	0.05	0.55	11.5	0.007	0.76
Slovenia	14.2	0.021	0.5	5.4	0.012	0.93
Jersey	13.9	0.156	0.98	1.2	0.0001	0.78
Germany	12.5	0.045	0.97	26.1	0.012	0.96
Moldova	12.1	0.008	0.11	1.5	0.016	0.73
Poland	11.7	0.032	0.7	12.9	0.01	0.96
Austria	11.4	0.03	0.74	22.2	0.002	0.92
Montenegro	11.1	0.021	0.41	9.6	0.003	0.62
Switzerland	10.9	0.04	0.97	17.9	0.015	0.95
Azerbaijan	10.8	0.021	0.89	7.6	0.006	0.98
Lithuania	10.8	0.004	0.87	12.7	0.006	0.97
Monaco	10.1	0.036	0.74	24	0.008	0.34
United Kingdom	9	0.267	0.84	20.2	0.015	0.96
Finland	8.9	0.063	0.72	17.5	0.008	0.67
Ukraine	8.9	0.027	0.96	0	0.01	0.95
France	8.7	0.273	0.87	21.9	0.008	0.84
Slovakia	8.7	0.015	0.63	14.1	0.005	0.69

Country	Feb1,2020 to Jul 30, 2020			Jun1, 2020 to Dec 31, 2020		
	Mean Delay (day)	Long run effect	R ²	Mean Delay(day)	Long run effect	R ²
North Macedonia	8.5	0.108	0.92	10.7	0.026	0.89
Luxembourg	8.4	0.026	0.42	15.6	0.005	0.82
Czech IA	8.3	0.032	0.81	8	0.018	0.95
Kosovo	7.9	0.076	0.68	0	0	0.5
Portugal	7.8	0.084	0.67	13.7	0.011	0.95
Hungary	7.6	0.059	0.89	8.9	0.01	0.96
Iceland	7.4	0.158	0.86	27.3	0.004	0.5
Andorra	6.5	0.005	0.52	0	0.01	0.47
Greece	6.5	0.06	0.66	19.5	0.005	0.93
Belgium	6.1	0.201	0.98	19.3	0.005	0.92
Ireland	5.9	0.006	0.53	4.8	0.005	0.48
Italy	5.3	0.071	0.84	15.2	0.016	0.98
Cyprus	3.9	0.014	0.31	12.3	0.004	0.65
Turkey	2.8	0.058	0.98	13.7	0.005	0.9
Spain	2.6	0.084	0.78	16	0.014	0.93
Albania	1.8	0.026	0.5	4.2	0.02	0.86
Denmark	1.8	0.042	0.86	13.3	0.009	0.91
Malta	1.5	0.023	0.65	25.7	0.002	0.61
Romania	0.9	0.046	0.8	4.6	0.013	0.94
Netherlands	0.4	0.027	0.45	9.9	0.008	0.92
Belarus	0	0	0.85	0	0.005	0.68
Liechtenstein	0	0.019	0.6	16.1	0.034	0.6
San Marino	0	0.027	0.94	23.3	0	0.61
Serbia	0	0.007	0.19	13.4	0.011	0.98

Figure 1 shows the geographical distribution of the mean delay for European countries in the first and second halves of 2020. As it can be seen, the mean delay in the first half of 2020 was the lowest in Western and Southern European countries, which increased in the next six months. In countries such as Spain and

Italy, the rate of change has been considerable. Also, in some countries, such as Belarus and Ireland, the mean delay rate has remained unchanged.

Figure 2 shows the geographical distribution of the long-term effects with respect to European countries in the first and second halves of 2020. As it can be seen, the long-term effect in the first six months of 2020 was the highest in Western European countries, which decreased in the next six months. In case of France and Britain, this decline has been significant. However, this long-term effect remained unchanged for some countries such as Russia.

Figure 3 shows the geographical distribution of the total number of tests conducted per million populations in European countries in the first and second halves of 2020. The total number of COVID-19 tests in all European countries has an increasing trend from the first half to the second half of 2020. Some countries, such as France and the United Kingdom, in the first half of 2020, had the fewest total numbers of tests conducted per million populations (between 5792 and 28,514.7 tests per million, respectively), but in the second half of 2020, their total number of tests considerably increased and they ranked at the top of European countries in terms of the total number of tests (between 498,810.8 and 2,300,752.7 tests per million, respectively).

Figure 4 shows a positive and significant correlation between the number of tests performed and the delay effect, but it shows no significant correlation between the number of tests performed and the long-term effect.

Discussion

The coronavirus disease escalated quickly and became a global pandemic. To prevent and control the spread of an epidemic, understanding the course of the disease outbreak is crucial. This knowledge assists governments and policymakers in appropriate allocation of medical resources and effective healthcare interventions. Mathematical and statistical methods play an important role in providing such crucial information and as a result, achieving the aim of disease prevention and control.

There is the phenomenon of a "death lag", which means that a rise in new cases does not immediately lead to a rise in new deaths[25]. In the present study, we aimed to model the delay effect of new daily cases and daily deaths for COVID-19 in European countries and adjust the mortality rate by considering lag times. To meet the objectives of this research, the dataset was divided into two periods of six months each (first half and second half of 2020) and each period was separately fitted with a Distributed Lag Model (DLM). Our findings showed that the average delay effect in the first six-month period of 2020 in the European countries varied between 0 and 24 days, and countries such as Spain, France, Denmark, the Netherlands and Turkey had the lowest delay, with the number of days between infection and death being 0 to 3 days. In the second six-month period of 2020, the delay time increased from 0 to 3 days to 15 to 17 days in these countries. We also found a significant relationship between the total tests conducted and mean delay time, but the correlation wasn't significant between the total tests conducted and the long-run effect.

The long-run effect, which represented a fatality rate, varied among different countries. In the first half of 2020, the highest mortality rate occurred in France and the lowest was observed in Belarus, with the values being 0.27 and 0, respectively. This high mortality rate may be attributable to the low frequency of tests conducted, which in turn led to an underestimation of the actual number of patients. But in the second half of 2020, as the frequency of the tests conducted in these two countries reached the highest level among European countries, the fatality rate decreased sharply, which indicates an improvement in patient screening and generally improving healthcare facilities. The mortality rates in France and the United Kingdom in the first six-month period ranged between 0.16 and 0.27, which changed significantly in the second six-month period to 0.0005 and 0.0037.

The R-squared measure, used to evaluate model fitting, for most countries was above 0.8, which indicated an adequate fit. We also provided a geographical representation of the average delay effect and long-term effect. In the first six-month period of 2020, Western and Southern European countries experienced a shorter delay time, but this delay time increased in the second six-month period of 2020. The long-term effect representation showed the highest long-term effect in Western Europe in the first six months. This long-term effect declined in the second six-month period.

The coronavirus has been the subject of numerous studies looking into time delays. We can examine the time gaps between infection, symptoms, hospitalization, and death [26]. A lot of research has been done to try to figure out how long it takes for symptoms to appear before someone dies [27–30]. Using data from longitudinal studies in 16 countries, including the US, the Netherlands, France, and the UK, researchers were able to establish how long it takes for a spike in new cases to be followed by a spike in fatalities. There was a mean lag time of 31 days, and a median lag time of 27 days. With a lag time of 55 days, the United Kingdom was the worst in Europe, while the Netherlands was the best with a lag time of 23 days. Chrusciel et al. analyzed data from 15 countries during the early stages of the Covid-19 pandemic in order to show lags between daily infections and mortality. They discovered a wide range of lag durations around the globe. The average lag time was 7 days, with a standard deviation of 0.3, according to their research. We found that in Sweden, there were more deaths than new infections; this indicates that the number of deaths outweighed the number of new infections.[14] As part of a descriptive and correlational investigation, Raymond looked for a connection between the patient's age and the time elapsed between infection and death. New cases and deaths were on average 8.053 days apart, according to him. He also discovered a correlation between the length of the lag and the age of the participants [10].

According to Faes and colleagues, 14,618 COVID-19 patients were admitted to 114 Belgian hospitals between the onset of symptoms and their hospitalization. In addition, they made a distinction between patients from the general population and those who reside in nursing facilities. Patients' age and whether or not they lived in a nursing home were found to have an effect on the median time between the beginning of symptoms and admission to the hospital. It lasted anywhere from three to ten and a half days. Patients who reside in nursing homes have a longer time to death than those who reside in hospitals [27]. Rastaghi et al. used distribution delay models to estimate the COVID-19 death rate in Iran, based on the delay impact of hospitalizations. They projected a lag time of 5 days and a long-term mortality rate of 12 percent. According to our findings, European countries had a mean lag time of 9.1 days [16]. Distributed log-linear time-lag

models were used to examine how the number of COVID-19 hospitalizations in Iran affects the relative risk of death from COVID-19. They discovered a strong link between the frequency with which patients are admitted to the hospital and an elevated risk of death both that day and the following day. A daily spike in hospitalizations of more than 2000 persons signaled trouble for the country's healthcare system, according to their findings [31].

In conclusion, taking note of the existence of a delay time between new cases and death, communities must remain alert about the rapidly increasing number of new cases, which, considering the delay effect will be followed by a surge in the number of deaths. An understanding of the time lags of COVID-19 must be integrated in the knowledge of the healthcare community to help make informed and effective decisions.

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Availability of data and materials

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Not applicable. In this study open-source data set was used.

Consent for publication

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

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Figures

Figure 1

Mean delay between new cases and death in European countries in the first (left) and second (right) halves of 2020.

Figure 2

Long-run effect between new cases and death in European countries in the first (left) and second (right) halves of 2020.

Figure 3

Total tests conducted per million populations in European countries in the first (left) and second (right) halves of 2020.

Figure 4

Moran's bivariate spatial correlation between the total tests conducted per million populations and mean delay and long run effect