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Effects of income inequality on COVID-19 infections and deaths during the first wave of the pandemic: Evidence from European countries

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Abstract

Evidence from research on infectious diseases suggests that income inequality is related to higher rates of infection and death in disadvantaged population groups. Our objective is to examine whether there was an association between income inequality and the numbers of cases and deaths during the first wave of the COVID-19 pandemic in European countries. We determined the duration of the first wave by first smoothing the number of daily cases, and then using a LOESS regression to fit the smoothed trend. Next, we estimated quasi-Poisson regressions. Results from the bivariate models suggest there was a moderate positive association between the Gini index values and the cumulated number of infections and deaths during the first wave, although the statistical significance of this association disappeared when controls were included. Results from multivariate models suggest that higher numbers of infections and deaths from COVID-19 were associated with countries having more essential workers, larger elderly populations and lower health care capacities.

Keywords: COVID-19; income inequality; first wave; European countries

1 Introduction

In early 2020, a new coronavirus, SARS-CoV-2, also called COVID-19, arrived in Europe from China. Mass outbreaks were first recorded in Italy and Spain, and the virus then spread rapidly across the continent. Although European governments adopted emergency measures to contain the pandemic's advance, differences in the

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numbers of infections and deaths have been observed between countries. While studies on the socioeconomic differences in the levels of COVID-19 infections and deaths have been conducted in several European countries, none of these studies compared these differences between countries.

The previous literature on this topic has pointed out that a disease can affect societies differently depending on the vulnerability of their populations due to conditions such as inequality or poverty. For instance, there is some evidence of a positive association between income or wealth and self-reported health status (Bor et al., 2017). Thus, health economists have argued that people with lower socioeconomic status face worse health outcomes than their counterparts with higher status, and that these differences can be explained in large part by two mechanisms: health behaviour and access to health care (Bor et al., 2017; Santerre and Neun, 2012). The first mechanism refers to the tendency of poorer and less educated people to be less well informed and less careful due to a lack of knowledge and awareness of their health. The second mechanism refers to evidence that poorer and less educated people tend to seek medical care less often, either because they cannot stop working, or because they are concerned about the costs associated with illness. Moreover, in the case of respiratory infectious diseases, social interaction is a crucial determinant of the likelihood of becoming ill. When infected people engage in economic or social activities, the risk of infection increases for healthy individuals (Jung et al., 2020). In the current pandemic, wealthier individuals have generally had more resources to self-isolate and telework, while people with lower incomes have often been performing essential or manual work that cannot be done remotely (Brown and Ravallion, 2020; Jung et al., 2020; Lekfuangfu et al., 2020; Papageorge, 2020; Takian et al., 2020). Thus, the transmission pathways and risk exposure levels have differed between socioeconomic groups. These societal inequities have highlighted the vulnerability of the least favoured groups.

Income inequality is one of the non-biological factors that has been used to explain adverse health outcomes, as it can affect the prevalence and consequences of poor health within societies. Compared to middle- and high-income households, low-income households tend to have lower life expectancy, higher mortality and worse health status, even in developed countries (Bor et al., 2017; Jijiie et al., 2019; Kawachi and Kennedy, 1999; Krisberg, 2016; Lynch et al., 1998, 2000; Meara et al., 2008; Neliss, 1999; Olshans et al., 2012; Pickett and Wilkinson, 2015; Rehnberg et al., 2019; Shkolnikov et al., 2007; Villegas and Haberman, 2014). Historically, life expectancy and mortality have been unequal between the richest and the poorest populations (Ahmed et al., 2020). In addition, more unequal societies tend to spend less on income redistribution policies, such as strengthening health care systems (Mello, 2006).

Disparities arising from income inequality have also been observed in analyses of the effects on populations of infectious respiratory diseases of viral origin. Studies on the impact of seasonal influenza have found associations between socioeconomic status and mortality, morbidity and symptom severity (Crighton et al., 2007; Tam et al., 2014). Evidence from research on the Spanish flu, a pandemic comparable to

COVID-19 in terms of its global reach, indicates that mortality rates were higher among the poorest people (Bengtsson et al., 2018; Grantz et al., 2016; Mamelund, 2006; Murray et al., 2006; Sydenstricker, 1931). However, no such mortality differences by socioeconomic status were found in countries with low levels of economic and social inequality (Rice, 2005; Summers et al., 2014). The findings of research on the effects of a more recent pandemic, the 2009 H1N1 influenza, were similar. For example, several studies have found that H1N1 influenza mortality was higher among the most deprived social groups in developed countries (Biggerstaff et al., 2014; Lowcock et al., 2012; Rutter et al., 2012), while a cross-country analysis showed that H1N1 influenza mortality was higher in low-income than in high-income countries (Charu et al., 2011). The socioeconomic disparities in H1N1 influenza mortality and morbidity have been attributed to differences in levels of exposure to the virus, susceptibility to the disease, and access to health care once the disease had developed (Rutter et al., 2012).

The evidence that large income differences have damaging health and social consequences is, therefore, strong. Moreover, it has been argued that the COVID-19 pandemic could exacerbate these differences, as inequality could increase the pace of the spread of the disease (Ahmed et al., 2020; Brown and Ravallion, 2020). For instance, it has been observed that people in countries with greater income inequality have been less likely to adopt preventive health measures, such as isolation, physical distancing, and the use of masks and hand disinfection (Elgar et al., 2020; Papageorge, 2020; Pirisi, 2000). In addition, initial findings on the effects of the pandemic suggest that people in the lower socioeconomic groups have been facing more severe consequences, and that income inequality might explain the differences in the numbers of cases and deaths within and across countries. Results from the United States show that infection and mortality rates from COVID-19 are higher in the states and counties where income inequality or poverty levels are higher (Brown and Ravallion, 2020; Chen and Krieger, 2020; Jung et al., 2020; Mollalo et al., 2020; Mukherji, 2020; Oronce et al., 2020). For Brazil, there is evidence of a positive and significant correlation between income inequality and COVID-19 mortality (Demenech et al., 2020; Martines et al., 2021). Studies conducted in Germany, Israel and Spain have shown that infection rates in these countries have varied based on income inequality, with socioeconomically disadvantaged populations being more likely to be infected (AQuAS, 2020; Arbel et al., 2020; Wachtler et al., 2020). A comparative study of the 10 countries worldwide that have been the most affected by the pandemic used a multidimensional index, including income inequality, to show that the worse off a country is, the greater the impact of COVID-19 has been (Ruiz Estrada, 2020). A study comparing the number of deaths per day in 80 countries concluded that mortality tends to increase more rapidly in countries where inequality is greater (Elgar et al., 2020).

During the first pandemic wave, one of the measures governments used to deal with the threat was the imposition of severe restrictions on mobility, which in most cases meant that the population was ordered to stay home whenever possible. Teleworking became widespread for all non-essential workers. However, essential workers, mostly in manual or machine-based activities, had to continue working face-to-face and commuting to their workplaces, or risk losing their jobs (Adams et al., 2020; Ahmed et al., 2020; Lekfuangfu et al., 2020). Studies conducted in England and Wales and in Thailand found that the use of public transport to commute to work was associated with increased risk of COVID-19 infection (Lekfuangfu et al., 2020; Sá, 2020). Analyses of geolocation data from the United States showed that lower-income workers continued to move around during lockdowns, while higher-income workers tended to stay at home and limit their exposure (Buchanan et al., 2020). Another study concluded that the U.S. counties with the highest levels of income inequality had higher rates of infection, as the lower-income workers in these counties were less able to maintain social distancing because of their work activities (Brown and Ravallion, 2020).

The research to date has analysed the effects of income inequality on variations in COVID-19 infections within countries. However, only a few cross-country comparative studies have analysed how the COVID-19 pandemic has affected countries depending on their socioeconomic differences, and none of these studies has focused on Europe. Thus, our objective is to examine whether there was an association between income inequality and the numbers of cases and deaths during the first wave of COVID-19 in European countries. Although Europe is considered to have lower inequality than other regions, evidence from past pandemics has shown that even in European countries, there have been differences in health outcomes associated with income distribution. Due to the rapid spread of the virus, and to a lack of knowledge about how to combat it among both scientists and the general public, governments did not have a plan for protecting the most deprived social groups. Thus, analysing the effects of the first wave of the COVID-19 pandemic on European countries can help us examine the differences in health outcomes associated with socioeconomic inequities. More unequal countries were already more likely to have adverse health outcomes and weaker health care systems. Therefore, income inequality may have played a significant role in exacerbating these existing vulnerabilities during the COVID-19 pandemic.

2 Data and methods

To conduct our analysis, we use as dependent variables the cumulated number of infections and deaths at the end of the first wave. We have collected the daily number of COVID-19 cases and deaths from Our World in Data (2020), one of the specialized data repositories that has compiled global information on the evolution of the pandemic.

It should be noted that although the virus spread rapidly through Europe, not all countries were affected at the same time, and the evolution of the disease differed from one country to another. Therefore, we have harmonized the analysis period by estimating the duration of the first wave for each country using the reported number of cases per day from January 2020 to January 2021. To do so, we first smoothed the daily number of infections using a seven-day moving average. Then, we used a local polynomial regression – i.e., locally estimated scatterplot smoothing (LOESS) – to fit the trend. As the result is a sinusoidal type pattern due to the multiple waves, we considered the first wave to be the first hump of the LOESS fit. We defined the onset as the day on which the 100th case was reported, and the end as the day on which the slope of the fitting curve did not show a statistically significant decrease after the number of cases per day was at least half that at the peak.

For illustrative purposes, Figure 1 shows the smoothed trends and fitting curves in several countries. For most European countries, the first wave lasted from mid-March to late June, and it did not go beyond August 2020 in any European country. Although the number of infections per day was already declining by the end of January 2021 in Moldova and Ukraine, these two countries were excluded as they showed no signs of having completed the first wave. Table 1 displays the details of the first wave.

Our variable of interest is income inequality. To measure income inequality, we use the Gini index, which is distributed from zero, indicating totally equal distribution, to 100, indicating totally unequal distribution. We collected the latest reported Gini index results from the World Bank Open Data repository (World Bank, 2020). Figure 2 displays the Gini index values across the countries included in our sample. The Gini index values range from 24.2 to 40.4, and the sample mean is 31.7. Europe is considered the most egalitarian continent in the world. At the regional level, the Scandinavian and Eastern European countries generally have the most egalitarian income distributions, while income inequality tends to be highest in the Balkan countries.

Since recent studies have found that certain socioeconomic and demographic characteristics can help to explain how COVID-19 has affected a particular country, we include them in our analysis to control our estimates. Most of these studies agree that the relevant characteristics include age structure, as age might reflect the incidence of pre-existing health conditions (Brown and Ravallion, 2020; Esteve et al., 2020; Gardner et al., 2020; Kashnitsky and Aburto, 2020; Nepomuceno et al., 2020); poverty and education, as they are strong determinants of health outcomes (Bor et al., 2017; Brown and Ravallion, 2020; Santerre and Neun, 2012); numbers of essential workers, as these workers are more exposed to infection because they use public transport and have face-to-face contact (Adams et al., 2020; Ahmed et al., 2020; Lekfuangfu et al., 2020; Sá, 2020); population density, as infected and uninfected individuals are more likely to interact in denser settings (Brown and Ravallion, 2020); social contact, as the risk of infection increases at higher levels of social contact (Aparicio and Grossbard, 2020; Cristini and Trivin, 2020); and health care capacities, as the pandemic has exposed vulnerabilities in health care systems (Hopkins Tanne et al., 2020; Mollalo et al., 2020; Nepomuceno et al., 2020), and health care capacities have played a role in how hard each country has been hit by the disease. To include these controls in our analysis, we collected information from various sources, while always using the latest reported data for each variable.

Figure 1:
Smoothing and fitting the number of infections per day in selected countries over a 180-day period

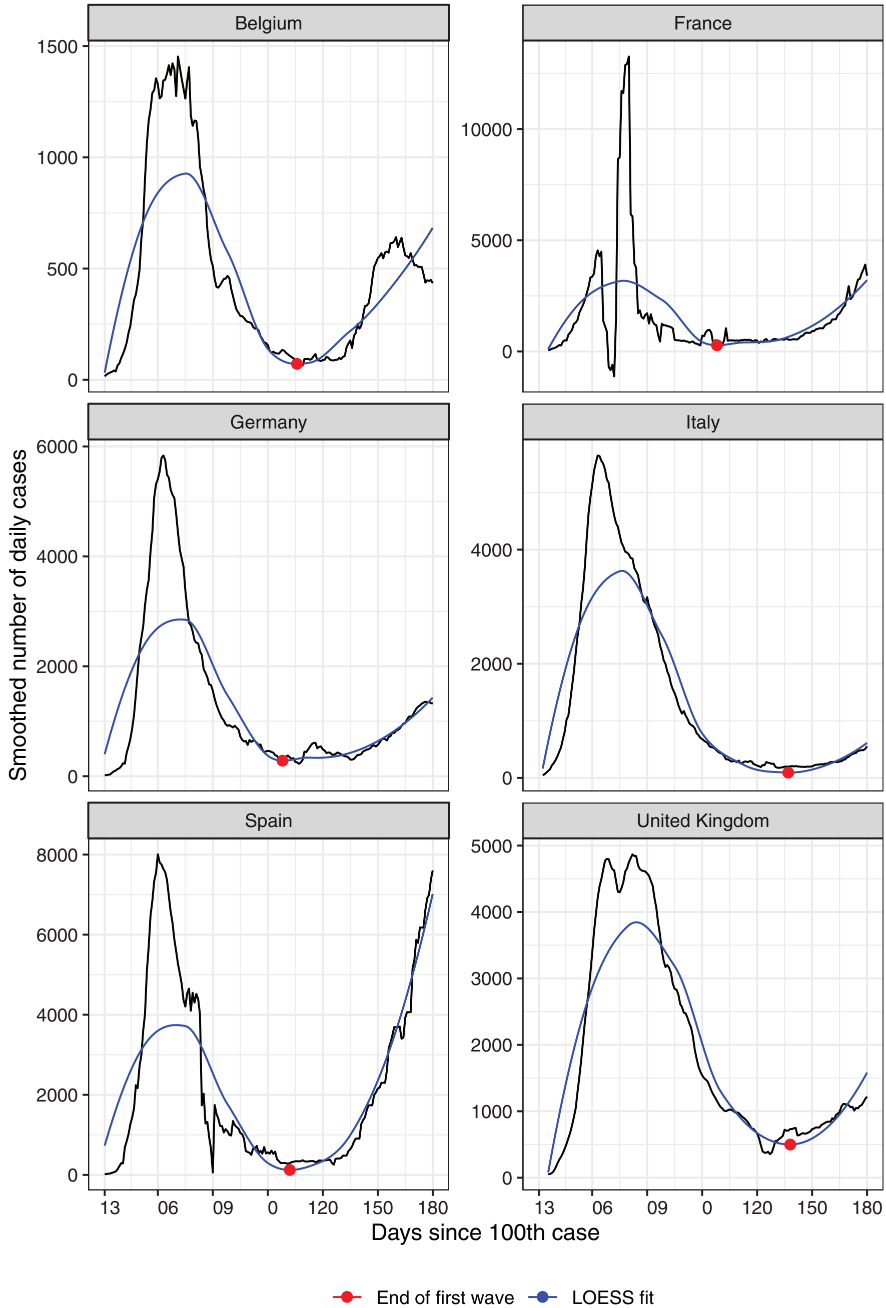
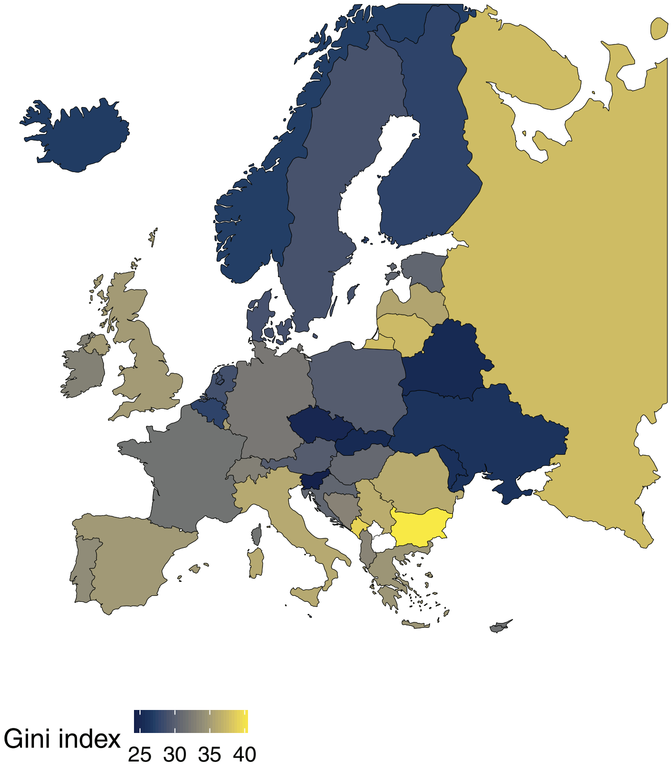


Table 1:
Details of the first wave of COVID-19 in European countries

Country	1st case	First wave				
		Start	End	Days	Total cases	Total deaths
Albania	March 09	March 23	May 14	53	898	31
Austria	February 25	March 08	May 22	76	16,436	635
Belarus	February 28	March 30	August 17	141	69,589	613
Belgium	February 04	March 06	June 19	106	60,476	9,695
Bosnia and Herzegovina	March 05	March 22	May 28	68	2,462	153
Bulgaria	March 08	March 20	May 25	67	2,433	130
Croatia	February 25	March 19	June 02	76	2,246	103
Cyprus	March 09	March 23	June 23	93	990	19
Czechia	March 01	March 13	May 20	69	8,721	304
Denmark	February 27	March 10	June 24	107	12,815	603
Estonia	February 27	March 14	July 04	113	1,993	69
Finland	January 29	March 13	July 09	119	7,273	329
France	January 24	February 29	June 05	98	192,450	29,114
Germany	January 27	March 01	June 06	98	185,450	8,673
Greece	February 26	March 13	May 28	77	2,906	175
Hungary	March 04	March 21	July 03	105	4,172	588
Iceland	February 28	March 12	May 23	73	1,804	10
Ireland	February 29	March 14	June 30	109	25,473	1,736
Italy	January 31	February 23	July 08	137	242,149	34,914
Latvia	March 02	March 20	June 23	96	1,111	30
Lithuania	February 28	March 22	June 09	80	1,727	72
Luxembourg	February 29	March 17	May 23	68	3,990	109
Malta	March 07	March 23	June 24	94	665	9
Montenegro	March 17	March 31	May 29	60	324	9
Netherlands	February 27	March 06	June 22	109	49,866	6,109
Norway	February 26	March 06	June 28	115	8,855	249
Poland	March 04	March 14	June 30	109	34,393	1,463
Portugal	March 02	March 13	August 02	143	51,463	1,738
Romania	February 26	March 14	June 07	86	20,479	1,333
Russia	January 31	March 17	August 12	149	900,745	15,231
Serbia	March 06	March 19	June 01	75	11,430	244
Slovakia	March 06	March 18	June 02	77	1,522	28
Slovenia	March 05	March 13	May 27	76	1,471	108
Spain	February 01	March 02	June 11	102	242,707	27,136
Sweden	February 01	March 06	August 29	177	83,958	5,821
Switzerland	February 25	March 05	June 05	93	30,936	1,921
United Kingdom	January 31	March 02	July 17	138	294,803	41,060

Figure 2:
Gini index in European countries



To account for (i) age structure, we use the latest projection of total population from the World Population Prospects (United Nations, 2020) to compute the share of people aged 65 and older. For (ii) education, we use the share of population with at least upper secondary school for the population aged 25 and older[1] (UNESCO, 2020). For (iii) essential workers, we use the share of people working in industry[2] (ILO, 2020). For (iv) population density, we use the share of the population living in urban areas (United Nations, 2018). For (v) social contact, we use the number of flight departures (domestic and international) (World Bank, 2020). For health capacities, (vi) we use the number of physicians – i.e., generalist and specialist medical practitioners – per thousand inhabitants (World Bank, 2020), and (vii)

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[1] Path to data is SDG/Sustainable Development Goals 1 and 4/Sustainable Development Goal 4/Target 4.4/Share of population by educational attainment.

[2] This information can be found as part of the "Employment distribution by economic activity" indicator.

the number of hospital beds per 10,000 inhabitants (WHO, 2020). In addition, to account for any possible effects of a government's response to the crisis, we include two controls: the number of days between the first case and the localized or national lockdown (Dunford et al., 2020), and the ideological orientation of the government (CIDOB, 2021). In the first case, we consider the possibility that a late response could have contributed to the pandemic hitting the country harder. It should be noted that only Belarus did not adopt a lockdown policy. Therefore, we use the duration of the first wave as the number of days. In the second case, we consider the possibility that the ideological orientation of the government may have had an effect on the dependent variables and the variable of interest through the unobserved preferences (of individuals or governing parties) regarding income redistribution, or through measures taken to control the pandemic. To account for this possibility, we include a dichotomous variable that takes the value of one when the ideology is right or centre-right, and a value of zero for other ideologies.

We use data from all European countries with complete information. Thus, we include 37 European countries in our study, and our sample covers 94% of Europe's population.

We first estimate a bivariate model for each dependent variable, including only the Gini index as an explanatory variable. Second, we estimate multivariate models that include the controls specified above. The reported numbers of cases and deaths are the count data. Poisson distribution is used for modelling the number of times an event occurs in an interval of time or space. Poisson regression assumes that the logarithm of its expected value can be modelled by a linear combination of its parameters:

$$\log(E(Y \mid X)) = X\beta$$
$$E(Y \mid X) = e^{X\beta}$$

where X is a vector of independent variables, and β is the set of parameters. While a Poisson model assumes that the variance ($var(Y)$) is equal to the mean ($E(Y \mid X) = \mu$), this assumption does not always hold true. When the variance is greater than the mean – i.e., when there is overdispersion – either quasi-Poisson or negative binomial regression models are more appropriate (Ver Hoef and Boveng, 2007). Quasi-Poisson models assume that the variance is a linear function of the mean, $var(Y) = \theta\mu$, where θ is an overdispersion parameter. Negative binomial models assume that the variance is a quadratic function of the mean, $var(Y) = \mu + \alpha\mu^2$, where the overdispersion is the multiplicative factor $1 + \alpha\mu$. Overdispersion tests on our sample showed that the null hypothesis $var(Y) = \mu$ is rejected. Then, following Ver Hoef and Boveng (2007), we have performed a diagnostic analysis (not shown) plotting the fit of the variance, using averaged squared residuals, to the mean. The results suggest that the quasi-Poisson model fits the variance-mean relationship better.

Finally, it should be noted that the values of the number of infections and deaths vary widely across countries due to their different population sizes. Thus, we include in all regressions the log of total population as an offset,

$$\log(E(Y \mid X)) = \log(pop) + X\beta$$

then,

$$\log(E(Y \mid X)) - \log(pop) = \log\left(\frac{E(Y \mid X)}{pop}\right) = X\beta$$

3 Results

In Europe, the first wave lasted an average of 98 days (see Table 1). During this time period, there were 2,581,181 confirmed COVID-19 cases and 190,564 confirmed deaths from the disease in the 37 countries included in our study. The longest first waves were in Sweden (177 days), Russia (149 days) and Portugal (143 days); while the shortest first waves were in Albania (53 days), Montenegro (60 days) and Bulgaria (67 days).

The upper panel of Figure 3 shows the cumulated number of infections per million population (p.m.p.) during the first wave by country. The solid line represents the average of the sample, which was 3,707.5 infections p.m.p. It is not a coincidence that the countries with the highest numbers of infections were Sweden (8,313.3 infections p.m.p.) and Belarus (7,364.4 infections p.m.p.). In both countries, no measures were taken to restrict social contact, which also explains why Sweden had the longest first wave. The countries with the lowest numbers of infections, coinciding with the shortest first wave durations, were Slovakia and Greece (both with 279 infections p.m.p.), followed by Albania (312 p.m.p.) and Bulgaria (350.1 p.m.p.).

The lower panel of Figure 3 displays the cumulated number of deaths during the first wave of COVID-19. The solid line shows the average in our sample, at 273.7 deaths p.m.p. Belgium had the highest mortality rate by far, at 836.5 deaths p.m.p., followed by the United Kingdom (604.8 deaths p.m.p.), Spain (580.4 deaths p.m.p.), Italy (577.5 deaths p.m.p.), Sweden (576.4 deaths p.m.p.) and France (446 deaths p.m.p.). Except in Sweden, a higher infection rate in a country did not necessarily predict higher mortality. Among the possible explanations for this finding are that complications from infections might have been exacerbated by vulnerabilities at the individual level, and that the responsiveness of the countries' hospital systems could have varied.

The upper panel of Figure 4 plots the Gini index and the number of infections. Pearson's correlation estimation suggests that there was a moderate positive association of 0.287 (95% CI = 0.076–0.474) between these two variables. The per capita risk of infection increased by 1.08 (95% CI = 1.03–1.14, se = 0.028) for every unit of increase in the Gini index (see column [1] of Table 2). After including controls (see column [2] of Table 2), the association became weaker (1.04), such that the confidence interval now included one (95% CI = 0.98–1.09, se = 0.027).

Figure 3:
Cumulated number of infections and deaths per million population (p.m.p.) during the first wave of COVID-19

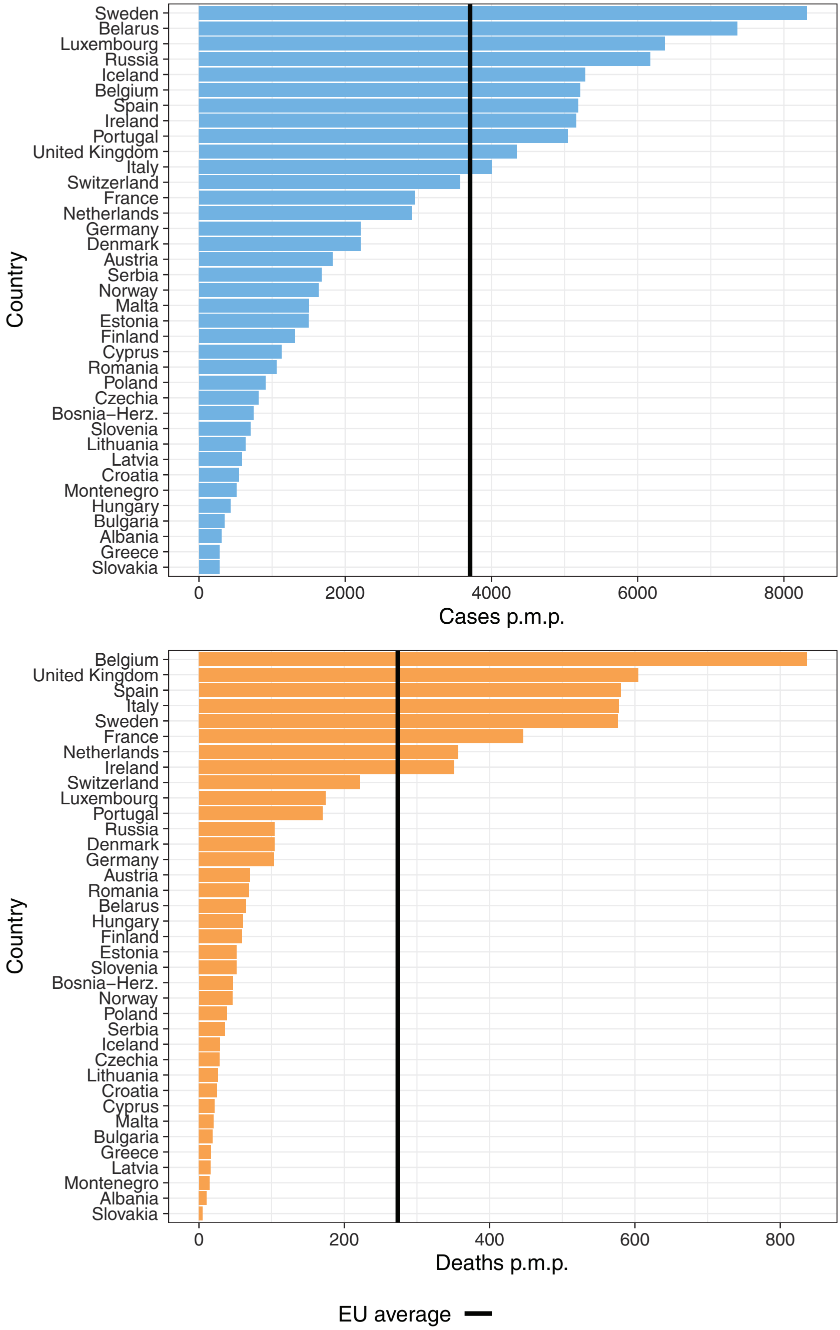
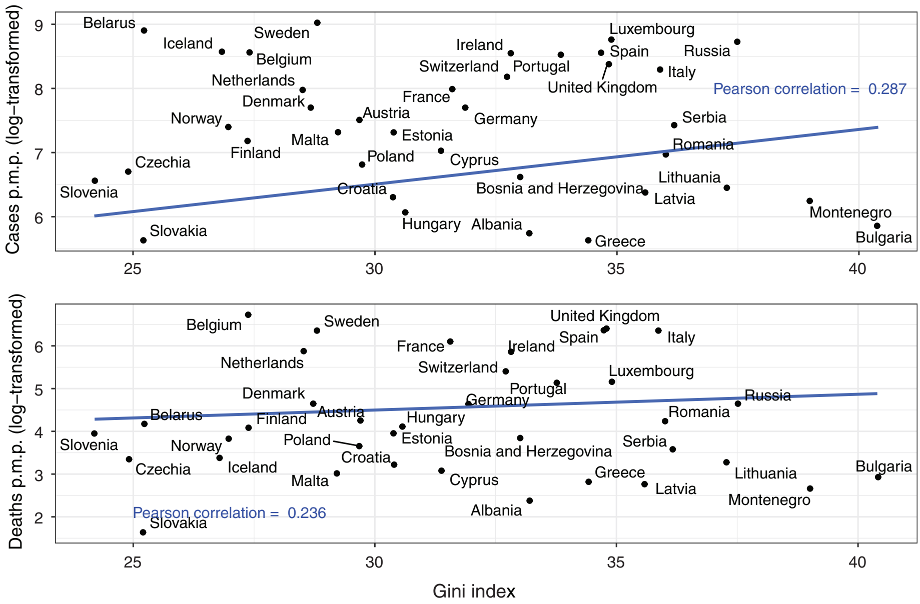


Figure 4:
Number of infections and deaths per million population (p.m.p.) during the first wave of COVID-19 and the Gini index



The lower panel of Figure 4 shows a positive correlation between the Gini index and the number of deaths, although it was weaker than the correlation found for infections. The Pearson's correlation estimation was 0.236 (95% CI = 0.02–0.43). The per capita risk of death increased by 1.01 (95% CI = 0.93–1.10, se = 0.043) for every unit of increase in the Gini index (see column [3] of Table 2). In this case, the per capita risk increased to 1.05 after the controls were included (see column [4] of Table 2), but the confidence interval still included one (95% CI = 0.97–1.14, se = 0.042).

The results for the other covariates are presented in columns [2] and [4] of Table 2. A higher share of the population with at least upper secondary school was connected to lower per capita risk. Our results indicate that the share of better educated people was associated with a reduction in the risk of infection of 0.99 (95% CI = 0.97–0.99, se = 0.008), and with a reduction in the risk of death of 0.98 (95% CI = 0.96–0.99, se = 0.011). Consistent with increased exposure to risk, the per capita risk of infection increased by 1.04 (95% CI = 1.01–1.09, se = 0.027) with the proportion of industrial workers. However, the evidence does not necessarily suggest that the proportion of industrial workers was related to the risk of death.

The more people who travelled, whether internationally or domestically, the faster the virus spread. Our results show that the risk of infection was 1.15 (95% CI = 1.01–1.34, se = 0.070) higher in countries where more flights departed. Similarly,

Table 2:
Per capita risk of the number of infections and deaths during the first wave of COVID-19. Quasi-Poisson regressions including log of population as an offset. Standard errors are in parentheses, and 95% confidence intervals are in brackets

	Cases		Deaths	
Variable	**[1]**	**[2]**	**[3]**	**[4]**
Gini	1.08 [1.03–1.14] (0.028)	1.04 [0.98–1.09] (0.027)	1.01 [0.93–1.10] (0.043)	1.05 [0.97–1.14] (0.042)
Education		0.99 [0.97–0.99] (0.008)		0.98 [0.96–0.99] (0.011)
Workers		1.04 [1.01–1.09] (0.027)		1.00 [0.93–1.08] (0.038)
65+		0.83 [0.77–0.90] (0.038)		1.07 [1.01–1.13] (0.049)
Urbanization		1.03 [1.01–1.06] (0.013)		1.05 [1.02–1.09] (0.017)
Flights		1.15 [1.01–1.34] (0.070)		1.30 [1.02–1.79] (0.144)
Physicians		1.32 [1.06–1.64] (0.112)		0.57 [0.39–0.79] (0.179)
Beds		0.99 [0.98–1.00] (0.005)		0.99 [0.98–0.99] (0.006)
Lockdown		1.01 [1.00–1.01] (0.004)		1.00 [0.97–1.02] (0.011)
Right party		0.74 [0.50–1.09] (0.201)		0.65 [0.34–1.18] (0.312)
Goodness of fit				
Deviance	704,869.71	195,864.68	147,246.63	20,676.46
Dispersion	20,177.68	7,048.83	4,126.82	851.25
Chi sq.	706,218.67	183,269.47	14,4438.64	22,132.6

the decision to impose restrictions on movement helped to slow the spread of the virus. According to our estimates, each additional day that a government delayed taking measures to restrict movement, such as lockdowns, increased the risk of infection by 1.01 (95% CI = 1.00–1.01, se = 0.004). On the other hand, having a right-wing or centre-right government was associated with a lower risk of infection, at 0.74 (95% CI = 0.50–1.09, se = 0.201), and of death, at 0.65 (95% CI = 0.50–1.09, se = 0.312).

Per capita risk increased with urbanization. As in the case of infections, a higher share of the population living in urban areas was associated with the virus spreading more rapidly. In our sample, the risk increased by 1.03 (95% CI = 1.01–1.06, se = 0.013) for each additional percentage point of urbanization. The higher risk of death (1.05, 95% CI = 1.02–1.09, se = 0.017) may be explained by the saturation that existed in hospitals during the peak of the pandemic. The countries where a higher proportion of the population was aged 65 and older had a lower risk of infection, at 0.83 (95% CI = 0.77–0.90, se = 0.038), but a higher risk of death, at 1.07 (95% CI = 1.01–1.13, se = 0.049). These findings show the two faces of this pandemic: i.e., most of those infected with COVID-19 were under age 50, while mortality was concentrated among the elderly.

The COVID-19 pandemic has tested the capacities of countries' health care systems, and has revealed weaknesses in many of them. Increasing one hospital bed per 10,000 inhabitants slightly decreased the risk of death from COVID-19 by 0.99 (95% CI = 0.98–0.99, se = 0.006). Of all of the variables included in our analysis, we found that the highest per capita risk was associated with the number of doctors. Increasing one physician per thousand population decreased the risk of death by 0.57 (95% CI = 0.39–0.79, se = 0.179). However, the presence of more physicians was associated with a higher risk of infections, at 1.32 (95% CI = 1.06–1.64, se = 0.112). One possible explanation for this result is that the presence of more physicians increased the likelihood of detecting infections, either because there was a greater capacity to test for COVID-19 when tests were carried out in physician practices, or because there was an increase in the number of doctor visits by symptomatic individuals who were subsequently referred to testing.

4 Discussion

Evidence from past pandemics has shown that the rates of infection and mortality tend to be higher in the most vulnerable socioeconomic status groups, especially in countries with higher levels of social inequality (Bengtsson et al., 2018; Grantz et al., 2016; Mamelund, 2006; Murray et al., 2006; Sydenstricker, 1931). Moreover, evidence from recent country case studies has suggested that this pattern has persisted during the COVID-19 pandemic. Our cross-country study focused on the question of whether varying levels of income inequality were associated with differences in the numbers of infections and deaths across European countries during the first wave of the pandemic.

Unlike other studies that analysed the effects of COVID-19 during its first stage, we did not use an ad-hoc analysis period. Instead, we developed a method to determine the duration of the first wave of the pandemic. To do this, we started our analysis period on the day on which the first case was reported, and ended it on the last day for which we could update the data (January 2021). Thus, our potential study period covered one year. Then, by smoothing the daily cases and fitting the smoothed trend, we determined the duration of the first wave for each country. To the best of our knowledge, this is the first study that has used this approach to homogenize the comparisons between countries.

After analysing the bivariate relationships, we found a moderate positive association between income inequality, as measured by the Gini index, and the numbers of infections and deaths during the first wave of COVID-19. To some extent, the Gini index captured the presence of groups living under vulnerable conditions within a given population. Previous evidence indicates that deprived groups tend to have worse health outcomes (Bor et al., 2017; Santerre and Neun, 2012). The positive relationship we found in the bivariate models suggests that the pandemic had a disproportionate impact on disadvantaged populations.

Based on our results, we draw several conclusions. First, unlike other known pandemics, the COVID-19 pandemic triggered a simultaneous global response aimed at stopping the spread of the virus. Thus, governments around the world imposed restrictions on movement and closed borders. In Europe, the pandemic-related lockdowns lasted approximately three months, and began an average of 20 days after the first case was reported. It appears that these measures protected countries with the highest levels of social vulnerability from the effects of the pandemic during the first wave. Indeed, there is evidence that the infection and death rates were higher during the second and third waves (Our World in Data, 2020), when the mobility restrictions were milder. We will analyse these differences in further research.

Second, methods for collecting the number of deaths varied from one country to another, which has led to underreporting in some cases (Harries, 2020; Hirsch and Martuscelli, 2020). In other words, the observed number of deaths varied across countries depending on the (unobserved) reporting policy, which may have led to biases. We intend to test our hypothesis using excess mortality as the dependent variable once data for all European countries (and for less developed countries) become available. Similarly, the number of infections may have been affected by differences in testing policies between countries. Testing levels were lower during the first wave than they were during subsequent waves.

Third, one of the characteristics of this pandemic has been the rapid speed of the spread of the virus across populations. Although the proportion of people infected with COVID-19 during the first wave who became severely and critically ill can be considered low, given the large numbers of people who were infected, this relatively small proportion resulted in high absolute numbers of critically ill people, which, in turn, placed great pressure on health care systems. In general, European countries have public and universal health care systems, which may reduce the effects of social inequity. However, our results show that even in Europe, there were differences between countries in the risk of death associated with more doctors and greater hospital capacity during the first pandemic wave. A potential explanation for this finding is that more unequal societies devote fewer resources to redistributive policies, such as health care (Mello, 2006).

Fourth, during the first pandemic wave, not everyone had the option to stay home and telework. Essential workers continued to commute to their workplaces, and were more exposed to the virus than white-collar workers (Adams et al., 2020; Ahmed et al., 2020; Lekfuangfu et al., 2020; Sá, 2020). In turn, the work activities of these individuals increased the risk of infection for their cohabitants (Aparicio and Grossbard, 2020). Our estimates show a clear relationship between infections and the proportion of the population working in essential activities. Given that most of these workers had lower incomes, our results show another dimension of the link between income inequality and the pandemic.

In summary, we found a moderate positive association between income inequality and the numbers of COVID-19 infections and deaths in our models without controls. However, after the controls were included, the statistical significance of this association disappeared. Thus, the link between socioeconomic inequalities and infectious diseases was no longer obvious once the correlations among multiple covariates were accounted for (Brown and Ravallion, 2020). Our results are consistent with previous evidence showing that the effects of socioeconomic inequalities on health outcomes tend to be smaller in countries that already had relatively low levels of social and economic inequality prior to the onset of the pandemic (Rice, 2005; Summers et al., 2014). In further research, we intend to explore this association at the subnational level (e.g., NUTS II level), or at the individual level.

Turning to the policy implications of our findings, we recommend that governments constantly prioritize the protection of vulnerable groups in their contingency plans. On the other hand, further research is needed about, among other pandemic-related topics, the effects of lockdowns. For instance, the closure of non-essential businesses across Europe has contributed to increased unemployment, poverty and inequality. Moreover, the impact on mental health of remaining isolated, of increased uncertainty, and of feeling vulnerable when social interactions are re-established should be assessed.

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