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Socioeconomic conditions and contagion dynamics of the COVID-19 pandemic with and without mitigation measures: Evidence from 185 countries

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ABSTRACT

It is well documented that COVID-19 contagion and mortality rates differed systematically across countries. Less is known, however, on whether these differences could be explained by socioeconomic conditions that may determine both the extent to which individuals voluntarily take protection measures in the absence of Non-Pharmaceutical Interventions (NPIs) or comply with imposed NPIs, when these are in place. Using data from 185 countries, we examine associations of COVID-19 infection and mortality dynamics with socioeconomic conditions, as measured by poverty rates, in periods before and after NPIs have been imposed. We find that, in the initial period of the pandemic, when no NPIs were in place, daily growth of COVID-19 cases and deaths are positively associated with the share of the population living in poverty, whereas, in the following period, when NPIs were implemented, these associations turn negative. We argue that these results could be explained by the fact that NPIs are expected to be more effective in countries with high poverty rates where voluntary physical distancing is low and physical distancing practices are more responsive to imposed measures.

1. Introduction

Recent empirical and theoretical work has highlighted that the effects of COVID-19 have been unequal across populations with infection rates varying across social groups within countries (for example, see Abrams and Szefler, 2020; Galanis and Hanieh, 2021; Georgiadis and Franco Gavonel, 2023; Jay et al., 2020; Kavanagh et al., 2021; Tsai and Wilson, 2020). While it is widely acknowledged that poor socioeconomic conditions (SECs) exacerbate the adverse effects of epidemics in general (Dingwall et al., 2013), this is not directly observed in the case of the COVID-19 pandemic across countries. For example, using COVID-19 infection data, Cash and Patel (2020) argue that "for the first time in the post-war history of epidemics, […] a reversal of which countries are most heavily affected by a disease pandemic" (Cash and Patel, 2020, p. 1687), suggesting that countries with higher poverty rates are less affected by COVID-19.

Fig. 1 shows the geographical variation in total COVID-19 cases per capita between 23/1/2020 and 13/12/2020 (before vaccination programmes become effective), where countries are allocated in five groups of equal size, as defined by the quintiles of the distribution of total cases per capita in the sample, with the group of countries with higher cases per capita presented in darker colours. Note that the 20 per cent of countries with the highest number of total COVID-19 cases per capita includes many high-income countries, such as the USA and several European countries, whereas the lowest 20 per cent of countries includes many low-income, such as countries from Africa. Similarly Fig. 2, presents the variation of total deaths per capita across countries in the same period as Fig. 1 and reveals a similar pattern as that in Fig. 1. Although, the figures are suggestive of higher COVID-19 impacts among high-income countries, consistent with the observation of Cash and Patel (2020), they cannot provide conclusive evidence on how SECs associate with the health impacts of COVID-19 across countries. This is because, first, these patterns may not be systematic and second, they may be driven by data issues, such as lack of data or underreporting of cases and deaths in poorer countries. Motivated by this observation, our paper examines the relationship between the growth of COVID-19 infection and mortality rates on the one hand and SECs, as measured by poverty rates, on the other hand, across countries, before and after Non-Pharmaceutical Interventions (NPIs) were imposed. Our paper also considers the extent to which differences in COVID-19 health impacts

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across countries with different SECs could be explained by differences in the effectiveness of NPIs. Given our focus on the effectiveness of NPIs, our analysis examines the period before COVID-19 vaccines become available around the World that avoids confounding related to differences in vaccination rates across countries.

Our contribution in the literature is to extend the scope of previous studies on how poverty influences the impacts of COVID-19 and the effectiveness of COVID-19 mitigation measures, which either focus on a single country or look at these relationships in the short run (Bargain and Aminjonov, 2021; Bennett, 2021; and Carlitz and Makhura, 2021), by documenting patterns across countries all over the World and over the medium run. Another key feature of our analysis is that it addresses potential biases related to sample selection which arise from missing data and measurement error associated with systematic underreporting of COVID-19 statistics in countries with high poverty levels. Studying the relationship between poverty and COVID-19 health impacts across countries separately before and after measures have been imposed provides a better understanding of this relationship. This is because the effects of COVID-19 fundamentally depend both on whether measures to mitigate the spread of infections have been taken across countries and on how effective these measures have been. Governments have resorted to NPIs to limit the infection rates, with the type (e.g., national or local) and level (e.g., lockdowns or recommendations) of NPIs varying greatly across countries (Lane et al., 2020; Lane et al., 2021). Hence, we test two different hypotheses focusing on the two periods, before and after NPIs were imposed.

The first hypothesis considers the period before NPIs were imposed and postulates that, in the absence of NPIs, higher levels of poverty are associated with higher growth rates of COVID-19 infections and deaths across countries. Our analysis shows that sample selection may lead to a negative association between poverty rates and infection dynamics, as relatively poorer countries are less likely to be influenced by the pandemic or to systematically collect and report statistics on infections and deaths at the beginning of the pandemic. After controlling for potential sample selection in the data, we find a positive and significant association between the share of the population living in poverty and the daily growth rate of new confirmed cases and deaths. Hence, our results support the hypothesis that higher poverty rates are associated with more adverse impacts of the COVID-19 pandemic.

Our second hypothesis postulates that, in the presence of NPIs, there is a negative association between poverty levels and COVID-19 infection and mortality growth rates. The key idea underlining this is that the effectiveness of interventions depends both on how much individuals can comply with these, and the extent to which individuals voluntarily take protective measures in the absence of interventions (Toxvaerd, 2020; Eichenbaum et al., 2021; Di Guilmi et al., 2022; Galanis and Hanieh, 2021). Hence, while on the one hand, it is reasonable to expect that the measures would be less effective in poorer countries, as individuals are less likely to comply with these, due to more binding economic and other constraints, on the other hand, NPIs may be more effective in these countries, if measures increase significantly physical distancing practices, which, in the absence of measures, are relatively low. Our analysis shows a negative and significant association between the share of the population living in poverty and the daily growth rate of new confirmed cases and deaths. Taken together with the results related to the first hypothesis, this implies that imposed measures have been more effective in countries with higher poverty rates where people are less able to engage in voluntary physical distancing in the absence of measures. The next section of the paper presents the conceptual framework and the associated formulated hypotheses; Section 3 presents the methods and the data employed to test the hypotheses of interest; Section 4 presents the results of the data analysis, and the final section provides concluding discussion.

2. Framework

Pandemics do not have uniform effects across populations with the most vulnerable being hit harder (Ahmed et al., 2020; Immel et al., 2022; Stantcheva, 2022). There are two closely related observations associated with the physical distancing behaviour of individuals and the impact of SECs on this behaviour.

The first observation is that, while NPIs play a major role in increasing levels of physical distancing and reducing contagion within populations (Courtemanche et al., 2020; Hsiang et al., 2020; Flaxman et al., 2020), individuals may voluntarily take their own measures to

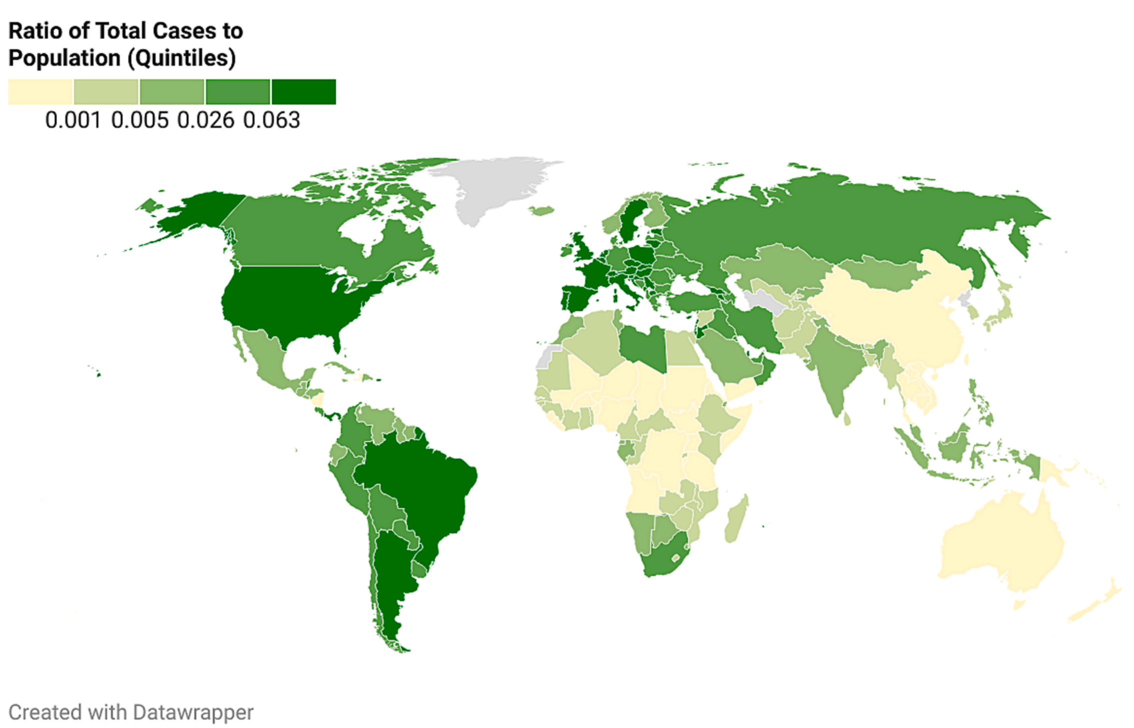

Fig. 1. Total Cases Per Capita across Countries, 23 Jan – 13 Dec 2020. *Notes:* Source, Our World in Data COVID-19 Data Set; data available for 185 countries.

mitigate the chance of infection in the absence of NPIs or may not comply with existing governmental measures (Chernozhukov et al., 2021). During the first period of the pandemic, before measures had been imposed, individuals had been engaging in voluntary physical distancing to protect themselves (Galanis et al., 2021; Di Guilmi et. al., 2022), while, in the following period, during which measures have been taken by national governments to mitigate the impact of COVID-19, parts of the population across countries did not comply with the measures taken (Singh et al., 2021; Bargain and Aminjonov, 2021; Carlitz and Makhura, 2021). This implies that epidemiological models that do not incorporate these behavioural responses of individuals, in the presence and absence of NPIs, are expected to systematically misrepresent the level and rate of infections. Many studies have extended the standard epidemiological models in the tradition of Kermack and McKendrick (1927) by assuming that levels of physical distancing are not only determined by NPIs, but also by individual behaviour (Toxvaerd, 2020; Eichenbaum et al., 2021; Galanis et al., 2021; Di Guilmi et al., 2022). Taking into account individual behaviour cannot only provide a better understanding of the infection rate dynamics in the absence of measures, but can also provide better insights regarding the effectiveness of NPIs as well as the extent to which individuals comply with these NPIs.

The second observation is that individual behaviour, including physical distancing decisions, is socially and economically constrained and poorer households may find it more difficult to take protective measures (Alon et al., 2020). This means that differences in poverty rates across countries are expected to result in systematic differences in infection dynamics and fatality rates. This idea is formally presented in the socioeconomic compartmental framework of Galanis and Hanieh (2021), which extends the standard SIRD (Susceptible-Infected-Recovered-Deceased) model in the tradition of Kermack and McKendrick (1927) by allowing for SECs to affect the infection rate and the case-to-fatality ratio respectively. More specifically, they consider the possible effects of three types of SECs which are directly related to poverty levels and are known to have an impact not only on COVID-19 infection dynamics but also on public health in general: employment conditions (Bartley et al., 1999; Gouzoulis and Galanis, 2021; Stringhini et al., 2010; Reeves, 2021); housing conditions (Shaw, 2004; Swope & Hernández, 2019); and conditions related to access to, and the quality of, public health systems (Murthy et al., 2015; Martinez-Alvarez et al., 2020). In particular, the model of Galanis and Hanieh (2021) predicts that high levels of poverty are associated with higher infection and fatality rates because poorer individuals are less able to voluntarily take protective measures due to less flexible employment conditions, e.g., ability to work remotely, more crowded housing conditions, and access to poorer health infrastructure (Brodeur et al., 2021; Papageorge et al., 2020). Nevertheless, it should be noted that Galanis and Hanieh (2021) do not consider the role of demographics in their framework, and this may have an impact especially on fatality rates, as we discuss below.

It is both interesting and important to consider these observations jointly to understand the effects of pandemics, including COVID-19, and the effectiveness of NPIs to mitigate these, across countries with different SECs as measured by poverty levels. Furthermore, it is crucial to distinguish between the physical distancing decisions of individuals living under different SECs, in the absence and in the presence of NPIs, and their implications for the (relative) effectiveness of NPIs as captured by the reduction in the growth rate of infections. Put it differently, individuals living in poorer SECs may be less able to comply with NPIs, as they are more constrained. These constraints, however, are also associated with low voluntary protection by individuals living in poverty in the absence of interventions. This may imply higher potential of interventions to increase protective measures among these individuals, and, thus, higher effectiveness of interventions in poorer contexts.

For example, using poverty and Google mobility data for 242 regions in nine countries in Latin America and Africa, Bargain and Aminjonov (2021) show that during the first lockdown, the decline in work-related mobility was lower in regions with higher poverty levels, leading to higher infection rates in these regions. Similarly, Carlitz and Makhura (2021) using data from South Africa, show that, while the population as a whole complied with governmental physical distancing measures, this was more difficult in poorer and rural regions. Although these studies suggest that people in poorer regions might be less able to comply with NPIs, this does not necessarily mean that NPIs are less effective in these regions, as, even under imperfect compliance, NPIs may still

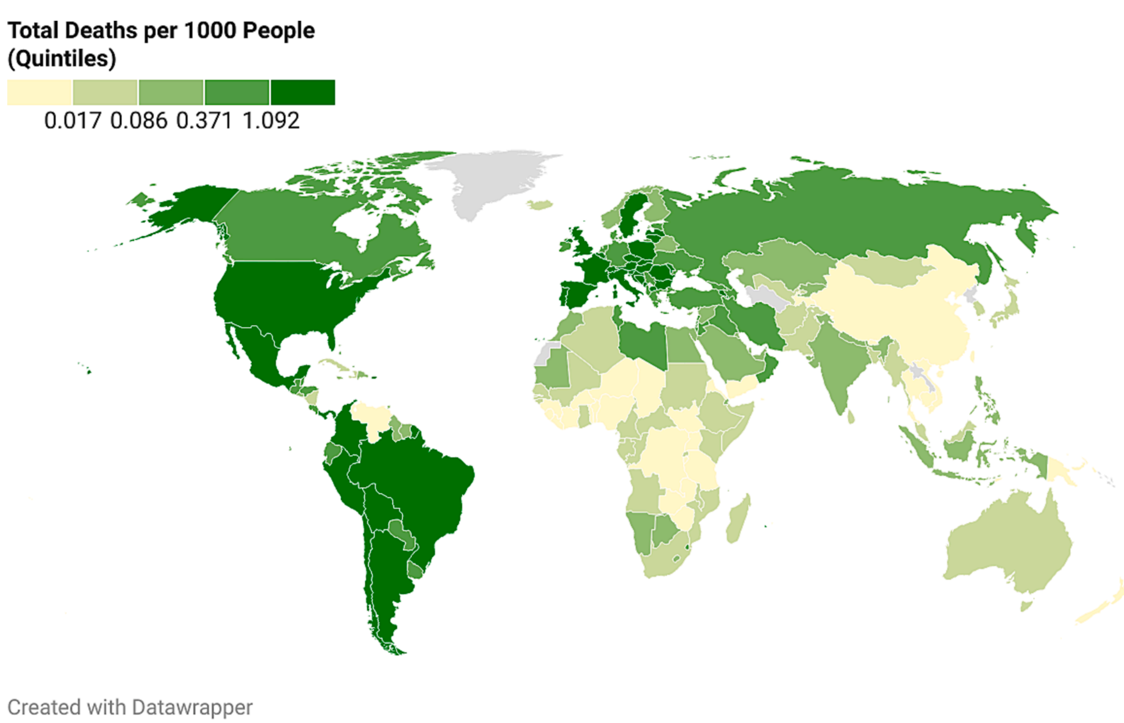

Fig. 2. Total Deaths Per Capita across Countries, 23 Jan – 13 Dec 2020. *Notes:* Source, Our World in Data COVID-19 Data Set; data available for 185 countries.

significantly increase protection by individuals against infection relative to regions with lower shares of the population living in poverty.

Furthermore, even if the number of deaths and fatality rates is associated with infections, the exact relationship between the two also depends on the demographics of a population as the probability that an infected individual becomes deceased is higher with age (Bonanad et al., 2020). Based on this, it has been argued that in low-income countries where the share of COVID-19 related deaths is higher within younger age cohorts (Demombynes, 2020), the overall death rate (across all the population) is lower (Cash and Patel, 2020). For this reason, it is crucial to analyse the dynamics of deaths explicitly and separately to infection dynamics both before and after measures have been imposed.

Conclusive inferences on the effectiveness of policies aiming to tackle pandemics require evidence on how infections and deaths change in the presence of these policies. The observations above and the related theoretical frameworks lead to two types of empirical questions related to contagion dynamics across countries with different socioeconomic conditions/poverty levels. The first is related to the theoretical argument of Galanis and Hanieh (2021) that, in the absence of NPIs, poor SECs will be associated with both higher infection and death rates. The second empirical question is related to the effectiveness of NPIs across countries with different SECs, and, in particular, to whether NPIs are less or more effective in countries with lower poverty levels. Conceptually, this is not clear, as there are arguments supporting either case. On the one hand, since poorer households and people are working under informal conditions and are living in more crowded households, they are less likely to be able to practice physical distancing measures (Alon et al., 2020; Bargain and Aminjonov, 2021; Bennett, 2021; Carlitz and Makhura, 2021). Thus, one would expect that NPIs are less effective in reducing contagion dynamics in countries with poorer SECs. On the other hand, measuring the effectiveness of a policy is a comparative exercise, hence, it has to be considered in relation to what would have happened if the policy had not been in place. From this viewpoint, as individuals take measures themselves independently of government measures (Galanis et al., 2021; Di Guilmi et. al., 2022), NPIs could be more effective in countries with higher poverty rates, as the latter limit the ability of individuals to take measures themselves. In other words, NPIs may lead to a higher increase in protective behaviour in populations with higher poverty levels, where voluntary protection is very low in the first place.

3. Methods

3.1. Data

The data used in our analysis include information on COVID-19 cases and deaths, poverty rates, as well as GDP per capita and Human Development Index (HDI) across all countries for the period between 23 January 2020 and 13 December 2020. The data on COVID-19 are from *Our World in Data* COVID-19 dataset[1] and the data on poverty rates, GDP per capita, and HDI are from the World Bank.[2]

3.2. Measures

3.2.1. Dependent variables: COVID-19 Impacts

As measures of COVID-19 impacts across countries we use the difference in logarithms of new daily COVID-19 cases and the difference in logarithms of new daily deaths related to COVID-19. To minimise noise, new daily COVID-19 cases and deaths were used to calculate the latter measures were smoothed using the average of the last 7 days. The difference in COVID-19 cases and deaths were preferred from their levels as measures of the impact of COVID-19 because the former may eliminate measurement error in the level of cases and deaths, provided that the measurement error remains fixed over time. This measurement error may not be random necessarily and it may be systematically associated with socioeconomic conditions. This would be the case, for example, if countries with poorer SECs tend to systematically underreport new daily COVID-19 cases and deaths. This is expected to lead to a downward bias in the estimates of the relationship between COVID-19 impact measures and measures of living standards.

3.2.2. Independent variable: SECs

As a measure of the three types of socioeconomic conditions, i.e., employment conditions, housing conditions, and conditions related to access to and quality of health infrastructure, discussed in Galanis and Hanieh (2021), we use the share of population living in poverty (poverty rate) calculated as the share of people with income below $1.90 per day using international dollars using the 2011 Purchasing Power Parity (PPP) exchange rates (Deaton, 1997). This closely follows previous studies, e.g., Brodeur et al. (2021) and Papageorge et al. (2020), establishing that, because individuals living in poverty are less able to engage in voluntary physical distancing due to less flexible employment conditions, e.g., ability to work remotely, more crowded housing conditions, and access to poorer health infrastructure, poverty is expected to be a valid proxy of poor SECs.

3.2.3. Control variable: measures of economic development

In our analysis, we also control for differences in the level of economic development/standards of living across countries, usually captured by either GDP per capita, measured in international dollars using the year 2017 PPP exchange rates to convert local currencies or HDI, that, reflects three dimensions of living standards: income, as measured by Gross National Income (GNI); education, as measured by average years of schooling; and health, as measured by life expectancy at birth (Deaton, 1997). These variables aim to control for differences in COVID-19-related data collection capabilities and COVID-19 testing capacities across countries (Brodeur et al., 2021; Silverman et al., 2020) that are expected to be correlated both with COVID-19 impact measures and poverty rates – as poverty is one of the many dimensions of underdevelopment. Thus, unless these factors are accounted for, they may lead to bias in the estimates of the relationship between growth in COVID-19 infection and deaths and poverty across countries, arising from sample selection and measurement error (see discussion in one of the next sections for details of the type of the relevant biases).

3.3. Periods

We consider two periods aiming to capture the effects before and after NPIs were imposed. For the first period, to capture the effects properly, we consider three types of observations. First, we assume as 23 March 2020 the date of imposition of NPIs in most countries globally (BBC, 2020). Second, we consider that there exists a time lag for measures to be effective both in reducing infection and death rates. This is mainly because there exists an incubation period that may vary between 2.33 and 17.60 days with a mean of 6.38 days (Elias et al., 2021). Furthermore, the length of the period between the onset of symptoms and death is estimated to be around 16 days (Hu et al., 2021, 2022). Based on these two observations, we expect that the peak of daily infections would be around the end of March or the beginning of April and the peak of deaths around the middle of April. This is supported by *Our World in Data* COVID-19 dataset showing that daily worldwide infections peaked on 3 April 2020 and that daily worldwide deaths peaked on 17 April 2020. Thus, we choose these two dates to be the cut off dates of the first period for cases and deaths respectively, with the first or initial period being that of 23 Jan 2020 – 3 April 2020 for cases and that of 23 Jan 2020 – 17 Apr 2020 for deaths.

Regarding the second period, there is no clear date when measures are lifted as different types of restrictions have been lifted across

[1] See https://github.com/owid/covid-19-data/tree/master/public/data.
[2] https://data.worldbank.org/.

countries in different periods. For this reason, we choose 13 December 2020 as the cut-off date, during which most countries, implemented some form of NPIs, while vaccination levels had been almost non-existent across countries (Mathieu et al., 2021), with the second or following period being that of 4 Apr 2020 – 13 Dec 2020 for cases and that of 18 Apr 2020 – 13 Dec 2020 for deaths.

3.4. Estimation

We estimate the association between COVID-19 impact and poverty rates employing the following specifications:

$$\Delta Y_{i,2020} = \beta_0 + \beta_1 Pov_{i,2019} + \beta_2 ED_{i,2019} + u_i \tag{1a}$$

$$\Delta Y_{it,2020} = \alpha_0 + \alpha_1 Pov_{i,2019} + \alpha_2 ED_{i,2019} + \gamma_t + \delta_i + v_{it} \tag{1b}$$

where $\Delta Y_{i,2020}$ in (1a) is the average change in log number of new daily COVID-19 cases or deaths in country i during a period of 2020 (either the initial period, before NPIs are imposed, or in the period after NPIs are imposed); $Pov_{i,2019}$ is the share of population in country i living in poverty in 2019; $ED_{i,2019}$, is a measure of economic development of country i, i.e., either GDP per capita or HDI, in 2019; and u_i is a random error term. Moreover, in (1b), $\Delta Y_{it,2020}$ is the change in log number of new daily cases or deaths in country i between day t and day $t-1$; γ_t is an aggregate time effect; δ_i is a random country-specific, time-invariant error component; and v_{it} is a random error that varies across countries and over time.

Equation (1a) is estimated via Ordinary Least Squares (OLS) whereas equation (1b) is estimated via Random Effects (RE) and both equations are estimated separately for cases and deaths and for the initial and the following period. The latter allow us to document the association between COVID-19 impact dynamics and poverty rates both in the absence and in the presence of NPIs. RE estimation in equation (1b) is employed because the dependent variable is longitudinal in nature, that is, it varies across countries and over time, i.e., daily, whereas the independent variable,$Pov_{i,2019}$, varies only across countries. RE applies a Generalized Least Squares (GLS) estimator that accounts for dependence in model errors over time, arising from accounting for a country-specific and time-invariant error component, δ_i (Wooldridge, 2010). In this way, by leveraging variation in the dependent variable both across countries and over time, RE is more efficient than OLS (Wooldridge, 2010).

Equations (1a) and (1b) include measures of the dependent variable observed in periods during year 2020 and the measure of the independent variable, $Pov_{i,2019}$, observed in year 2019, in order to avoid potential problems arising from simultaneity and reverse causality, considering the dramatic economic impacts of COVID-19.

One potential problem in the estimation of the association between COVID-19 impacts and poverty rates via estimation of equations (1a) and (1b) is sample selection bias, which may arise because more developed countries were hit by the pandemic and started the systematic collection of data on COVID-19 earlier than less developed countries. Thus, on average, more developed countries are likely to be over-represented in our sample, particularly in the initial periods of our analysis; in the following periods, we expect that sample selection would be less of a concern, as, during these periods, more countries have been affected and collected and reported COVID-19 statistics. Following Greene (2020), sample selection would lead to bias in the estimates of the coefficient of poverty rate in (1a) and (1b) if it is correlated with the poverty rate.[3] We find evidence consistent with this, as we find a negative and significant association between sample selection, measured by a binary indicator taking the value 1 for observations included in our sample and 0 for observations not included in our sample, and the poverty rate, only for the initial period (see Tables A1 and A2 in the Appendix for results). This confirms our hypothesis that countries with higher poverty rates are more likely to be excluded from the sample in the initial period and implies that this will plague the estimates of the association between COVID-19 health impact measures and poverty rates in this period with bias. Following Greene (2020), under the assumption that sample selection is negatively associated with COVID-19 health impacts, it is expected to lead to a downward bias in the estimated coefficient of poverty rate.[4]

To address sample selection bias, equations (1a) and (1b) include a measure of economic development/living standards, $ED_{i,2019}$, such as GDP per capita or HDI, as a control. As discussed in one of the previous sections, this is expected to control for differences in COVID-19 data collection capabilities and COVID-19 testing capacities across countries that in turn can explain differences in the timing countries started collecting data on COVID-19 as well as differences in data quality. In this way, the coefficient of poverty rate in models (1a) and (1b), which control for a measure of economic development, expresses the association between COVID-19 health impacts and poverty rates among countries with the same level of economic development that, because of similar data collection capabilities, are expected to have started collecting data around the same time.

We find evidence supporting that the above approach effectively controls for sample selection bias in the estimates of the coefficient of the poverty rate produced via estimation of models (1a) and (1b). In particular, we find that in models of sample selection for both the growth of cases and growth of deaths in the initial period, including both the poverty rate and a measure of economic development, such as GDP per capita or HDI, sample selection is not significantly associated with the poverty rate, but it is significantly associated with GDP per capita or HDI (see Tables A1 and A2 in the Appendix). Therefore, based on the above discussion, this addresses concerns related to sample selection bias in the estimates of the coefficient of the share of the population living in poverty, $Pov_{i,2019}$, in models (1a) and (1b) in the initial period, as this is picked up by the included measure of economic development,$ED_{i,2019}$.

Note that controlling for differences in economic development across countries in estimation is expected to control for a range of unobserved factors, associated with both COVID-19 and poverty rates – subsumed in the error terms of (1a) and (1b) – which may lead to bias in the estimates of the coefficients of interest. For example, one such source of bias may arise from measurement error in the level of cases and deaths, arising from systematic underreporting that, as discussed in one of the previous sections, may not be fixed over time. In the case, for example, that this measurement error declines over time, as data collection and testing capacities increase, then it will affect our measures of dependent variables, that is, the growth of cases and deaths. This may in turn lead to bias in the coefficient of interest, if the measurement error is correlated with poverty, as the rate of decline of underreporting may be correlated with the level of economic development because less poor countries may improve data collection and testing capacities faster than more poor countries (Brodeur et al., 2021; Silverman et al., 2020). In this case, including controls for differences in economic development, as measured by GDP per capita and HDI, is expected to address this problem.

4. Results

Table 1 presents descriptive statistics of the variables used in our analysis for the full period (23 Jan 2020 – 13 Dec 2020), and separately

[3] This is based on the formula sign(sample selection bias)= − sign(correlation of sample selection with dependent variable)xsign(correlation of sample selection with independent variable) (Greene, 2020, pp. 783).

[4] This is based on the formula for the direction of the sample selection bias and evidence that sample selection is negatively associated with the poverty rate (see Tables A1 and A2 in the Appendix).

Table 1
Descriptive Statistics of the Key Variables Used in the Analysis, 23 Jan 2020 – 13 Dec 2020.

	Full Period	Cases		Deaths	
		Initial Period	Following Period	Initial Period	Following Period
Change in log new daily cases	0.016	0.091	0.008		
	(0.196)	(0.194)	(0.195)		
Change in log new daily deaths	0.007			0.028	0.003
	(0.120)			(0.108)	(0.121)
Poverty rate 2019	0.134	0.068	0.141	0.091	0.141
	(0.208)	(0.147)	(0.212)	(0.174)	(0.212)
Gross Domestic Product (GDP) per capita 2019	21948.81	28305.02	21307.78	26033.23	21281.52
	(21256.81)	(22941.52)	(20973.04)	(22513.02)	(20969.26)
Human development index 2019	0.728	0.782	0.723	0.763	0.723
	(0.150)	(0.135)	(0.151)	(0.142)	(0.151)
Number of countries	185	171	185	178	185
Number of observations	50,495	4520	45,975	6976	43,476

Notes: Figures are averages with standard deviations in parentheses. The initial period for cases is 23 Jan 2020 – 03 Apr 2020 and for deaths is 23 Jan 2020 – 17 Apr 2020; the following period for cases is 04 Apr 2020 – 13 Dec 2020, and for deaths 18 Apr 2020 – 13 Dec 2020. New daily cases and new daily deaths are smoothed through taking the average of the last seven days. Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita.

for the initial periods for cases (23 Jan 2020 – 3 Apr 2020) and deaths (23 Jan 2020 – 17 Apr 2020) as well as the following periods for cases (4 Apr 2020 – 13 Dec 2020) and deaths (18 Apr 2020 – 13 Dec 2020).

Table 1 shows that there are 185 countries and 50,495 observations in the full period of interest in our sample. A comparison of means of the key variables between the initial and the following period for both cases and deaths suggests that a) there was a higher daily growth of new COVID-19 cases and deaths in the initial period when measures were not in place; and b) that the poverty rate was, on average, lower – and GDP per capita and HDI, were on average, higher – in the sample of countries in the initial periods compared to the following periods. The pattern in a) suggests that NPIs implemented across countries in the following periods mitigated impacts of COVID-19, whereas the pattern in b) provides further support to our claim that, on average, countries with higher shares of population living in poverty are more likely to be excluded from the samples in the initial periods. This is either because more poor countries were affected later by the pandemic compared to less poor countries or because they started collecting data and reporting statistics of COVID-19 impacts later than less poor countries, which, as discussed in the previous section, implies concerns of sample selection bias in our estimates in the initial periods.

Figs. 3 and 4 present the geographical variation of daily growth of COVID-19 cases in the initial period and following period respectively. The juxtaposition of the two figures shows that several high-income countries, such as countries in Europe and North America, which, in the initial period, are in the group of countries with the highest daily growth in COVID-19 cases, move to groups with medium to low daily growth in cases in the following period. Moreover, several low-income countries, such as countries in Africa, and middle-income countries, including India and Russia, move from groups with relatively low growth of COVID-19 cases in the initial period to groups with higher growth of cases in the following period. A similar pattern is revealed by a comparison of Figs. 5 and 6 that present the variation of daily growth in deaths due to COVID-19 across countries in the initial and following period.

It is not clear, however, whether these patterns reflect an actual shift in the relationship between COVID-19 dynamics and poverty rates in the initial and following period; or, as discussed in the previous section, are due to sample selection, i.e., a mere consequence of the fact that countries with high poverty rates countries are less likely to systematically report COVID-19 statistics in the initial period.

In order to clarify this and test whether the patterns suggested by the geographical variation in COVID-19 impact measures presented in the Figures reflect a systematic relationship between COVID-19 and poverty rates, we turn to the estimation of equations (1a) and (1b). Table 2 presents estimates of associations between poverty rates with growth in daily cases and growth in daily deaths in the initial period.

Coefficients in the upper panel of Table 2 reported in specifications (1), including only the poverty rate and no controls, estimated both via OLS and RE, show a negative and significant association between growth in cases and poverty rates. This suggests that, on average, countries with lower poverty rates experienced higher growth of new daily cases during the initial period of the COVID-19 onset. Nevertheless, estimates in the upper panel of Table 2 reported in specifications (2) and (3) show that associations between the growth of new daily cases and poverty become positive and significant[5] in specifications that also control for either GDP per capita or HDI. This is in line with our discussion in the previous section suggesting that controlling for either GDP per capita or HDI is expected to correct for a downward bias in the coefficient of poverty in univariate regressions of growth of new daily cases, arising from sample selection bias. Thus, this can be viewed as evidence that, after correcting for sample selection, new daily infections grew more rapidly in poorer countries during the initial period of the COVID-19 onset.

A similar pattern is revealed by the lower panel of Table 2, which presents estimates of associations between the growth of new daily deaths due to COVID-19 and poverty rates: a) growth of new daily COVID-19-related deaths is negatively and significantly associated with poverty in specifications that do not include GDP per capita or HDI as a control; b) estimated statistical associations of growth of COVID-19 deaths and poverty are positive, but insignificant, in all specifications that control for either GDP per capita or HDI estimated either by OLS or RE. This again supports our discussion in the previous section highlighting the concern of a downward sample selection bias in the coefficient of poverty, which is corrected via conditioning on a measure of economic development/living standards in the estimated models. The downward sample selection bias supports our assumption that there is a systematic negative relationship between selection, and thus living

[5] Only RE estimates are significant, which, given that they are more efficient than OLS (Wooldridge, 2010), are our preferred estimates.

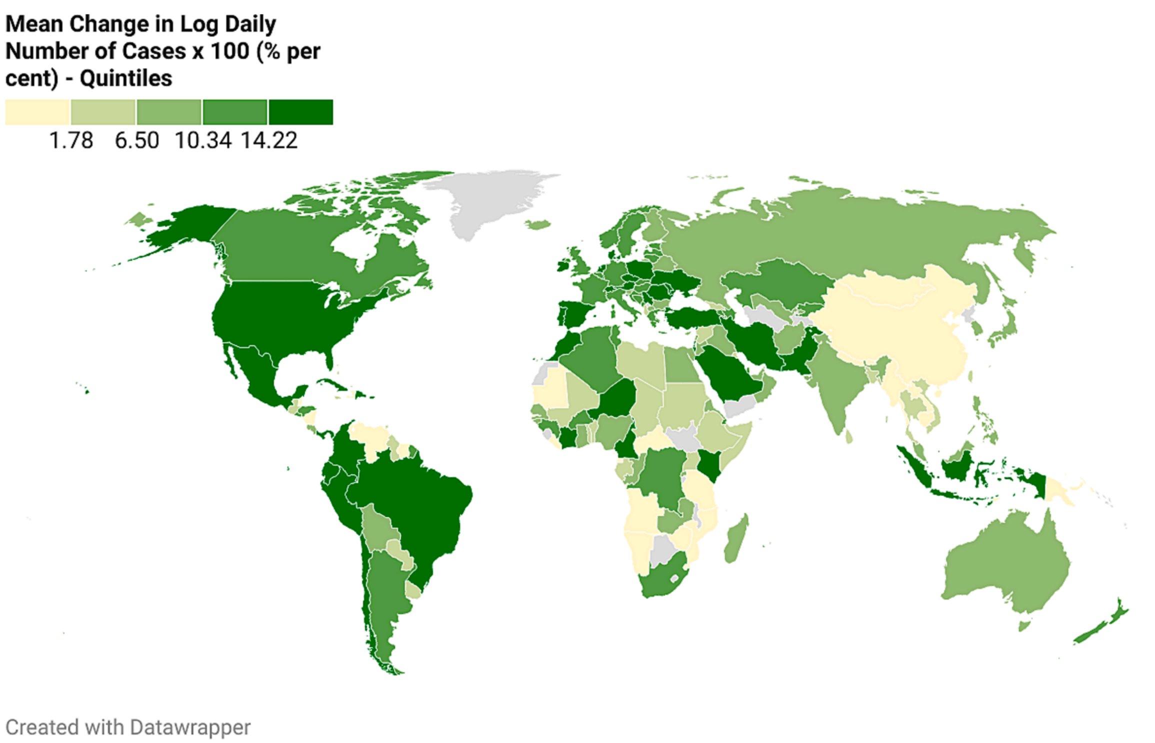

Fig. 3. Average Daily Growth in COVID-19 Cases, 23 Jan – 3 Apr 2020. *Notes:* Source, Our World in Data COVID-19 Data Set; data available for 171 countries; new daily cases are smoothed through taking the average of the last seven days.

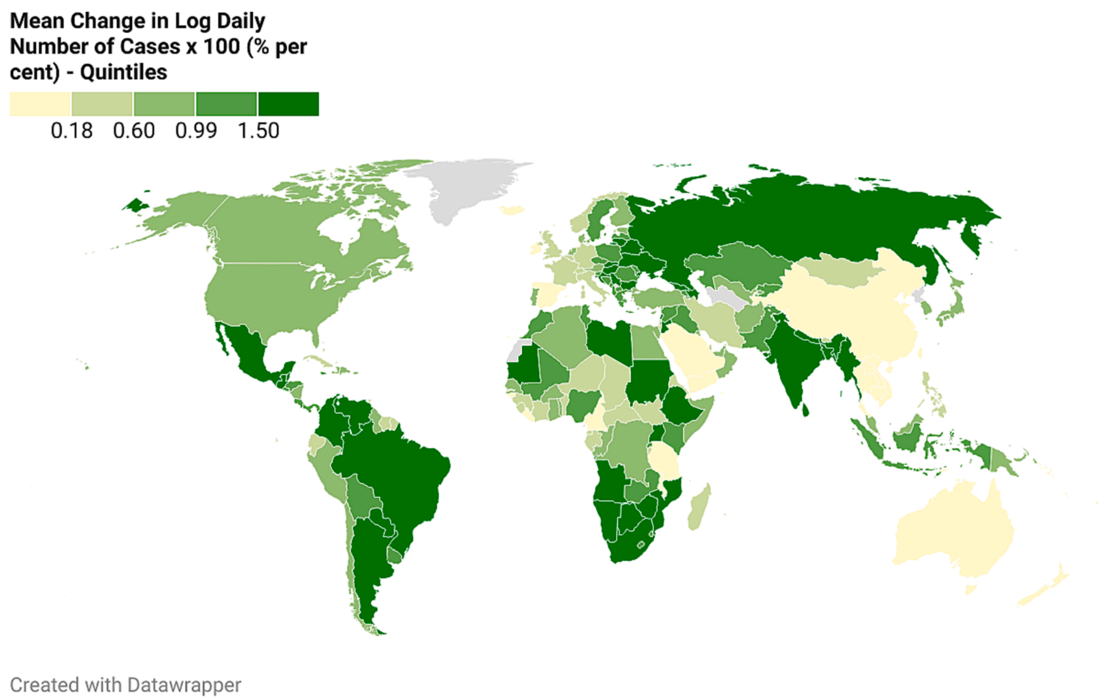

Fig. 4. Average Daily Growth in COVID-19 Cases, 4 Apr – 13 Dec 2020. *Notes:* Source, Our World in Data COVID-19 Data Set; data available for 185 countries; new daily cases are smoothed through taking the average of the last seven days.

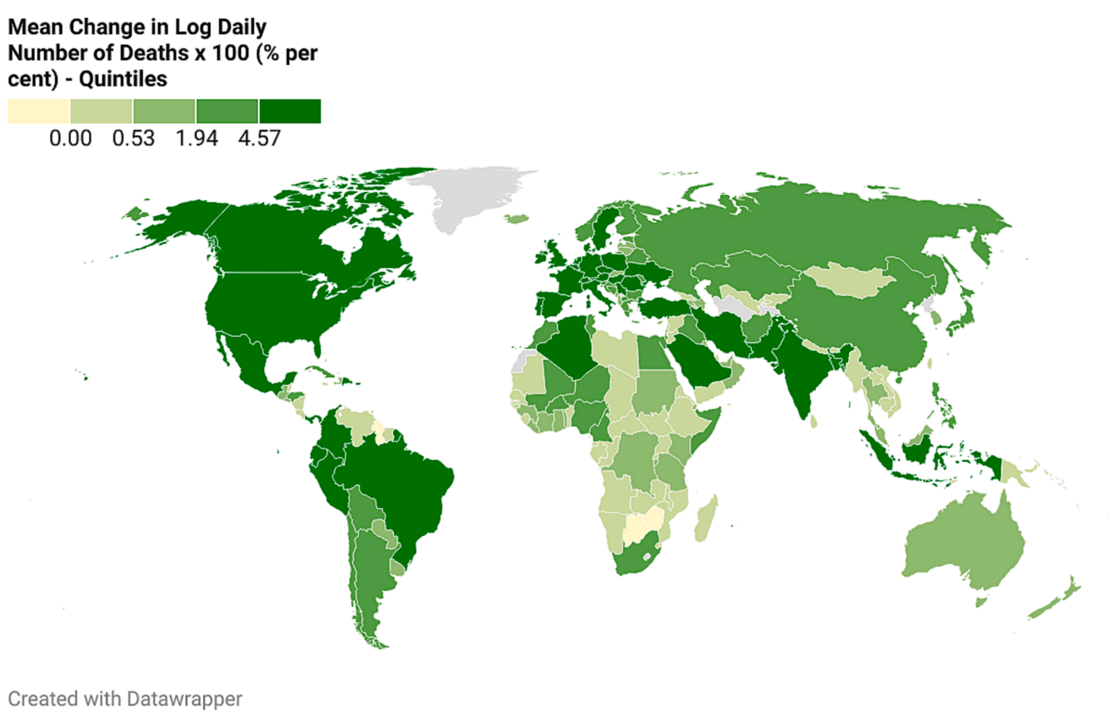

Fig. 5. Average Daily Growth in COVID-19 Deaths, 23 Jan – 17 Apr 2020. *Notes:* Source, Our World in Data COVID-19 Data Set; data available for 178 countries; new daily deaths are smoothed through taking the average of the last seven days.

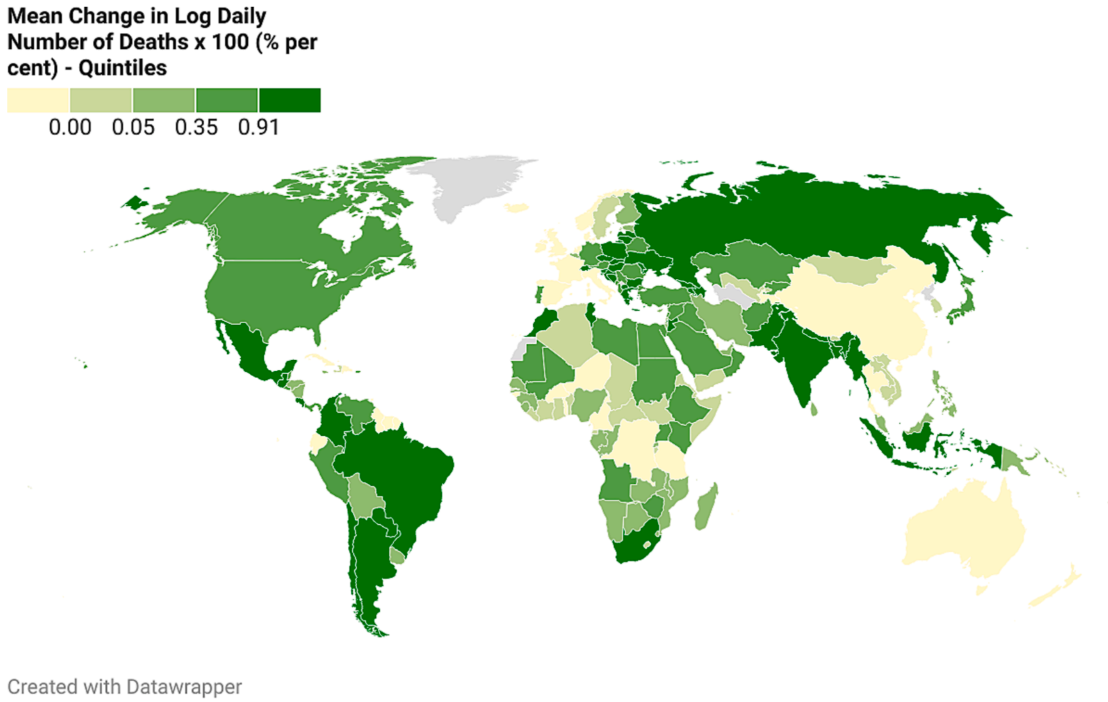

Fig. 6. Average Daily Growth in COVID-19 Deaths, 18 Apr – 13 Dec 2020. *Notes:* Source, Our World in Data COVID-19 Data Set; data available for 185 countries; new daily deaths are smoothed through taking the average of the last seven days.

Table 2
Estimated Associations between Covid-19 Impacts (Cases and Deaths) and the Poverty Rate, Initial Period.

	Change in log daily new cases					
	OLS			Random Effects		
	(1)	(2)	(3)	(1)	(2)	(3)
Poverty rate 2019	(0.026)	(0.041)	(0.039)	(0.023)	(0.033)	(0.033)
Log gdp per capita 2019			0.231***			0.181***
			(0.053)			(0.041)
Human development index 2019	0.074	0.167	0.177	0.129	0.138	0.138
Number of countries	138	137	137	138	137	137
Number of observations	138	137	137	3814	3801	3801
	Change in log daily new deaths					
Poverty rate 2019	(0.008)	(0.014)	(0.012)	(0.008)	(0.016)	(0.014)
Log gdp per capita 2019		0.016***			0.018***	
Human development index 2019			(0.020)			(0.023)
R-squared	0.150	0.266	0.285	0.045	0.060	0.061
Number of countries	144	142	143	145	142	144
Number of observations	144	142	143	5808	5772	5781

Notes: Robust standard errors under OLS estimates in parentheses; standard errors clustered at the country level under Random Effects estimates in parentheses; ***significant at 1%, **significant at 5%, *significant at 10%. The initial period for cases is 23 Jan 2020 – 03 Apr 2020 and for deaths is 23 Jan 2020 – 17 Apr 2020. Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita. Random Effects estimated models include time dummies as control variables.

standards, and the growth of deaths due to COVID-19 in the initial period.[6]

Overall, the evidence here reveals a systematic positive association between poverty and the growth of new daily COVID-19 infections and deaths which provides support to the hypothesis that countries with higher levels of poverty were hit harder by COVID-19 during the initial period of the pandemic, during which NPIs were not in place.

Table 3 presents estimates of associations between the poverty rate and growth in daily cases and growth in daily deaths in the following periods, when NPIs were implemented across countries. Coefficients in the upper panel of Table 3, from models including only the poverty rate as an explanatory variable and no controls, estimated via OLS and RE, show a weakly significant and negative association between the growth of COVID-19 infections and the poverty rate. Based on our discussion in our previous section, these are our preferred estimates of associations between measures of living standards and measures of COVID-19

[6] This is derived using the formula for the sign of the sample selection bias and the evidence that selection is negatively and significantly associated with the poverty rate in the initial period (see Table A1 and A2 in the Appendix). Note that, despite the fact that estimates are insignificant, as RE estimates are at the margin of being weakly significant at 10% and as we also find that they turn significant depending on the choice of cut-off (these results are available from the authors upon request).

Table 3
Estimated Associations between Covid-19 Impacts (Cases and Deaths) and the Poverty Rate, Following Period.

	Change in log daily new cases					
	OLS			Random Effects		
	(1)	(2)	(3)	(1)	(2)	(3)
Poverty rate 2019	(0.002)	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)
Log gdp per capita 2019			−0.009			−0.012*
			(0.006)			(0.006)
Human development index 2019	0.015	0.028	0.029	0.006	0.006	0.006
Number of countries	151	148	150	151	148	150
Number of observations	151	148	150	37,552	36,809	37,298
	Change in log daily new deaths					
Poverty rate 2019	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)
Log gdp per capita 2019		0.001			−0.001	
Human development index 2019			(0.004)			(0.004)
R-squared	0.058	0.060	0.054	0.008	0.008	0.008
Number of countries	151	148	150	151	148	150
Number of observations	151	148	150	35,515	34,795	35,275

Notes: Robust standard errors under OLS estimates in parentheses; standard errors clustered at the country level under Random Effects estimates in parentheses; ***significant at 1%, **significant at 5%, *significant at 10%. The following period for cases is 04 Apr 2020 – 13 Dec 2020 and for deaths 18 Apr 2020 – 13 Dec 2020. Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita. Random Effects estimated models include time dummies as control variables.

Table 4
Estimated Associations of Sample Selection with Poverty Rate, GDP per Capita, and Human Development Index, Change in Log Daily New Cases.

	Sample Selection – Initial Period									
	OLS					Random Effects				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Poverty rate 2019		−0.316**		0.270	−0.055		−0.423***		0.054	0.043
		(0.144)		(0.227)	(0.236)		(0.048)		(0.083)	(0.077)
Log gdp per capita 2019	0.037			0.117***		0.073***			0.097***	
	(0.026)			(0.038)		(0.011)			(0.018)	
Human development index 2019			0.479***		0.509**			0.683***		0.811***
			(0.158)		(0.251)			(0.072)		(0.123)
R-squared	0.017	0.047	0.062	0.113	0.088	0.340	0.350	0.368	0.391	0.395
Number of countries	186	154	186	151	152	186	154	186	151	152
Number of observations	186	154	186	151	152	17,484	14,476	17,484	13,982	14,288
	Sample Selection – Following Period									
Poverty rate 2019		0.036		0.195*	0.079		0.033		0.385***	0.192**
		(0.027)		(0.113)	(0.057)		(0.035)		(0.145)	(0.086)
Log gdp per capita 2019	−0.032**			0.035*		−0.013			0.077***	
	(0.016)			(0.021)		(0.018)			(0.028)	
Human development index 2019			−0.030		0.104			0.050		0.301**
			(0.059)		(0.076)			(0.071)		(0.122)
R-squared	0.027	0.003	0.001	0.034	0.009	0.005	0.005	0.005	0.081	0.030
Number of countries	186	154	186	151	152	186	154	186	151	152
Number of observations	186	154	186	151	152	47,244	39,116	47,244	38,354	38,608

Notes: Robust standard errors under OLS estimates in parentheses; standard errors clustered at the country level under Random Effects estimates in parentheses; ***significant at 1%, **significant at 5%, *significant at 10%. The initial period is 23 Jan 2020 – 03 Apr 2020 and the following period is 04 Apr 2020 – 13 Dec 2020. The dependent variable is an indicator that is 1 if the observation is included in the sample and 0 otherwise; GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita. Random Effects estimated models include time dummies as control variables.

impact, as they are not affected by sample selection bias. Note, however, that our results for the following periods (see Tables A1 and A2 in the Appendix) support that sample selection bias is likely to be present in coefficient estimates of models including both poverty and another measure of living standards in Table 3. Therefore, our results suggest that, in the following period, when NPIs were in place, countries with low poverty rates experienced, on average, higher growth of COVID-19 cases. This is also supported by the evidence of a downward sample selection bias in coefficient estimates of models including both poverty and a measure of economic development/living standards in Table 3. Given the formula for the direction of sample selection bias, our results that the poverty rate is positively and significantly associated with sample selection in the following periods (see Tables A1 and A2) implies a positive relationship between sample selection, and thus, living standards, and COVID-19 infections and deaths.

Again, a similar pattern is revealed by estimates of associations between poverty rates and growth in deaths related to COVID-19, presented in the lower panel of Table 3. In particular, estimates from models including only the poverty rate as an explanatory variable suggest a negative and strongly significant association between the poverty rate and growth in daily deaths due to COVID-19 for both OLS and RE estimation results. This further supports that the growth of COVID-19-

Table 5
Estimated Associations of Sample Selection with Poverty Rate, GDP per Capita, and Human Development Index, Change in Log Daily New Deaths.

	Sample Selection – Initial Period									
	OLS					Random Effects				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Poverty rate 2019		−0.833***		−0.007	−0.192		−0.379***		0.126	0.069
		(0.173)		(0.313)	(0.292)		(0.046)		(0.094)	(0.077)
Log gdp per capita 2019	0.136***			0.189***		0.065***			0.112***	
	(0.029)			(0.046)		(0.012)			(0.019)	
Human development index 2019			1.332***		1.206***			0.630***		0.782***
			(0.190)		(0.325)			(0.070)		(0.119)
R-squared	0.128	0.164	0.215	0.264	0.264	0.434	0.487	0.433	0.436	0.440
Number of countries	186	154	186	151	152	186	154	186	151	152
Number of observations	186	154	186	151	152	20,088	16,632	20,088	16,308	16,416
	Sample Selection – Following Period									
Poverty rate 2019		0.036		0.195*	0.079		0.042		0.375***	0.186**
		(0.027)		(0.113)	(0.057)		(0.035)		(0.145)	(0.085)
Log gdp per capita 2019	−0.032**			0.035*		−0.015			0.074***	
	(0.016)			(0.021)		(0.018)			(0.028)	
Human development index 2019			−0.030		0.104			0.033		0.276**
			(0.059)		(0.076)			(0.070)		(0.121)
R-squared	0.027	0.003	0.001	0.034	0.009	0.008	0.013	0.017	0.083	0.039
Number of countries	186	154	186	151	152	186	154	186	151	152
Number of observations	186	154	186	151	152	49,290	40,810	49,290	40,015	40,280

Notes: Robust standard errors under OLS estimates in parentheses; standard errors clustered at the country level under Random Effects estimates in parentheses; ***significant at 1%, **significant at 5%, *significant at 10%. The initial period is 23 Jan 2020 – 17 Apr 2020 and the following period is 18 Apr 2020 – 13 Dec 2020. The dependent variable is an indicator that is 1 if the observation is included in the sample and 0 otherwise; GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita. Random Effects estimated models include time dummies as control variables.

related deaths was higher in countries with lower poverty rates, in the presence of measures, and, thus, supports our second hypothesis.

Overall, a comparison of our key results between the initial and following period suggests a marked shift in the association between the growth of COVID-19 daily cases and deaths and the poverty rate. In particular, we find that, although in the initial period, when no NPIs were in place, countries with higher poverty rates experienced higher growth in daily COVID-19 cases and growth in daily deaths due to COVID-19, in the following period, they experienced systematically lower growth in COVID-19 cases and deaths than in countries with lower poverty levels. These results could be explained by differences in the extent to which individuals engage in physical distancing, either voluntarily or by complying to imposed NPIs. In particular, our results regarding the initial period, when no NPIs are in place, could be explained by lower voluntary engagement in physical distancing by individuals in countries with higher poverty rates. This is due to binding constraints associated with poorer SECs, particularly those constraints associated with employment, housing, and public health infrastructure. This result is in line with existing studies presenting cross-country evidence, such as Maloney and Taskin (2020) who find that voluntary engagement in physical distancing in high-income and middle-income countries is higher compared to low-income countries, where voluntary protection measures are low, due to inability of individuals to abandon livelihoods. Also, our finding is consistent with studies presenting within-country evidence, such as Coven and Gupta (2020) who find that low-income individuals in the US are less likely to voluntarily engage in physical distancing compared to high-income individuals.

Similarly, our results in the following period, when NPIs were in place, could be explained by higher responsiveness of individuals in countries with higher poverty levels to NPIs. Thus, higher effectiveness of NPIs in these countries, which could be partly due to the low voluntary engagement in physical distancing by individuals in these countries in the absence of NPIs. Again, this is in line with existing cross-country and within-country evidence. Maloney and Taskin (2020) present evidence that in low-income countries physical distancing increased by significantly more relative to high-income countries as a result of government measures, particularly the closure of transportation that restricts mobility for employment purposes. Moreover, these authors conclude that the lower responsiveness of individual physical distancing practices to NPIs in high-income and middle-income countries could be explained by the fact that physical distancing was already high in these countries, before NPIs are imposed, relative to low-income countries and, thus, it is expected to happen regardless of the presence of NPIs, whereas the same is not the case in low-income countries. Additional evidence on the positive relationship between poverty and effectiveness of NPIs is presented by Bonaccorsi et al. (2020), who find that lockdowns reduced mobility by significantly more in municipalities with lower income levels in Italy.

We have tested for alternative explanations of our findings and the extent to which our results are robust to different model specifications. For example, one explanation of our result in the following period that countries with higher poverty rates were hit less hard by the pandemic could be explained by more stringent NPIs in these countries. We investigated this possibility by extending our specifications to control for measures of the stringency and duration of NPIs, as well as the timing NPIs are introduced – included in *Our World in Data* COVID-19 dataset – during the period of our analysis. Our results, presented in Table A3 in the Appendix, show that our preferred estimates (Random Effects) of the associations between COVID-19 health impacts and the poverty rate remain negative and significant. Thus, accounting for a range of differences in NPIs across countries does not alter our main conclusion that, in the presence of NPIs, COVID-19 health impacts were less adverse in countries with higher poverty rates. We also find that countries with higher poverty rates imposed less stringent NPIs, but also had NPIs in place for a longer period and first introduced these later in the year compared to countries with lower poverty rates.[7]

We have also investigated whether our results, in both periods, could be explained by differences in demographics across countries, as, based on our discussion in one of the previous sections, in more poor countries

[7] These results are available by the authors upon request.

Table 6
Random Effects Estimates of Associations between Covid-19 Impacts (Cases and Deaths) and the Poverty Rate, Following Period; Including Controls for NPI Stringency, Duration, and Timing, as well as Demographics.

	Change in log daily new cases								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Poverty rate 2019	(0.003)	(0.003)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Log gdp per capita 2019							−0.016**	−0.016*	−0.013
							(0.007)	(0.009)	(0.010)
Human development index 2019	−0.005*		−0.006*	−0.006**		−0.006**	−0.006*		−0.006*
	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)		(0.003)
Log number of days NPIs were in place	0.075**		0.096**	−1.699***		−1.701***	0.087*		0.090*
	(0.034)		(0.042)	(0.361)		(0.362)	(0.049)		(0.050)
Share older than 65		−0.012	−0.024**		0.010	−0.004		0.011	−0.006
		(0.009)	(0.011)		(0.012)	(0.014)		(0.014)	(0.015)
Dummies for month of introduction of NPIs	Yes	No	Yes		No	Yes	Yes	No	Yes
				Yes					
R-squared	0.007	0.006	0.007	0.007	0.007	0.007	0.007	0.007	0.007
Number of countries	142	151	142	139	148	139	141	150	141
Number of observations	35,539	37,552	35,539	34,796	36,809	34,796	35,285	37,298	35,285
	Change in log daily new deaths								
Poverty rate 2019	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log gdp per capita 2019				−0.001*	−0.002***	−0.003***			
Human development index 2019							(0.005)	(0.006)	(0.007)
Log stringency index	0.003*		0.003*	0.002		0.003*	0.002*		0.003**
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)		(0.001)
Log number of days NPIs were in place	0.048***		0.042***	−1.345***		−1.331***	0.050***		0.034**
	(0.012)		(0.012)	(0.220)		(0.218)	(0.014)		(0.016)
Share older than 65		0.005	0.007		0.027***	0.031***		0.024**	0.029**
		(0.008)	(0.009)		(0.010)	(0.011)		(0.012)	(0.012)
Dummies for month of introduction of NPIs									
	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
R-squared	0.009	0.008	0.009	0.009	0.009	0.009	0.009	0.009	0.009
Number of countries	142	151	142	139	148	139	141	150	141
Number of observations	33,592	35,515	33,592	32,872	34,795	32,872	33,352	35,275	33,352

Notes: Standard errors clustered at the country level in parentheses; ***significant at 1%, **significant at 5%, *significant at 10%. The following period for cases is 04 Apr 2020 – 13 Dec 2020 and for deaths 18 Apr 2020 – 13 Dec 2020. Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita. All estimated models include time dummies as control variables.

Table 7
Random Effects Estimates of Associations between Covid-19 Impact (Cases and Deaths) and the Poverty Rate, Initial Period; Including Controls for Demographics.

	Change in log daily new cases			Change in log daily new deaths		
	(1)	(2)	(3)	(1)	(2)	(3)
Poverty rate 2019	(0.028)	(0.033)	(0.033)	(0.010)	(0.015)	(0.014)
Log gdp per capita 2019 Human development index 2019			0.144**			0.101***
			(0.068)			(0.033)
Share older than 65	0.259***	0.107	0.080	0.205***	0.098*	0.071
	(0.070)	(0.106)	(0.113)	(0.046)	(0.059)	(0.066)
R-squared	0.14	0.14	0.14	0.007	0.007	0.007
Number of countries	138	137	137	145	142	144
Number of observations	3,814	3,801	3,801	5,808	5,772	5,781

Notes: Standard errors clustered at the country level in parentheses; ***significant at 1%, **significant at 5%, *significant at 10%. The initial period for cases is 23 Jan 2020 – 03 Apr 2020 and for deaths 23 Jan 2020 – 17 Apr 2020 Poverty rate is the percentage of the population living on less than $1.90 a day at 2011 international prices (PPP). GDP per capita is in international dollars using 2017 purchasing power parity (PPP) exchange rates to convert local currency units. Human development index (HDI) reflects three dimensions: health, as measured by life expectancy at birth; education, as measured by average years of schooling; and standard of living, as measured by Gross National Income (GNI) per capita. All estimated models include time dummies as control variables.

elderly individuals account for a smaller share of the population compared to less poor countries. There is evidence that this could explain differences in mortality and may be also related to differences in the effectiveness of NPIs across countries (Jinjarak et al., 2020). Our results, presented in Tables A3 and A4 in the Appendix, from estimation of models that control for differences in the share of population above 65 years old across countries, suggest that our key conclusion remain unchanged even after accounting for demographic differences.

All in all, our results highlight the increased importance of NPIs in poorer countries and, to some extent, cast doubt on recent studies implying that NPIs have been less effective in poorer countries (for example, see Jinjarak et al., 2020). The rationale for our results, both in the absence and in the presence of NPIs, is that individuals make physical distancing decisions, and these decisions are constrained by SECs, as measured by poverty rates. In the absence of (national or regional) measures, individuals living under better SECs are more able to engage in physical distancing, as they are less constrained. Therefore, given the relatively higher voluntary engagement in physical distancing practices among these individuals, the imposition of NPIs is not expected to increase physical distancing much in countries with better SECs. In contrast to this, applying the same logic, the imposition of measures is expected to generate a more significant change in the physical distancing practices of individuals living in poor SECs, who are much less likely to adopt them in the absence of measures.

5. Conclusion

The goal of this paper has been to provide an analysis of differences in contagion and mortality dynamics of COVID-19 across countries considering that SECs, as reflected in the level of poverty: (a) vary globally; and (b) influence infection rates through affecting individuals' decisions to engage in voluntary physical distancing, which can mitigate the spread of infections, in the absence of NPIs and to comply with NPIs, when these are present. We investigate two hypotheses regarding the association of poverty rates and infection and mortality growth rates across countries, both in the absence and in the presence of NPIs.

Using data from 185 countries, we find evidence supporting the hypothesis that during the initial phase of the COVID-19 pandemic, when no NPIs were in place, higher poverty rates were positively associated with higher growth in infection and death rates. In the following phase of the pandemic, however, during which NPIs were implemented across countries, we find significantly lower growth of infection and death rates among countries with higher poverty rates. We argue that the latter finding implies higher effectiveness of NPIs in countries with higher poverty rates. This is because individuals in these countries are more likely to engage in physical distancing in the presence than in the absence of NPIs compared to individuals in countries with lower poverty rates, even if physical distancing may be on average relatively more costly to them than to individuals in countries with lower poverty rates.

Our results highlight the significance of NPIs in relatively poorer contexts, where poverty may limit individuals' decisions to effectively protect themselves against the spread of infection. Our study contributes to existing evidence on how global socioeconomic inequalities may impact the extent of infections and deaths from pandemics.

CRediT authorship contribution statement

Giorgos Galanis: Conceptualization, Writing – original draft, Writing – review & editing. **Andreas Georgiadis:** Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Abrams, M. E., & Szefler, S. J. (2020). COVID-19 and the impact of social determinants of health. *The Lancet Respiratory Medicine, 8*(7), 659–661.
Ahmed, F., Ahmed, N., Pissarides, C., & Stiglitz, J. (2020). Why inequality could spread COVID-19. *The Lancet Public Health, 5*(5), E240.
Alon, T., M. Kim, D. Lagakos, and M. VanVuren (2020). How should policy responses to the COVID-19 pandemic differ in the developing world? *NBER Working paper no. 27273*.
Bargain, O., & Aminjonov, U. (2021). Poverty and COVID-19 in Africa and Latin America. *World Development, 142*.
Bartley, M., Ferrie, J., & Montgomery, S. (1999). Health and labour market disadvantage: Unemployment, non-employment and job insecurity. In M. Marmot, & R. Wilkinson (Eds.), *The social determinants of health*. Oxford: Oxford University Press.
BBC, (2020). *Coronavirus: The world in lockdown in maps and charts*. Available at https://www.bbc.co.uk/news/world-52103747.
Bennett, M. (2021). All things equal? heterogeneity in policy effectiveness against covid-19 spread in Chile, *World Development* 137.
Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., et al. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences, 117*(27), 15530–15535.
Bonanad, C., García-Blas, S., Tarazona-Santabalbina, F., Sanchis, J., Bertomeu-González, V., Fácila, L., et al. (2020). The effect of age on mortality in patients with COVID-19: A meta-analysis with 611,583 subjects. *Journal of the American Medical Directors Association, 21*(7), 915–918.
Brodeur, A., Grady, D., Islam, A., & Bhuiyan, S. (2021). A Literature Review of the Economics of COVID-19. *Journal of Economic Surveys, 35*, 1007–1044.
Carlitz, R. D., & Makhura, M. N. (2021). Life under lockdown: Illustrating tradeoffs in South Africa's response to covid-19. *World Development, 137*.
Cash, R., & Patel, V. (2020). Has COVID-19 subverted global health? *Lancet*, 395(10238), 1687–1688. https://doi.org/ 10.1016/S0140-6736(20)31089-8.
Chernozhukov, V., Kasaha, H., & Schrimpf, P. (2021). Causal impact of masks, policies, behavior on early covid-19 pandemic in the U.S. *Journal of Econometrics, 220*(1), 23–62.
Courtemanche, C., Garuccio, J., Le, A., Pinkston, J., & Yelowitz, A. (2020). Strong social distancing measures in the United States reduced the COVID-19 growth rate. *Health Affairs (Millwood), 39*(7), 1237–1246.
Coven, J. and A. Gupta. (2020) Disparities in Mobility Responses to COVID-19, NYU Stern Working Paper.
Deaton, A. (1997). *The analysis of household surveys: A microeconometric approach to development policy*. Washington, D.C.: World Bank Group.
Di Guilmi, C., Galanis, G., & Baskozos, G. (2022). A behavioural SIR model: Implications for physical distancing decisions. *Review of Behavioral Economics, 9*(1).
Demombynes, G., (2020). COVID-19 age-mortality curves are flatter in developing countries. World Bank Policy Research Working Paper No. 9313.
Dingwall, R., Hoffman, L. M., & Staniland, K. (2013). Introduction: Why a sociology of pandemics? *Sociology of Health & Illness, 35*(2), 167–173. https://doi.org/10.1111/1467-9566.12019
Elias, C., Sekri, A., Leblanc, P., Cucherat, M., & Vanhems, P. (2021). The incubation period of COVID-19: A meta-analysis. *International journal of infectious diseases: IJID: Official publication of the International Society for Infectious Diseases, 104*, 708–710.
Eichenbaum, M., Rebelo, S., & Trabandt, M. (2021). The macroeconomics of epidemics. *the Review of Financial Studies, 34*(11), 5149–5187.
Flaxman, S., Mishra, S., Gandy, A., et al. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature, 584*, 257–261. https://doi.org/10.1038/s41586-020-2405-7
Galanis, G., Di Guilmi, C., Bennett, D. L., & Baskozos, G. (2021). The effectiveness of non-pharmaceutical interventions in reducing the COVID-19 contagion in the UK, an observational and modelling study. *PLoS One1, 16*(11), e0260364.
Galanis, G., & Hanieh, A. (2021). Incorporating social determinants of health into modelling of COVID-19 and other infectious diseases: A baseline socio-economic compartmental model. *Social Science & Medicine, 274*.
Georgiadis, A. & Franco Gavonel, M. (2023). Minimum Wage in the Time of Pandemic. Leeds University Business School Working Paper, no. 4473110.
Gouzoulis, G., & Galanis, G. (2021). The impact of financialisation on public health in times of COVID-19 and beyond. *Sociology of Health Illness, 43*, 1328–1334.
Greene, W. (2020). *Econometric analysis*. New York: Pearson.
Hsiang, S., Allen, D., Annan-Phan, S., et al. (2020). The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature, 584*, 262–267.
Hu, B., Guo, H., Zhou, P., et al. (2021). Characteristics of SARS-CoV-2 and COVID-19. *Nature Reviews. Microbiology, 19*, 141–154.
Hu, B., Guo, H., Zhou, P., et al. (2022). Author Correction: Characteristics of SARS-CoV-2 and COVID-19. *Nature Reviews Microbiology*.
Immel, L., Neumeier, F., & Peichl, A. (2022). The unequal consequences of the covid-19 pandemic: Evidence from a large representative German Population Survey. *Review of Income and Wealth*. in press.
Jay, J., Bor, J., Nsoesie, E. O., et al. (2020). Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature Human Behaviour, 4*, 1294–1302.
Jinjarak, Y., Ahmed, R., Nair-Desai, S., Xin, W., & Aizenman, J. (2020). Accounting for global COVID-19 diffusion patterns, January–April 2020. *Economics of Disasters and Climate Change, 4*, 515–559.
Kavanagh, N. M., Goel, R. R., & Venkataramani, A. S. (2021). County-level socioeconomic and political predictors of distancing for COVID-19. *American Journal of Preventive Medicine., 61*(1), 13–19.
Kermack, W.O., McKendrick, A.G., (1927). A contribution to the mathematical theory of epidemics', *Proceedings of the royal society of London*. Series A 115 (772), 700–721.
Lane, J., Garrison, M. M., Kelley, J., Sarma, P., & Katz, A. (2020). Strengthening policy coding methodologies to improve COVID-19 disease modeling and policy responses:

A proposed coding framework and recommendations. *BMC Medical Research Methodology*.
Lane, J., Means, A. R., Bardosh, K., et al. (2021). Comparing COVID-19 physical distancing policies: Results from a physical distancing intensity coding framework for Botswana, India, Jamaica, Mozambique, Namibia, Ukraine, and the United States. *Global Health., 17*, 124.
Maloney, W. F., & Taskin, T. (2020). Determinants of social distancing and economic activity during COVID-19: A global view. *World Bank Policy Research Working Paper, 9242*.
Martinez-Alvarez, M. A., Jarde, E., Usuf, M. B., Bittaye, A. L., Samateh, M., Antonio, J., et al. (2020). COVID-19 pandemic in west Africa. *Lancet Global Health, 8*(5), e631–e632.
Mathieu, E., Ritchie, H., Ortiz-Ospina, E., et al. (2021). A global database of COVID-19 vaccinations. *Nature Human Behaviour, 5*, 947–953.
Murthy, S., Leligdowicz, A., & Adhikari, N. K. (2015). Intensive care unit capacity in low-income countries: A systematic review PloS. *One, 10*(1).
Papageorge, N. W., Zahn, M. V., Belot, M., van den Broek-Altenburg, E., Choi, S., Jamison, J. C., et al. (2020). Socio-demographic factors associated with self-protecting behavior during the Covid-19 pandemic. *Journal of Population Economics, 34*, 691–738.
Reeves, A. (2021). The health effects of wage setting institutions: How collective bargaining improves health but not because it reduces inequality. *Sociology of Health and Illness, 43*(4), 1012–1031.
Shaw, M. (2004). Housing and public health. *Annual Review of Public Health, 25*, 397–418.
Silverman, D., Hupert, N., & Washburne, A. (2020). Using influenza surveillance networks to estimate state specific prevalence of SARS-CoV-2 in the United States. *Science Translational Medicine*. https://doi.org/10.1126/scitranslmed.abc1126
Singh, S., Shaikh, M., Hauck, K. & Miraldo, M. (2021). Impacts of introducing and lifting nonpharmaceutical interventions on COVID-19 daily growth rate and compliance in the United States. *Proceedings of the National Academy of Sciences of the United States of America* 118 (12).
Stringhini, S., Sabia, S., Shipley, M., Brunner, E., Nabi, H., Kivimaki, M., et al. (2010). Association of socioeconomic position with health behaviors and mortality. *Journal of the American Medical Association (JAMA), 303*, 1159–1166.
Stantcheva, S. (2022). *Inequalities in the times of pandemics*. NBER Working Paper.
Swope, C. B., & Hernández, D. (2019). Housing as a determinant of health equity: A conceptual model. *Social Science & Medicine, 243*, Article 112571.
Toxvaerd, F. (2020). *Equilibrium social distancing*. University of Cambridge. Working Paper,.
Tsai, J., & Wilson, M. (2020). COVID-19: A potential public health problem for homeless populations. *The Lancet Public Health, 5*, e186–e187.
Wooldridge, J. (2010). *Econometric analysis of cross section and panel data*. Cambridge: MIT Press.
Data: The data that support the findings of this study are openly available at https://github.com/owid/covid-19-data/tree/master/public/data; https://data.worldbank.org/.