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# Relative deprivation, inequality and the Covid-19 pandemic

Debajyoti Chakrabarty *, Bhanu Bhatia, Maneka Jayasinghe, David Low

*Asia Pacific College of Business and Law, Charles Darwin University, 21 Kitchener Dr. Waterfront, Darwin City, Northern Territory, 0800, Australia*

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A B S T R A C T

There is a growing concern that inequalities are hindering health outcomes. This paper's primary objective is to investigate the role of relative deprivation and inequality in explaining the daily spread of the Covid-19 pandemic. For this purpose, we use secondary cross-sectional data across 119 (developed and developing) countries from January 2020 – to April 2021. For the empirical analysis, we use a recent dynamic panel data modelling approach that allows us to identify the role of time-invariant variables such as degree of globalisation, political freedom and income inequality on the dynamics of the pandemic and fatality rates across countries. We find that new cases per million and fatality rates are highly persistent processes. After controlling for time-varying mobility statistics from the Google mobility database and region-specific dummy variables, the two significant factors that explain the severity of Covid-19 spread in a country are per-capita Gross Domestic Product (GDP) and Yitzhaki's relative income deprivation index. Lagged value of new cases per million significantly explains cross-country variations in the daily case fatality rates. A higher proportion of the older population and pollution increased fatality rates while better medical infrastructure reduced it.

## 1. Introduction

The Covid-19 pandemic has had an unprecedented impact on people's health, well-being, and health care systems globally. We have witnessed a rapid spread of the virus, with some stark differences in the incidence and mortality across countries. Even though advanced nations initially were the worst-hit nations, developing countries soon caught up with cases reaching millions in South Asia, Africa and Latin America. Biomedical factors associated with the spread and fatality of Covid-19 have been the main drivers of policy prescriptions suggested by medical professionals and governments. However, historically, one of the critical parameters in the spread of infectious disease is socio-economic, with the marginalised communities often carrying the most significant disease burden (Buckee et al., 2021; Inhorn and Brown, 1990). Similar patterns have been observed in the spread of Covid-19, but few studies exist that systematically investigate the impact of inequality through a macroeconomic prism providing a nuanced big picture view (Elgar et al., 2020).

This paper investigates the role of relative deprivation and inequality on the spread and fatality rate of Covid-19. Relative deprivation of an individual is the difference in income between that individual and all other individuals with a higher income in that person's reference group, considering the size of the reference group (Yitzhaki, 1979). When we aggregate the individual relative deprivations over the population, Yitzhaki (1979) showed that it is equivalent to the Gini coefficient of the population income distribution.

There is extensive literature documenting the negative impact of relative deprivation and inequality on health outcomes, including evidence based on infectious diseases (Bucchianeri, 2010; Pickett and Wilkinson, 2015; Rutter et al., 2012; Wilkinson, 1992). In the United States, Deaton (2001), Eibner and Evans (2005), and Subramanyam et al. (2009) find that relative income deprivation harms reported health. They find this relationship even after controlling for household income. Similar patterns have also been observed in Norway and Japan by Dahl et al. (2006) and Kondo et al. (2008) respectively. Rutter et al. (2012) attributed disparities in H1N1 mortality to socio-economic disadvantages resulting in greater exposure to the virus, susceptibility to the disease and poorer access to health care. However, an important gap in existing research is that they primarily focus on individual countries. In this study, we examine the inequality and infectious diseases outbreak at a substantially larger scale through a cross-country study of 119 countries that consists of developed and developing countries. By doing so, we intend to highlight that this issue is of critical concern to countries in any stage of development.

* Corresponding author.
*E-mail addresses:* debajyoti.chakrabarty@cdu.edu.au (D. Chakrabarty), bhanu.bhatia@cdu.edu.au (B. Bhatia), maneka.jayasinghe@cdu.edu.au (M. Jayasinghe), david.low@cdu.edu.au (D. Low).

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Relative deprivation increases the likelihood of death due to diseases such as coronary heart disease, HIV and tuberculosis (Bucchianeri, 2010; Durevall and Lindskog, 2012; Eibner and Evans, 2005). These diseases are typically associated with stress and poor living conditions, hazards at work, and risky behaviour suggesting a link between social inequities and public health. Early research on the Covid-19 pandemic also suggests that socio-economic inequalities have played an essential role in spreading the pandemic and mortality rates across countries (see, for instance, Elgar et al., 2020). It is possibly due to the inability of countries with high inequality to manage adequate nutrition, adhere to physical distancing measures, practice proper hygiene, reduce mobility, as well as due to compromised health outreach capacity, unstable work conditions and heightened stress and high prevalence of comorbidities in the population (Deaton, 2003; Malani et al., 2021; Mena et al., 2021; Patel et al., 2020).

One of the difficulties of gleaning the impact of relative deprivation on the severity of the Covid-19 pandemic is methodological. The data on Covid-19 cases and mortality are dynamic and evolving daily, while the measures of relative deprivation (usually the Gini coefficients of variables of interest) are static. To overcome this issue, Elgar et al. (2020) study the effect of inequality and social capital of a country on the number of deaths at a particular point in time (within the 30 days after recording their tenth death). In another panel study, Sorci et al. (2020) evaluate the role of cross-country heterogeneity in health characteristics such as incidence of cardiovascular disease and diabetes. To overcome the static nature of country-specific characteristics, they interact all variables with a linear-quadratic time-trend. It allows them to study the impact of cross-country demographic, economic and political variables on Covid-19 fatality rates. However, the interaction of linear-quadratic trends with all the explanatory variables renders many estimated parameters insignificant. Hence, it is difficult to understand the overall impact of country-specific characteristics on case fatality rates. Addressing some of the gaps in the existing methodological approaches to investigate the link between inequality and disease outbreak, in this paper, we propose a dynamic panel data model using a recent two-step estimation procedure suggested by Kripfganz and Schwarz (2019) to measure the impact of relative deprivation on the severity of the Covid-19 pandemic in a country. This procedure uses a sequential approach to estimating the dynamic model and is more robust against model misspecification while allowing time-invariant regressors.

Having access to appropriate data in a timely manner is the key for any research but more so for an ongoing pandemic situation. In this study, we have overcome that challenge by innovatively using Google mobility data as time-varying explanatory variables for the spread of the Covid-19 pandemic. We found that a percentage change in retail and recreation (GMRR), grocery and pharmacy (GMGP), parks (GMPARKS), and residential (GMRES) are significant in explaining new per-capita Covid-19 cases (NCASESPM). After incorporating the dynamics of NCASESPM and controlling for region-specific effects, we find that per-capita GDP and Yitzhaki's index measuring relative income deprivation are the only factors that significantly explain the cross-country variation in the spread of the pandemic. Interestingly, these are the very two variables that have been widely used in the public health literature to study other health outcomes (see, for instance, Deaton, 2001). We also studied the dynamics of the case fatality rate (CFR). It is a highly persistent process, and a higher lagged value of NCASESPM increases CFR. It suggests that the higher caseload of the pandemic stretches the health system in all countries. A higher proportion of the old-age population and pollution (proxied by $CO_2$ emissions) increased the fatality rates. Medical infrastructure proxied by hospital beds and the number of physicians helps reduce the mortality rates.

The findings emerging from this study are of importance to healthcare providers and policymakers in three ways. Firstly, the findings further reinforce the need to reduce inequality as it adversely impacts the spread of infectious diseases in countries across the globe. Secondly, this study provides further insights that inequality is not only an economic phenomenon but also has significant implications social and health landscape in a country. In other words, addressing inequality will also act as a preparedness strategy to control future infectious disease outbreaks. The increased evidence base on the link between relative deprivation and infectious diseases, therefore, facilitates policymakers to direct resources to address this critical issue, such as improving safety nets for people living with disadvantaged economic conditions, enhance employment opportunities, and facilitate affordable housing. Thirdly, in recent years we have observed a notable growth in wealth inequality both within and between nations in all stages of development (Alvaredo et al., 2018). Therefore, the UN Sustainable Goals place a substantial emphasis on ensuring inclusive growth through eradicating poverty (goal 1), ensuring good health for all (goal 3) and reducing social inequalities (goal 10). Therefore, the findings of this paper contribute to a better understanding of the severity of the impact of inequality on the health outcomes of people and facilitate the achievement of Sustainable Development Goals by effectively addressing the problem.

The rest of the paper is organized as follows: Section 2 reviews the related literature on relative deprivation and infectious diseases. Data, model, and the econometric procedure are discussed in section 3. Section 4 presents our empirical results and discussion, followed by concluding remarks and policy implications in Section 5.

## 2. Relative income and infectious diseases

Infectious diseases are the second biggest cause of death, and their spread has become ever so lethal, with Covid-19 taking only 13 days from identification in China to materialising in other countries (Dilcher et al., 2020). Covid-19 is from a family of other pathogenic human respiratory coronaviruses (severe acute respiratory syndrome coronavirus [SARS-CoV]) and results in severe respiratory diseases with human-to-human transmission mechanisms (Perlman, 2020). With goods and people rapidly transported worldwide, infectious diseases can reach diverse ecological terrains with ease (Dilcher et al., 2020; Fidler, 2004; Selvanathan et al., 2021).

The role of human behaviour has historically been central to the transmission of infectious diseases across populations (Inhorn and Brown, 1990). As a result, the burden of infectious disease is not equally spread within nations or sub-populations nor limited to biological factors interacting with economic, demographic, social, political, and environmental dimensions in a heavily interconnected world. A similar story is evident in the spread of Covid-19 (Elgar et al., 2020).

The link between income and health is well-established. In simplistic terms, it implies that financially better-off tend to be in better health due to superior nutrition, access to healthcare, enhanced ability to process new information, early life development, healthier lifestyle and lower physical and psychosocial hazards at work (Galama and Van Kippersluis, 2013). At a macroeconomic level, we can understand this using the historic Preston curve that plots income and life expectancy showing poorer nations gain substantial increases in life expectancy for small increases in income (Deaton, 2003). While this empirical exercise shows a correlation between income and health, it proves to be important in understanding the impact of inequality as well. The relationship between individual health and income is concave, such that each additional dollar of income raises individual health by decreasing amount. It implies that an income redistribution from the rich to the poor will improve the average health outcome within a society. A similar principle is also applicable across societies. Hence, higher inequality or relative deprivation will lead to poorer average health outcomes (Subramanian and Kawachi, 2004). Beyond the concavity effect, societies with greater inequality suffer from malice such as more stress, less support and social cohesion (Deaton, 2003). Also, another mechanism is that highly unequal societies have more significant socio-economic stressors because we seem to care about our status (Galama and Van Kippersluis, 2013).

A causal relation between relative income and average health has been found in several studies (Eibner and Evans, 2005; Kondo et al., 2008; Subramanyam et al., 2009). Previous research further confirms correlations between high levels of socio-economic inequality, including measures of income and education, and poor population health outcomes (see, for example, Adams-Prassl et al., 2020; Castelló-Climent and Doménech, 2002; Chakraborty and Das, 2005; Contoyannis and Jones, 2004; Marmot and Wilkinson, 2005; Wilkinson and Pickett, 2011). Similarly, for infectious diseases, relative deprivation can increase the risk of infection and mortality through poor access to healthcare, poor living conditions, anxiety and depression, low social capital, isolation and higher prevalence of chronic diseases (French et al., 2009; Gupta et al., 2008; Krieger and Higgins, 2002).

While only 10% of the world population resides in Sub-Saharan Africa, it accounts for most HIV infections (Lyon and Farmer, 2005). Multiple studies confirmed the association of HIV infections with relative deprivation channelled through the inability to mitigate the risk of exposure (Gupta et al., 2008). The United Kingdom witnessed treatment delays for Tuberculosis patients amongst the most disadvantaged ethnic groups and recent migrants (French et al., 2009).

The 2002 outbreak of SARS, with its origin in China and a rapid spread across the globe albeit with a lower contagion rate, provides a ready comparison point for Covid-19 in the contemporary climate with a strong historical counterpart in the Spanish Flu causing 50 million deaths worldwide. Both confirm the critical roles of socio-economic realities in incidence and CFR. The Spanish influenza pandemic showed a clear difference in mortality rates between high and low-income countries (Murray et al., 2006). Within a country, these differences translated to greater mortality in poorer regions and towns with higher social inequality (Grantz et al., 2016; Mamelund, 2006). While affluent cities of Toronto and Hong Kong formed the focal points of the SARS pandemic, capturing the susceptibility of higher-income nations due to greater travel and socio-economic interlinkages (Bucchianeri, 2010); economic modelling analysis of SARS showed that a negative correlation between median income and infection rate in Hong Kong and was associated with less affluent migrant groups in other regions (Biao and Wong, 2003; Bucchianeri, 2010; Sanford and Ali, 2005).

Early research on Covid-19 also shows inequalities surfacing. Covid-19 appeared to have spread to more affluent and urbanised parts of the world, travelling through trade routes (Wuhan, Milan, Paris, London, New York). As these places started bringing the disease under control, the disease spread to poorer places. Socio-economic inequalities in the spread of disease started appearing, and familiar patterns are emerging (Deaton and Schreyer, 2022). Covid-19 impacts the elderly more severely, with mortality much higher in the older age groups, even though the young tend to be the carriers of the disease (Surico and Galeotti, 2020). The pronounced differences in demographic profiles of developing countries, with a much younger population than developed nations, provided some protection in the face of the crisis despite poor infrastructure (Dowd et al., 2020). Marginalised groups in the United States showed more significant morbidity and mortality (Mackey et al., 2021; Oronce et al., 2020). For example, Chicago has a 30% black population, but more than 50% of patients diagnosed with Covid-19 cases and nearly 70% of Covid-19 deaths involved black individuals (Yancy, 2020). At the same time, slums in Mumbai faced higher sero-prevalence rates and fatality rates (Malani et al., 2021). Social distancing measures, hygiene, and quarantine measures are more difficult to observe for the homeless, people in dense neighbourhoods, people relying on public transport and low-skilled workers without the option of exercising work-from-home measures (Bavel et al., 2020; Jordan et al., 2020; Qiu et al., 2020; Rutter et al., 2012). Response measures of lockdown disproportionately impacted lower socio-economic groups more heavily through the loss of employment and social contact, compromising their capacity to effectively engage with public health protocols (Adams-Prassl et al., 2020; Kass, 2001; Yancy, 2020); thus, deepening the possibility of a more wide-spread impact of Covid-19 in less equitable settings. At the same time, low socio-economic status (SES) groups showed a greater prevalence of comorbidities making the Covid-19 infection even more lethal in these groups (Contoyannis and Jones, 2004; Yancy, 2020).

The SES factors are further embedded in ecological and political spaces. Integrated health systems have been vital in controlling the outbreak with rapid testing, contact tracing, medical resources, number of doctors and hospitalisation of severe cases, along with the self-regulation measures such as social distancing and quarantine (Anderson et al., 2020; Greenstone and Nigam, 2020; Stock, 2020). Emerging evidence on Covid-19 confirms that public health capacity is often compromised in disadvantaged neighbourhoods (Mena et al., 2021).

While these racial, ethnic and income disparities point towards relative deprivation and Covid-19, they do not conclusively establish this connection after controlling for average income. Some of the most substantial evidence on relative deprivation and Covid-19 mortality is presented by Elgar et al. (2020) in the context of cross-country comparisons using multiple regression techniques. However, due to methodologic difficulties, the study cannot fully unpack the effect of many of the estimated parameters. In another study, Oronce et al. (2020) found a higher death rate among disadvantaged groups in the United States after adjusting for confounding variables in state-level regressions. At the same time, data from the United States shows that regions with higher income and education are more at risk of higher Covid-19 infections (Abedi et al., 2021). These contradictory results are further complicated because Covid-19 initially spread more rapidly in advanced nations than in less developed countries. Although an SES-health link is well established, relative deprivation and infectious diseases in the contemporary globalised world follow more complex dynamics creating an urgent need to establish the key relationships to accelerate the identification of vulnerable groups (Bucchianeri, 2010). Our cross-country study allows us to study the impact of significant variations in socio-economic, political and demographic factors across countries on the spread of the Covid-19 pandemic and its mortality. Such significant variations are difficult to find within a country.

## 3. Methodology and data

We are interested in the dynamics of two country-specific dependant variables, the natural log of daily new per-capita Covid-19 cases (NCASESPM) and the case fatality rate (CFR). To account for different population sizes across countries, we normalize new cases by population size. CFR is the deaths as a percentage of covid-19 cases, with values ranging between 0 and 100. We use the data on daily Covid-19 cases in 119 countries from January 2020 – to April 2021. We restrict our sample to before the widespread approval and implementation of vaccinations programmes across countries. We believe that the effect of relative deprivation on the Covid-19 pandemic is most starkly understood in the pre-vaccination phase. Many developed countries made vaccinations freely available to their population and subsequently enacted some incentives for their population to be vaccinated. It would mitigate the negative impact of inequity in rich countries alone, thus biasing our results.

Our strategy is to estimate the following dynamic panel data model:

$$y_{it} = \sum_{k=1}^{L} \rho_k y_{it-k} + \mathbf{x}_{it}^{'} \boldsymbol{\beta} + \mathbf{z}_i^{'} \boldsymbol{\gamma} + \alpha_i + u_{it}, \tag{1}$$

where $i = 1, 2, ..N$ and $t = 1, 2, ..T$ represents countries and date respectively. $y_{it} = \{\text{NCASESPM}_{it}, \text{CFR}_{it}\}$ represents the dependant variables of interest. $\mathbf{x}_{it}$ is a $\text{J}_x \times 1$ vector of country specific time-varying variables and, $\mathbf{z}_i$ is a $\text{J}_z \times 1$ vector of observed country specific time-invariant variables including the regression constant. The variables making up the vectors $\mathbf{x}_{it}$ and $\mathbf{z}_i$ may vary based on the dependant variable. $\alpha_i$ is an unobserved country-specific effect. We estimate the relationship described in equation (1) using the two-stage estimation procedure outlined in Kripfganz and Schwarz (2019). In the first stage, we estimate the model by including only the time-varying regressors.

$$y_{it} = \sum_{k=1}^{L} \rho_k y_{it-k} + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \widetilde{\boldsymbol{\alpha}}_i + e_{it}, \widetilde{\boldsymbol{\alpha}}_i = \alpha_i + \mathbf{z}_i^{'}\boldsymbol{\gamma} \quad (2)$$

Equation (2) is estimated using the generalised method of moments estimator. In the second stage, the residual derived from equation (2) estimation is regressed on country-specific time-invariant variables. All our estimation was done in STATA 17 using "xtseqreg" command provided by Kripfganz and Schwartz (2019).

The dynamic panel data formulation allows us to deal with the temporal autocorrelation of the data. The dependent variables can be persistent processes and exhibit delayed endogenous adjustments. This also means that the estimated coefficients of the country-specific variables of the model only reflect the short-term effects. The long-term effects can be significantly higher depending on the coefficients of the lagged dependent variables.

An important diagnostic test in dynamic panel data models is the test for autocorrelation of the residuals. Suppose the assumption of serial independence in the original errors is warranted. If the model is correctly specified, the first-differenced errors, $\Delta e_{it} = e_{it} - e_{it-1}$, should not exhibit significant second-order autocorrelation. We determine the lag length of the dependent variable using the Arellano–Bond test for zero second-order autocorrelation in the first-differenced errors. For both the dependent variables, new per-capita Covid-19 cases (NCASESPM) and the case fatality rate (CFR), we find the optimal lag length to be two periods.

In the generalised method of moments estimation, lagged values of regressors are used as instruments. This can lead to a proliferation of instruments and overidentification of the model, i.e., the number of instruments is more than the number of regressors. To reduce the proliferation of instruments, we restrict the lag length of the instruments. We follow Roodman (2009) and perform Hansen's test for overidentifying restrictions to ensure that we have chosen the instruments appropriately.

Our estimation strategy has another crucial theoretical contribution. It allows initial conditions to play a role in the dynamics of an infectious disease. By using an estimation technique that allows us to identify the importance of time-invariant variables, we can ascertain which initial country-specific characteristics played the most significant role in determining the spread of Covid-19 cases and case fatality rates.

### 3.1. Factors affecting Covid-19 cases

For country-specific time-varying explanatory variables, we used Google mobility data sourced from Google mobility trends report, 2021. The rapid spread of the Covid-19 pandemic worldwide highlighted the need for a quick and effective policy response. To help public health officials and policymakers, Google made community mobility trends available, which chart daily movement trends by geography across distinct categories such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residential. All the information is in percentage changes relative to a baseline period of 6th January – February 3, 2020. Google mobility reports have been used to estimate economic losses (Fernández-Villaverde and Jones, 2020), as an effective forecasting tool (Sampi and Jooste, 2020), and measure social distancing (Cot, Cacciapaglia & Sannino, 2021, 2021,2021). In our analysis, we used percentage change in retail and recreation (GMRR), grocery and pharmacy (GMGP), parks (GMPARKS), and residential (GMRES) components of the google mobility data. Mobility related to transit and work was highly correlated with retail and recreation (GMRR). We take the average of the past seven days of the Google mobility data to overcome sudden movement spikes or weekend effects.

We also used the policy response to the pandemic measured by the stringency index sourced from the Oxford Covid-19 Government Response Tracker data (OxCGRT) (Hale et al., 2020) to capture the effect of government response on Covid-19 cases. However, we acknowledge that several authors (for instance, Bjørnskov, 2021 and Gibson, 2022) have highlighted that the government response to the Covid-19 pandemic is a poor indicator of Covid-19 related outcomes such as incidence and mortality. They argue that often government response is delayed and playing catch-up rather than being proactive.

For country-specific time-invariant variables, we used the KOF Globalization index collected from the KOF Swiss Economic Inhorn and Brown (1990) database, Freedom index (Freedom 20) sourced from Freedom House (2020), Gini coefficient of post-tax income sourced from Solt (2019) database - the Standardised World Income Inequality Database (SWIID), Gini coefficient of human capital (Human capital Gini) gathered from Barro and Lee (2013) dataset, the proportion of urban population, per capita GDP (in natural logs) and population density (in natural logs) gathered from World Bank (2020). The data on Covid-19 cases and deaths were sourced from the Johns Hopkins University (Hopkins University, 2020) Covid-19 database.

The KOF Globalisation Index (scaled between 1 and 100) measures the economic, social and political dimensions of globalisation (see Gygli et al., 2019 for more details). We include it in our regression to control for a range of factors, such as cross-border movements of people, international trade and other international socio-political links that may have affected the number of Covid-19 cases in a country. Freedom 20 (scaled between 1 and 100) measures political freedom in a country in 2020. We included this variable as there is considerable debate in the literature regarding liberal democracies' ability to combat the pandemic (Sen, 2001). We use population density (in natural logs) and the proportion of urban population (scaled between 1 and 100) to control for the impact of tightly packed populations in the spread of Covid-19 cases. Apart from Freedom 20, we expected all other country specific time-invariant variables to affect daily new cases positively.

In particular, in the early phase of Covid-19, most of the covid-19 cases were emerging in developed countries. Hence we anticipated a strong positive relationship between Covid-19 cases and GDP per capita. This high correlation is depicted in Fig. 1A. Nevertheless, as covid-19 started to spread rapidly in countries across the globe, irrespective of their development stage, we anticipated the relationship between Covid-19 cases and GDP per capita to weaken. This is depicted in Fig. 1B (May to November 2020). The relationship for the entire period is shown in Fig. 1CFig. 2A.

As is common in the literature, we use Yitzhaki's index to measure relative income deprivation in the economy (Yitzhaki, 1979). Yitzhaki's relative deprivation index, which in the case of a country is equivalent to the Gini coefficient of post-tax income (Income Gini), is widely used in the health literature (see, for instance, Deaton, 2001, 2003) to measure the overall level of relative deprivation in the economy. We also used the Gini coefficient of human capital (Human capital Gini) to measure relative deprivation in terms of another essential household asset. Human capital Gini can provide insights into another dimension of inequality as it reflects deprivation in terms of opportunity. In addition, it has a very low correlation with Income Gini (0.259). The health literature suggests that income inequality generally affects health outcomes negatively.

Fig. 2A shows the relationship between average daily growth in Covid-19 cases and the Gini coefficient of disposable income in April 2022, while Fig. 2B shows the same for May–November 2022. As can be seen, initially, there seems to be a weak relationship between the two variables. However, the relationship becomes stronger from May to November 2020, indicating that income inequality turned out to be strongly correlated to increased Covid-19 cases across the world. The relationship for the overall period is shown in Fig. 2C.

In order to control for spatial correlation, we include a dummy variable if a country belongs to a geographical region. We follow Barro and Lee's (2013) classification of the grouping of countries into specific regions and treat North America and Western Europe as our reference regions. We included dummy variables for East Asia and Pacific (DEAP), Europe and Central Asia (DECA), Latin America and the Caribbean (DLAC), the Middle East and North Africa (DMENA), South Asia (DSA),

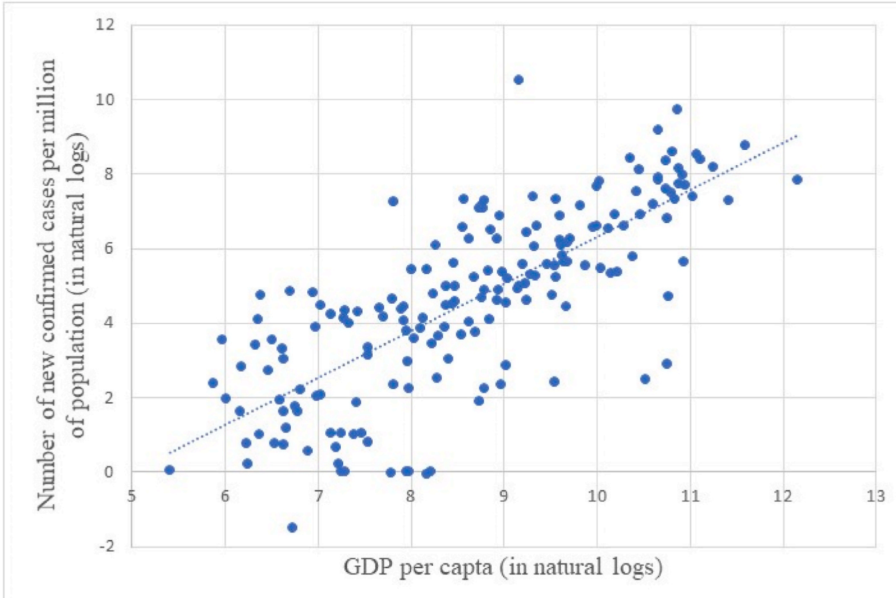


**Fig. 1A.** Covid cases and Per capita GDP: April 2020.

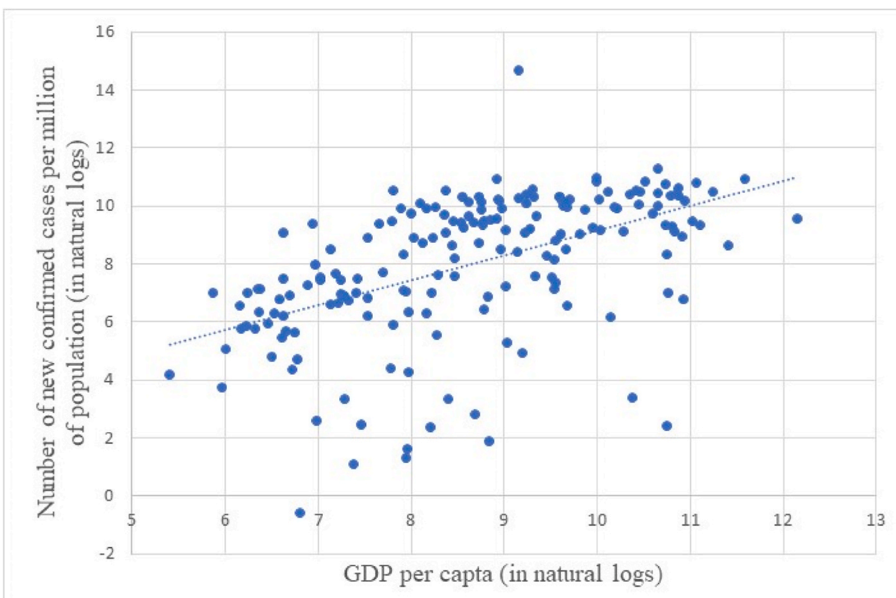


**Fig. 1B.** Covid cases and Per capita GDP: May–November 2020.

and Sub-Saharan Africa (DSSA) to control for region-specific effects. Table 1 presents our estimation results.

### 3.2. *Factors affecting case fatality rate*

CFR is the deaths as a percentage of Covid-19 cases, with values ranging between 0 and 100. For CFR, the country-specific time-varying explanatory, which we felt was most relevant, was lagged value of per capita new cases (NCASESPM). It encapsulates all the country-specific factors and would also be a good proxy for the extent of pressure on the medical system. However, following Sorci et al. (2020), we controlled for other health-related factors. These factors are the time-invariant regressors in our model. To control for the level of preparedness of the health system in a country, we used the number of hospital beds (Hospital beds) and physicians (Physicians) per thousand of the population, sourced from the World Bank (2020). We also control for demographic factors (proportion of over 65 population), comorbidities such as cardiovascular diseases, diabetes and $CO_2$ emissions for air pollution, gathered from the World Bank (2020). Interacting with governance are ecological factors, such as air pollution, which impacts the mortality of respiratory diseases (Brims and Chauhan, 2005; Garg, 2011; Lee et al., 2014). Table 2 presents our estimation results related to CFR.

## 4. Results and discussion

### 4.1. *Factors affecting Covid-19 cases: results*

We present the estimation results of our baseline specification in the first column of Table 1 (Model 1). In the subsequent models, we added

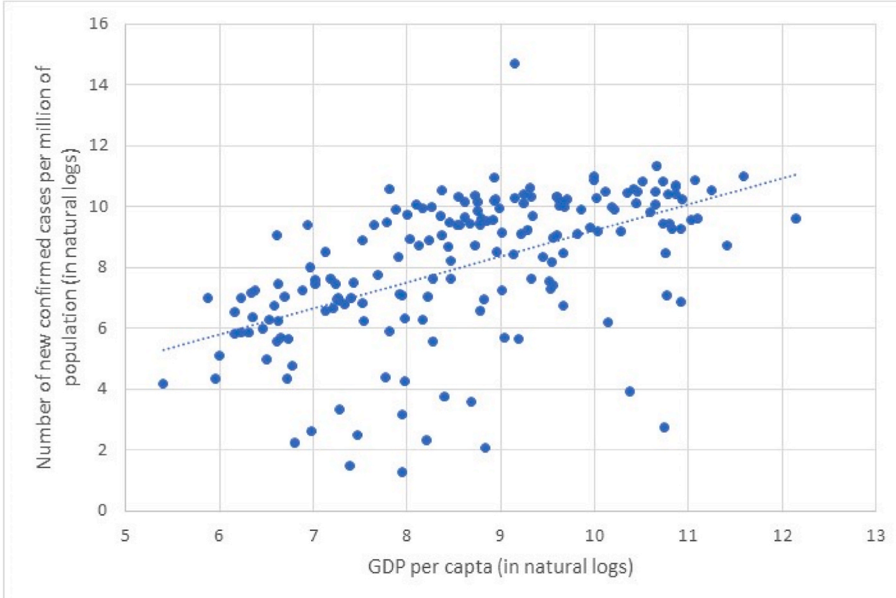


**Fig. 1C.** Covid cases and Per capita GDP: April–November 2020.

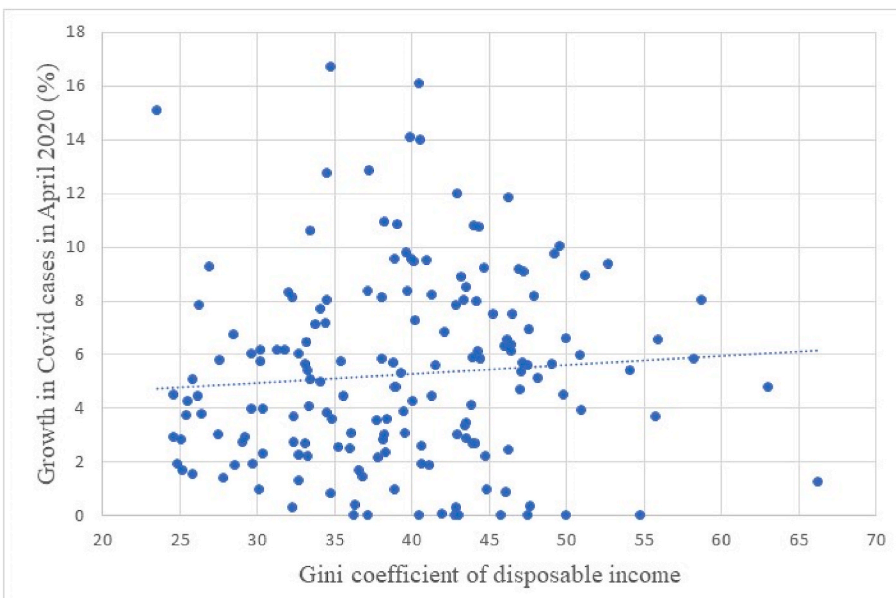


**Fig. 2A.** Covid cases and Inequality: April 2020.

per capita GDP (in natural logs) and Human Capital Gini as additional time-invariant regressors. In all three models, we determined the optimal lag length of the dependant variable to be two periods using the Arellano–Bond test for zero autocorrelation in the first-differenced errors. We used lagged values of time-varying regressors as instruments. Hansen's *J*-test confirms the validity of our instruments.

The results of all three models confirm the highly virulent nature of the pandemic. The coefficient of the first lagged value of NCASESPM is positive and significant at the 1% level. An increase in grocery and pharmacy (GMGP) visits by 1% compared to the baseline period is associated with a 3.2% increase in per-capita new cases. A similar increase in time spent at residence (GMRES) reduces the NCASESPM by 5.2%. Visits to retail & recreation and parks (GMRR & GMPARK) also reduced NCASESPM. It perhaps signifies the persistent nature of NCASESPM and that most governments heavily curtailed the movement of the population to public places. As we mentioned before, most governments have reacted to pandemic cases rather than being good at forecasting them.

For time-invariant explanatory variables, the regions of East Asia and Pacific and Sub-Saharan Africa to a certain extent were less severely impacted than the reference regions of North America and Western Europe. Freedom index (Freedom 20) and proportion of the urban population positively affect NCASESPM. Income Gini, the variable that we are most interested in, is positively and significantly related to NCASESPM. An increase in Income Gini by 1% results in a 3.3% increase in new cases per capita. The proportion of the urban population is also significant and has a positive effect on NCASESPM.

In the initial phase of the Covid-19 pandemic, the more affluent countries were disproportionately affected. We expected the high degree of globalisation of rich countries to be the reason behind this and used

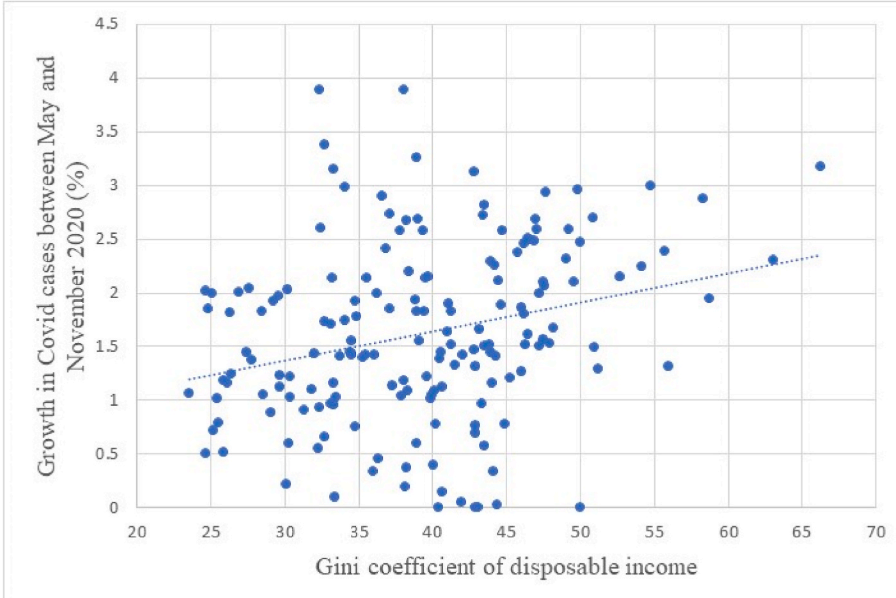


**Fig. 2B.** Covid cases and Inequality: May–November 2020.

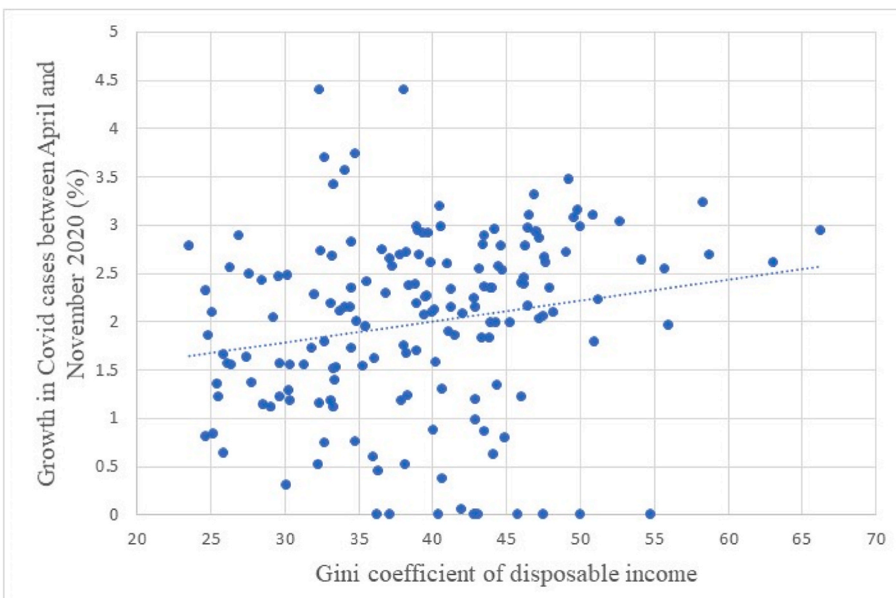


**Fig. 2C.** Covid cases and Inequality: April–November 2020.

the Globalisation index to capture this effect. However, as globalisation did not turn out to be significant in our first model, we introduce per-capita GDP (in natural logs) as a new time-invariant regressor in Model 2. It has a significant and positive effect on new Covid-19 cases. As per-capita GDP is measured in natural logs, the estimated coefficient (0.283) measures the elasticity of NCASESPM with respect to per-capita GDP. The introduction of this variable renders Freedom 20 and the proportion of the urban population insignificant. The rest of the results are relatively unaffected. Model 3 introduces another dimension of relative deprivation regarding human capital (Human capital Gini). While the sign of the estimated coefficient is not what we expected, it is not significant.

Interestingly, the estimated impact of relative deprivation measured by the Gini coefficient of post-tax income is always positive and significant. In a recent paper, Bhattacharya et al. (2021) highlighted a mechanism through which higher pre-pandemic inequality can lead to a greater risk of the spread of disease in social interactions. Using a behavioural Susceptible, Infectious or Recovered (SIR) model where precautionary measures are costly, they explain how inequality can increase unprotected social interactions leading to a greater risk of infections in social settings. Although not modelled in their paper, higher inequality may lead a more significant proportion of the population to forego following prudent and straightforward preventative measures such as mask-wearing and self-isolating when experiencing symptoms. After we include per-capita GDP (in natural logs) in the model, we find that most region-specific dummy variables are no longer significant. This suggests that spatial correlation is unlikely to explain the spread of Covid-19 cases within a country significantly.

**Table 1**
New Covid-19 cases per million (NCASESPM in natural logs).

| Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| *First level* | | | |
| Constant | 1.743*** (0.214) | 1.743*** (0.214) | 1.680*** (0.241) |
| NCASESPM Lag 1 | 0.208*** (0.041) | 0.208*** (0.041) | 0.207*** (0.047) |
| NCASESPM Lag 2 | 0.023 (0.014) | 0.023 (0.014) | 0.024 (0.016) |
| GMRR | −0.046*** (0.008) | −0.046*** (0.008) | −0.051*** (0.008) |
| GMGP | 0.032*** (0.008) | 0.032*** (0.008) | 0.034*** (0.009) |
| GMPARKS | −0.003* (0.002) | −0.003* (0.002) | −0.003* (0.002) |
| GMRES | −0.052*** (0.016) | −0.052*** (0.016) | −0.057*** (0.017) |
| *Second level* | | | |
| Constant | −3.492*** (0.877) | −4.964*** (1.087) | −4.502*** (1.360) |
| Globalisation index | 0.007 (0.012) | −0.001 (0.104) | −0.002 (0.673) |
| Income Gini | 0.033** (0.013) | 0.029** (0.013) | 0.026* (0.118) |
| Freedom 20 | 0.008* (0.004) | 0.006 (0.013) | 0.006 (0.015) |
| Proportion of urban population | 0.014* (0.008) | 0.006 (0.005) | 0.004 (0.005) |
| Population density (natural logs) | 0.096 (0.075) | 0.095 (0.008) | 0.107 (0.008) |
| Per capita GDP (natural logs) | | 0.283*** (0.074) | 0.277*** (0.077) |
| Human capital Gini | | | −0.488 (0.433) |
| East Asia and Pacific (DEAP) | −1.503*** (0.410) | −1.283 (0.426) | −1.291*** (0.319) |
| Europe and Central Asia (DECA) | 0.696*** (0.275) | 0.877 (0.281) | 0.711*** (0.442) |
| Latin America and the Caribbean (DLAC) | 0.060 (0.395) | 0.407 (0.419) | 0.431 (0.444) |
| Middle East and North Africa (DMENA) | 0.261 (0.427) | 0.433 (0.412) | 0.459 (0.544) |
| South Asia (DSA) | −0.434 (0.449) | −0.108 (0.500) | −0.089 (0.519) |
| Sub-Saharan Africa (DSSA) | −0.727* (0.433) | −0.321 (0.479) | −0.113 (0.014) |
| **Number of observations** | 36,980 | 36,980 | 33,667 |
| **Hansen's J-test $\chi^2$ *p* value** | 2.589 0.274 | 2.589 0.274 | 4.330 0.114 |

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are in parenthesis. Hansen's J-test $H_0$: overidentifying restrictions are valid.

### 4.2. Factors affecting case fatality rate: results

We present the estimation results of our model concerning the case fatality rate in Table 2. In all our models, we included lagged NCASESPM as the time-varying regressor. The optimal lag length of the dependant variable again turned out to be two periods. The results of all three models confirm that CFR is a highly persistent process. Except for Model 3, the coefficient of both the first and second lagged values of CFR are positive and significant at the 1% level. Lagged value of NCASESPM also has a positive and significant impact on the case fatality rate. NCASESPM is measured in natural logs. Its coefficient implies that doubling the number of Covid-19 cases would increase CFR between 0.011 and 0.013 in the short run. Given the persistent nature of CFR, the long-run effect is likely to be twice as high.

Regarding time-invariant explanatory variables, we found that variables essential in explaining NCASESPM did not have an independent effect on CFR. In all our models, the number of hospital beds significantly lowers the case fatality rates. Countries with a larger proportion of the population over 65 years old and higher $CO_2$ emissions had higher case fatality rates. Although not directly comparable, our results are qualitatively similar to Sorci et al. (2020). The incidence of cardiovascular diseases has a positive coefficient but is not significant. In Models 2 and 3, we added the number of physicians (per thousand of the population) and the extent of diabetes prevalence as additional variables, respectively. The number of physicians lowered CFR, but diabetes prevalence had no significant effect.

**Table 2**
Case fatality rate (CFR).

| Variable | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| First level | | | |
| **Constant** | 1.386*** (0.463) | 1.573*** (0.510) | 1.575*** (0.510) |
| **CFR Lag 1** | 0.358*** (0.128) | 0.313** (0.134) | 0.306** (0.133) |
| **CFR Lag 2** | 0.106** (0.049) | 0.088* (0.050) | 0.091* (0.051) |
| **NCASESPM Lag 1** | 0.013*** (0.004) | 0.012*** (0.004) | 0.011*** (0.004) |
| Second level | | | |
| **Constant** | −1.617** (0.802) | −1.975** (0.962) | −1.678** (0.870) |
| **Hospital beds** | −0.203** (0.093) | −0.218** (0.099) | −0.226** (0.103) |
| **Proportion of over 65 population** | 0.075** (0.031) | 0.118** (0.047) | 0.104** (0.041) |
| **Cardiovascular rate** | 0.001 (0.001) | 0.002 (0.002) | 0.002 (0.002) |
| **$CO_2$ emissions (natural logs)** | 0.120** (0.057) | 0.157** (0.072) | 0.187** (0.084) |
| **Physicians** | | −0.217* (0.122) | −0.181** (0.106) |
| **Diabetes prevalence** | | | −0.063 (0.040) |
| **Number of observations** | 50,224 | 48,362 | 48,039 |
| **Hansen's J-test $\chi^2$ *p* value** | 3.722 0.156 | 3.454 0.178 | 3.473 0.176 |

Note: *p < 0.10, **p < 0.05, ***p < 0.01. Standard errors are in parenthesis. Hansen's J-test $H_0$: overidentifying restrictions are valid.

## 5. Conclusion and policy implications

The Covid-19 pandemic has had an unprecedented global impact on people's health and well-being. Against this backdrop, we investigated the role of socio-economic factors, particularly relative deprivation and inequality, in the Covid-19 pandemic. We use a novel econometric approach that identifies the role of time-invariant variables such as degree of globalisation, political freedom and income inequality on the dynamics of Covid-19 cases (NCASESPM) and case fatality rates (CFR) across countries.

We find both NCASESPM and CFR to be highly persistent processes. After controlling for time-varying mobility statistics from the Google mobility database, and region-specific dummy variables, the two significant initial factors that explain the severity of Covid-19 spread in a country are per-capita GDP and Yitzhaki's index measuring relative income deprivation. Interestingly, these are the very two variables used by Deaton (2001) to explain variation in mortality across the states in the US. As far as CFR is concerned, the only time-varying explanatory variable of significance is the lagged value of NCASESPM. A higher value of NCASESPM increases fatality rates. It suggests that the higher caseload of the pandemic stretches the health system in all countries. A higher proportion of the over 65 population and pollution (proxied by $CO_2$ emissions) increased CFR. Medical infrastructure proxied by hospital beds and the number of physicians helps reduce the mortality rates.

Our findings are consistent with public health and epidemiology studies (Pickett and Wilkinson, 2015) that confirm the negative relationship between income inequality and health. Socio-economic status directly impacts health due to its positive relationship with access to resources, lifestyle factors and the ability to process information (Bucchianeri, 2010; Shavers, 2007). Other factors include lower social cohesion, trust, greater violence, and social distance in more unequal societies. Relative deprivation has been a fundamental concern in economics as well. Economic theory articulates a concave relationship between health and income such that while income has a positive impact on health but has diminishing returns. Relative deprivation emerges as a critical variable in this point of view. Due to the concavity effect, a dollar more to the less well-off impacts health more than the same dollar provided to the rich. Alternatively, if we re-distribute income from the rich to the poor, we will observe a rise in average health (Deaton, 2003). Our findings support these theoretical paradigms, but more research is needed to unpack the exact causal pathways.

An important policy insight emerging from this study's findings is that addressing inequality needs to be a key concern from the perspective of health policy as well. Ensuring healthcare accessibility and affordability for the most vulnerable segments of the population across the globe may facilitate them overcoming barriers to access quality healthcare even for the poorest of the poor. Governments across the globe need to take adequate steps to reduce income inequality to enhance the health and well-being of people.

Our study further confirms the urgency of redistributive policies to overcome the adverse effect of the Covid-19 pandemic, especially for poorer sections of society. This task is even more pressing given that Covid-19 has exacerbated the existing economic inequalities through loss of lives and livelihood, sowing the seeds of a perpetual poverty trap and 'virulent inequality' (Hill and Narayan, 2020; Charlton, 2020). Lastly, the exact causal pathways through which relative deprivation impacts Covid-19 remain underexplored. Understanding the multidimensional nature of relative deprivation holds the key to managing future outbreaks and is likely to be more prominent in the context of climate change.

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## Credit author statement

The co-authors jointly contributed 40–50% of the work.

## Declaration of competing interest

The authors declare that they have no conflict of interest.

## Data availability

Data will be made available on request.

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