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Non-healthcare system interventions and COVID-19 daily cases: a multilevel time series analysis

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Abstract

Background The global COVID-19 pandemic has significantly impacted public health and socio-economic development worldwide. This study aims to investigate the effects of non-healthcare system interventions on the daily new cases of COVID-19 from January 2020 to October 2022.

Methods With the aid of multilevel approach, we identified income group, region and country as stratification factors that affect the number of COVID-19 daily new cases. Data on COVID-19 cases collected by Johns Hopkins University were used, and policy implementation details were recorded through the Oxford COVID-19 Government Response Tracker dataset. To analyze the effects of national, regional, and income group factors on the number of daily new COVID-19 cases, we implemented three multilevel sequential mixed-effects models and applied restricted maximum likelihood to estimate the variance of random effects.

Results Our results indicate a correlation between income group and the rise in intercepts of random effects in the multilevel sequential mixed-effects models. High-income countries recorded the highest intercept at 713.26, while low-income countries showed the lowest at -313.79. Under the influence of policies, the implementation of "Canceling public events" and "International travel restrictions" has been shown to significantly reduce the daily number of new COVID-19 cases. In contrast, "Restrictions on gatherings" appear to have the opposite effect, potentially leading to an increase in daily new COVID-19 cases.

Conclusions In designing epidemic control policies, due consideration should be given to factors such as income group, as well as medical, demographic, and social differences among nations influenced by economic factors. In policy-making, policymakers should pay greater attention to policy implementation and people's responses, in order to maximize the effectiveness and adherence of such policies.

Keywords COVID-19, Non-healthcare system interventions, Multilevel model, Policy implementation, Income group, Region

Introduction

In 2020, the world was struck by a global outbreak of the Coronavirus Disease 2019 (COVID-19), which had significant impacts on health, economy, and society [1]. Governments worldwide have implemented various measures to prevent the spread of the virus, including city lockdowns, travel restrictions, and restrictions on gatherings, among others. The success of these policies depends on many factors, such as the timing of policy

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implementation, policy type, population density, and economic conditions [2].

The rapid spread of SARS-CoV-2 has outpaced the response of many governments. In response to initial shortcomings in epidemic control, non-pharmaceutical interventions (NPIs) targeting specific populations were implemented [3, 4]. Within the scope of NPIs, we focus on policies categorized as non-healthcare interventions, as these policies impose societal-level restrictions rather than individual-level recommendations. However, the effectiveness of non-healthcare interventions remains controversial, and the impacts of larger scale on the effectiveness of these interventions are frequently ignored. The effectiveness of epidemic prevention measures in a country is significantly influenced by its region and level of economic development. For instance, with a higher economic development level, Europe has access to more convenient tools to implement ideal isolations such as more effective curfews based on quality government and infrastructure, while only a few African countries possess such capabilities [5]. Thus, even if the intensity of policies is identical, the effects after policy implementation may differ, or even contradict each other. The objective of this study is to conduct a stratified analysis across as many countries as possible to determine how region and economic indicators influence the effectiveness of epidemic prevention and control.

Regional economic inequality is apparent, and it is widely acknowledged that the COVID-19 pandemic poses a greater threat to the lives and livelihoods of lower-income populations in comparison to higher-income populations. However, when income is carefully considered as a factor, the converse result was obtained. Studies have found that the pandemic has reduced international income inequality, manifested in the lower COVID-19 death rates per capita in poorer countries than in richer ones in 2020 [6]. Although it cannot be ruled out that the case numbers in lower-income countries may have been underestimated, other factors such as population age structure and climate can explain this situation, making the results still practically significant but full of ambiguity.

The objective of this study is to explore the effects of non-healthcare interventions on daily new cases during the COVID-19 pandemic. We applied multilevel approaches, stratifying by income group (measured by per capita Gross National Income), region, and country to evaluate the impact of these factors on cases. Furthermore, we aim to furnish essential data for formulating preventive policies for COVID-19 and identifying factors associated with epidemic prevention and control.

Materials and methods

Data

Independent variable

The Oxford COVID-19 Government Response Tracker (OxCGRT) dataset from the OxCGRT / COVID-policy-tracker repository provides comprehensive information on the policies adopted by different countries [7]. In this study, we utilized the economic policies and the containment and closure policies, along with their sub-indices. The economic policies reflect the level of economic support offered to households, such as income support for those who lost their jobs or were unable to work and debt relief such as a freeze on loan payments. The containment and closure policies record the strictness of the 'lockdown style' policies that primarily restrict people's behavior. All these indicators measure policies on an ordinal scale of severity, with 0 being the least severe and higher numbers indicating the more severe. Please refer to the OxCGRT codebook for the relevant code list (https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md) [8].

Dependent variable

The COVID-19 data used in this study was sourced from Johns Hopkins University (JHU) a leading institution in tracking the spread and impact of COVID-19 worldwide. JHU's data provides a comprehensive record of cases, deaths, tests, hospitalizations, and vaccinations (https://github.com/govex/COVID-19/tree/master/data_tables/demographic_data) [9]. This study used the daily new cases of COVID-19 from the database as the dependent variable.

Covariates

The covariates used in this study were obtained from "Our World in Data" an organization founded by the University of Oxford(https://ourworldindata.org/coronavirus) [10]. In monitoring global COVID-19 data, their initial consultation was based on three data sources: the World Health Organization (WHO), the European Centre for Disease Prevention and Control (ECDC), and Johns Hopkins University. In selecting covariates, we consider the choices made in similar studies and focus on key factors related to the control of COVID-19 that align with the objectives of this research. Eventually, the covariates included hospital beds per thousand, population density, proportion of individuals aged 65 or older, and hand-washing facilities. Variables were screened using the Variance Inflation Factor (VIF), calculated based on the classical linear regression model (Ordinary Least Squares, OLS). Variables with a VIF exceeding 10 will be excluded due to collinearity.

Classification standards

In accordance with the World Bank's latest standards updated in July 2022, countries were stratified into four income groups: Low-income (GNI per capita less than $1,085), Lower-middle-income (GNI per capita between $1,086 and $4,255), Upper-middle-income (GNI per capita between $4,256 and $13,205), and High-income (GNI per capita exceeding $13,205). The WHO's global regional classification method divided the world into six regions: Africa, Americas, South-East Asia, Europe, Eastern Mediterranean, and Western Pacific.

Analytical strategy

The analyzed data covers the period from January 2020 to October 2022. After October 2022, several countries and regions ceased to implement policies such as quarantine and nucleic acid testing and instead adopted a policy of coexisting with the epidemic, rendering policies ineffective.

Computational experiments in this study were carried out using R-4.2.3 tools to examine the impact of government policy responses on the number of COVID-19 daily new cases. Multilevel sequential mixed-effects models were fitted, and Restricted Maximum Likelihood (REML) was used to estimate the random effects [11]. Multilevel mixed-effects models allow for simultaneous estimation of fixed and random effects, thereby providing a more accurate description of data variability. Modeling data from different hierarchical sources enhances the precision of parameter estimates and effectively handles nested data structures, preventing biases introduced by ignoring the hierarchical nature of the data. REML considers the uncertainty in fixed effect parameter estimates when estimating the variance of random effects, thus reducing bias in variance estimates. In contrast, ordinary Maximum Likelihood (ML) estimation may overestimate the variance of random effects, especially with smaller sample sizes. REML estimation is theoretically sound, exhibiting consistency and asymptotic normality.

The REML first adjusted the random effects and then estimated the parameters of the fixed effects, thereby eliminating the influence of fixed effects and more accurately estimating the variance of the random effects. Three models were utilized, including Model 1 (stratifications by income group and country), Model 2 (stratifications by region and country), and Model 3 (stratifications by region, income group, and country). Stratification factors were implemented to capture the multilevel structure and potential heterogeneity of the data and to overcome potential ecological fallacies. As independent variables, economic policies and containment and closure policies were manipulated and controlled and regarded as the fixed effects. The data used in this study exhibits significant time-series characteristics and a hierarchical nested structure. To accurately capture these features, the model employs an autoregressive structure of order 1 [AR(1)] with a time series autocorrelation coefficient to describe the degree of correlation between adjacent observations [12]. Based on prior research, the AR(1) model effectively links the current observation to the previous one by modeling it as a linear function of the preceding value and incorporating a random error term [13]. Through recursive predictions, the AR(1) model captures the dynamic evolution of the entire time series and accurately represents dependencies between adjacent time points. When combined with the REML method, the AR(1) model efficiently handles the hierarchical structure and nested nature of the data while addressing interactions between fixed and random effects. Additionally, it mitigates the risks of overfitting or interference with multilevel mixed-effects models, which are common in ARIMA or higher-order AR models. This study employed an exploratory analysis approach, using the False Discovery Rate (FDR) to control for the false positive rate in multiple comparisons (FDR = 0.05). Results with FDR-adjusted *P*-value below 0.05 were considered statistically significant.

Results

Our study covers a total of 176 countries, divided into six WHO regions: 33 countries in the Americas, 42 in Africa, 24 in the Eastern Mediterranean, 19 in the Western Pacific, 8 in Southeast Asia, and 50 in Europe. Using Model 1, which incorporates income groups and country stratifications, the analysis found that the number of new cases was highest in high-income countries (713.26) and lowest in low-income countries (−313.79). Compared to the overall reference level, low-income countries exhibited relatively fewer new cases, and there was a clear upward trend in the number of new cases as income levels increased, as shown in Table 1. Despite the inclusion of hierarchical factors at the regional level, this phenomenon persists, albeit with a significantly reduced proportion in the random effects.

The intercept term of a random effect in a multilevel model represents the unexplained variation in the dependent variable across different levels that is attributed to unobserved factors such as cultural or educational differences, rather than the independent variable. In Table 2, the random effects of Model 2 indicate that the case number is lowest in the African region (−1208.81) and highest in the Americas region (805.65).

In the set of fixed effects, certain variables including Cancel public events, Restrictions on gatherings, International travel controls, and Hospital beds per thousand

Table 1 Random effects of different income groups in multilevel models

Model ID[a]	Income groups			
	Low income	Lower-middle income	Upper-middle income	High income
Model 1[b]				
	−313.79	−270.54	−128.94	713.26
Model 3[c]				
Africa	−0.35	−0.29	−0.11	−0.04
America	NA	−0.24	−0.02	0.78
Europe	NA	−0.16	−0.19	0.45
Southeast Asia	NA	0.39	0.01	NA
Western Pacific	0.20	−0.14	−0.11	0.20
Eastern Mediterranean	−0.12	−0.08	−0.04	−0.15

NA Not applicable. Samples did not meet grouping requirements

[a] The random intercept in multilevel models is considered as the random effect value, representing the unobserved factors between different groups that affect the dependent variable

[b] Multilevel sequential mixed effects model stratified by income group and country

[c] Multilevel sequential mixed effects model stratified by region, income group, and country

Table 2 Random effects of the region in multilevel models

Model ID	Africa	America	Eastern Mediterranean	Western Pacific	Europe	Southeast Asia
Model 2[a]						
	−1208.81	805.65	−606.47	226.32	154.20	629.10
Model 3[b]						
	−1209.10	805.86	−606.69	226.42	154.12	629.38

[a] Multilevel sequential mixed effects model stratified by region and country

[b] Multilevel sequential mixed effects model stratified by region, income group, and country

were found to be statistically significant. Cancel public events ($\beta = -629.88$, $P = 0.002$) and International travel restrictions ($\beta = -522.26$, $P < 0.001$) were found to significantly reduce the number of new cases. In contrast, restrictions on gatherings ($\beta = 352.77$, $P < 0.001$) and an increased number of hospital beds per thousand ($\beta = 553.65$, $P < 0.001$) were associated with an increase in the number of new cases (Table 3).

To examine the correlation among the variables, Spearman's correlation analysis was employed. The results of the analysis revealed a correlation (absolute value of 0.432) between "Cancel public events" and "Restrictions on gatherings," while "Income support" and "Debt relief" also exhibited a correlation (absolute value of 0.318). These findings are not unexpected, as these variable pairs represent closely related policy measures that are often implemented together. However, the presence of such correlations could potentially inflate the standard errors of the regression coefficients, thereby affecting the precision of the estimates for these variables. Despite this, our VIF analysis confirmed that multicollinearity is not a significant concern, as all VIF values were within acceptable limits. While these correlations indicate some overlap in

Table 3 Fixed effects results in region, income group and country multilevel model

Parameters—fixed	Coefficient [a]	SE	*t*-value	*P*-value[b]
Independent variable				
School closing	−33.22	123.93	−0.268	0.789
Workplace closing	2.57	156.44	0.016	0.987
Cancel public events	−629.88	200.73	−3.138	0.002*
Restrictions on gatherings	352.77	99.34	3.551	< 0.001**
Close public transport	277.94	192.42	1.444	0.149
Stay at home requirements	257.11	155.68	1.652	0.099
Movement restrictions	−229.42	156.42	−1.467	0.142
International travel controls	−522.26	105.52	−4.950	< 0.001**
Income support	−28.28	211.24	−0.134	0.894
Debt relief	−19.51	181.03	−0.108	0.914
Covariate				
Hospital beds per thousand	553.65	149.24	3.710	< 0.001**
Population density	−0.39	0.29	−1.363	0.173

[a] The coefficient refers to the regression coefficient of each independent variable. It indicates the impact of a one-unit change in an independent variable on the dependent variable, while holding all other variables constant

[b] Asterisks denote level of statistical significance: ** $P < 0.001$; * $P < 0.05$

the information captured by the variables, they do not compromise the robustness or validity of our multilevel models (Table 4).

Table 5 presents the indicators used to evaluate the model fit. The ICC values of the four models range from 0.225 to 0.242, with Model 2 explaining 24.2% of the variance through random effects. An ICC between 0.11 and 0.40 is generally considered to indicate moderate explanatory power, making this an important metric in the present study. Considering the inclusion of 173,888 records from 176 countries, the AIC and BIC values are within an acceptable range. Although the AIC, BIC, and log-likelihood values are almost identical across models, Model 2 (stratifications by region and country) demonstrated a higher ICC and slightly better performance compared to the others. Additionally, the Phi values of all models (approximately 0.816–0.817) indicate strong within-group correlation, which is instrumental in capturing group-level effects and dependencies. This further supports the use of multilevel modeling to account for such dependencies.

Discussion

In this study, income group is an important variable that deserving of attention. The results show that as income group increases, the initial value of the case also increases. We believe that this phenomenon is influenced by multiple factors. Firstly, from a data perspective, higher income countries have greater efficiency in reporting cases compared to countries with lower income groups. This increased efficiency can be attributed to better medical facilities, more testing and treatment resources, and an increased likelihood of conducting large-scale nucleic acid testing [14]. Additionally, people with higher income groups subjectively pay more attention to their health and are more likely to seek medical help [15]. This effect ultimately also manifests in different disease reporting rates. This phenomenon does not imply that people from lower income groups do not desire or deserve medical resources. Rather, they may suppress their medical seeking due to the lack of facilities, cultural practices, and privacy concerns. Meadows AJ et al. demonstrated that a country's preparedness was positively associated with reporting [16]. To improve reporting rates, govern correlation ments need to make the correct decisions and adequately prepare for outbreaks in a timely fashion. Thirdly, from a policy execution perspective, the centralized nature of decision-making in autocracies should enable their leaders to react swiftly. Therefore, low-income countries may be more decisive in policy execution because democratic countries account for only about 45% of low-income countries, compared to 90% of high-income countries. However, this advantage is not absolute, as the distorted information flow, lack of national capacity, and a tendency to ignore problems may limit the potential for decisive action [17]. Therefore, this aspect needs to be looked at specifically on a country-by-country basis.

From an epidemiological perspective, firstly, by comparing population groups, it can be observed that younger populations are more prevalent in low-income countries, while older populations are higher in high-income countries. According to a study by O'Driscoll et al., French people over 65 years old had a 1.70 times higher incidence of infection than the general population. Similarly, many European countries reported a higher incidence of deaths in older individuals than expected [18]. Although COVID-19 can infect people of all ages, older populations are more susceptible to severe outcomes, which may increase the reporting rate due to their higher tendency to seek medical treatment. Secondly, climate and environmental conditions can affect the spread of the virus. Low-income countries are often located in tropical and subtropical regions, which are less conducive to virus transmission compared to high-latitude regions. The virus is easily inactivated in high-temperature and high-humidity environments [19]. It is worth noting that many epidemiological characteristics are difficult to change. Therefore, it is crucial to develop the most appropriate policy for the country based on the epidemiologist's and the government's understanding of the national situation.

We cannot fully explain the differential incidence of cases due to geographical factors with a single or several variables, but there are still some noteworthy aspects. First, employment status: in areas where labor-intensive industries are relatively concentrated, workers have more frequent contact. Due to the instability of the labor market, some workers may have to live in areas where work is concentrated, increasing the risk of virus transmission [20]. This phenomenon is more common in developing countries. Second, trade exchanges: frequent trade exchanges may cause the virus to spread to other areas through the flow of goods and personnel. This situation is more prominent in economically developed areas. Third, population density: it is closely related to urbanization. According to the study of Ganasegeran K et al., the propagation effect and the spread of disease were greater in urbanized districts or cities [21]. The increase in population density reflects not only the easier transmission, but also the dual challenges of protecting susceptible populations [22, 23].

The timing of intervention measures can significantly affect their effectiveness. In the early stages, such as early 2020, global responses to COVID-19 were often swift but may have lacked experience and precise data support.

Table 4 Spearman's correlation analysis between variables

Variables	Intercept	School closing	Workplace closing	Cancel public events	Restrictions on gatherings	Close public transport	Stay at home requirements	Movement restrictions	International travel restrictions	Income support	Debt relief	Hospital beds per thousand
School closing	−0.002											
Workplace closing	−0.024	−0.148										
Cancel public events	−0.032	−0.147	−0.239									
Restrictions on gatherings	−0.014	−0.047	−0.111	−0.432								
Close public transport	0.000	−0.057	−0.138	−0.008	−0.041							
Stay at home requirements	−0.002	−0.087	−0.174	−0.017	−0.153	−0.123						
Movement restrictions	0.009	−0.089	−0.078	−0.063	−0.026	−0.184	−0.219					
International travel restrictions	−0.086	−0.196	−0.035	−0.085	−0.083	−0.047	−0.039	−0.078				
Income support	−0.027	−0.032	−0.036	−0.022	−0.074	0.020	−0.017	0.013	−0.072			
Debt relief	−0.029	−0.060	0.000	−0.023	−0.044	−0.011	−0.032	−0.035	−0.093	−0.318		
Hospital beds per thousand	−0.278	−0.023	−0.019	−0.030	−0.031	−0.001	0.013	0.001	−0.016	−0.078	−0.038	
Population density	0.034	0.008	−0.006	0.014	−0.008	0.002	0.004	0.006	0.004	−0.013	0.021	−0.352

Table 5 Evaluation of the goodness-of-fit of the multilevel analysis

Model ID	ICC[a]	AIC	BIC	Log Likelihood	Phi[b]
Null model					
	0.241	3690985	3691036	−1845488	0.817
Model 1					
	0.240	3690818	3690989	−1845392	0.816
Model 2					
	0.242	3690818	3690989	−1845392	0.816
Model 3					
	0.225	3690820	3691001	−1845392	0.816

[a] ICC refers to Intra-class correlation, which measures the proportion of the total variance that is due to the differences in random effects

[b] Phi refers to the phi correlation coefficient, which represents the correlation between data points and their previous data points

Measures such as canceling public events, restricting gatherings, implementing international travel controls, and increasing hospital beds were quickly implemented to curb virus spread [24]. These measures could have a crucial impact on controlling the initial outbreak, despite initial challenges in execution and societal acceptance. As time progressed and the pandemic evolved, the effectiveness of these measures and societal responses may have varied. Increased public understanding of virus transmission and protective measures, along with optimizations in healthcare treatment and management, could have diminished the impact of these interventions or revealed new challenges [25]. For instance, prolonged implementation of restrictions may have led to societal and economic fatigue and public opposition [26, 27]. Furthermore, the speed and severity of measures implemented varied among countries and regions, influencing the assessment of their effectiveness. The impact of international travel restrictions and increases in hospital resources could differ based on the country's epidemic situation, healthcare system resilience, and levels of government and public cooperation. Therefore, evaluating the effectiveness of intervention measures requires consideration of temporal factors and implementation contexts to comprehensively understand their contributions and limitations in controlling the pandemic.

Canceling public events and international travel controls have positive effects on mitigating epidemics because reducing gatherings and personnel flow is an effective way to cut off transmission routes and can lead to positive effects [28, 29]. However, the policy of restrictions on gatherings, which can also cut off transmission routes, would increase the number of confirmed cases. We believe that this is due to the issue of "initiative". The policies of canceling public events and controlling international travel controls are being executed by the government, so their effects can be guaranteed. However, the policy of restricting on gatherings is being executed by the people, which means that the effect of the policy relies on the people's initiative. This kind of adherence did not happen overnight, as a study by Sehar-Un-Nisa Hassan et al., gender, psychological quality of life, social quality of life, and environmental quality of life are significantly associated with healthcare adherence [30]. The point is to improve the quality of people's lives and to boost the government's prestige. There are other explanations for the negative effects of restrictions on gatherings. As policies last longer, people become more eager for face-to-face communication. In such situation, private gatherings may occur, and it will be more difficult to have qualified disease prevention conditions in these private places than in gatherings organized by responsible parties. Moreover, the government or relevant authorities lack sufficient resources to detect and stop such behavior. While a lot of attention had focused on large gatherings, Boyer CB et al. had shown that small gatherings, due to their frequency, can also be important contributors to transmission dynamics [31]. How to appease the emotions of the masses and improve the compliance of the people is something that many countries need to consider.

Researchers often consider hospital beds per thousand as a proxy for the extent of health expenditures [32]. Hospital beds per thousand is statistically significant in our study. We do not believe that the increase in cases is due to the number of hospital beds, but rather that increased healthcare spending has detected more cases. If we discard the *p*-value, we will find policies that that people can disobey, such as restrictions on gatherings, close public transport, stay at home requirements. All of these policies can be resisted by the people using their own means and may have hidden negative effects. Does this imply that policies relying on people's autonomy to achieve their effects have hidden risks? And if so, how significant are these risks? These are questions worth considering.

Recommendations

Based on our research results, we should not only consider the country's economic factors as a single variable in research but also consider the multiple factors behind the economy. We should carry out more detailed research on differences in different regions and populations. This also indicates that it is not appropriate to simply copy the epidemic prevention policies of other countries. Instead, we should have in-depth thinking based on the national conditions.

In policy-making, governments should pay more attention to the effectiveness of policy execution and people's reactions. Policy-making and execution should be more aligned with the needs and feelings of the people to improve the effectiveness of policy execution and people's compliance.

Conclusions

In summary, this study shows that income groups can deeply influence the effect of prevention policies. While taking into account income groups, it is also important to consider inherent medical, demographic, and social differences within the country itself. As for policies, we believe that more attention should be paid to those relying on people's autonomy to achieve their effects, as these may have significant pitfalls and uncertainties. We hope that more in-depth and specific studies will be carried in the future to provide recommendations for controlling COVID-19.

Strengths and limitations

We believe that our study had several strengths, including the use of multilevel models to consider country, region and individual factors, as well as the comprehensive analysis of the impact of epidemic control factors. This study conducted an in-depth exploration of the role of different income groups and epidemic control factors and the possible outcomes, providing a reference for epidemic control measures. However, the study also has its limitations. Although we used the REML method to estimate random effects more accurately, fixed effects may still have biases. Additionally, REML cannot show ICC. Moreover, the population density should not be simply used, due to the lack of corresponding data, we still used the unprocessed population density of the country. Finally, due to various constraints, we were unable to find sufficient data suitable for our analysis. Therefore, the COVID-19 data used in our study does not specifically account for variant specificity and measure population compliance with government policies. Finally, there are missing values (NA) for three regions in Model 3 (Table 1), which may cause fluctuations in the estimation of fixed effects and an underestimation of between-group variance for these regions. As a result, the applicability of this study's conclusions to these regions may be diminished.

Abbreviations

COVID-19	Coronavirus Disease 2019
OxCGRT	Oxford COVID-19 Government Response Tracker
JHU	Johns Hopkins University
ECDC	European Centre for Disease Prevention and Control
WHO	World Health Organization
NPIs	Non-pharmaceutical Interventions
REML	Restricted Maximum Likelihood
ML	Maximum Likelihood
ARIMA	Autoregressive Integrated Moving Average Model
AR(1)	Autoregressive Structure of Order 1
GNI	Gross National Income
FDR	False Discovery Rate
VIF	Variance Inflation Factor
ICC	Intra-Class Correlation Coefficient
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
Phi	Phi Correlation Coefficient

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

HM has made significant contributions to the conception and design of the study. LL is responsible for data analysis using R software. HM and AL were responsible for writing and grammatically revising the article. YY provided comprehensive guidance throughout the writing of the entire paper. All authors reviewed the manuscript.

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Data availability

The comprehensive information on the policies adopted by different countries generated and analysed during the current study is available in the Oxford COVID-19 Government Response Tracker (OxCGRT) dataset, https://github.com/OxCGRT/covid-policy-tracker.
The COVID-19 data generated and analysed during the current study are available from Johns Hopkins University (JHU), https://github.com/govex/COVID-19/tree/master/data_tables/demographic_data.
The covariate data generated and analysed during the current study are available in "Our World in Data", an organization founded by the University of Oxford, https://ourworldindata.org/coronavirus.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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References

1. Wang C, Horby PW, Hayden FG, Gao GF. A novel coronavirus outbreak of global health concern. Lancet. 2020;395(10223):470–3. https://doi.org/10.1016/S0140-6736(20)30185-9.
2. Tang SGH, Hadi MHH, Arsad SR, Ker PJ, Ramanathan S, Afandi NAM, Afzal MM, Yaw MW, Krishnan PS, Chen CP, Tiong SK. Prerequisite for COVID-19 prediction: a review on factors affecting the infection rate. Int J Environ

Res Public Health. 2022;19(20): 12997. https://doi.org/10.3390/ijerph192012997.
3. Perra N. Non-pharmaceutical interventions during the COVID-19 pandemic: a review. Phys Rep. 2021;913:1–52. https://doi.org/10.1016/j.physrep.
4. Rowan NJ, Moral RA. Disposable face masks and reusable face coverings as non-pharmaceutical interventions (NPIs) to prevent transmission of SARS-CoV-2 variants that cause coronavirus disease (COVID-19): Role of new sustainable NPI design innovations and predictive mathematical modelling. Sci Total Environ. 2021;772: 145530. https://doi.org/10.1016/j.scitotenv.2021.145530.
5. Harrow J, Hancock J, ELIXIR-EXCELERATE Community, Blomberg N. ELIXIR-EXCELERATE: establishing Europe's data infrastructure for the life science research of the future. EMBO J. 2021;40(6):e107409. https://doi.org/10.15252/embj.2020107409.
6. Hsiang S, Allen D, Annan-Phan S, Bell K, Bolliger I, Chong T, Druckenmiller H, Huang LY, Hultgren A, Krasovich E, Lau P, Lee J, Rolf E, Tseng J, Wu T. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature. 2020;584(7820):262–7. https://doi.org/10.1038/s41586-020-2404-8.
7. Hale T, Angrist N, Goldszmidt R, Kira B, Petherick A, Phillips T, Webster S, Cameron-Blake E, Hallas L, Majumdar S, Tatlow H. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nat Human Behav. https://doi.org/10.1038/s41562-021-01079-8.
8. Codebook for the Oxford Covid-19 government response tracker. University of Oxford. 2020. https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md.
9. COVID-19 demographic data. Johns Hopkins University Coronavirus Resource Center. 2022. https://github.com/govex/COVID-19/tree/master/data_tables/demographic_data.
10. Mathieu E, Ritchie H, Rodés-Guirao L, Appel C, Gavrilov D, Giattino C, Hasell J, Macdonald B, Dattani S, Beltekian D, Ortiz-Ospina E, Roser M. Our World in Data. 2020. https://ourworldindata.org/coronavirus.
11. Thai HT, Mentré F, Holford NH, Veyrat-Follet C, Comets E. A comparison of bootstrap approaches for estimating uncertainty of parameters in linear mixed-effects models. Pharm Stat. 2013;12(3):129–40. https://doi.org/10.1002/pst.1561.
12. Jongerling J, Laurenceau JP, Hamaker EL. A multilevel AR(1) Model: allowing for inter-individual differences in trait-scores, inertia, and innovation variance. Multivariate Behav Res. 2015;50(3):334–49. https://doi.org/10.1080/00273171.2014.1003772.
13. Lee M-H, Kim S-H. Breast cancer screening rates-related factors Korea women ever considering area environmental characteristics: the fourth Korea National Health and Nutrition Examination Survey (KNHANES IV). Journal of Digital Convergence. 2014;12(11):437–49.
14. Manski CF, Molinari F. Estimating the COVID-19 infection rate: anatomy of an inference problem. J Econom. 2021;220(1):181–92. https://doi.org/10.1016/j.jeconom.2020.04.041.
15. Farrer L, Marinetti C, Cavaco YK, Costongs C. Advocacy for health equity: a synthesis review. Milbank Q. 2015;93(2):392–437. https://doi.org/10.1111/1468-0009.12112.
16. Meadows AJ, Oppenheim B, Guerrero J, Ash B, Badker R, Lam CK, Pardee C, Ngoon C, Savage PT, Sridharan V, Madhav NK, Stephenson N. Infectious disease underreporting is predicted by country-level preparedness, politics, and pathogen severity. Health Secur. 2022;20(4):331–8. https://doi.org/10.1089/hs.2021.0197.
17. Koehler K, Schulhofer-Wohl J. Governing the covid-19 pandemic in the Middle East and North Africa: containment measures as a public good. Middle East Law Governance. 2021;14(1):5–25. https://doi.org/10.1163/18763375-13040003.
18. O'Driscoll M, Ribeiro Dos Santos G, Wang L, Cummings DAT, Azman AS, Paireau J, Fontanet A, Cauchemez S, Salje H. Age-specific mortality and immunity patterns of SARS-CoV-2. Nature. 2021;590(7844):140–5. https://doi.org/10.1038/s41586-020-2918-0.
19. Liu M, Li Z, Liu M, Zhu Y, Liu Y, Kuetche MWN, Wang J, Wang X, Liu X, Li X, Wang W, Guo X, Tao L. Association between temperature and COVID-19 transmission in 153 countries. Environ Sci Pollut Res Int. 2022;29(11):16017–27. https://doi.org/10.1007/s11356-021-16666-5.
20. Zhao H, Chen N. Medium and long-term impact of SARS on total factor productivity (TFP): empirical evidence from Chinese industrial enterprises. J Asian Econ. 2022;82: 101507. https://doi.org/10.1016/j.asieco.2022.101507.
21. Ganasegeran K, Jamil MFA, Ch'ng ASH, Looi I, Peariasamy KM. Influence of population density for COVID-19 spread in Malaysia: an ecological study. Int J Environ Res Public Health. 2021;18(18): 9866. https://doi.org/10.3390/ijerph18189866.
22. Baser O. Population density index and its use for distribution of Covid-19: a case study using Turkish data. Health Policy. 2021;125(2):148–54. https://doi.org/10.1016/j.healthpol.
23. Md Iderus NH, Lakha Singh SS, Mohd Ghazali S, Yoon Ling C, Cia Vei T, Md Zamri ASS, Ahmad Jaafar N, Ruslan Q, Ahmad Jaghfar NH, Gill BS. Correlation between population density and COVID-19 cases during the third wave in Malaysia: effect of the delta variant. Int J Environ Res Public Health. 2022;19(12): 7439. https://doi.org/10.3390/ijerph19127439.
24. Wang Z, Fu Y, Guo Z, Li J, Li J, Cheng H, Lu B, Sun Q. Transmission and prevention of SARS-CoV-2. Biochem Soc Trans. 2020;48(5):2307–16. https://doi.org/10.1042/BST20200693.
25. Reed-Thryselius S, Fuss L, Rausch D. The relationships between socioeconomic status, COVID-19 risk perceptions, and the adoption of protective measures in a Mid-Western City in the United States. J Community Health. 2022;47(3):464–74. https://doi.org/10.1007/s10900-022-01070-y.
26. Rodenberg H. Understanding the likely motivations behind opposition to public health measures in times of pandemic. Am J Public Health. 2021;111(4):590–1. https://doi.org/10.2105/AJPH.2021.306184.
27. Petherick A, Goldszmidt R, Andrade EB, Furst R, Hale T, Pott A, Wood A. A worldwide assessment of changes in adherence to COVID-19 protective behaviours and hypothesized pandemic fatigue. Nat Hum Behav. 2021;5(9):1145–60. https://doi.org/10.1038/s41562-021-01181-x.
28. Mendez-Brito A, El Bcheraoui C, Pozo-Martin F. Systematic review of empirical studies comparing the effectiveness of non-pharmaceutical interventions against COVID-19. J Infect. 2021;83(3):281–93. https://doi.org/10.1016/j.jinf.2021.06.018.
29. Lai S, Ruktanonchai NW, Zhou L, Prosper O, Luo W, Floyd JR, Wesolowski A, Santillana M, Zhang C, Du X, Yu H, Tatem AJ. Effect of non-pharmaceutical interventions to contain COVID-19 in China. Nature. 2020;585(7825):410–3. https://doi.org/10.1038/s41586-020-2293-x.
30. Hassan SU, Zahra A, Parveen N, Khatoon F, Bangi NA, Hosseinzadeh H. Quality of life and adherence to healthcare services during the COVID-19 pandemic: a cross-sectional analysis. Patient Prefer Adherence. 2022;16:2533–42. https://doi.org/10.2147/PPA.S378245.
31. Boyer CB, Rumpler E, Kissler SM, Lipsitch M. Infectious disease dynamics and restrictions on social gathering size. Epidemics. 2022;40: 100620. https://doi.org/10.1016/j.epidem.2022.100620.
32. Arbel Y, Arbel Y, Kerner A, Kerner M. What is the optimal country for minimum COVID-19 morbidity and mortality rates? Environ Sci Pollut Res Int. 2023;1–21. https://doi.org/10.1007/s11356-023-26632-y.

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