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Effectiveness of social distancing interventions in containing COVID-19 incidence: International evidence using Kalman filter

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ABSTRACT

The epidemiological literature has widely documented the importance of social distancing interventions in containing the spread of the COVID-19 pandemic. However, the epidemiological measure of virus reproduction, $R_0$, provides a myopic view of containment, especially when the absolute number of cases is still high. The paper investigates cross-country variations concerning the impact of social distancing interventions on COVID-19 incidence by employing a statistical measure of containment, which models the daily number of cases as a structural time-series, state-space vector. Countries that adopt strict lockdown policies and provide economic support in the form of income augmentations and debt relief improve the response towards the pandemic. Countries like China and South Korea have been most influential in containing the spread of infections. European nations of France, Italy, Spain and the UK are witnessing a second wave of the virus, indicating that re-opening the European economy perhaps has instigated an exponential spread.

1. Introduction

On March 11, 2020, the World Health Organization (WHO) declared SARS-CoV-2 (Severe Acute Respiratory Syndrome), commonly known as COVID-19, a pandemic. In late December 2019, the first case of COVID-19 was reported. Since then, the virus has spread to over 200 countries (Deb et al., 2020). On account of the unavailability of an effective treatment or a vaccine, several countries have responded by imposing social distancing measures (Kissler et al., 2020). Although the timelines of these measures differ from country to country, 70% of the pandemic-affected nations have implemented a majority of these policies by mid-April 2020 (Castex et al., 2020). Dealing with the virus outbreak can be briefly summarized as a problem of constrained optimization involving both costs and benefits (Alimohamadi et al., 2020b). Social distancing interventions involve economic costs reflected in terms of unemployment and lost output, along with social and psychological costs resulting from sudden unemployment (Moosa, 2020; Le and Nguyen, 2021). To date, however, there is not much evidence on the quantifiable effects of social distancing measures. Given the profound economic, social and psychological consequences of COVID-19, quantifying the impact of social distancing interventions on COVID-19 incidence is essential to support the decision-makers and inform policymaking, which, so far, has been dependent upon epidemiological modelling studies (Prem et al., 2020; Hamman, 2021). However, with the accumulation of cases, it has reasonably become possible to corroborate the estimates of epidemic modelling studies on the influence of social distancing interventions on COVID-19 incidence with empirical data (Roh et al., 2020).

Social distancing is a set of non-pharmaceutical interventions (NPIs) intended to curtail the spread of the contagious disease by minimizing the physical contact between individuals. It involves a wide array of measures such as conducting business over the phone or through an online medium, cancelling mass gatherings, quarantine, avoiding unnecessary travel, cordon sanitaire, school and workplace closures, travel restrictions, and protective sequestration (Moosa, 2020). These non-pharmaceutical interventions can be traced to a plethora of natural experiments and epidemiological studies undertaken during previous epidemics (Hsiang et al., 2020). However, the actual impact of social distancing measures in the current pandemic is not known.

Despite the fact that many countries have imposed social distancing measures, the divergence across countries concerning the containment of the virus is quite conspicuous. Judging the cross-country differences...
concerning the impact of social distancing measures on COVID-19 incidence is an arduous task. While some countries have responded to the crisis by not imposing such measures, others have imposed the same but vary in terms of the degree of severity. Furthermore, while some countries had imposed social distancing measures when the cases were at the lowest level, others had decided to intervene when the number of cases reached a higher level. Herewith, we quote a few such instances. Five days post the declaration of COVID-19 as a pandemic, President Donald Trump urged US citizens to limit travel. However, lockdown measures were implemented across individual US states at different times by their respective governors. While states such as California and New York imposed lockdown measures on March 19, 2020, and March 22, 2020, respectively, Georgia was one of the last to go into lockdown on April 3, 2020. Italy delayed in enacting social distancing measures. While China and Australia imposed official lockdown when reported cases per million were at the lowest level, the US and the UK started lockdown when the confirmed cases had reached the highest levels. Brazil, Sweden and South Korea, however, opted not to impose lockdown. After one week of confirming the first case, the Korean government opened up as many as 600 testing centres to undertake mass testing of people in the shortest possible time. Furthermore, as the Korean government had put an intrusive surveillance apparatus that thwarted people’s privacy, a common consensus is that this high cost regarding privacy loss is worth paying for making out of the crisis. Sweden, however, followed voluntary social distancing with bars, restaurants and elementary schools kept open.

In this paper, we put forward an argument that the epidemiological measure of containment, based on the reproduction rate of the virus, may provide a myopic view of the situation as what matters is not only that the rate of reproduction of the strain is less than one but also whether the incremental increase in the number of reported cases is under control. Focusing on this limitation, we propose a new, statistical measure of containment by modelling the daily number of reported cases as a structural time-series state-space model with two latent vectors. A Kalman filter methodology is employed to recursively obtain the conditional mean and variance of the time-series for 20 select countries across the European Union, North America, South America, Asia-Pacific, and Africa. Based on the work of Moosa (2020), we establish seven categories of containment, ranging from a situation beyond control to a situation where the magnitude and the spread of infection are under control. Containment is defined as a situation wherein the level and the slope of the state-space model are kept insignificant for a sufficient period of time (Moosa, 2020).

Further, the spread of the virus depends on a host of factors, of which the government’s policy response is of principal importance. To this end, we examine the impact of pandemic-induced policies, such as the degree of stringency in mandatory lockdowns, containment policies, health policies, and economic policies on the spread and mortality rate of COVID-19 infections after controlling for the influence of several country-specific factors. To date, there is not much evidence on the quantitative impact of these policies. While most countries have adopted stringent policy measures in response to the pandemic, it remains unclear why countries differ in containing the spread of the virus. In the present study, we thus, attempt to address this knowledge gap in the literature and explain observed divergence across countries concerning the evolution of the pandemic post the implementation of pandemic-induced measures. To analyse these differences, we determine how the influence of various policy measures on COVID-19 incidence varies across a matrix of country-specific characteristics such as demographic, environmental and health dimensions. These characteristics are related to divergence in behavioural response and divergence in resource availability to governments that likely forms a requisite for policy enforcement. Therefore, we examine the moderating effect of population density, the proportion of the elderly population, and countries’ overall health scenario in influencing the associations between government policies and COVID-19 incidence. Pandemic-induced policies may be less favourable in highly populated countries in congruence with the view that higher population density augments the recurrence of human interactions and places more demand on resources for compliance with these policies. Further, while voluntary social distancing before the enactment of interventions is likely to be less evident in countries with lower proportions of elderly and access to better public health systems on account of lower perceived risk, pandemic-induced policies may be more advantageous in countries with significant proportions of youngsters and availability of better health systems.

The rest of the paper is organized as follows. Section 2 critically evaluates the available literature on the influence of non-pharmaceutical interventions in containing the pandemic. Section 3 illustrates the modelling strategy and data sources. Section 4 provides a detailed analysis of the results. Section 5 contains an array of checks to lend robustness to the results. Section 6 concludes the study.

2. Literature review

The importance of social distancing interventions can be traced back to previous pandemics. Glass et al. (2006) highlight that targeted social distancing measures, including keeping children at home and school closures, can reduce the attack rate of influenza pandemic by approximately 90%. Tunçer et al. (2018) comment upon the influence of several control measures in containing the Ebola outbreak in Liberia. The authors confirm that several control measures implemented, social distancing interventions have the most significant impact in mitigating the 2014 Ebola epidemic in Liberia. In addition, several studies in the literature confirm that social distancing measures are beneficial in reducing influenza cases (Milne et al., 2008, 2013; Lee et al., 2010; Mao, 2011; Zhang et al., 2012).

The literature on the influence of social distancing measures in controlling the COVID-19 pandemic is also rapidly expanding. Employing the daily data on confirmed COVID-19 cases for a set of 10 countries, Moosa (2020) advocates that social distancing measures, in general, are beneficial in controlling the spread of the virus. The author reports an insignificant level and slope of the stochastic trend for countries such as Australia and China, highlighting that they have successfully contained the infection’s spread over the sampled timeframe by imposing social distancing measures when the reported cases were lower. South Korea, however, is cited as an anomaly. Even in the absence of government-imposed restrictions, the country is observed to perform reasonably well, perhaps attributable to the intrusive surveillance by the Korean government. Furthermore, the author observes a significant level of the stochastic trend for countries such as the UK and the USA, highlighting no containment of the virus over the period analysed given the non-timely and less stringent imposition of lockdown. On similar lines, Wong et al. (2020) highlight the importance of implementing stringent social distancing measures immediately upon confirmation of the first case in controlling the spread of the virus in Hong Kong. The authors further cite several social distancing measures, including the closure of primary and secondary schools, work from home arrangements, closure of leisure facilities, banning non-Hong Kong residents from overseas countries, the prohibition of public gatherings, mandatory 14-day quarantine for people entering from the mainland, mandatory self-quarantine for those who have come in close contact with infected persons together with close surveillance using electronic wristband among others, which have played an essential role in containing the infection. Using daily data on reported cases and real-time data on containment measures, Deb et al. (2020) attempt to assess the relationship between containment policies and the spread of the virus for a sample of 129 countries. The authors demonstrate that containment measures are successful in flattening the pandemic curve. Furthermore, the authors explore the cross-country heterogeneity in baseline associations by employing several country-specific factors and document that the influence of containment measures in minimizing the spread is more pronounced in countries with faster implementation of
containment measures, lower population density and a larger proportion of elderly in the population.

Cowling et al. (2020) examine the influence of non-pharmaceutical interventions on COVID-19 transmission in Hong Kong SAR and report that social distancing measures lead to a substantial drop in the virus transmission rate. Employing a standard SIR epidemiological model, Brotherwood et al. (2020) analyse the influence of quarantine measures. Their findings suggest that confining mobility for the young can extend the pandemic as herd immunity is delayed while exposing the elderly to risk. In a quasi-experimental framework, Alimohamadi et al. (2020a) empirically analyse the implications of social distancing measures on COVID-19 incidence in Iran. The authors observe that while new cases and mortalities exhibit an increasing trend before the intervention period, a declining trend is observed post-intervention. Overall, the findings highlight that irrespective of the economic and psychological influence of NPIs, their importance in containing the COVID-19 incidence is undeniable. Employing a network-based SEIR model, Lai et al. (2020) undertake a quantitative assessment of the impact of NPIs in managing COVID-19 incidence in China. The authors predict that in the absence of NPIs, by February 29, 2020, COVID-19 cases would have been higher by 67-fold. The authors further identify three NPIs implemented in China: intercity travel restrictions, early detection and isolation of cases, and contact reduction. The findings suggest that while NPIs successfully contain the spread, a quantitative comparison of the three highlights that early detection and isolation of cases are far more effective in infection prevention than travel restrictions and contact reduction. Further, commenting upon the timing of interventions, the authors report that early implementation of NPIs could have reduced the cases significantly. The authors cite that three weeks earlier implementation of NPIs vis-à-vis the actual implementation date could have reduced COVID-19 cases by 95% in China. Thus, the authors advocate the importance of proactively planning NPIs and earlier implementation to maximize the benefits and minimize the social and economic costs of NPIs.

Koh et al. (2020) empirically assess the impact of social distancing measures in containing the virus transmission for a sample of 142 countries. While the study employs several social distancing measures broadly divided into three categories (international travel restrictions, lockdown-type measures, and cancellation of mass gatherings), an average of the basic reproduction number for two weeks after the 100th reported case is used to capture the viral transmission. The findings suggest that stringent social distancing measures are beneficial in reducing the reproduction number. Further, the authors demonstrate that for countries with a stringency score of less than 50, the imposition of social distancing interventions cannot bring the reproduction number below one in two weeks after the 100th reported case. Further, commenting upon the three different categories of social distancing measures that vary in terms of intensity and implementation time, the authors note that lockdown measures and complete travel bans effectively contain the COVID-19 crisis. The authors further highlight the importance of early implementation of social distancing measures (computed using the observed global median timing of implementation of intervention across countries) in confining the spread of the virus.

Kucharski et al. (2020) identify that stringent travel restrictions are instrumental in containing COVID-19 transmission in China. Duc Huynh (2020) highlights that strong public health messaging, combined with lockdown measures, has effectively slowed down the spread of the COVID-19 virus in Vietnam. Sposato et al. (2020) reports that mandatory physical distancing measures, including wearing masks, maintaining silence while travelling in public transport, and avoiding handshakes, are critical in containing the infection. Using data from Italy, France, China, South Korea, Iran and the USA, Hsiang et al. (2020) analyse the impact of anti-contagion policies in containing the growth rate of infections. Applying reduced-form econometric methodology, the authors observe that policy interventions significantly reduce the infection growth rate. For a panel of 69 countries, Ullah and Ajala (2020) empirically investigate the association between lockdown measures and COVID-19 transmission. Employing the two-step system Generalized Method of Moments (GMM) estimator, the authors report that policy interventions effectively contain viral transmission. Further, the findings suggest that while it takes seven days for lockdown measures to reduce cases significantly, it takes around 21 days for testing to impact confirmed cases after implementation. Fang et al. (2020) analyse the quantitative impact of lockdown in Wuhan, China, on human mobility and containment of the virus. Employing the difference-in-differences approach, the authors observe that the lockdown significantly reduced human mobility inside, outside and within Wuhan. Findings suggest that the lockdown substantially reduced virus transmission outside of Wuhan, even though other cities delayed imposing social distancing policies. The authors further document that had the lockdown not been imposed in Wuhan, cases outside Hubei province would have been higher by 64.81%.

While several studies have highlighted the significance of NPIs in managing the spread of the virus, Barro (2020), in contrast, demonstrates the failure of NPIs in reducing overall deaths during the Spanish Influenza pandemic in 1918. The author attributes the findings to the view that the interventions were not maintained for a long time. Barro et al. (2020) state that with everything else held constant, the mortality rate of 2.1% during the 1918 Spanish Influenza pandemic is estimated to result in 150 million deaths worldwide during the recent COVID-19 pandemic, which in turn, eventually corresponds to a decline of 8% in private consumption and 6% in the gross domestic product (GDP). Carlsson-Szlezak et al. (2020) expect the economic recovery post the COVID-19 pandemic not to be straightforward, unlike the ‘V-shaped’ recoveries during the past pandemics, as the employment effects owing to the social distancing interventions are expected to be much larger. Gourinchas (2020) argues that half of the working population may suffer from transitory unemployment. Baldwin (2020) describes the role of COVID-19 in disrupting the income flows in the economy. Lu et al. (2020) report the negative influence of social distancing interventions on the psychological well-being of individuals through financial loss, exclusion by neighbours, boredom and lack of availability of essential supplies. Tubajdi et al. (2020) confirm that the diffusion of toll statistics on public death negatively impacts public mental health. Given the profound social and economic impact of NPIs, the present study attempts to empirically test the impact of NPIs on COVID-19 spread and associated mortalities and explain the reasons for the observed divergence across countries.

3. Methodology and data

We collect data on the daily number of infections for 20 select countries spanning the European Union, North America, South America, Asia-Pacific, and Africa. The countries, in alphabetical order, are Argentina, Australia, Brazil, China, Colombia, France, Germany, India, Italy, Japan, Mexico, New Zealand, Russia, South Africa, South Korea, Spain, Sweden, Turkey, United Kingdom, and The United States of America. Some of these countries have been the epicentre of the COVID-19 pandemic. The data is collected from the European Centre for Disease Prevention and Control, which reports data for daily cases and deaths of countries all over the world. For empirical analysis, data for each country is collected from the data when the first case was reported to November 30, 2020 (cut-off date).

The epidemiological measure of containment does not provide an exact representation of containment, especially when the number of cases is high (Moosa, 2020). The measure also distorts across demographics, as highly populated countries fulfilling the condition (R ≤ 1) may continue to depict a swift growth in the magnitude of cases. Further, the measure does not accurately enumerate the prevalence of the infection in a country, thereby underestimating the severity of the pandemic. To circumvent this problem, we propose a statistical measure of containment based on the number of daily reported cases. Following
In Harvey (1989), we propose a structural time-series (STS) model represented as:

\[ y_t = \mu_t + \epsilon_t \]  

(1)

where, \( y_t \) represents the number of daily cases, and \( \mu_t \) and \( \epsilon_t \) are latent variables, representing a trend component and a stochastic error component, respectively. The trend component can be written in the form of:

\[ \mu_t = \mu_{t-1} + z_{t-1} + v_{1t}; \quad v_{1t} \sim NID(0, \sigma^2_{v1}) \]  

(2)

where, \( z_t \) follows a first-order autoregressive process, represented as:

\[ z_t = z_{t-1} + v_{2t}; \quad v_{2t} \sim NID(0, \sigma^2_{v2}) \]  

(3)

The above model is based upon an assumption that \( v_{1t} \) and \( v_{2t} \) are normally distributed,\(^2\) and mutually and serially uncorrelated with one another. The unobserved trend component, \( \mu_t \) follows a random walk with drift factor, \( z_t \), which in itself follows a first-order autoregressive process. \( v_{2t} \) ensures that the slope of the equation remains a stochastic process.

Defining the STS model in terms of unobservable components plays a vital role in time series analysis. For model selection, plotting the observed variable across time may provide a preliminary understanding of the series. Fig. 1 depicts the seven-day moving average of daily cases for the countries. Most countries depict aggressive upward and downward movements of cases across time, indicating that the local level of the series. The LLTM is essentially an ARIMA (0,2,2) process. The stochastic nature of \( v_{1t} \) allows for the upward (downward) movement in the level of the trend and the stochastic nature of \( v_{2t} \) allows for the upward (downward) movement in the slope. The LLTM provides a superior method of modelling a dynamic phenomenon such as COVID-19 having exponential growth and decay. Further, Harvey (1989) justifies introducing a slope in the initial specification as incorrectly constraining the slope component to zero can have computational consequences. The LLTM can also be represented as a linear state-space model with observable and latent equations written in the form of:

**Observed equation:**
\[ y_t = \mu_t + \epsilon_t \]

**State equations:**
\[ \begin{pmatrix} \mu_t \\ z_t \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_{t-1} \\ z_{t-1} \end{pmatrix} + \begin{pmatrix} v_{1t} \\ v_{2t} \end{pmatrix} \]

(4)

The idea behind state-space representation is to capture the dynamics of estimates of an observable time-series through an unobservable, latent state vector of equations (Anderson and Moore, 1979; Brockwell and Davis, 1991). We specify the observable and latent equations in the covariance form, including error terms in each equation. The above equations are parameterized through the maximum likelihood (ML) procedure by employing the Newton-Raphson algorithm. For stationary models, we employ the Kalman filter to recursively obtain the conditional mean and variances of the observable and latent vectors. This process uses the initial values from the state vector to

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\[^3\] Non-linear structural time-series models, consisting of quadratic, cubic and higher-order polynomials, can also be specified as linear state-space models. For simplicity, we limit the discussion to a linear STS model. A discussion of stochastic versus non-linear trends can be found in Appendix D.

\[^4\] For stationary models which are normally distributed, the estimates of the Kalman filter remain consistent and efficient. However, if the normality assumption is relaxed, Hamilton (1994) highlights that the quasi-maximum likelihood (QML) estimator provides asymptotically consistent estimates, as long as the variance-covariance matrix is estimated using robust standard errors (White, 1980). We follow the same methodology for dealing with non-normality.
initialize the Kalman filter, on the assumption of stationarity. For nonstationary models, we employ a diffuse Kalman filter (De Jong, 1988; De Jong and Chu-Chun-Lin, 1994). The estimates of $\mu_t$ and $z_t$, representing the level and the slope of the state-space model, are analogous to the intercept and the slope term in a conventional regression model, respectively. For this analysis, COVID-19 is considered to be under control if the level and the slope of the STS model are statistically insignificant and continue to remain so for a sufficient period of time (Moosa, 2020).

Modelling variables in the form of a stochastic STS model has some attractive advantages. Traditionally, the unobserved components (trend, cycle, seasonality, or irregular) of any time series were modelled in a deterministic manner. However, the presence of high-frequency time series makes it challenging to assume that the series depicts a fixed pattern across time (Brockwell and Davis, 1991). Deterministic models also fixate assumptions on the time series, contaminating the underlying data generating process (Hamilton, 1994). In this context, STS models allow for introducing the unobservable components in a stochastic manner. Specifically, these models are built upon an assumption that the components of a time series are stochastic processes having random disturbances (Harvey, 1989). Further, modelling time series components as stochastic, iterative processes that update as more information becomes available is a superior method vis-à-vis a deterministic trend. This is achieved through the prediction and correction mechanism of the Kalman filter. Under a state-space representation, the filter operates a recursive least squares estimation of the state parameters and identifies a new state by adding to the previous estimation a proportional correction term to the prediction error, such that the latter is minimized (Jalles, 2009). The recursive estimation of the parameters using the Kalman filter provides a distinct advantage as the estimates are affected by the distant history of the series and are continuously updated with the incorporation of new observations. This is effective in modelling highly dynamic and unobservable phenomena, such as the spread of COVID-19.\footnote{One of the greatest advantages of the Kalman filter is its ability to model the past, present and future of the time series, even when the precise natural (underlying data generating process) is unknown. The filter characterizes dynamic modelling of a state-space representation. Dynamic linear models are models with linear transition from one period to the next, which in fact can describe the majority of models commonly used in time series applications (Jalles, 2009).}

The Kalman filter encompasses a set of mathematical equations that aims at the recursive prediction of the state vector at time $t$, based on the values of time $t - 1$, and updates these estimates with the additional information available at time $t$. A notable advantage of applying the Kalman filter is its ability to estimate the past, present, and future state of the state vector, even when the precise nature of the modelled system is unknown, a feature not possible in conventional forecasting applications such as ARIMA modelling. In the absence of a priori knowledge about the nature of the time series, ARIMA models are susceptible in the sense that it is easy to select a wrong model. This is often true of elaborate, overparameterized models that usually pass diagnostic tests but do not provide reliable forecasts. Further, ARIMA assumes that a series can achieve stationarity through differencing. In contrast, STS models estimated by the Kalman filter lay less emphasis on differencing transformations for achieving stationarity. In the presence of high-frequency time series, the estimates of the Kalman filter are continuously updated with new information, and hence are more reliable than those provided by ARIMA modelling.

The spread and subsequent containment of the COVID-19 pandemic is a continuously evolving process. The response towards the pandemic is often dependent upon the prevalence and severity of infections in a country. Considering the possible economic, social, and psychological costs of mandatory lockdowns, the need for such strict measures is continuously evaluated with respect to the magnitude of incremental cases. It is observed that easing lockdown measures are positively associated with the number of cases because of the negligence of the population in following necessary precautionary measures. This gives an indication of the possibility of the virus affecting an individual country in waves, as evident from many European countries like Italy, Spain, and the UK witnessing a second and a possible third wave of infections. The recurrence of waves of infections justifies re-imposing lockdowns and strict containment policies. Hence, a nation’s response to the pandemic is a dynamic phenomenon. It is difficult for countries to achieve the “best-possible” state and sustain it for an extended period of time. Considering the flow nature of the pandemic and our statistical measure of containment, we create seven possible outcomes based upon the significance and the sign of the level and the slope of the state-space model. The proposed statistical measure of containment not only indicates whether a particular country under consideration is successful in containing the spread of the virus but also tracks country-specific movements across the sampled timeframe (Table 1).

Modelling the daily number of cases in the form of a state-space vector of equations provides valuable information for explaining across-country differences in COVID-19 incidence. However, the measure in itself is limited as it does not identify the impact of specific policy measures in response to the pandemic. The success (or lack of success) of a country in controlling COVID-19 incidence depends on a host of factors. Some of these are related to the country’s demographics. For instance, the mortality rate resulting from COVID-19 is higher in countries with a greater proportion of the aging population (Deb et al., 2020). Others can be traced back to the government’s response towards the pandemic, including policy measures such as mandatory lockdowns, public information campaigns, closure of workplaces, and restrictions on domestic and international movements. A significant proportion of policy measures are also connected to enhancing public health systems’ efficacy, including investments in healthcare, isolation centres, contact tracing and testing measures, and vaccine development. Apart from these, economic policy incentives in income support and debt relief (at a micro level) and fiscal and monetary policy reforms (at the macro level) also gauge a country’s response towards the pandemic. To supplement the findings from the proposed measure of containment, we also determine the impact of various interventions undertaken by the government in containing the pandemic. For this purpose, we use the data provided by the Oxford COVID-19 Government Response Tracker.

### Table 1: Classification of degree of containment of the COVID-19 pandemic.

| $\mu_t$ | $z_t$ | Category | Description |
|----------|--------|----------|-------------|
| Significant | Significant and positive | 1 | Beyond control |
| Significant | Insignificant and positive | 2 | High level of infection, stabilizing slowly |
| Significant | Insignificant and negative | 3 | High level of infection, in the process of stabilizing quickly |
| Significant | Significant and negative | 4 | High level of infection, stabilizing quickly |
| Insignificant | Significant and positive | 5 | Low level of infection, rising quickly |
| Insignificant | Insignificant and positive | 6 | Under control, slow progress towards containment |
| Insignificant | Insignificant and negative | 7 | Under control, rapid progress towards containment |

Note: The table describes the success of countries in containing the COVID-19 pandemic, based on the statistical significance (insignificance) and the sign of the level and slope of the state-space model, with 1 representing the worst possible outcome and 7 representing the best possible outcome. Refer to Moosa (2020) for further details.
(OxCGRT), which collates information across 18 indicators concerning measures undertaken by governments in response to the pandemic for more than 180 countries. The tracker gauges the country’s response on three parameters: containment and closure policies, economic policies, and health system policies. Based on these responses, we make use of four indices viz. a stringency index, which measures the strictness of lockdown measures undertaken by the government; a containment and health index, which measures the efficacy of public health systems, including contact tracing, vaccination policies, and investment in healthcare; an economic support index, which quantifies the economic relief at a micro and macro level; and an overall government response index, which measures the variation in all the indicators over the course of the outbreak. All measures vary between 1 and 100. Apart from policy-oriented measures, we also use population density and age structure indicators to control for country demographics. Both indicators are extracted from The World Development Indicators database. Further, we control for economic growth by using the natural logarithm of per capita gross domestic product at constant prices. Lastly, we account for countries’ present health conditions by employing the health index mentioned in the 2019 Global Competitiveness Report published by the World Economic Forum. We create a panel dataset and estimate the following regression model:

\[ \ln y_{it} = \alpha_0 + \sum_{j=1}^{J} X_{jit} + \sum_{k=1}^{K} Z_{kit} + \epsilon_{it} \]  

where, \( y_{it} \) is the response variable representing the natural logarithm of daily cases and daily deaths in separate regression models. \( X_{jit} \) represents the index of the \( j \)th type, based on the OxCGRT dataset, \( Z_{kit} \) is a vector of control variables, \( l \) is the number of lags, and \( \epsilon_{it} \) is the stochastic disturbance term.

A classic econometric issue in estimating the above regression model is reverse causality, as many countries strengthen (or weaken) their policy measures in response to the degree of spread of the virus. For instance, India imposed a nationwide lockdown from March 23, 2020, to contain the spread of the virus. As the spread appeared under control after two months, it adopted a policy of staggered re-opening of public places and transport systems. In the meantime, the country responded to the pandemic by concentrating on policy measures that circumvent additional stress on the healthcare system. The presence of an endogenous response may create an upward bias in estimates (Deb et al., 2020). To circumvent this problem, we introduce lags in the estimation process. Specifically, we hypothesize that there is a sufficient lag as countries attempt to modify their policy measures to respond to the current spread of the virus. To this end, we provide for a seven-day and a fourteen-day lag response. Providing for lags reduces endogeneity in government interventions in response to the spread of the virus. We also include country dummies to address endogeneity concerns. Nevertheless, some endogeneity can also be traced to a misspecification bias. To this end, we control for population density, population age structure, economic growth, temperature, and the overall effectiveness of public health care systems of countries. However, some endogeneity may still be present in the regression model. In the absence of suitable instrumental variables, it is challenging to take care of endogeneity. Further, generalized moment estimators, such as those provided by Arellano and Bond (1991) and Blundell and Bond (1998), are only suitable for micro panel (large \( N \), small \( T \)) models. In addition, serial correlation and cross-sectional dependence create significant estimation issues for long panels, such as in this analysis. To this end, we employ a feasible generalized least squares (FGLS) estimator with an AR (1) autoregressive process. Further, we provide for a heteroscedastic error structure with a cross-sectional correlation to resolve cross-sectional dependence. The estimator is suitable for small \( N \), large \( T \) models and provides efficient estimates corrected for heteroscedasticity and autocorrelation.

\[ \text{Fig. 2. 7-day moving average of daily deaths till November 30, 2020 Note: The above figure illustrates 7-day moving averages of COVID-19 deaths. The horizontal axis measures the days relative to the onset of the outbreak. Countries are aligned in the order of when they report the first death.} \]

\[ \text{We also estimation the regression by employing a 21-day and a 28-day lagged response. However, the estimates of most of the policy measures were insignificant.} \]
4. Results and discussion

As a preliminary analysis, Fig. 1 and Fig. 2 illustrate seven-day moving averages of daily cases and daily deaths reported in 20 countries when the first case was reported until November 30, 2020. Fig. 3 illustrates the cumulative number of reported cases. Countries like Australia, China, Japan, New Zealand, and South Korea appear to have flattened the curve across the sampled timeframe. However, most European nations such as France, Germany, Italy, Spain, and the UK are witnessing the second wave of COVID-19 infections. Further, Brazil and Sweden, two countries initially apprehensive in imposing mandatory lockdowns, reported a surge in infections. Highly populated countries like India and the USA are witnessing an exponential rise in infections and deaths, albeit the curve has flattened marginally for the former. Latin American countries like Argentina and Colombia are also witnessing a late surge in COVID-19 infections, and a similar trend is also noticeable for countries such as Mexico, Russia, and Turkey. On similar lines, Table 2 provides detailed COVID-19 statistics of the sampled countries. When normalized for population, the USA, France, Argentina, and Colombia have shown the highest number of reported cases. However, the mortality rate from the infection has been the highest in Italy, UK, Mexico, and the USA. Unsurprisingly, since the number of infections is a positive function of the number of tests, UK, USA, France, and Russia lead in tests conducted per million. Hospital beds per million, a preliminary indicator of the adequateness of healthcare systems, are the highest in Japan, closely followed by South Korea, France, and Australia.

![Fig. 3. Cumulative cases till November 30, 2020.](image)

**Table 2**

COVID-19 statistics (as of November 30, 2020).

| Country       | First case (day) | Total cases | Total deaths | Cases per million | Deaths per million | Tests per million | Population (millions) | Hospital beds per thousand |
|---------------|-----------------|-------------|--------------|-------------------|---------------------|-------------------|-----------------------|--------------------------|
| Argentina     | 04/03/2020      | 1,413,375   | 38,332       | 31,519.162        | 856.938             | 75,876            | 45,195,777            | 5                        |
| Australia     | 25/01/2020      | 27,893      | 907          | 1094.593          | 35.608              | 392,011           | 25,499,881            | 3.84                     |
| Brazil        | 26/02/2020      | 6,290,272   | 172,561      | 29,807.563        | 814.455             | 100,423           | 212,559,409           | 2.2                      |
| China         | 31/12/2019      | 93,465      | 4750         | 64.546            | 3.295               | 101,469           | 1,459,522,774         | 4.34                     |
| Colombia      | 07/03/2020      | 1,299,613   | 36,401       | 25,879.154        | 722.561             | 99,478            | 50,882,884            | 1.71                     |
| France        | 25/01/2020      | 2,179,481   | 51,965       | 54,882.051        | 34,882.051          | 446,259           | 65,273,512            | 5.98                     |
| Germany       | 28/01/2020      | 1,053,869   | 16,248       | 34,769.893        | 25,197              | 348,513           | 83,849,945            | 8                       |
| India         | 30/01/2020      | 9,431,691   | 157,139      | 1,377,086         | 99,725              | 101,724           | 1,380,004             | 0.53                     |
| Italy         | 31/01/2020      | 1,585,178   | 54,904       | 26,488.68         | 919.192             | 362,958           | 60,461,828            | 3.18                     |
| Japan         | 15/01/2020      | 146,760     | 219          | 1,177,784         | 16,414              | 25,402            | 128,476,458           | 13.05                    |
| Mexico        | 14/01/2020      | 1,100,683   | 105,459      | 8636.619          | 821.669             | 20,056            | 128,932,753           | 1.38                     |
| New Zealand   | 28/02/2020      | 1700        | 25           | 426.981           | 5.184               | 264,509           | 4,822,233             | 2.61                     |
| Russia        | 01/02/2020      | 2,295,654   | 39,895       | 15,595.604        | 270,608             | 525,961           | 145,934,460           | 8.05                     |
| South Africa  | 06/03/2020      | 787,702     | 21,477       | 32,732,207        | 363.1               | 90,764            | 59,208,690            | 2.32                     |
| South Korea   | 20/01/2020      | 34,201      | 526          | 675.884           | 10.26               | 58,472            | 51,269,183            | 12.27                    |
| Spain         | 01/02/2020      | 1,163,268   | 46,300       | 35,251.73         | 963.944             | 409,869           | 46,754,783            | 2.97                     |
| Sweden        | 05/02/2020      | 254,834     | 7125         | 24,073.918        | 661.533             | 363,856           | 10,099,270            | 2.22                     |
| Turkey        | 12/03/2020      | 586,091     | 15,588       | 7574.746          | 162.985             | 84,339,067        | 281,002,647           | 2.81                     |
| UK            | 01/02/2020      | 1,617,331   | 58,245       | 24,085.83         | 862,402             | 603,802           | 67,886,004            | 2.54                     |
| USA           | 21/01/2020      | 13,082,877  | 263,946      | 41,085.762        | 810.16              | 331,002,647       | 2.77                   |


Table 3
Country-wise estimates of the state-space model using Kalman filter.

| Country       | $\mu$  | $\sigma$ | $\sigma_v$ | $\sigma_y$ | $N$   | $Q$   | ADF  | Category |
|---------------|--------|----------|------------|------------|-------|-------|-------|----------|
| Argentina     | 0.028*** | -0.434*** | 6.378      | 2.709      | 4.648 | 269   | 2.395 | -2.955   | 4        |
| Australia     | 0.936 (0.001) | 0.651 (0.001) | 2.596      | 3.483      | 6.334 | 311   | 2.213 | -5.167   | 6        |
| Brazil        | -1.108*** | 1.170***  | 0.001      | 6.289      | 4.451 | 279   | 19.079*** | -5.234   | 1        |
| China         | 0.887 (0.569) | -0.227 (1.235) | 4.674      | 1.151      | 5.074 | 336   | 1.171 | -9.297   | 7        |
| Colombia      | 1.496*** | 1.209***  | 1.209      | 6.890      | 3.029 | 265   | 2.459 | -2.307   | 1        |
| France        | 0.199*** | -0.863*** | 0.001      | 1.681      | 1.778 | 311   | 2.451 | -4.041   | 4        |
| Germany       | 0.065 (0.005) | 0.639 (0.554) | 2.221      | 9.368      | 1.458 | 308   | 2.891 | -2.064   | 6        |
| India         | -1.103*** | -1.442*** | 2.220      | 8.033      | 5.681 | 305   | 4.631 | -1.250   | 4        |
| Italy         | -0.112*** | -1.012*** | 7.228      | 1.378      | 1.907 | 305   | 2.977 | -1.024   | 3        |
| Japan         | 0.945 (0.038) | 2.772 (1.617) | 5.913      | 3.112      | 1.368 | 321   | 1.962 | -5.757   | 6        |
| Mexico        | 1.751 (1.483) | 2.891***  | 4.025      | 0.176      | 1.697 | 322   | 1.743 | -6.997   | 5        |
| New Zealand   | 0.090 (1.158) | 1.283 (16.449) | 32.473     | 8.021      | 94.073 | 268 | 1.717 | -5.490   | 6        |
| Russia        | 0.070*** | 1.008     | 1.428      | 5.057      | 3.285 | 304   | 2.738 | -1.890   | 2        |
| South Africa  | -0.072*** | -0.143*** | 2.876      | 1.168      | 6.018 | 268   | 2.510 | -2.294   | 4        |
| South Korea   | 0.864 (0.886) | -1.319 (6.710) | 1.367      | 2.333      | 6.019 | 316   | 2.558 | -3.810   | 7        |
| Spain         | 0.936 (0.748) | 3.125***  | 5.157      | 7.998      | 3.512 | 304   | 3.235* | -12.095  | 5        |
| Sweden        | 0.740**  | 0.636     | 2.226      | 3.936      | 1.008 | 300   | 3.530** | -3.130   | 2        |
| Turkey        | 0.944*** | 0.529     | 4.316      | 4.125      | 3.067 | 262   | 2.424 | 0.217    | 2        |
| UK            | -0.098*** | 1.191     | 6.162      | 1.508      | 4.877 | 304   | 3.909* | -1.885   | 2        |
| USA           | 0.975*** | 0.326     | 6.337      | 0.005      | 2.891 | 315   | 2.881 | -2.032   | 3        |

Note: *** , ** , and * indicate significance at 1, 5, and 10 per cent, respectively. Robust standard errors in parentheses. For non-converging models, the estimation was limited to 1000 iterations.

The situation is worrisome for India, Mexico, and Colombia, which have the availability of 0.53, 1.38, and 1.71 beds, respectively, for every thousand individuals.

Table 3 contains the maximum likelihood estimates of the unobservable, time-series components, $\mu$, and $\sigma_v$, representing the level and the slope of the series, respective. Kalman filter (or a diffuse Kalman filter, in the case of nonstationary series) is employed to recursively obtain the conditional mean and variances of the state vector. Further, Q represents the Box-Pierce test statistic for checking the presence of autocorrelation in the residuals of the fitted model, and ADF represents the augmented Dickey-Fuller unit-root test for examining whether the series has been generated from a stationary process. Consistent with the specified state-space model, the statistic has been calculated assuming a null hypothesis that the series follows a random walk with nonzero drift.

As per the definition of containment given by Moosa (2020), the infection is assumed to be under control if both the parameters of the state-space model are insignificant and are kept so for a sufficient period of time. Based on the estimates, we conclude that China and South Korea have been most influential in containing the spread of infections in the sampled timeframe, with the level and the slope of time-series being insignificant. Further, the estimates of Australia, Japan, and New Zealand depict that the infection is under control, and these countries are slowly moving towards the path of zero infections. The situation is worrisome for European nations of Sweden, the UK, Italy, France, and Spain, with most of these countries persistently depict a high level of infection. These countries were the epicentre of the virus in mid-April, and all of these imposed some form of mandatory containment and lockdown measures, barring Sweden, which continued practicing voluntary social distancing measures. As infections appeared to be under control, policy measures were relaxed, and containment was limited to severely affected areas. However, the EU countries are witnessing a second (and a possible third wave) of infections, indicating that restrictions might have been relaxed at an inappropriate juncture. A unique example of an EU country that has been able to handle the spread...
of the virus in later waves is Germany, which is still depicting slow stabilization of COVID-19 infections. The situation is worrisome for Latin-American countries of Brazil, Colombia, and Argentina as well as nations such as Russia, Turkey, India, South Africa, and the USA, which are continuously reporting a high level of infection, without any sign of stabilization in the near horizon. Brazil, in particular, has been adamant in imposing lockdown restrictions and has witnessed anti-lockdown protests from large sections of the population, which may have resulted in an outbreak. Similar protests have also been witnessed in the USA, which has been most severely affected country. The position is also alarming for highly populated countries like the USA, Russia, and Turkey, as the trend continues to increase without any evidence of stabilization. India, however, presents a unique case. The country is reporting a high level of infections, chiefly because of a vast population and high population density. However, the country presently lies in the 4th category, implying that the infection spread is stabilizing at a quicker pace. The result may be due to the policy actions undertaken by the Indian government in response to the pandemic, specifically increasing the testing capacity and rapid contact tracing and testing measures.

Concerning the cyclical nature of the spread of infections and the resultant response of the government in controlling it, it is essential to analyse how individual countries have attempted to control the spread of the virus over the sampled timeframe. To this end, we estimate the STS model on a three-month (90-day) rolling window to smoothly track changes in the level and slope components for each country. The first window ($R_1$) begins from the day when a country reports its first case, signalling the onset of the outbreak. Subsequently, fixed intervals (except the last one for each country) of 90 days are constructed using 30-day increments. This serves three purposes. First, the above construction accounts for the staggered timing of outbreak onset among countries. Hamman (2021) shows that conceptualizing time relative to the outbreak onset provides a better way for measuring the spread of COVID-19 vis-à-vis calendar time. Second, analysing country-specific movements in COVID-19 incidence across fixed windows of data provides smoother estimates of containment. Third, from an econometric perspective, estimating an STS model using rolling windows tests for stability in time-varying parameters (Inoue et al., 2017). Fig. 5 depicts these results. Countries like Australia, Japan, China, New Zealand, and South Korea represent rapid movements towards zero infections, as indicated by an improvement of ranks across samples. Specifically, the Korean government has focused on stringent, regional implementation of social distancing measures accompanied with a rapid “test, trace, isolate” strategy, which has ensured rapid progress towards containment. Within two weeks of reporting the first case, the government established a large-scale contact testing and tracing programme with the help of private healthcare institutions. Instead of imposing a nationwide lockdown, the policy of localized containment was adopted, and people were encouraged to stay at their homes in these containment zones. Tracing individuals who could have come in contact with COVID-19 patients was achieved by employing intrusive surveillance systems. Further, businesses were advised to ensure proper distancing among employees and customers, adequate ventilation and maintaining proper records of visitors (Moosa, 2020).

On the other hand, the EU nations of Italy, France, Spain, and the UK represent mixed results, with improvements in the country’s rank followed by deteriorations. This corroborates with the time when most of the EU nations witnessed the second wave of infections. Relaxations in social distancing measures overlapping with the summer season can be one of the reasons for the second wave. In hindsight, the staggered reopening guidelines established by the European Commission were implemented hastily, as governments tried to boost economic and social life by reinvigorating the tourism industry. Even though international travel was restricted, internal borders (in line with the EU’s objective of making Europe a free-movement zone) were opened, leading to spillovers of infections to unaffected countries. Unsurprisingly, Spain and UK depict an exponential increase in the speed of infections after marginal improvements. The case of Sweden is particularly interesting as the nation was hesitant in imposing strict lockdown measures. The Swedish government’s strategy of managing the pandemic through non-coercive...

\[ \text{For a tabular presentation of estimates and rankings across 90-day rolling windows, refer Appendix G.} \]
measures has been widely criticized across the world. Further, Germany and Russia have made continuous improvements towards reducing the spread, albeit suffering from a high number of infections across the sampled timeframe. India, on the other hand, portrays improvement in controlling the speed of transmission of infections, albeit showcasing a higher number of infections. Latin-American countries depict mixed results, with nations such as Brazil and Colombia showcasing deteriorating performance across the windows, while countries like Argentina depicting improvements in controlling the transmission of cases. Finally, the spread and transmission of the virus were beyond control in the USA

![Graph showing country-wise estimates of the state-space model across 90-day rolling windows.](image)

*Fig. 5. Country-wise estimates of the state-space model across 90-day rolling windows. Note: The above figure depicts 95% confidence intervals of the level and slope estimates of the state-space model across 90-day rolling windows (R₁ to R₉) to track country-specific movements over the course of the pandemic. Equally spaced windows (except the last one for each country) are constructed using 30-day increments. For non-converging models, the estimation was limited to 1000 iterations. For some countries, the disturbances are non-Gaussian, which can also be insinuated from the fact that the point estimates of \( z_t \) do not lie in the middle of their confidence intervals. Nevertheless, the QML estimation through the Kalman filter with robust standard errors still yields the MMLSE of the state vector, which is asymptotically consistent. For more details, see Appendix A.*
from the advent of the outbreak. Nevertheless, the speed of infections has been stabilizing, albeit depicting a continuous rise in the number of infections. Although testing for significance relative to a null of 0 may provide evidence for containment when observing a country in isolation, any interpretations of a country’s containment relative to others must also account for the precision of each estimate. Fig. 4 depicts 95% confidence intervals of the state vector’s components over the sampled timeframe, while Fig. 5 depicts the same across 90-day rolling windows. When comparing the slope terms across countries, we observe that the estimates of Australia, New Zealand, South Korea, and the USA depict wider confidence intervals. Further, the slope estimates of Australia, South Korea, and the USA portray wider intervals across windows. In addition, the local level estimates of Mexico, New Zealand, South Korea, and Spain are less precise vis-à-vis those of Brazil, France, India, Italy, and the UK.

The spread of COVID-19 infections is a function of a country’s
response to the pandemic. Even though the findings of the state-space model provide evidence regarding the success (or lack of success) of containment, the measure is limited in identifying which specific containment measures have been advantageous in controlling the spread of the COVID-19 pandemic across nations. To this end, we employ a matrix of four indices viz. a stringency index (SI), government response index (GRI), containment and health index (CHI), and economic support index (ESI), provided by the OxCGRT database in order to gauge the relationship between government’s policy response and the spread of COVID-19 infections and associated deaths. Table 4 reports the FGLS results with the natural logarithm of daily cases as the dependent variable, while Table 5 employs the natural logarithm of daily reported deaths as the dependent variable. The stringency index reports negative and statistically significant coefficients with daily cases and deaths at a seven-day lag period, implying that countries that impose stringent lockdown measures such as the closure of schools and workplaces, restrictions on social gatherings and public events, and control over internal and external movements have been able to reduce the spread of infections. Further, countries that have provided adequate economic support in the form of debt relief and income augmentations have better addressed the spread of the virus. This is an expected result as individuals, specifically from the lowest economic stratum of the population, are compelled to leave their homes in search of economic opportunities in the absence of these policies. Further, response-oriented policies, such as contact tracing and testing measures, public information campaigns, and emergency investments in healthcare facilities reductions in the daily number of reported cases and deaths. Further, the spread of infections is higher in countries with higher population density or where a more significant proportion of people are above 65 years of age, highlighting that practicing social distancing measures is difficult in densely populated countries, as depicted by the countries such as India, Brazil, and Mexico. The mortality rate is higher for countries where a more significant proportion of people are above 65 years of age. The findings are in line with the expected result as the virus tends to affect the older population severely.

Lastly, there exists a negative association between temperature and the spread of infection. Apart from the epidemiological nature of the infection, a primary reason behind this observation may lie in the fact that higher temperatures cause activities to be undertaken outdoors in well-ventilated conditions.

In line with the above discussion, we study cross-country variations by focusing on the moderating effect of demographic, economic, and health dimensions on the association between pandemic-induced measures and the spread of COVID-19 infections. The following discussion highlights the effect of country-specific differences, which, to a greater extent, dictate the selection and the influence of specific policies adopted by nations. Panels (B), (C), and (D) of Tables 4 and 5 report such results with a seven-day and fourteen-day lag period. Concerning demographic dimensions, we hypothesize that countries with high population density result in individuals increasing the frequency of social interactions, and hence, the effect of government-imposed lockdowns might be less effective in containing the spread of the virus. Higher population density also affects compliance to government-imposed lockdowns, making NPIs ineffective. An opposite sign on the interaction term indicates that the benefits accruing to a country by imposing stringent lockdown measures get weakened for densely populated nations. In other words, social distancing measures are more beneficial in reducing the spread of the virus for countries with lower population density. While social distancing is a more behaviour-oriented process than a policy-oriented one, ipso facto, countries with higher population density such as India, Brazil, and Mexico must devote substantial resources to ensure strict compliance to social distancing measures for reducing transmission rates. On similar lines, the positive effects of social distancing in containing COVID-19 infections and mortalities become more pronounced for countries where a lesser proportion of people are more than 65 years of age. The findings are in line with Castex et al. (2020). Further, the presence of an older population weakens the positive impact of containment and health policies undertaken by the government in controlling the pandemic. This is an expected result as the virus tends to affect the older population severely. Countries like Japan and South Korea, where the population pyramid leans towards the older population, must implement stringent policy...
measures to handle the mortalities from the pandemic. Concerning health dimensions, the importance of stringent social distancing restrictions becomes paramount for countries that inherently have a lower standard of public healthcare systems. On the other hand, robust public healthcare systems complement emergency health policy measures and enhance the nation’s ability to reduce cases and mortalities.

5. Robustness checks

The statistical measure of containment, as proposed in this paper, attempts to model the pandemic through the daily number of reported cases. However, case data are a function of testing and reporting quality, both of which were very poor early on and continued to be deficient in many countries throughout the study period. For instance, the UK conducted as many as 6,03,802 tests per million over the sample period compared to Mexico, which conducted a little over 20,000 tests per million. Disparities in testing figures may distort the time-varying parameters of the STS model. Hamman (2021) advocates that mortalities may provide a more accurate description of the severity of infection. Likewise, by considering deficiencies in testing numbers, case incidence more uniformly than daily figures. To provide robustness to endogenous response, we provide for seven-day and fourteen-day lags in policy measures. Popdens errors in parentheses.

Table 4

| Cases | A | B | C | D |
|-------|---|---|---|---|
|       | K = 7 lags | K = 14 lags | K = 7 lags | K = 14 lags |
|       | (1) | (2) | (3) | (4) |
|       | (5) | (6) | (7) | (8) |

| Stringency index\(_k\) | -0.039*** | -0.032*** | -0.068*** | -0.050*** |
|-------------------------|-----------|-----------|-----------|-----------|
| (0.004) | (0.004) | (0.013) | (0.013) |
| Government response index\(_k\) | 2.312 | 0.555 | 6.992 | -8.687 |
| (2.731) | (2.671) | (8.739) | (8.648) |
| Containment and health index\(_k\) | -1.952 | -0.410 | -6.013** | 7.077 |
| (2.390) | (2.337) | (2.645) | (7.565) |
| Economic support index\(_k\) | -0.282*** | -0.064 | -0.856 | -1.104 |
| (0.101) | (0.334) | (1.092) | (1.081) |

Note: The above table contains results of cross-sectional time-series feasible generalized least squares (FGLS) regressions, focusing on the impact of government policy measures on the number of COVID-19 infections. Dependent variable is the natural logarithm of daily reported cases. To address reverse causality and resulting endogeneity problem, we provide for seven-day and fourteen-day lags in policy measures. Popdens = population density; Above65 = proportion of population above 65 years of age; GDPPC = natural logarithm of GDP per capita at constant prices. Health index = health score provided by the Global Competitiveness Report, 2019. Temperature = Mean daily temperature in Fahrenheit. ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively. Heteroskedasticity corrected standard errors in parentheses.
country-wise classifications for daily cases and its seven-day moving average are symmetrical for all the countries. Similar results accrue for daily deaths and its seven-day moving average, except for Brazil, France, and Germany. When comparing the classifications for daily cases over daily deaths, we observe deteriorations in classifications for the latter in countries like Argentina, Italy, Mexico, Russia, and Sweden, implying that the virus has resulted in higher mortalities for these countries.

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In line with the direction of the paper in identifying the impact of social distancing measures, we also examine the impact of specific containme policies on COVID-19 incidence, deaths, and case positivity rate. Specifically, we analyse the influence of four containment measures: (1) Closure of schools and universities, (2) Closure of workplaces, (3) Restrictions on gatherings, and (4) Cancellation of public events, and stay at home requirements were also adopted by some countries. However, since most of the countries introduced an array of measures at a particular point in time, we limit ourselves to these four measures for circumventing multicollinearity problems.

10 Other policy measures such as restrictions on gatherings, cancellation of public events, and stay at home requirements were also adopted by some countries. However, since most of the countries introduced an array of measures at a particular point in time, we limit ourselves to these four measures for circumventing multicollinearity problems.
Table 6
Country-wise estimates of the state-space model under various observed variable specifications.

| Country   | Deaths | Positiveity | Cases: 7-day moving average | Deaths: 7-day moving average |
|-----------|--------|-------------|-----------------------------|-----------------------------|
|           | $\mu_1$ | $\mu_2$ | $\mu_3$ | $\mu_4$ | $\mu_5$ | $\mu_6$ | $\mu_7$ | $\mu_8$ | $\mu_9$ | $\mu_{10}$ |
| Argentina | 0.128 | 0.049 | 0.026 | 0.031 | 0.032 | 0.033 | 0.034 | 0.035 | 0.036 | 0.037 |
| Australia | 0.393 | 0.039 | 0.040 | 0.041 | 0.042 | 0.043 | 0.044 | 0.045 | 0.046 | 0.047 |
| Brazil    | 0.502 | 0.114 | 0.115 | 0.116 | 0.117 | 0.118 | 0.119 | 0.120 | 0.121 | 0.122 |
| China     | 0.706 | 0.087 | 0.088 | 0.089 | 0.090 | 0.091 | 0.092 | 0.093 | 0.094 | 0.095 |
| Colombia  | 0.091 | 0.040 | 0.041 | 0.042 | 0.043 | 0.044 | 0.045 | 0.046 | 0.047 | 0.048 |
| France    | 0.233 | 0.051 | 0.052 | 0.053 | 0.054 | 0.055 | 0.056 | 0.057 | 0.058 | 0.059 |
| Germany   | 0.119 | 0.070 | 0.071 | 0.072 | 0.073 | 0.074 | 0.075 | 0.076 | 0.077 | 0.078 |
| India     | 0.023 | 0.015 | 0.016 | 0.017 | 0.018 | 0.019 | 0.020 | 0.021 | 0.022 | 0.023 |
| Italy     | 0.284 | 0.075 | 0.076 | 0.077 | 0.078 | 0.079 | 0.080 | 0.081 | 0.082 | 0.083 |
| Japan     | 0.239 | 0.058 | 0.059 | 0.060 | 0.061 | 0.062 | 0.063 | 0.064 | 0.065 | 0.066 |
| Mexico    | 0.040 | 0.045 | 0.046 | 0.047 | 0.048 | 0.049 | 0.050 | 0.051 | 0.052 | 0.053 |
| New Zealand | 0.158 | 0.125 | 0.126 | 0.127 | 0.128 | 0.129 | 0.130 | 0.131 | 0.132 | 0.133 |
| Russia    | 0.002 | 0.042 | 0.043 | 0.044 | 0.045 | 0.046 | 0.047 | 0.048 | 0.049 | 0.050 |
| South Africa | 0.006 | 0.077 | 0.078 | 0.079 | 0.080 | 0.081 | 0.082 | 0.083 | 0.084 | 0.085 |
| South Korea | 0.007 | 0.070 | 0.071 | 0.072 | 0.073 | 0.074 | 0.075 | 0.076 | 0.077 | 0.078 |
| Spain     | 0.186 | 0.067 | 0.068 | 0.069 | 0.070 | 0.071 | 0.072 | 0.073 | 0.074 | 0.075 |
| Sweden    | 0.596 | 0.692 | 0.187 | 0.269 | 0.629 | 0.729 | 0.639 | 0.711 | 0.151 | 0.266 |
| Turkey    | 0.171 | 0.012 | 0.189 | 0.190 | 0.192 | 0.193 | 0.194 | 0.195 | 0.196 | 0.197 |
| UK        | 0.229 | 0.026 | 0.027 | 0.028 | 0.029 | 0.030 | 0.031 | 0.032 | 0.033 | 0.034 |
| USA       | 1.295 | 0.294 | 0.002 | 0.045 | 1.059 | 0.602 | 1.636 | 0.227 | 0.459 | 0.190 |

Note: The above table describes the level and slope estimates of the state-space model under different observed variable specifications. For non-converging models, the estimation was limited to 1000 iterations. ***, **, and * indicate significance at 1%, 5%, and 10% per cent, respectively. Robust standard errors in parentheses.

(3) restrictions on internal movement and (4) Restrictions on public transport. Table 8 reports these results. We observe that a few estimates are significant, albeit small in terms of magnitude. Hence, the results must be interpreted with caution. It is quite challenging to draw any substantial conclusion concerning any specific containment policy. Nonetheless, a general interpretation from the findings reported in Table 8 is that containment policies are advantageous in reducing COVID-19 incidence, mortalities and case positivity rate.

6. Conclusion

The COVID-19 pandemic has raised serious epidemiological, health, economic, and social consequences for nations all over the world. The government’s response towards the pandemic has been variable across countries, which, to a large extent, explains observed divergence across countries in terms of containing the spread of infections and associated mortalities. However, most countries have adopted some form of social distancing measures to contain the spread of the virus. The World Health Organization recommends implementing social distancing practices as a non-pharmaceutical intervention to flatten the curve of the virus. While some studies have highlighted the importance of social distancing measures, the literature on COVID-19 lacks in terms of studies that empirically validate these findings.

In this paper, we put forward an argument that the epidemiological measure of containment, based on the reproduction rate of the virus, may provide a myopic view of the situation as what matters is not only that the rate of reproduction of the strain is less than one but also the incremental increase in the number of reported cases is under control. Focusing on this limitation, we propose a new, statistical measure of containment by modelling the daily number of reported cases as a structural time-series state-space model with two latent vectors. A Kalman filter methodology is employed to recursively obtain the conditional mean and variance of the time-series. Based on the work of Moosa (2020), we establish seven categories of containment, ranging from a situation beyond control to a situation where the magnitude and the spread of infection are under control. Containment is defined as a situation wherein the level and the slope of the state-space model are kept insignificant for a sufficient period of time. We contend that countries like Australia, China, New Zealand, Japan, and South Korea have been able to contain the spread of the virus. Further, European nations of France, Italy, Germany, Spain, and the UK are witnessing a second wave of the virus, indicating that re-opening the European economy might have resulted in an exponential spread. The situation seems worse for countries like the USA, Colombia, Brazil, Mexico, Turkey, India, and Sweden, all of which are reporting a higher number of cases and an increase in the speed of infections. Brazil and Sweden, two countries that were primarily averse to implementing social distancing policies, have reported a higher number of infections in the sampled timeframe.
Table 7
Impact of pandemic-induced government’s policy response under various dependant variable specifications.

| Variables                      | Case positivity rate | Cases: 7-day moving average | Deaths: 7-day moving average |
|--------------------------------|---------------------|-------------------------------|-----------------------------|
|                                | K = 7 lags (1)      | K = 14 lags (2)               | K = 7 lags (3)              | K = 14 lags (4)              | K = 7 lags (5) | K = 14 lags (6) |
| Stringency index<sub>k</sub>   | 0.005               | 0.000                         | -0.047***                   | -0.049***                   | -0.016**       | -0.024***       |
|                                | (0.004)             | (0.001)                       | (0.004)                     | (0.004)                     | (0.007)        | (0.008)         |
| Government response index<sub>k</sub> | -2.697***          | 0.003                         | 8.088                       | 5.827                       | -3.717         | -1.37***        |
|                                | (0.407)             | (0.064)                       | (6.164)                     | (6.092)                     | (5.391)        | (5.217)         |
| Containment and health index<sub>k</sub> | -2.354***          | -0.003**                      | -6.942                      | -4.976***                   | 3.290          | 8.021           |
|                                | (0.356)             | (0.001)                       | (1.063)                     | (1.056)                     | (4.715)        | (7.616)         |
| Economic support index<sub>k</sub> | -0.333              | 0.000                         | -0.995                      | -0.716                      | -0.481***      | 1.153           |
|                                | (0.558)             | (0.008)                       | (0.761)                     | (0.226)                     | (0.949)        |                 |
| GDPPC                          | -0.098***           | -0.070***                     | -2.190***                   | -1.051                      | -1.216**       | -1.264**        |
|                                | (0.005)             | (0.019)                       | (0.869)                     | (0.599)                     | (0.665)        |                 |
| Popdenst                       | 0.008***            | 0.006                         | 0.037                       | 0.290***                    | 0.521          | 0.532           |
|                                | (0.001)             | (0.002)                       | (0.050)                     | (0.348)                     | (0.365)        |                 |
| Above55                        | -0.003              | -0.006                        | 0.196**                     | 0.104                       | -0.077         | -0.088          |
|                                | (0.004)             | (0.003)                       | (0.098)                     | (0.105)                     | (0.103)        | (0.109)         |
| Health index                   | -0.003**            | 0.003                         | -0.047***                   | -0.031***                   | -0.082*        | -0.083*         |
|                                | (0.001)             | (0.007)                       | (0.015)                     | (0.002)                     | (0.050)        | (0.049)         |
| Temperature                    | 0.001               | 0.000                         | -0.025                      | 0.059                       | -0.053         | -0.056          |
|                                | (0.001)             | (0.000)                       | (0.042)                     | (0.046)                     | (0.092)        | (0.097)         |
| Constant                       | 0.953***            | 0.659***                      | 25.668***                   | 17.436***                   | -3.949         | -3.463          |
|                                | (0.050)             | (0.171)                       | (6.700)                     | (8.123)                     | (6.065)        | (6.645)         |

Note: The above table describes the results of FGLS regressions under various observable variable specifications. To address reverse causality and ending endogenous response, we provide for seven-day and fourteen-day lags in policy measures. *** and ** indicate significance at 1, 5, and 10 per cent, respectively. Heteroscedasticity corrected standard errors in parentheses.

Table 8
Impact of specific containment policies on COVID-19 pandemic.

| Variables                      | Cases                          | Deaths                          | Case positivity rate |
|--------------------------------|--------------------------------|--------------------------------|----------------------|
|                                | K = 7 lags (1)                | K = 14 lags (2)                 | K = 7 lags (1)       | K = 14 lags (2)       |
| Closure of schools and universities<sub>k</sub> | -0.036 (0.025)                | -0.005 (0.025)                 | -0.053* (0.030)     | -0.022 (0.042)       |
| Closure of workplaces<sub>k</sub> | -0.008 (0.031)                | 0.041 (0.029)                  | -0.067* (0.035)     | 0.021 (0.050)       |
| Restrictions on internal movement<sub>k</sub> | -0.032 (0.034)                | -0.056* (0.033)                | -0.031 (0.036)      | -0.186*** (0.052)   |
| Public transport<sub>k</sub>   | -0.010 (0.046)                | -0.144*** (0.044)              | -0.035 (0.045)      | 0.020 (0.088)       |
| Stringency Index<sub>k</sub>   | -0.025*** (0.005)             | -0.022*** (0.005)              | -0.005 (0.005)      | 0.011 (0.005)       |
| Government response index<sub>k</sub> | -0.083*** (0.007)             | -0.072*** (0.006)              | 0.059*** (0.007)    | -0.045*** (0.010)   |
| Economic support index<sub>k</sub> | -0.007*** (0.007)             | -0.007*** (0.001)              | -0.005** (0.001)    | -0.005** (0.001)    |
| GDPPC                          | -0.713 (1.083)                | -0.641 (1.078)                 | -0.181 (1.412)      | -2.171 (2.742)      |
| Popdenst                       | 2.201** (0.986)               | 1.954** (0.950)                | 1.705* (1.027)      | 0.954 (0.909)       |
| Above55                        | 0.198** (0.091)               | 0.177* (0.090)                 | 0.206* (0.114)      | 0.426 (0.403)       |
| Health index                   | -0.904*** (0.301)             | -0.827*** (0.291)              | -0.775** (0.335)    | 0.307 (0.346)       |
| Temperature                    | -0.001 (0.003)                | -0.001 (0.001)                 | -0.009*** (0.001)   | -0.023*** (0.002)   |
| Constant                       | 79.205** (30.746)             | 73.715** (30.190)              | 61.566 (37.439)     | 0.000 (0.001)       |

Note: The above table describes the impact of specific containment policies on COVID-19 cases, deaths, and case positivity rate. The first four variables are the subcomponents of the containment and health index (CHI), as per the OxCGRT definitions. To address reverse causality and ending endogenous response, we provide for seven-day and fourteen-day lags in policy measures. *** and ** indicate significance at 1, 5, and 10 per cent, respectively. Heteroscedasticity corrected standard errors in parentheses.

Nevertheless, the spread of the virus depends on a host of factors, of which the government’s policy response is of primary importance. To this end, we determine the influence of pandemic-induced policies, such as the degree of stringency in mandatory lockdowns, containment policies, health policies, and economic policies on infections’ spread and mortality rate. The results are consistent with our previous findings that countries that adopt strict lockdown policies have been more successful in containing the spread of the virus. On similar lines, providing economic support in the form of income augmentations and debt relief, and rapid investments in contact tracing, testing and emergency health measures improve the response towards the pandemic. However, the significance of government policies is ultimately contingent upon a matrix of demographic, economic and environmental dimensions. We conclude that the benefits derived from adopting stringent lockdown practices are enhanced for rich countries having better overall healthcare systems. On the other hand, these benefits diminish in the presence...
of high population density or where a significant number of individuals are above 65 years of age. An array of checks under various specifications lends robustness to our findings.

The study has some limitations. First, the statistical measure of containment is based upon the reported case data. Many countries had inadequate testing procedures at the onset of the pandemic, resulting in the early under-reporting of cases. Further, discrepancies in testing policies (such as lower testing on weekends and holidays) and reporting policies (such as whether tests are assigned to the date when they are conducted or when the report is available) across countries tend to contaminate the statistical significance of coefficients. In addition, there have been suspicions of massive under-reporting of COVID-19 cases and deaths in some countries. Another econometric issue may also occur as countries with more noise in the time-series will be less likely to be classified in categories where parameters are statistically significant.

The study attempts to circumvent these issues by employing an array of observable variables in the form of daily deaths, moving average of cases and moving average of deaths under different specifications. Nevertheless, all estimates are contingent upon the accuracy of the reported data. The study also employs the case positivity rate as another outcome measure that better reflects the prevalence of infection relative to the reported case data by addressing divergence in testing figures across nations. However, the case positivity rate may not provide a true incidence of infection unless there is random sample population testing. This was rare across countries. Further, it is recognized that as testing strategies not only vary across countries but also over the course of the pandemic, the case positivity rate does not reflect the actual prevalence of infection. Second, as with any epidemiological study on COVID-19, the present study attempts to model the pandemic, a highly dynamic phenomenon. For instance, at the onset of the outbreak, many policymakers did not have an accurate understanding of the speed and severity of the virus. In the absence of a vaccine, social distancing measures were considered a preliminary action by many countries to counter the spread of infection. As the virus propagated to other countries with a lag, advances in epidemiological research may have allowed those countries to behave more rationally in implementing social distancing measures (for example, it has been widely acknowledged that the creation of localized containment zones where infection have spiralled are more optimal from an economic perspective rather than imposing nationwide lockdowns). Further, the mere presence of a pharmacological intervention may lessen the need for a country to rely on NPIs, which are only optimal in a finite game framework. In an ideal scenario, the results would have been more robust when the pandemic had ended, as we would have had more information on its antecedents.

Although the findings suggest that social distancing is a beneficial mitigation strategy to control the propagation of the COVID-19 virus and the related mortalities, it bears economic, social and psychological consequences – an appalling situation that can be dealt with the recent pharmacological intervention. Therefore, it is also essential to discuss the findings in a post-vaccine setting. With the recent development of vaccines, it is acknowledged that while the spread of cases continues, severe illness and death are heavily (to nearly exclusively) concentrated among the unvaccinated. In settings where vaccines are abundant unless the objective is to eliminate all cases, including mild asymptomatic cases, countries have the leverage to relax social distancing measures. However, there are specific issues identified with the administration of vaccines that cannot be neglected. First, the success of novel vaccines is immensely contingent upon population uptake and the precise vaccine properties. Second, there is an unequal distribution of vaccines across countries, which is both epidemiologically and economically self-defeating. As of July 28, 2021, of the doses administered, 84% of doses have gone to individuals in high and upper-middle-income nations. In contrast, this figure is at a sharply low at 0.3% for low-income countries. A big part of the problem is that far more vaccines doses have been pre-ordered by the wealthier nations than they need to vaccinate their populations. Even though the COVAX initiative by the WHO is in place, it itself suffers from several bottlenecks. Vaccine equity is thus one of the biggest challenges post the rollout of the vaccine administration programme. Hence, the benefits of social distancing interventions in containing the virus spread and the related deaths cannot be ignored. Moreover, given that it takes considerable time for vaccine development post the virus outbreak, the present study’s findings serve as a stepping-stone for future pandemics that can be even more deadly viz-a-viz the current COVID-19 outbreak.

The paper provides significant policy implications. On the one hand, we answer cross-country differences in managing the pandemic across 20 countries, specifically focusing on the role of social distancing measures in controlling the spread of the virus and associated mortalities. As highlighted by Brazil, Sweden and the USA’s examples, we recommend countries adopt extensive social distancing measures as a non-pharmaceutical intervention to reduce the infection’s spread and the associated mortalities. On the other hand, we provide evidence that the impact of social distancing measures is dependent upon a host of demographic, environmental, and economic dimensions. Hence, the matrix of government policies adopted as a pandemic-induced response must be correlated with these dimensions to determine an effective strategy that not only controls the magnitude and speed of infections but also minimizes COVID-19 induced deaths.

CRediT authorship contribution statement

Navendu Prakash: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization. Bhavya Srivastava: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Data curation. Shveta Singh: Writing – review & editing, Supervision, Project administration. Seema Sharma: Writing – review & editing, Supervision, Project administration. Sonali Jain: Writing – review & editing, Supervision, Project administration.

Declaration of interest

The authors have no competing interests to declare.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2021.101091.

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