Health Policy OPEN 8 (2025) 100140

Contents lists available at ScienceDirect

Health Policy OPEN

journal homepage: www.elsevier.com/locate/hpopen

The effectiveness of the states' crisis response policies: Survival analysis on the COVID-19 transmission suppression in the United States

Hanvit Kim, Kyungmin Lee, Jungwon Yeo *

School of Public Administration, University of Central Florida, Dr. Phillips Academic Commons, Room 446, 528 W Livingston St, Orlando, FL 32801, USA

ARTICLE INFO

Keywords:
Survival analysis
Crisis response policy
Policy effectiveness
Crisis management
COVID-19
United States

ABSTRACT

Objective: This study aims to evaluate the effectiveness of various COVID-19 response policies in the United Sates that facilitated rapid virus transmission suppression and promoted quick return to normalcy during the first three years of the pandemic.

Method: We constructed comprehensive and unique time-to-event panel data that tracks the timeline of all policy implementations, and transmission waves, specifically measuring the duration from peak transmission to the desired suppression level, over 157 weeks. We then conducted a survival analysis to estimate the effectiveness of COVID-19 response policies in relation to the virus transmission dynamics. Our analysis focuses on the ten most populous U.S. states, representing diverse geographic, cultural, and political landscapes across the country. The survival analysis leverages the extensive time-to-event panel data collected from multiple sources.

Results: Our findings indicate that not all policies were equally effective in facilitating rapid transmission and promoting swift suppression return to normalcy. Containment or closure policies, such as school closures and stay-at-home orders, are associated with a shorter duration for returning to normalcy, highlighting their effectiveness in curbing COVID-19 transmission. In contrast, health system policies and vaccine policies showed mixed results.

Conclusion: The findings from our survival analysis of the novel data set provide practical insights for prioritizing policy measures among various options to effectively and timely suppress the transmission of highly contagious diseases. These insights can also enhance resource utilization and allocation within and across public health systems, while minimizing restrictions on people's daily lives.

1. Introduction

Understanding the complex relationship between the pandemic and policy interventions is crucial for effective public health crisis management at global, national, and local levels [1–4]. Over the course of the COVID-19 pandemic, the severity and uncertainty surrounding the disease—including its symptoms, fatality rates, transmission dynamics, and long-term effects—made controlling transmission the top policy priority [5–10]. However, public health systems and policy makers faced significant challenges in identifying and implementing effective response measures due to limited information and resources [2,11–13]. Moreover, policies designed to curb disease transmission often imposed additional restrictions on daily life and societal functions, which, in some cases, inadvertently delayed a return to normalcy [4,14]. To prepare for future public health crises, it is essential to examine the impact of these policies. Such understanding can refine strategies for rapid disease suppression, optimize resource utilization, and facilitate effective policy implementation while minimizing unnecessary disruptions to society.

However, our understanding of which policies were effective in suppressing transmission in different contexts over extended periods remains limited. While previous studies have provided valuable insights into the impact of response policies on reducing COVID-19 incidence, mortality, and transmissions across various settings—such as U.S. states and counties, as well as countries [9,15,16]—much of this research has focused on specific policies or measures (e.g., face covering, hand-washing, social distancing, or closures), contexts and settings (i.e., schools, elderly, and hospitals), or short observation periods—typically up to six months during the early outbreak phase [3,17]. There is, therefore, a pressing need for evidence on effective policy measures that

* Corresponding author at: School of Public Administration, University of Central Florida, Dr. Phillips Academic Commons, Room 446, 528 W Livingston St, Orlando, FL 32801, USA.

E-mail addresses: hanvit.kim@ucf.edu (H. Kim), kyungmin.lee@ucf.edu (K. Lee), Jungwon.Yeo@ucf.edu (J. Yeo).

https://doi.org/10.1016/j.hpopen.2025.100140
Received 1 October 2024; Received in revised form 18 November 2024; Accepted 17 March 2025
Available online 20 March 2025
2590-2296/© 2025 Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

can sustain rapid disease suppression over longer health crises while also ensuring the effective functioning of public health systems and society at large in a long term.

In response to this need for understanding the effectiveness of COVID-19 response policies, this study examines the impact of various policy measures implemented across the United States during the first three years of the pandemic. We focus specifically on state-level variations, which provides a unique context for evaluating policy effectiveness. Constructing a novel time-to-event panel dataset, we track the timeline of policy implementations and transmission waves as well as measure the duration from peak transmission to the point of baseline suppression over a span of 157 weeks. Through survival analysis, we assess the effectiveness of COVID-19 policies in relation to the temporal dynamics of virus transmission, i.e., rapid transmission suppression and return to normalcy, across the states that adopted different response measures.

Our findings suggest that not all policies were equally effective in rapid return to normalcy over time. Based on the findings we discuss policy implications that can guide public health professionals and policy makers in designing targeted interventions that not only reduce virus transmission, facilitate rapid return to normalcy, but also ensure the ongoing effectiveness of public health systems.

The following section details the methods used in this study, including descriptions of the study design, data, variables, and model specifications. Subsequently, we will present the results, discuss the findings and limitations, and conclude with a summary and policy implications.

2. Methods

2.1. Data

We created a comprehensive and unique 'time-to-event' panel dataset that tracks the timeline of policy implementations, and transmission waves during the first three years of the pandemic. In our dataset, an "event" refers to the suppression of virus transmission, operationalized as the transition from the peak transmission referred to as ("peak") to the desired transmission level of a specific wave (referred to as "normalcy"). Specifically, "peak" denotes the highest number of confirmed cases during a wave, while "normalcy" represents the point at which transmission levels return to or are closely align with, those observed at the onset of the wave and are sustained for at least two weeks. Our time-to-event data captures the duration of this transition within each wave of COVID-19 transmission, with the durations influenced by implemented policy measures and other covariates [18].

Our time-to-event dataset is derived from the Oxford COVID-19 Government Response Tracker (OxCGRT) [19] and the U.S. Census. OxCGRT is an open-source initiative that monitors COVID-19 policies and transmission data across 180 counties using publicly available sources such as news articles, official government reports, and press releases. The OxCGRT data has been widely regarded for its validity, having undergone systematic reviews [19,20]. From the source, we extracted information on the independent variables—COVID-19-response policy measures—and the dependent variable, policy effectiveness. Additionally, we collected covariate data from the U.S. Census, which may influence the variation in our dependent variables.

We consolidated our time-to-event dataset from the aforementioned sources into a panel dataset covering the ten most populous states in the U.S., which together represent diverse geographical, cultural, and political landscapes. Our rationale for focusing on these ten states is threefold. Frist, while our sample includes ten out of the 50 U.S. states, it accounts for 59.2 % of the total US population [21]. Given that population density and urban play a crucial role in the transmission of highly infectious viruses [11,22], focusing on densely populated states enhances the efficacy of data collection and reliability of our findings [23]. Second, these ten states span a range of geographic, cultural, political, and climate landscapes (see Table 1). Additionally, the sample states represent diverse distribution of vulnerable population (% elderly and % poverty). This diversity likely influenced the variation in response policy measures adopted during the observation period as well as the duration for transmission suppressions. Lastly, data availability constraints led us to select these ten states, allowing for construction of a comparable dataset across states. The dataset includes various policy measures, transmission waves, transition from peak to normalcy, and other covariates observed weekly from January 1, 2020, to December 31, 2022 (a total of 157 weeks). By focusing on these ten states, we captured a significant portion of the U.S. population, ensuring robust and reliable findings while enabling a nuanced analysis of the effects of different policies over the time.

2.2. Variables

Dependent variable. Our dependent variable is the effectiveness of response policies, operationalized as the duration of COVID-19 transmission suppression during each wave. This variable was measured by the time it takes for the transition from peak to normalcy, based on the weekly confirmed case data for each sample state. Table 2 provides the details of the variables.

The process of computing the values for the variable involves two main steps: identifying distinct waves and calculating the duration of transmission suppression within each wave. First, we identified the distinct waves for each sample state by analyzing the natural pattern of peaks and valleys in the weekly confirmed case data [5]. Specifically, a wave was defined as a period characterized by a significant increase in cases, followed by a substantial decline, with the decrease sustained for at least two weeks. For example, as shown in Fig. 1, which presents a trend of weekly confirmed cases, 6 distinct waves can be identified. Each wave consists of a peak followed by a return to normalcy (baseline levels)–defined as the level of cases at the start of the wave, which remains stable for at least two weeks.

Second, we calculated the duration (in weeks) of transmission suppression within each wave. As presented in Fig. 2 (Example of New York state), spaces between two red-dotted lines indicate the duration for each wave. For example, during the first wave, we identified the 13th week as the peak and the 17th week as the return to normalcy. Based on this, we coded the duration of the transmission suppression in the first wave as four (4) weeks as for New York state.

Independent variable. Our independent variables are the COVID-19 response policy measures, operationalized as the intensity of the policies. Using information from the OxCGRT, we identified 17 policy measures implemented by U.S. state governments. However, we focused on 14 specific policy indicators, which were grouped into three categories that targeted virus transmission suppression: (1) containment or closure policies, (2) health system policies, and (3) vaccine policies.

First, containment and closure policies include measures such as school closure, workplace shutdowns, the cancellation of public events, restrictions on gatherings, suspension of public transport, stay-at-home orders, and controls on international travel. For example, the intensity of school closures, which involves the shutdown of schools and universities, was measured on a four-level scale. 0 indicates no measures have been implemented. 1 reflects state governments recommending closure or allowing schools to remain open with modifications. 2 signifies that state governments have mandated partial closures, affecting specific categories or education levels (e.g., high schools or public schools). Finally, 3 denotes full-scale school closures at all educational levels.

Second, health system policies encompass public information campaigns, testing protocols, contract tracing, facial coverings, and the protection of vulnerable populations, such as the elderly. These variables were measured on an ordinal scale. For instance, public information campaigns are assessed based on their level of implementation, with three values: 0 indicates no COVID-19 public information campaign, 1

Table 1
Sample State Characteristics (2020–2022).

State	Percentile Elderly population Rate	Percentile Poverty rate	Cultural & Geographic Region	Political Environment	Temperate Climate zone
California	Low	Med	West	Democratic	Hot
Texas	Low	High	Southwest	Republican	Mixed
Florida	High	High-Med	Southeast	Republican	Hot
New York	Med	Med	Northeast	Democratic	Cold
Pennsylvania	High	Low-Med	Northeast	Democratic	Cold
Illinois	Med-Low	Low-Med	Midwest	Democratic	Cold
Ohio	Med-High	High-Med	Midwest	Republican	Cold
Georgia	Low	High	Southeast	Democratic	Mixed
North Carolina	Med-Low	High-Med	Southeast	Republican	Mixed
Michigan	Med-High	Med	Midwest	Democratic	Cold

Sources: U.S. Census data on elderly populations (https://www.census.gov/topics/population/older-aging/data.html); U.S. Census poverty data (https://www.census.gov/topics/income-poverty/poverty.html); U.S. Census regions and divisions (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf); party affiliation by state from Pew Research Center (https://www.pewresearch.org/religious-landscape-study/database/compare/party-affiliation/by/state/); and U.S. climate regions data from the National Centers for Environmental Information (https://www.ncei.noaa.gov/access/monitoring/reference-maps/us-climate-regions).

indicates public officials urged caution regarding COVID-19, and 2 indicates implementation of a coordinated public information campaign across both traditional and social media platforms.

Third, vaccine policies include eligibility, financial support, and mandates for vaccinations. All of these variables were measured on an ordinal scale. For example, the mandate for vaccination is a binary variable, where a value of 1 indicates that the state government required the vaccine at that time, and a value of 0 indicates that no vaccine mandate was in place at the time.

Additionally, Fig. 3 visualizes how the intensity of these policy measures was incorporated into our time-to-event dataset. It shows the timeline of COVID-19 policy implementation alongside the transmission waves in New York. The blue lines represent the initial week of each policy's implementation, while the red lines indicate the week of its withdrawal. Thicker lines represent weeks when multiple policies were introduced simultaneously. As illustrated, most COVID-19 policies were implemented at the onset of the first wave and were withdrawn as the waves had stabilized.

Covariates. We included three state-level characteristics as control variables to account for factors that could influence our dependent variable: population size, population density, and the proportion of individuals aged 65 and older in each state. Population size and density were particularly important to control due to their potential impact on COVID-19 transmission rate [24]. Additionally, because older adults are more vulnerable to severe outcomes from the virus, we also controlled for the proportion of the population aged 65 and older.

2.3. Model specification

This study employed survival analysis to evaluate the effectiveness of COVID-19 response policies on public health outcomes. Survival analysis is particularly useful for examining the relationship between risk factors or exposures and survival time [25]. To assess goodness of fit and compare different model specifications, we used the Akaike Information Criterion (AIC), a common method for model selection. The AIC helps identify the model that best balances fit and complexity, with a lower AIC indicating a better fit to data [32]. We compared the parametric and semi-parametric survival analysis models, including the exponential, Weibull, Log-normal, and Cox proportional hazards model. Based on the AIC results, we selected the Weibull model, as it produced the lowest AIC and Bayesian Information Criterion (BIC) values.

The Weibull model was particularly suited to our data for several reasons. Firstly, it offers flexibility in modelling hazard functions that can either increase or decrease over time, depending on the value of its shape parameter (γ). This allows the model to both monotonically increasing and decreasing hazard rates [26]. In the context of COVID-19, the hazard rate is likely to fluctuate over time in a non-linear fashion, reflecting the dynamic nature of the pandemic and varying policy interventions. Second, The Weibull distribution is well-equipped to capture this variability. The parametric Weibull distribution provides explicit estimates of the hazard rates, allowing for a more precise interpretation of how different policies impact outcomes over time [26]. This is particularly useful for estimating the time until states return to normalcy following the varying intensities of implementation of specific intervention [27].

Using the Weibull model, we estimated the probability of returning to normalcy and identified the most influential policies affecting this likelihood. To address potential confounding from both observed and unobserved time-invariant state characteristics, we incorporated state fixed-effects into the model. To account for the potential correlation of errors within states over time, given the presence of time-varying covariates and multiple events in our data structure, we applied clustering at the state level. This approach accounts for the interdependence of observations within states, ensuring robust standard errors in our estimates.

The model is specified as follows:

$$t = \exp[b_1x_1 + b_2x_2 + \cdots + b_kx_k]$$

$$t \geq 0, k = 1, 2, \cdots n \tag{1}$$

$$H(t) = \gamma\lambda^{\gamma}(t)^{\gamma-1}\exp[b_1x_1 + b_2x_2 + \cdots + b_kx_k]$$

$$\gamma\lambda > 0 \text{ and } t \geq 0 \tag{2}$$

$H(t)$ denotes, effectiveness of response policies, which is estimated as a hazard function of time t. b_k denotes the coefficient, and x_k denotes the covariates: COVID-19 response policies, while controlling for multiple underlying state factors.

Our model calculates the hazard ratio (HR), a key metric in survival analysis that quantifies the relative probability of experiencing the event of interest, i.e., returning from a peak to normalcy in our case, across different groups or levels of a categorical variable, while accounting for the time it takes for the event to occur. In survival analysis, a HR of 1 is considered the baseline, indicating no difference in the likelihood of the event between different groups [26]. A HR greater than 1 suggests an increased likelihood of the event between groups, while HR less than 1 indicates a decreased likelihood [26]. For example, if the HR for school closure is 1.5, it means that for each unit increase in the policy's intensity, the time to return to normalcy is reduced by 50 %, reflecting faster/effective transmission control. In our model, HR greater than 1 indicates the effectiveness of a COVID-19 response policy. Specifically, it suggests that the policy has contributed to more rapid suppression of disease transmission, resulting in a steeper negative slope in the trajectory of the pandemic waves.

We estimated two Weibull models applying time lags—one-week and two-week–for our dependent variable to account for potential delays

Table 2
Variable description.

Variable	Values
States' COVID-19 response policy effectiveness	Duration of a state's COVID-19 transmission suppression for each wave(Number of weeks)
Containment and closure policy	
School closure	0 = no measures 1 = recommend closing or all schools open with alterations resulting in significant differences compared to non-Covid-19 operations 2 = require closing (only some levels or categories, e.g., just high school, or just public schools) 3 = require closing all levels
Workplace shutdowns	0 = no measures 1 = recommend closing (or recommend work from home) or all businesses open with alterations resulting in significant differences compared to non-Covid-19 operation 2 = require closing (or work from home) for some sectors or categories of workers 3 = require closing (or work from home) for all-but-essential workplaces (e.g., grocery stores, doctors)
Cancellation of public events	0 = no measures 1 = recommend cancelling 2 = require cancelling
Restrictions on gatherings	0 = no restrictions 1 = restrictions on very large gatherings (the limit is above 1000 people) 2 = restrictions on gatherings between 101–1000 people 3 = restrictions on gatherings between 11–100 people 4 = restrictions on gatherings of 10 people or less
Suspension of public transport	0 = no measures 1 = recommend closing (or significantly reduce volume/route/means of transport available) 2 = require closing (or prohibit most citizens from using it)
Stay-at-home orders	0 = no measures 1 = recommend not leaving house 2 = require not leaving house with exceptions for daily exercise, grocery shopping, and 'essential' trips3 = require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc.)
Controls on international travel	0 = no restrictions 1 = screening arrivals 2 = quarantine arrivals from some or all regions 3 = ban arrivals from some regions 4 = ban on all regions or total border closure
Health system policy	
Testing policy	0 = no testing policy 1 = only those who both (a) have symptoms AND (b) meet specific criteria (e.g., key workers, admitted to hospital, came into contact with a known case, returned from overseas) 2 = testing of anyone showing Covid-19 symptoms 3 = open public testing (e.g., "drive through" testing available to asymptomatic people)
Contact tracing	0 = no contact tracing 1 = limited contact tracing; not done for all cases 2 = comprehensive contact tracing; done for all identified cases
Facial coverings	0 = No policy 1 = Recommended 2 = Required in some specified shared/public spaces outside the home with other people present, or some situations when social distancing not possible 3 = Required in all shared/public spaces outside the home with other people present or all situations when social distancing not possible 4 = Required outside the home at all times regardless of location or presence of other people
Protection of elderly people	0 = no measures 1 = Recommended isolation, hygiene, and visitor restriction measures in LTCFs and/or elderly people to stay at home 2 = Narrow restrictions for isolation, hygiene in LTCFs, some limitations on external visitors and/or restrictions protecting elderly people at home 3 = Extensive restrictions for isolation and hygiene in LTCFs, all non-essential external visitors prohibited, and/or all elderly people required to stay at home and not leave the home with minimal exceptions, and receive no external visitors
Vaccine policy	
Eligibility for vaccination	0 = no categories are receiving vaccines 1 = vaccines are available to some categories 2 = vaccines are available to anyone over the age of 16 yrs. 3 = vaccines are available to anyone over the age of 16 yrs. PLUS one or both of 5–15 yrs. and 0–4 yrs.
Financial support for vaccination	0 = no availability 1 = full cost to the individual for all categories identified in V2 2 = full cost to the individual for some categories identified in V2, some subsidy for other categories 3 = partial funding by the government for all of the categories identified in V2 4 = partial funding by the government for some categories identified in V2, full funding for other categories 5 = all categories fully funded by the government
Mandate for vaccination	0 = no requirement to be vaccinated 1 = requirement to be vaccinated is in place for one or more groups
State-level characteristics	
Population	Population/1,000
Population density	Population per square mile
Ratio of aged 65 and older	Aged 65 and older/Population

Note. Data of state policies is derived from Oxford COVID-19 Government Response Tracker (OxCGRT), and data of state-level characteristics is derived from the U.S. Census.

between policy implementation and its effects on the return to normalcy. The two different time lag applications also correspond to typical delays in COVID-19 test confirmation following infection. According to the U.S. Centers for Disease Control and Prevention (CDC), the average incubation period for COVID-19 is 5 days, with a range of 2 to 14 days [28]. This suggests that confirmation of COVID-19 infections would be delayed by approximately one to two weeks.

3. Results

3.1. Descriptive statistics

Table 3 provides descriptive statistics for all variables used in our analysis. On average, the duration from peak to normalcy was 49.5 weeks across multiple waves. California, New York, Georgia, and North Carolina experienced shorter-than-average durations, while Texas, Pennsylvania, and Michigan were close to the average. Florida, Illinois, and Ohio had longer-than-average durations. Notably, California recorded the shortest duration from peak to normalcy, while Florida and Illinois had the longest.

In terms of policy responses, California consistently scored higher across all policy categories, suggesting a more aggressive and comprehensive approach to COVID-19 response. In contrast, Florida scored lower across all policy categories, indicating a less stringent response. Overall, the data shows significant variation in both the durations for transmission suppression and the intensity of policy measures across states during the observation period.

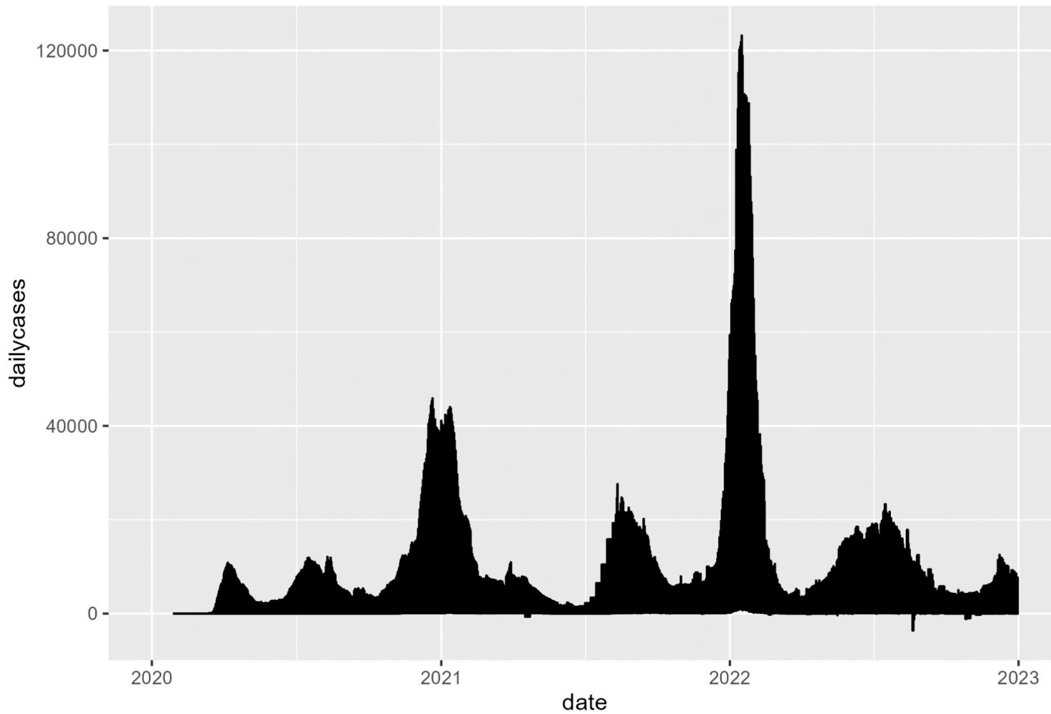

Fig. 1. Number of Covid-19 cases.

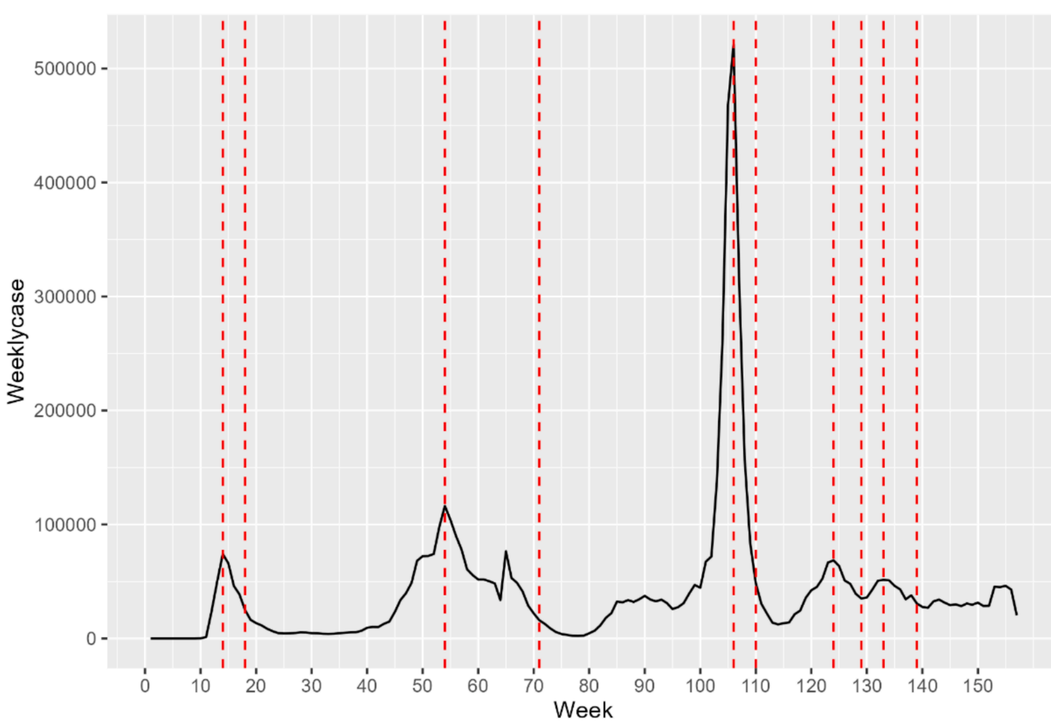

Fig. 2. Number of Covid-19 cases in New York.

3.2. Findings and discussions

Table 4 presents the findings from the survival analysis, which evaluates how effective response policies are facilitating a swift transition from peak to normalcy, incorporating two distinct time lags.

First, most containment or closure policies, except for workplace shutdowns and suspension of public transportation, appear to be effective, as evidenced by a HR greater than 1. However, only the effects of school closure and stay-at-home orders are statistically significant at the 0.1 % significance level ($p < 0.001$). The results align with existing research suggesting that nonpharmaceutical interventions—particularly those aimed at reducing mass contact among populations—have been effective in controlling transmission [10,16,29,30]. Our findings contribute to this body of knowledge by demonstrating that, among many nonpharmaceutical measures, school closures and stay-at-home orders not only have a significant impact on controlling transmission

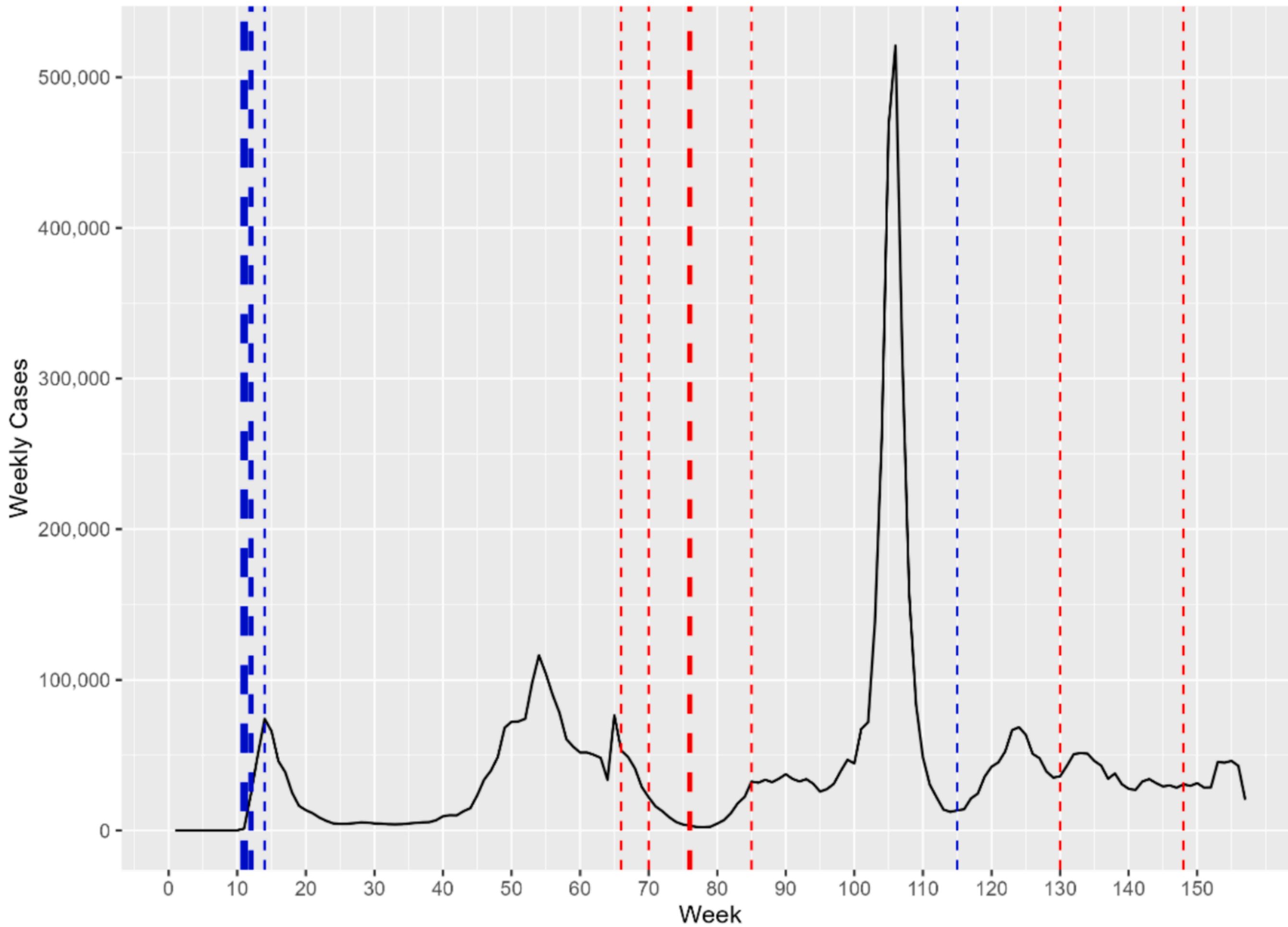

Fig. 3. Covid-19 policy timeline in New York.

Table 3
Descriptive statistics.

State	Duration from Peak to Normacy	Containment and Closure Policies	Health System Policies	Vaccine Policies
Average	49.5	1.03	1.98	1.82
California	35	1.19	2.11	1.90
Texas	49	1.00	1.83	1.58
Florida	61	0.98	1.76	1.75
New York	41	1.09	2.11	1.91
Pennsylvania	51	1.04	2.04	1.89
Illinois	61	0.93	2.04	1.90
Ohio	56	0.98	2.03	1.80
Georgia	46	0.98	1.91	1.76
North Carolina	45	1.00	1.87	1.90
Michigan	50	1.06	2.11	1.80

Note. Duration (in weeks) from peak to normalcy refers to the total number of weeks from the peak point to normalcy of transmission. Among policies, a higher value indicates a more intensive policy.

but also help facilitate a faster return to normalcy, with their effect persisting over time.

Second, mixed effects of health system policies have been observed. Among these policies, only the one aimed at protecting elderly populations shows a HR greater than 1, which aligns with public health recommendations to prioritize more vulnerable groups, especially elderly population, during the pandemic [7]. However, the policy did not reach statistical significance at the 5 % significance level in either

Table 4
Survival analysis on duration from peak to normalcy.

	Hazard Ratio (robust std. err)	
	Model 1 (1-week lag)	**Model 2 (2-week lag)**
Containment or closure policy		
School closure	6.343 (2.845) ***	6.960 (3.067) ***
Workplace closure	0.550 (0.376)	0.421(0.337)
Cancellation of public events	2.100 (1.441)	3.534 (2.277)
Restrictions on gatherings	1.373 (0.510)	1.165 (0.423)
Public transport closure	0.624 (0.761)	1.067 (1.322)
Stay-at-home order	27.732 (24.750) ***	30.721(30.337) ***
International travel control	1.590 (1.758)	1.235
Health system policy		
Testing policy	0.382(0.277)	0.172 (0.138) *
Contact tracing	0.433(0.224)	0.474(0.246)
Facial coverings	0.645(0.182)	0.777(0.250)
Protection of elderly people	1.936 (1.107)	1.711(0.987)
Vaccine policy		
Vaccine eligibility	3.215 (1.281) **	2.566 (1.049) *
Financial support	0.086 (0.029) ***	0.100 (0.030) ***
Vaccine mandate	1.515(1.010)	1.843 (1.252)
State-level characteristics		
Population	0.998 (0.001) **	0.998 (0.001) **
Population density	1.067 (0.136)	1.109 (0.128)
Ratio of aged 65 and older	0.000 (0.001) *	0.000 (0.000) **
State fixed effect	Yes	Yes
Observations	495	495

Note. Hazard Ratio > 1 indicates the event is more likely to occur. Robust standard errors in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

time-lag model.

In contrast, policies related to testing, contact tracing, and face covering all yielded HRs of less than 1, but they were not statistically significant at the 5 % level, suggesting their limited effectiveness in facilitating a rapid return to normalcy. These findings imply that the impact of health system policies, regardless of their directions, may be overshadowed by the stronger influence of containment or closure policies that target broader transmission control.

Lastly, we observed mixed effects across different vaccine policies. Both vaccine eligibility and vaccination mandates resulted in a HR greater than 1, suggesting that these policies have a positive impact on rapid transition to normalcy. This finding aligns with studies that assess the transmissibility of infectious diseases, particularly through controlling reproduction rates [4,8,10]. Expanding eligibility and enforcing mandates for vaccination can increase the vaccinated population, thereby slowing the virus' reproduction and curbing further transmission of infectious diseases [24,31,32]. However, our results show that only vaccine eligibility was statistically significant in both models at the 5 % significance level ($p < 0.05$), suggesting that broadening eligibility contributes more substantially to quicker return to normalcy than intensifying vaccination mandates.

In contrast, financial support for vaccination shows a HR smaller than 1 and was statistically significant in both models at the 0.1 % significance level ($p < 0.001$). Traditionally, financial support has been considered a key strategy to improve vaccine access and address equity issues [33–36]. However, our findings suggest that greater financial support may actually delay the return to normalcy. This counterintuitive result can be explained by the relationship between vaccine hesitancy, the strategies used to address it, and limited resources in public health systems. In the U.S., vaccine hesitancy has been prevalent even before the pandemic [6,37,38]. Studies show that incentive-based interventions, such as financial support, are among the least effective vaccine strategies to overcome vaccine hesitancy compared to other measures, such as expanding target groups, enforcing stricter mandates, or investing in public awareness campaign and dialogues [39]. Furthermore, it is possible that states providing greater financial support for vaccination may have allocated fewer resources to more effective policy measures, such as expanding vaccine eligibility, or enforcing containment or closure policies.

Overall, our findings suggest that not all policies were equally effective in facilitating a rapid return to normalcy. Additionally, the results indicate the potential for competition or trade-offs among different policy effects. These insights can help guide public health professionals and policy makers in prioritizing policy options and designing more targeted interventions that not only reduce virus transmission and promote quick return to normalcy, but also ensure the sustained effectiveness of public health operations during the crisis. Moreover, our results may inform more efficient resource allocation and utilization across health systems, enabling a focus on implementing the more effective policy measures. Evidence-based policy decisions such as these also can contribute to minimizing unnecessary restrictions on daily life, while supporting the continued functioning of society during future health crises.

4. Conclusions

This study examines the effectiveness of COVID-19 response policies in facilitating a rapid return to normalcy in the U.S. during the first three years of the COVID-19 pandemic. Using survival analysis and a novel time-to-event panel dataset, we identified policies that were particularly effective in achieving quicker suppression over an extended period. These findings offer valuable insights for public health professionals and policy makers, supporting evidence-based decisions on prioritizing relevant intervention measures. Additionally, the results have broader implications for optimizing resource allocation for crisis responses and minimizing unnecessary restrictions to daily life and societal functions during future public health crisis.

The contribution of this research is threefold, First, the primary contribution of this study is the construction and analysis of a unique time-to-event dataset that measures the interaction between diverse response policies and the duration of transition from peak to normalcy. This approach goes beyond existing studies, which typically focus on simple transmission trends (e.g., virus reproduction rates, transmission, mortality overtime) [3,4], by incorporating the temporal dynamics of transmission control. Second, by examining the impacts of all relevant policies over an extended period of the COVID-19 pandemic, this study identifies not only which policies were effective, but also which ones produced sustained effects over time, providing a more nuanced understanding of policy effectiveness. Third, this study offers evidence that supports the design and implementation of more targeted and focused policies, which can effectively and efficiently save both lives and resources in future crisis. The findings contribute to a more robust discourse on how to select and implement policies that minimize physical contact while safeguarding individual rights, offering valuable insights for managing future public health emergencies.

Despite the contributions of this study, we acknowledge several limitations. First, our study is limited to the context of ten populous U.S. states during the COVID-19 pandemic. As such, the findings may not be directly applicable and generalized to other geographic, cultural, or public health contexts, particularly those involving different infectious diseases with distinct characteristics. To improve the limitations, future studies could replicate our study design in other countries, or in the context of different disease outbreaks, or expand our dataset to include all 50 U.S. states. Second, our study is observational in nature, while we controlled for potential confounding factors and considered time lags, unmeasured confounders may still influence the results. Future research employing experimental or quasi-experimental designs could provide stronger evidence for more rigorous causal relationships. Lastly, our study focuses on the duration of transmission suppression as a measure of policy effectiveness. Future studies may explore policy effectiveness in terms of the volume of transmission suppression, expanding the understanding of policy impact.

Funding sources

Article processing charges were provided in part by the UCF College of Graduate Studies Open Access Publishing Fund.

CRediT authorship contribution statement

Hanvit Kim: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Kyungmin Lee:** Writing – original draft, Conceptualization. **Jungwon Yeo:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization.

Ethics approval

Ethics approval is not required because the primary data was collected from open sources and public documents, which did not involve any human subjects

Declaration of competing interest

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

Appendix A

A. Covid-19 cases in 10 States (2020–2022).

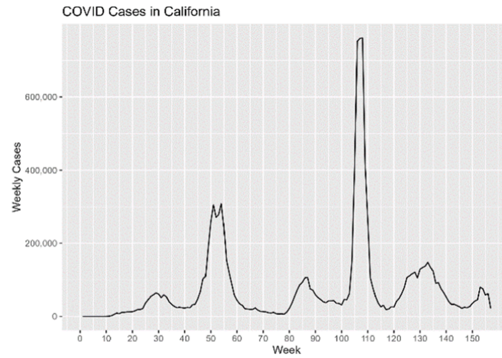

Fig. A1. California.

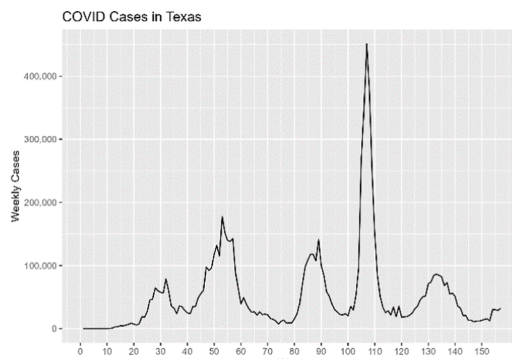

Fig. A2. Texas.

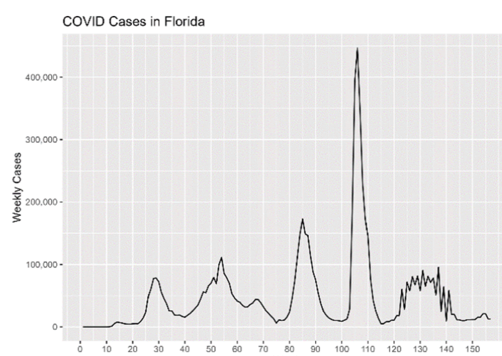

Fig. A3. Florida.

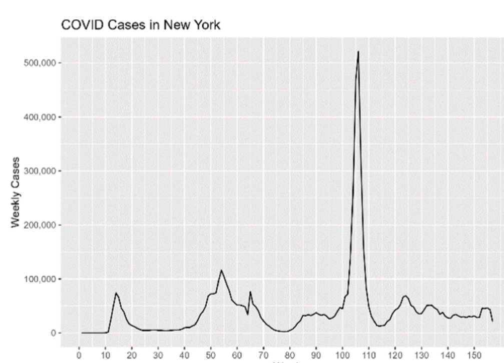

Fig. A4. New York.

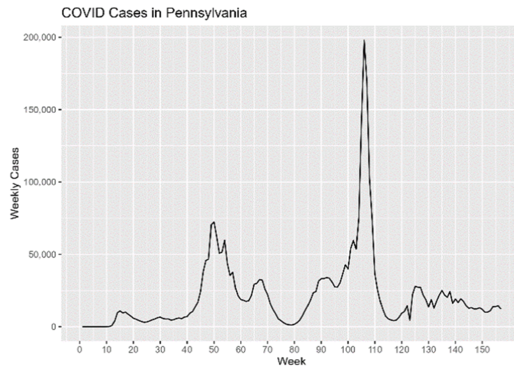

Fig. A5. Pennsylvania.

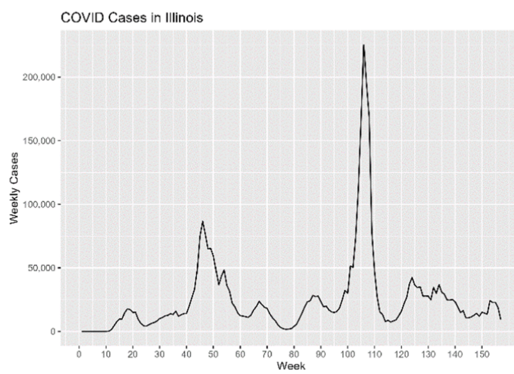

Fig. A6. Illinois.

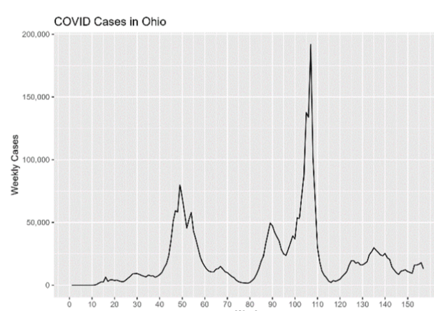

Fig. A7. Ohio.

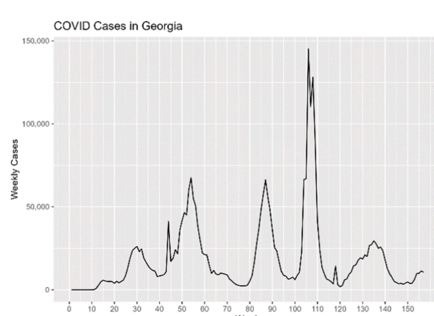

Fig. A8. Georgia.

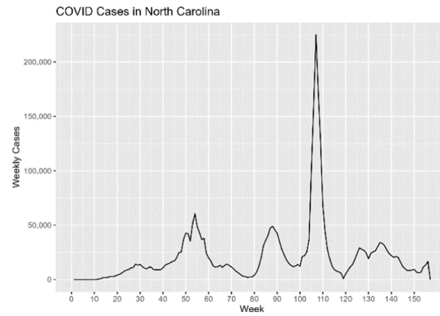

Fig. A9. North Carolina.

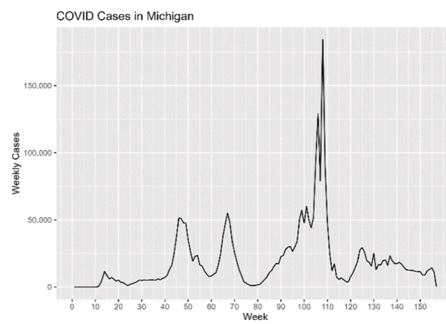

Fig. A10. Michigan.

Data availability

Data will be made available on request.

References

[1] Lee E-Y. Can suicide resulting from disconnection and alienation be designated as solitude? Focusing on the new formulation of concept and object of solitude. Human Being Environ Thier Fut 2018;21:71–102.
[2] Yang K. What can COVID-19 tell us about evidence-based management? Am. Rev. Public Admin. 2020;50(6–7):706–12.
[3] Talic S, et al. Effectiveness of public health measures in reducing the incidence of covid-19, SARS-CoV-2 transmission, and covid-19 mortality: systematic review and meta-analysis. BMJ 2021;375:e068302.
[4] Yang Chan EY, et al. Narrative review of non-pharmaceutical behavioural measures for the prevention of COVID-19 (SARS-CoV-2) based on the Health-EDRM framework. Br Med Bull 2020;136(1):46–87.
[5] Zhang SX, et al. A second wave? What do people mean by COVID waves?–a working definition of epidemic waves. Risk Manage. Healthcare Pol. 2021:3775–82.
[6] Yasmin F, et al. *COVID-19 vaccine hesitancy in the United States: a systematic review*. Front Public Health 2021;9.
[7] Williamson EJ, et al. *Factors associated with COVID-19-related death using OpenSAFELY*. Nature 2020;584(7821):430–6.
[8] Wiersinga WJ, et al. *Pathophysiology, transmission, diagnosis, and treatment of coronavirus disease 2019 (COVID-19): a review*. J Am Med Assoc 2020;324(8):782–93.
[9] Warner ME, Zhang X. *Social safety nets and COVID-19 stay home orders across US states: a comparative policy analysis*. J Comparat Pol Anal: Res Pract 2021;23(2):176–90.
[10] Vlachos J, Hertegård E, Svaleryd HB. *The effects of school closures on SARS-CoV-2 among parents and teachers*. Proc Natl Acad Sci 2021;118(9):e2020834118.
[11] Lyu W, Wehby GL. *Community use of face masks and COVID-19: evidence from a natural experiment of state mandates in the US*. Health Aff 2020;39(8):1419–25.
[12] Van Wart M, Kapucu N. *Crisis management competencies: the case of emergency managers in the USA*. Public Manag Rev 2011;13(4):489–511.
[13] Xiang Y, et al. *COVID-19 epidemic prediction and the impact of public health interventions: A review of COVID-19 epidemic models*. Infect Disease Model 2021;6:324–42.
[14] Han E, et al. *Lessons learnt from easing COVID-19 restrictions: an analysis of countries and regions in Asia Pacific and Europe*. Lancet 2020;396(10261):1525–34.
[15] Patel P, et al. *Impact of nonpharmacological interventions on COVID-19 transmission dynamics in India*. Ind J Public Health 2020;64(6):142–6.
[16] Ambikapathy B, Krishnamurthy K. *Mathematical modelling to assess the impact of lockdown on COVID-19 transmission in India: model development and validation*. JMIR Public Health Surveill 2020;6(2):e19368.
[17] Dreher N et al. Policy Interventions, Social Distancing, and SARS-CoV-2 Transmission in the United States: A Retrospective State-level Analysis. Am J Med Sci 2021;**361**(5):575-584.
[18] Control CfD and Prevention. CDC Yellow Book 2024: Health Information for International Travel, ed. J.B. Nemhauser. Oxford University Press; 2023.
[19] Hale T, et al. *A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)*. Nat Hum Behav 2021;5(4):529–38.
[20] Roser M. What is the COVID-19 Stringency Index? 2021; Available from: https://ourworldindata.org/metrics-explained-covid19-stringency-index.
[21] U.S. Census Bureau. 2020 Census of Population and Housing. Census Bureau: Washington, DC: U.S.; 2021.
[22] Dasgupta S, et al. *Differences in rapid increases in county-level COVID-19 incidence by implementation of statewide closures and mask mandates — United States, June 1–September 30, 2020*. Ann Epidemiol 2021;57:46–53.
[23] Harris JE. *COVID-19 Incidence and hospitalization during the delta surge were inversely related to vaccination coverage among the most populous U.S Counties*. Health Pol Technol 2022;11(2):100583.
[24] Sy KTL, White LF, Nichols BE. *Population density and basic reproductive number of COVID-19 across United States counties*. PLoS One 2021;16(4):e0249271.
[25] Abd ElHafeez S, et al. *Methods to analyze time-to-event data: the Cox regression analysis*. Oxid Med Cell Longev 2021;2021:1–6.
[26] Kleinbaum DG, Klein M. Survival Analysis: A Self-Learning Text. Third Edition ed. Statistics for Biology and Health. New York: Springer New York; 2012.
[27] Hosmer DW, Lemeshow S, May S. Applied survival analysis: regression modeling of time-to-event data. Wiley; 2008.
[28] Lauer SA, et al. *the incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application*. Ann Intern Med 2020;172(9):577–82.
[29] Sun P, et al. *Understanding of COVID-19 based on current evidence*. J Med Virol 2020;92(6):548–51.
[30] Amir H. *Strategies in preventing the transmission of covid-19 a quarantine, isolation, lockdown, tracing, testing and treatment (3t): Literature review*. Asia Pacific J. Health Manage. 2022;17(2):1–6.
[31] Rocklöv J, Sjödin H, Wilder-Smith A. *COVID-19 outbreak on the Diamond Princess cruise ship: estimating the epidemic potential and effectiveness of public health countermeasures*. J Travel Med 2020;27(3). p. taaa030.
[32] Harris K, et al. *Workplace efforts to promote influenza vaccination among healthcare personnel and their association with uptake during the 2009 pandemic influenza A (H1N1)*. Vaccine 2011;29(16):2978–85.
[33] Hardt K, et al. *Vaccine strategies: optimising outcomes*. Vaccine 2016;34(52):6691–9.
[34] Diekema DS. *Improving Childhood Vaccination Rates*. N Engl J Med 2012;366(5):391–3.

[35] Saitoh A, Okabe N. *Recent progress and concerns regarding the Japanese immunization program: addressing the "vaccine gap"*. Vaccine 2014;32(34):4253–8.
[36] Turner HC, Thwaites GE, Clapham HE. *Vaccine-preventable diseases in lower-middle-income countries*. Lancet Infect Dis 2018;18(9):937–9.
[37] Jacobson RM, St. Sauver JL, Finney Rutten LJ. Vaccine Hesitancy. Mayo Clinic Proceedings 2015;**90**(11):1562–1568.
[38] Siddiqui M, Salmon DA, Omer SB. *Epidemiology of vaccine hesitancy in the United States*. Hum Vaccin Immunother 2013;9(12):2643–8.
[39] Jarrett C, et al. *Strategies for addressing vaccine hesitancy – A systematic review*. Vaccine 2015;33(34):4180–90.