Characterizing Population-level Changes in Human Behavior during the COVID-19 Pandemic in the United States

Tamanna Urmi[1,2,*], Binod Pant[1,2,*], Alexi Quintana-Mathé [2], Iris Lang[1,3], George Dewey[1,2], Hong Qu[2], James N. Druckman[4], Katherine Ognyanova[5], Matthew Baum[6], Roy H. Perlis[7], Christoph Riedl[8], David Lazer[2,9,10,11], Mauricio Santillana[1,2,12]†

[1] *Machine Intelligence Group for the Betterment of Health and the Environment, Northeastern University, Boston, Massachusetts*
[2] *Network Science Institute, Northeastern University, Boston, Massachusetts*
[3] *Harvard College, Cambridge, Massachusetts*
[4] *Department of Political Science, University of Rochester, Rochester, New York*
[5] *School of Communication and Information, Rutgers University, New Brunswick, New York*
[6] *Harvard University's John F. Kennedy School of Government and Department of Government, Cambridge, Massachusetts*
[7] *Department of Psychiatry, Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts*
[8] *D'Amore–McKim School of Business, Northeastern University, Boston, Massachusetts*
[9] *Department of Political Science, Northeastern University, Boston, Massachusetts*
[10] *Khoury College of Computer Sciences, Northeastern University, Boston, Massachusetts*
[11] *Institute for Quantitative Social Science, Harvard University, Cambridge, Massachusetts*
[12] *Department of Epidemiology, Harvard T.H. Chan School of Public Health, Massachusetts*

Abstract

The transmission of communicable diseases in human populations is known to be modulated by behavioral patterns. However, detailed characterizations of how population-level behaviors change over time during multiple disease outbreaks and spatial resolutions are still not widely available. We used data from 431,211 survey responses collected in the United States, between April 2020 to June 2022, to provide a detailed description of how human behaviors fluctuated over the first two years of the COVID-19 pandemic. Our analysis suggests that at the national and state levels, people's adherence to recommendations to avoid contact with others (a preventive behavior) was highest early in the pandemic but gradually –and linearly– decreased over time. Importantly, during periods of intense COVID-19 mortality, adherence to preventive behaviors increased –despite the overall temporal decrease. Our spatial-temporal characterization may help improve our understanding of how outbreak severity may influence changes in human behavior and vice-versa. It may benefit both computational modeling teams developing methodologies to predict the dynamics of future epidemics, and policy-makers designing strategies to mitigate the effects of future disease outbreaks.

Keywords: disease outbreak dynamics, pandemic preparedness, epidemiology, human behaviors, COVID-19, non-pharmaceutical interventions, policy making, infectious disease modeling

*These authors contributed equally to this study
†Corresponding author: Mauricio Santillana (email: msantill@g.harvard.edu)

1 Introduction

Population-level changes in human behavior have been known to impact the spread of communicable diseases during epidemic outbreaks. For example, Ignaz Semmelweis's work in the mid 1800s in Vienna, Austria, linking the absence of hand-washing to high mortality in maternity wards [1] began a revolution that would lead to the enshrinement of hand-washing as a preventive health behavior in Western society. More recently, the rise in adoption of preventive behaviors such as adhering to stay-at-home recommendations, and/or facial mask wearing, substantially slowed the spread of infections during the COVID-19 pandemic [2, 3, 4, 5, 6] before vaccines or other treatments were widely available. However, population-level behavior can also foster the spread of infection: the migration of people from the countryside into densely packed, overpopulated cities contributed to the spread of plague in Europe and Asia from the times of the Roman Empire until the 19^{th} century [7]. Behaviors at the population level can also promote intermittent patterns of transmission: for example, continuous movements of human groups across the Globe during the first World War may have induced the onset of multiple waves (as opposed to a continuous outbreak) during the 1918 influenza pandemic in England [8].

Similarly, in moments of high mortality induced by an ongoing disease outbreak, people may change their behavior patterns to reduce their risk of infection and potential death [9]. For example, people may use bed nets to prevent being bitten by mosquitoes that transmit malaria or dengue fever during times of severe transmission [10]. During periods of increased mortality during the West African Ebola outbreaks of the mid 2010s, people chose to opt out of the cultural practice of touching bodies of deceased relatives when they learned that the disease could be transmitted through contact with bodily fluids from corpses [11, 12]. Similarly, during the COVID-19 pandemic, people reduced their visits to crowded places, such as music concerts and museums, during times when the number of COVID-19-attributable deaths was high as will be shown in this study.

This bi-directional feedback between human behavior patterns and epidemiological dynamics has not consistently been characterized across diseases and outbreaks, in part due to poor epidemiological surveillance and the unreliability of estimates of human behavior indicators. Accurate and timely epidemiological surveillance is challenging. It would be impractical, in terms of economic resources and people's consent, to test everyone in a population to fully establish the ground truth of the number of people getting infected at any single point in time. Instead, we use various proxies such as the number of reported cases, hospitalization, mortality, and the amount of viral RNA in wastewater to estimate the degree of spread of a disease in the population [13, 14, 15]. These proxies are imperfect for assessing the spread of the disease because of factors such as testing availability, test accuracy, reporting delays, and under-reporting. In the context of COVID-19, mortality data in the United States was impacted by reporting delays over the weekends [16] and under-reporting of nursing home deaths due to inconsistent data collection [17]. Wastewater data can be unreliable because fluctuations in environmental factors such as rainfall, snowmelt, and temperature directly impact wastewater viral RNA by diluting samples through increased water flow or accelerating RNA degradation at higher temperatures. Moreover, aggregated data (such as state-level or country-level data) can suffer from heterogeneous degrees of delay from each reporting unit (such as hospitals, testing centers, or wastewater treatment plants) leading to poor characterizations of disease dynamics across spatial scales.

Characterizing human behavior at the population-level is also challenging. Alternate sources of data have been used to track disease trends and changes in human behavior during an outbreak. For example, Nsoesie et al. [18] used hospital parking lot traffic data to estimate the incidence of respiratory viruses. Airline travel data has also been incorporated into modeling strategies to infer disease transmission across the globe as well as changes in human behavior that follow [19, 9, 20]. Mobile phone data has also been used to track disease spread and change in human behavior [21, 22, 23, 24]. By analyzing data collected through surveys (n = 9,743), Feehan and Mahmum [25] showed that interpersonal contact was dramatically reduced during the first wave of the COVID-19 pandemic in the United States. Survey results, however, have been frequently limited due to low sample size, recall bias, survey participants' dishonest responses, and the framing of survey questions. Efforts to infer human behavior through the Oxford Stringency Index [26, 27, 28, 29], an index that attempts to quantify the stringency of government mandates to mitigate disease transmission, have also been made [30, 31], however, as it will be shown in this study, government mandates may not reflect how individuals in a community choose to behave.

In summary, the interplay between certain human behaviors and outbreak severity has so far been sparsely characterized. Adding to this complexity, this behavior-severity feedback may be very different for diseases with distinct transmission modalities –mosquito-borne, airborne, or transmitted via bodily fluids. As a consequence of these poor characterizations of the influence between human behavior and outbreak severity, public health officials often find themselves designing mitigation strategies, in the face of imminent disease outbreaks, based on intuition rather than past evidence. In addition, researchers designing and implementing mathematical models of infectious disease transmission to predict upcoming disease events often fail to include this feedback in their formulations, leading to discrepancies between model predictions and the eventually observed epidemic trajectories [32].

In this study, we contribute to the literature aimed at characterizing human behaviors and disease dynamics. Specifically, we used data from a national, large-scale representative survey conducted in the United States during the COVID-19 pandemic to characterize the temporal changes in *risk-averting* (e.g., avoiding contact with others) and *risk-exposing* behaviors (e.g., going to visit a friend). We analyzed the temporal evolution of 15 behaviors at the state and national levels in the US, aggregated from survey respondents, and evaluated how their temporal trends changed as the severity of COVID-19 outbreaks fluctuated. Characterizing the relationship between time and people's willingness to participate in protective (or exposing) behaviors, especially in relation to the current state of the epidemic and to social factors such as political leaning, is key to understanding how behavior should be integrated into predictive tools used to guide policy and decision-making.

We hypothesized that the time-varying estimates of behaviors would reveal how communities adapted to real-time information capturing the severity of local and national outbreaks. We additionally hypothesized that the estimates would vary across states, especially between states of different political leanings. Finally, we hypothesized that community adherence to government-led state-level non-pharmaceutical recommendations –to promote social distancing or mask-wearing, for example– would be significantly different even in states with similar levels of mandate stringency as recorded by the Oxford Stringency Index.

2 Results

Our national and state-level results can be summarized as follows: first, people were most willing to adhere to protective behaviors during the earlier stages of the pandemic, when uncertainty about the biology and consequences of COVID-19 infections was highest; second, protective behaviors decreased linearly and systematically over time; and third, there was synchronicity between temporal oscillations of protective behavior adoption and pandemic severity, indicating that higher proportions of people practiced behaviors such as social distancing and mask wearing during intense disease transmission periods as captured by times when COVID-19 attributable mortality was high. We also found that community adherence to government-led state-level non-pharmaceutical recommendations were substantially different even in states with similar levels of mandate stringency as recorded by the Oxford Stringency Index and that behavior adherence at the state level differed across states with different political leanings: specifically, Democrat-leaning states had higher proportions of people adhering to preventive behaviors compared to Swing and Republican leaning states.

2.1 Survey characteristics

We analyzed survey data from 431,211 responses to 19 survey waves of the COVID States Project (https://www.covidstates.org) collected between April 2020 and June 2022 in the United States. Each survey wave contained about 20,000 responses and lasted two to four weeks, providing both national and state-level samples. The survey is weighted to be representative of the U.S. population, and separate state-level weights are used for the state-level analysis. Given the large sample sizes and the usage of weights, we are confident that the trajectories of each behavior we observe are meaningful and representative of behavioral trends at the national level.

We use three different questions from the survey to obtain 15 different variables describing the levels of adherence to behaviors mitigating or exacerbating COVID-19 spread. The survey data was interpolated to ensure that we had monthly behavior estimates that would correspond to each data point from our COVID-19 severity observations (i.e., mortality, hospitalizations, and cases). Interpolation is used to generate monthly data from April 2020 to May 2020, using survey-collected behavior data from April 2020 to June 2022. Hence, the study period is April 2020 to May 2020. See Methods for details.

2.2 Protective behaviors were more prevalent when mortality was high and exhibited temporal linear decrease

We analyzed the national-level temporal trends of the risk-averting and risk-exposing behaviors by decomposing them into a linear decay (or increase) component and an oscillatory component **(Fig. 1)**. This decomposition revealed several findings. First, participation in risk-averting behaviors was highest at the start of the pandemic (in April 2020), with about 70% of respondents reporting *washing hands frequently* and/or *avoiding contact with others*. Conversely, participation in risk-exposing behaviors, such as *going to visit a friend*, was lowest in April 2020, with about only 8% of individuals engaging in these activities. Second, adherence to risk-averting behaviors decayed linearly over time (**Fig. 1b**), with a decrease of people *avoiding contact with others* of about 50% points over two years, a three-fold decrease from roughly 68% of respondents social distancing in April 2020 to about 22% in May 2022. Conversely, people willing to participate in risk-exposing behaviors such as *going to visit a friend* increased linearly over time (**Fig. 1e**), tripling in the same two-year period from about 8% to 28%. Third, the oscillatory components indicated that higher proportions of the population would practice social distancing (and other risk-averting behaviors) when COVID-19 transmission was most severe (as measured by real-time mortality indicators). Conversely, when COVID-19 severity was low, higher proportions of the population would engage in risk-exposing behaviors (**Fig. 1c, Fig. 1f**). We confirmed this using lag-correlation analysis (**Fig. 2**) which showed that the correlations between oscillatory components of risk-averting behaviors and reported COVID-19 deaths were highest at lag 0 (synchronous). The correlations between COVID-19 hospitalizations or cases and the behavior trends were demonstrated a different pattern, with similarly high correlations between those two severity metrics and behavior at lag 0 and with behavior values shifted one month into the future.

For clarity and communication purposes, Figure **Fig. 1** shows the time evolution of only two behaviors: *Avoiding contact with other people* and *Go visit a friend*. In Figures **Fig. S1** we show the time evolution, decomposition, and synchronicity analysis for all behaviors at the national level. Visually, the qualitative results described in the previous paragraph hold true for each risk-averting and risk-exposing behavior. To further quantify this finding, we analyzed the extent to which the time evolution of these behaviors were co-linear with each other over the two year time period of this study using Principal Component Analysis (PCA). The PCA (See Methods for details) allowed us to identify that about 88% of the variance of all 15 behaviors could be captured by the first principal component (eigen-behavior). This finding suggests that survey participants respond to survey questions with consistency, *i.e.*, a respondent who chooses to avoid contact with others in times of high mortality, very likely chooses to not go to the gym, and washes their hands frequently. This is also supported by the fact that, on average, the 15 behaviors considered in this study are highly correlated (see **Fig. S13**). Mathematically speaking, the decomposition and synchronicity analyses conducted for the two behaviors in Figure **Fig. 1** yields very similar results across behaviors as shown in **Fig. S1** and Supplementary Materials.

2.3 Geographic and temporal differences of behavior trends and their relationship to mortality

Because population-level behavioral responses to the severity of outbreaks varied significantly across different geographic regions, we also conducted the decomposition and synchronicity analyses of behaviors at the state level (**Supplementary Fig. S1, Supplementary Table S1, Table 1**). We conducted these analyses only in states that had sample sizes that would yield meaningful insights over the two years of our study. Specifically, we included in our analysis 40 states that had at least 200 responses to behavioral questions for each survey wave (we tolerated failing this criterion for at most one survey wave out of 19). The states that were not included in this analysis were Alaska, Wyoming, North Dakota, South Dakota, New Mexico, Vermont, Rhode Island, Montana, Hawaii, and the District of Columbia.

Overall, we observed that the linear components of behaviors in the 40 analyzed states displayed similar patterns to those observed at the national level, *i.e.*, risk-averting behaviors linearly decreased over time, and risk-exposing behaviors linearly increased over time. For example, in April 2020, the median adherence to avoiding contact with others was 66.9% (95% percentile range [PR]: 56.4%-76.9%), falling to a median adherence of 20.0% (95% PR: 13.7%-27.3%) in May 2022 **Supplementary Fig. S2A**. Examples of states with low adherence at the start of the study period include Utah and Missouri, while states with high adherence include

California and New Jersey. Conversely, in April 2020, the state-level median for going to visit a friend was 8.1% (95% PR: 4.2%-14.8%), increasing to a median of 27.5% (95% PR: 21.1%-32.7%) in May 2022 (**Supplementary**Fig. S2**B**). Examples of states with high participation in this behavior at the start of the study period were Oklahoma and Mississippi, while Michigan and New York had low participation.

We observed similar synchronicities between behaviors' oscillatory components and state-level mortality, albeit with a slightly increased variation compared to our observations at the national level. Of the 40 states analyzed, XX states had the highest correlation between protective behaviors and mortality at lag 0, while XX states had the highest correlation between protective behaviors and hospitalization at lag 0. We also did not observe strong correlations between cases and protective behaviors at the state-level, mirroring our national-level result.

materials/images/mainpic_v10.png

Figure 1: **Decomposition of behavior trends into a linear decay component and an oscillatory component. a, d**: The relationship between risk-averting behaviors (orange) or risk-exposing behaviors (green) and disease severity (mortality data, black) is not readily apparent. **b, e**: The linear decay components capture how the prevalence of risk-averting behaviors decreased over time, while the prevalence of risk-exposing behaviors increased over time. **c, f**: The oscillatory components are synchronized with trends in risk-averting behaviors and oppose the risk-exposing behavior trends.

2.4 State-level policies and political leaning are associated with differences in adherence to preventive health behaviors

We next examined how political leaning (as defined in Methods) and differences in recommendations or policies implemented by different states contributed to differences in behavior trends. We found that on average, people in Democratic states were more likely to adhere to to protective behaviors at the start of the pandemic compared to those in swing or Republican states **Fig. 3 (a, d)**. A complete comparison of political leaning and all 15 behaviors can be found in **Fig. S4**. These results concur with those from the decomposition analysis mentioned previously, as shown by the higher y-intercepts among linear components of each behavior trend among Democratic states compared to those for swing and Republic states (**Table 1**). The slopes of the linear components were not substantially different across political leanings, suggesting that changes in behavioral patterns across the nation were fairly uniform.

We also compared participation in both risk-averting and risk-exposing behaviors at the state level at the start of the pandemic to values of the Oxford Stringency Index (OSI) [33], a measure of the strictness of government policies in response to COVID-19, for a single risk-averting and risk-seeking behavior in **Fig. 3 (b, d)**. We find that for a single value of OSI, participation in behaviors varied across states. Republican states on average exhibited lower participation in risk-averting behaviors and higher participation in risk-exposing behaviors compared to Democratic states, implying that there were discrepancies between the rate of adherence to preventive behaviors as recommended by health authorities and the actual rate of participation as reported by respondents to our survey. For example, for an OSI value of 75 (indicating relatively high stringency of government recommendations), a greater proportion of respondents in the two Democratic states (Massachusetts (MA) and Virginia (VA)) adhered to risk-averting behaviors compared to respondents in the three Republican states (Louisiana (LA), Nebraska (NE) and Alaska (AK)).

For these five states, we also compared the level of adherence to the risk-averting behavior "avoiding contact with other people" to the OSI value for the states across our study period (Supplementary **Fig. S6**). We observed that the behavior curve fits closer to the OSI curve in Democratic states over time compared to in Republican states, even though all 5 states started with very similar OSI values. We repeated this analysis for all states for the "avoiding contact with other people" behavior **Fig. S6** and similarly observed higher adherence and closer trajectories between OSI and adherence among Democratic states versus swing and Republican States. Collectively, these analyses show a discrepancy in how the government would like individuals to behave (based on suggested mandates) and how individuals claim they are behaving (as inferred through the survey data). Similar figures to **Fig. 3 (a, c)** and **Fig. 3 (b, d)** for the remaining behaviors are respectively provided in **Fig. S4** and **Fig. S6** and the results are consistent with our findings above.

materials//images/lag_short_corr_mort_hosp_case_national_singlegrid_behcolored.png

Figure 2: **Correlations between oscillations in behavior trends and mortality are strongest at lag zero, while behavior trends anticipate cases and hospitalizations**. Risk-averting behaviors (orange outline) are strongly positively correlated with mortality (**a**) at lag zero. Risk-exposing behaviors (green outline) are similarly strongly negatively correlated with mortality at lag zero. Correlations comparing current behavior to cases and hospitalizations in the future are stronger than current or past cases and hospitalizations. Red boxes indicate positive correlations, while blue boxes indicate negative correlations. Darker hues represent strong correlations, while lighter hues represent weaker correlations.

materials/images/trend_osi_state_political.png

Figure 3: **State political leaning influences both trends in behavior and responses to differing levels of stringency of public health recommendations**. **a, c**: Survey respondents in Democratic states (blue) were more likely to adhere to preventive health behavior recommendations and less likely to take part in risk-exposing behaviors than those in Republican states (red), even as the adoption of preventive behaviors decreased and participation in risk-exposing behaviors increased over time. **b, d**: For a fixed level of the Oxford Stringency Index (OSI), survey participants from Democratic states were more likely to be strongly adherent to risk-averting recommendations and less likely to take part in risk-exposing behaviors compared to their Republican counterparts. Lines in panels **a** and **c** represent trajectories of behavior participation. Each dot in panels **b** and **d** represents an individual US state.

Table 1: **Democratic states reported higher baseline adherence to risk-averting behaviors and lower baseline adherence to risk-exposing behaviors compared to Swing and Republican states.** The mean y-intercept for the linear components of behavior trends in Democratic states was substantially higher than the y-intercepts in Swing and Republican states. Conversely, the y-intercepts for risk-exposing behaviors were substantially lower in Democratic states compared to Swing or Republican states. The similarity of slopes across political leanings suggests that Democratic, Swing, and Republican states experienced simliar rates of decreases (or increases) in adherence even though the baseline levels of adherence differed. SD: Standard deviation.

Behavior type	Avg. slope (SD)	Avg. y-intercept (SD)
	NATIONAL	
Risk-averting	-1.300 (0.405)	72.627 (8.814)
Risk-exposing	0.366 (0.232)	10.943 (11.960)
	DEMOCRATIC	
Risk-averting	-1.310 (0.435)	74.629 (9.132)
Risk-exposing	0.373 (0.256)	10.189 (11.025)
	SWING	
Risk-averting	-1.318 (0.419)	70.364 (8.616)
Risk-exposing	0.366 (0.234)	10.995 (11.634)
	REPUBLICAN	
Risk-averting	-1.231 (0.353)	66.014 (10.461)
Risk-exposing	0.307 (0.218)	12.660 (13.207)

3 Discussion

In this study, we used data from a representative, non-probability survey to highlight temporal trends of both risk-averting and risk-exposing behaviors during the COVID-19 pandemic in the United States. We found that adherence to risk-averting behavior recommendations was highest at the start of the pandemic and that this adherence waned over time; conversely, participation in risk-exposing behaviors steadily increased over time. We showed that these trends could be decomposed into a linear component and an oscillatory component and that the oscillations were synchronized with trends in disease severity measurements such as mortality and hospitalizations. This synchronization indicated that people were more likely to adhere to risk-averting recommendations when the risk of COVID-19 was highest and that people were most likely to expose themselves to COVID-19 infection when the mortality or hospitalization rate was low. Additionally, we identified that at the state level, adherence to risk-averting behaviors and participation in risk-exposing behaviors varied based on state political leaning and that this variation is not comprehensively captured by single-item stringency metrics like the Oxford Stringency Index [34].

Our national-level results have several important implications. First, we found that adherence to the four risk-averting behaviors we analyzed (avoiding contact with other people, avoiding public or crowded places, frequently washing hands, and wearing a face mask outside of your home) was high at the start of our study period in April 2020, with between 60% to 80% of survey respondents reporting adherence to each of these behaviors. These behaviors were all recommended by public health authorities as ways for people to reduce their risk of COVID-19 infection; their high prevalence is a testament to successful messaging of these non-pharmaceutical interventions at the start of the pandemic. Second, the linear, consistent decreases in adherence to the risk-averting behaviors over the course of the pandemic are evidence of a combination of factors that wore away at people's willingness to reduce their risk of infection, such as pandemic fatigue [35, 36], getting infected with SARS-CoV-2, or the growing availability of vaccinations. We observed that for similar levels of COVID-19 attributable mortality, the corresponding proportion of survey respondents adhering to "avoiding contact with other people" decreased from 68% in April 2020 to 50% in September 2021 and to 30% in February 2022. Third, the correlation of the oscillations of the behavior trends with COVID-19 severity implies that some individuals paid attention to the changes in COVID-19 mortality, hospitalizations, or case counts and synchronized their behaviors to the trajectory of the pandemic.

It is noteworthy that wearing a face mask in public demonstrated a different trajectory at the start of the pandemic compared to the other risk-averting behaviors, experiencing an increase in prevalence prior to declining (see fourth row of **Fig. S1**). This is reflected mathematically in the PCA analysis as mask-wearing behavior makes a significant contribution to the first two eigen-behaviors (see **Fig. S11** and **Fig. S12**); these eigen-behaviors respectively account for 87.80% and 10.44% variance of our 15 behavior data. In reality, such change in mask-wearing behavior may be due to factors such as the limited availability of masks and a lack of clear communication from the Centers for Disease Control and Prevention (CDC) and government agencies about the benefit of masking in the early phase of the pandemic [37]. For instance, on February 29, 2020, the U.S. Surgeon General advised against buying masks because "they are NOT effective" in preventing the general public from being infected with COVID-19 (although he argued that masks were much needed among the healthcare worker community) [37].

Differences in the temporal relationship between behaviors and COVID-19 mortality compared to the relationship between behaviors and the counts of COVID-19 hospitalizations or cases also have implications for messaging and policy-making. The synchronization of the behavior oscillations and the mortality data at monthly level (i.e., strongest correlations at lag 0) suggest a bidirectional feedback loop: information about deaths contributed to changes in behavior just as changes in behavior resulted in shifts in the number of deaths. However, we found that correlations between hospitalizations or cases were relatively strong when the behavior trend was shifted one month forward in addition to at lag 0, indicating that changes in severity were followed by changes in behavior. This supports the hypothesis that estimates of the pandemic's severity could trigger large-scale changes in peoples' behavior. For example, news reports of high case counts or hospitals at full capacity could lead to a reduction in the number of people choosing to travel for a holiday weekend. With these relationships in mind, we can hypothesize further that people may consider hospitalizations or cases (measures of severity that are more likely for any individual) a stronger stimulus for immediate behavior change that is realized over the coming weeks but that deaths (a serious, more concerning endpoint for a disease) are a stronger marker for the overall state of the pandemic.

Conducting the analyses at the state level expanded the context of the national-level results. Our finding that trajectories of behavior change were similar for almost all states but that there was noticeably higher adherence to risk-averting behaviors in Democratic states compared to

Swing or Republican states both at the start of the pandemic and over time lends credence to calls for differing levels of support for public health programs in states of different political backgrounds. This finding correlates with our observation that OSI values (reflecting the estimated stringency of non-pharmaceutical interventions in individual regions) more accurately reflected the adherence levels of respondents in Democratic states compared to those in Swing states or Republican states (because those respondents were more likely to be adherent in general). These findings, combined with evidence highlighting increased excess mortality due to COVID-19 among Republican voters compared to Democratic voters [38] and differences in COVID-19 testing consistency and reporting based on the political leaning of state governors[39] suggests that baseline differences in attitudes toward public health and pandemic preparedness could be potential targets for improvement as opposed to addressing policies governing the deployment of emergency services during a future pandemic.

With these policy considerations in mind, our data and our analyses aim to fill a gap in the availability of high-quality epidemiological data relating the severity of an epidemic and human behavior. Past research has shown that accounting for behavior change improves epidemiological models' ability to capture the trajectory of a disease and make predictions compared to models that do not explicitly account for behavior change [8, 40, 41]. However, in the absence of data like the survey data we present, these models often rely on disease severity metrics to serve as proxies of human behavior. For example, the transmission rate parameter of a susceptible-exposed-infectious-recovered (SEIR) model can be written as a function of the prevalence of the disease, such that when cases increase, transmission decreases and vice versa. Our analyses shows that behavior data were more correlated with mortality data than reported hospitalization or case data during our study period. This suggests that it may be more accurate to induce behavior change in COVID-19 models as a response to the number of deaths than to the number of cases or even hospitalizations. Additionally, the decreasing linear trends we observed for protective behaviors suggest that implementation of these behaviors into epidemiological models should take into account changes in behavior over time. This would ensure that the model could account for differences in behavior for the same level of degree of mortality as the modeling period extended forward in time as we observed in this study.

Furthermore, it is known that human behavior can vary by region, thus potentially requiring region-specific behavior-related parameters in a model. The time series data of 15 risk-averting and risk-seeking behaviors across all states may help modelers parameterize their models specifically for their region of interest. For example, modelers looking to capture granular data (such as changes in patterns in visits made to a workplace, restaurant, or a hospital) through a complex agent-based model (ABM) may benefit from our time series state-level data on these behaviors. Furthermore, although numerous models have incorporated masking behavior, very few, if any, have included time series masking behavior data into their model. The inclusion of this time series masking data (which for the above-discussed reasons might be different than what one might intuitively think) may not only add realism to the model but also help us accurately assess the impact of masking. Overall, incorporating region-specific time series risk-averting and risk-exposing behaviors into models would add realism to the modeling effort.

Our study has several limitations. First, the survey data we used in this study were collected in waves that varied in duration and frequency, thus requiring us to use interpolation methods to ensure we had data for each month of the study period. The survey was also not restricted to responses to yes/no binary questions and included responses from participants who participated multiple times; results from sensitivity analyses (see Supplementary Fig. S8), Supplementary Fig. S9) found that neither of these factors substantially influenced our results. Second, since we analyzed monthly data, we could not infer the lag between behavior anomalies and COVID-19-induced mortality and hospitalization at a weekly or daily level. Further studies should be conducted to pinpoint this lag to a more granular level or to conclusively determine if trends in behavior data precede or succeed those of disease severity metrics such as mortality, hospitalization, and cases. Finally, although this study was able to show differences in behavior across Democratic, Swing, and Republican states, the magnitude of these behavior differences at the state level was small, contrasting with other studies which found noticeable disparities in health outcomes across political affiliation. Further studies should to be conducted to confirm the state-level analyses wash out individual differences that could contribute to disparities in behavior. Kaashoek and colleagues [42] found that Republican-leaning counties with loose mask mandates experienced higher death rates than Democratic-leaning counties, so it is possible that looking at a finer resolution of the behavior data may reveal larger disparity in behaviors among individuals who identify as Democrats or Republicans.

In conclusion, we expect that the available survey data will be useful in the parameterization of epidemiological models that integrate behavior into their processes by providing multiple behavior change metrics over the course of an extended outbreak. Such data should be especially useful for long-term prediction of disease trajectories or the building of policies that seek to provide effective prevention tools before the onset of disease outbreaks.

4 Methods

4.1 Survey data

We used survey data from the COVID States Project [43], a non-probability survey started on April 16, 2020 in the United States. Following the American Association for Public Opinion Research (AAPOR) reporting guidelines [44], we provide details on the recruitment, weighting, and survey content of the survey data here. Most respondents are recruited through PureSpectrum, a survey platform that aggregates survey respondents from different online survey vendors. An additional small percentage of survey responses (4.6%) are recruited through Facebook ads. The recruitment through PureSpectrum does not specify the focus of the survey on COVID-19 related topics, reducing the risk of selection bias. Survey respondents are 18 years or older and reside in the United States.

The data consists of several survey waves, defined as the distinct periods of time in which responses are gathered from survey respondents, that were fielded approximately every 6 weeks. Each survey wave contains about 20,000 survey responses, with viable sample sizes for most U.S. states in most waves (see Section 5 for details on the states with smaller samples). For this study, we used data from 19 survey waves, collected between April 2020 and June 2022. A detailed description of the fielding period of each survey wave and its total sample size can be found in Supplementary Table S3. We also provide the sample size for each state, for each survey wave and for each survey question used in SM Table XX. Survey respondents were permitted to participated in more than one survey wave; in total, we used 431,211 survey responses from 307,771 different respondents. We test for the robustness of our results to the removal of responses from repeat participants in Supplementary Section 5.

We use quotas and post-stratification weights to ensure the representativity of the COVID States samples, nationally and at the state level. State-level quotas for age, gender and race/ethnicity were used at the sampling stage to approximate the demographic composition of each state in the survey sample. Weights based on interlocking race/ethnicity-gender-age subgroups as well as education, rurality, and region were used at the national level. A separate set of weights was used at the state level, matching the gender, race, age, education, and rurality composition of the survey samples with the composition of the state from which responses were collected. The top and bottom 1% of the weights are trimmed to reduce the influence of a small set of respondents. Population benchmarks are taken from the US Census Bureau. The surveys also include multiple closed and open-ended attention checks, with the goal of filtering out inattentive respondents, addressing a common issue associated with online opt-in surveys [45, 46]. Around 25% of respondents are filtered due to failed attention checks, and the attrition rate is roughly 15%-20%. The surveys include questions on health, social, informational, and political issues related to the COVID-19 pandemic. The questions analyzed in this study were included in blocks of questions related to preventive behaviors (such as vaccinations or avoiding infection risks) and social behaviors, typically included around the middle of the survey. We provide in Supplementary Section 5 the full survey text of one of the survey waves. The study design was determined to be exempt by the institutional review boards of Harvard University and Northeastern University. Moreover, survey participants accepted an electronic informed consent online before having access to the survey.

4.2 Survey collected behavior data

The behavior data was obtained from survey questions encompassing both risk-averting and risk-exposing behaviors. For risk-averting behaviors, we used survey answers to the question "In the last week, how closely did you personally follow the health recommendations listed below?", that was followed-up by four behaviors: "Avoiding contact with other people", "Avoiding public or crowded places", "Frequently washing hands", and "Wearing a face mask when outside of your home". Possible responses to these questions ranged from 1 to 4, where 1 represented "Not at all closely", 2 represented "Not very closely", 3 represented "Somewhat closely", and 4 represented "Very closely". We defined adherence or participation in risk-averting behaviors as answering "Very closely", but also include a sensitivity analysis in Supplementary **Fig. S9** where we defined adherence as the proportion of participants that answered "Somewhat closely" or "Very closely."

For risk-exposing behavior, we asked, "In the last 24 hours, did you or any members of your household do any of the following activities outside of your home?", which included possible responses such as "Go visit a friend" and "Go to a cafe, bar, or restaurant", and "In the last 24 hours, have you been in a room (or another enclosed space) with people who were not members of your household?", with answers options ranging from "No, I have not" to "Yes, with over 100 other people". We aggregate the answers to this question in four different groups for our main analysis and test two additional groupings in Supplementary **Fig. S9**. Details of the questions, answers, and aggregation procedures as well as the missing data for each question can be found in the Supplementary Materials 5. We calculate the 95% confidence intervals corresponding to each survey estimate, at the national level and for each state, using the standard error provided by the *survey* package in R, that uses a design effect to take into account the influence of survey weights on errors. A table with all survey estimates (nationally, for each state, for each wave, and for each behavior) and their corresponding 95% confidence interval is provided in SM table XX. A summary of the states with larger error margins on average can be found at 5. Results presented at the national level include data from all 50 states and the District of Columbia; however, state-level results related to behavior data include only the 40 states that had less than

200 responses for each behavior question for no more than one survey wave (the excluded regions were Alaska, Wyoming, North Dakota, South Darkota, New Mexico, Vermont, Rhode Island, Montana, Hawaii, and the District of Columbia).

4.3 Data preparation

To account for differences in the length of each survey wave and the time interval between individual waves, we used polynomial interpolation (specifically, second-order interpolation) to generate estimates of behavioral data for each month of the study period. For simplicity, we refer to the data generated through interpolation as *behavior data*.

Since the behavior data in some form is compared with disease severity data (namely, mortality, hospitalization, and case data) monthly time series disease severity data is generated. Specifically, COVID-19 death data is obtained from the Johns Hopkins University COVID-19 Data Repository [47] while COVID-19 hospitalizations and detected case data are obtained from Our World in Data [48].

4.4 Decomposition of behavior data

We decomposed behavior data into a linear and an oscillatory component. The linear trends were obtained by fitting a linear model to each of the 15 risk-averting and risk-exposing behaviors. The oscillatory component of the behavior data is the deviation of the behavior data from the linear model. In other words, the oscillatory component is the residual of the linear model.

4.5 Demographic data

To assess the influence of political leaning on each individual behavioral trend, we categorized each state as either a Democratic, Republican, or swing state based on the voting results in the past two United States presidential elections (2016 and 2020; see Table S2 in Supplementary Materials for more information). States were classified as swing states if the state did not vote to elect a presidential candidate from the same political party in consecutive elections (for example, in 2016, Wisconsin voted to elect Donald Trump, the Republican candidate, but voted in 2020 to elect Joe Biden, the Democratic candidate).

We also evaluated if a simple stringency measure could serve as a proxy for our behavioral time-series data by comparing the prevalence of each behavior during survey wave 1 for fixed levels of stringency. We chose the Oxford Stringency Index (OSI) [34, 49, 33] for our comparison, which is a composite index that reflects the average level of restriction in a geographic sub-region. OSI is based on nine mitigation policies, including cancellation of public events, school closures, gathering restrictions, workplace closures, border closures, internal movement restrictions, public transport closure, recommendations to stay at home, and stay-at-home orders [50]. The OSI ranges from 0 to 100, where 100 is the most stringent level of restriction. We hypothesized that our time-varying prevalence estimates would be useful if we observed differences in prevalence across different values of the OSI.

4.6 Correlation analysis

Lagged correlation analysis is conducted by temporally shifting the oscillatory component of risk-averting and risk-exposing behaviors with respect to the trends in disease severity metrics, namely COVID-19 mortality, hospitalizations, and detected cases. A lag of zero indicates no temporal shift in the oscillatory component of behavior, that is disease severity metrics are being correlated with this month's behavior. Meanwhile, a positive lag indicates that disease severity metrics are correlated with future months' behavior, and a negative lag indicates that disease severity metrics are correlated with past months' behavior.

4.7 Principal component analysis

Principal component analysis (PCA) is used to transform a large set of variables (here, fifteen risk-exposing and risk-averting behavior data) into a smaller set that contains most of the information of the original variables. This is done by creating new variables, called principal components (referred in this study as the *eigen-behaviors*), which are linear combinations of the original variables. The first eigen-behavior explains the largest variance of the behavior data. The subsequent eigen-behaviors explain the next largest amount of variance while remaining orthogonal to all previous eigen-behaviors (i.e., the subsequent eigen-behaviors capture variance that is not captured by the earlier eigen-behaviors). The contribution of each variable towards the eigen-behaviors can be assessed from principal component coefficients (loadings). A positive or negative loading respectively indicates a positive or negative correlation towards the eigen-behaviors.

4.8 Data availability

Data and analysis code used in the study can be found in the following Github Repository: `https://github.com/tam-urmi/behavior_covid_states/tree/main/data`. Behavior data was obtained from surveys conducted by the COVID States Project, a consortium of researchers from multiple disciplines which aims to identify connections between social behaviors, communication, and virus transmission during the COVID-19 pandemic [43]. We obtained COVID-19 mortality data from the Johns Hopkins University COVID-19 Data Repository [47] and COVID-19 hospitalization and detected case data from Our World in Data [48].

We used the 2021 United States Census estimates [51] to scale survey response levels to the population of each state. State political leaning was determined by aggregating publicly available data from CNN on the results of the 2016 and 2020 United States presidential elections [52]. We obtained the Oxford Stringency Index (OSI) values from the University of Oxford's Coronavirus Government Response Tracker GitHub page [53].

References

[1] First Global Patient Safety Challenge. "WHO Guidelines on Hand Hygiene in Health Care". In: *Retrieved from: whqlibdoc who int/publications/009 pdf* (2009).

[2] Benjamin Rader et al. "Mask-wearing and control of SARS-CoV-2 transmission in the USA: a cross-sectional study". In: *The Lancet Digital Health* 3.3 (2021). doi: 10.1016/S2589-7500(20)30293-4, e148–e157. ISSN: 2589-7500. DOI: 10.1016/S2589-7500(20)30293-4. URL: https://doi.org/10.1016/S2589-7500(20)30293-4.

[3] Jeremy Howard et al. "An evidence review of face masks against COVID-19". In: *Proceedings of the National Academy of Sciences* 118.4 (2021). doi: 10.1073/pnas.2014564118, e2014564118. DOI: 10.1073/pnas.2014564118. URL: https://doi.org/10.1073/pnas.2014564118.

[4] Nazrul Islam et al. "Physical distancing interventions and incidence of coronavirus disease 2019: natural experiment in 149 countries". In: *BMJ* 370 (2020), p. m2743. DOI: 10.1136/bmj.m2743. URL: https://www.bmj.com/content/bmj/370/bmj.m2743.full.pdf.

[5] Shengjie Lai et al. "Effect of non-pharmaceutical interventions to contain COVID-19 in China". In: *Nature* 585.7825 (2020), pp. 410–413.

[6] Seth Flaxman et al. "Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe". In: *Nature* 584.7820 (2020), pp. 257–261.

[7] Jocelyne Piret and Guy Boivin. "Pandemics Throughout History". In: *Frontiers in Microbiology* 11 (2021). ISSN: 1664-302X. DOI: 10.3389/fmicb.2020.631736. URL: https://www.frontiersin.org/journals/microbiology/articles/10.3389/fmicb.2020.631736.

[8] Daihai He et al. "Inferring the causes of the three waves of the 1918 influenza pandemic in England and Wales". In: *Proceedings of the Royal Society B: Biological Sciences* 280.1766 (2013), p. 20131345.

[9] Sandro Meloni et al. "Modeling human mobility responses to the large-scale spreading of infectious diseases". In: *Scientific reports* 1.1 (2011), p. 62.

[10] Harrysone E Atieli et al. "Insecticide-treated net (ITN) ownership, usage, and malaria transmission in the highlands of western Kenya". In: *Parasites & vectors* 4 (2011), pp. 1–10.

[11] Abdihamid Warsame et al. "Performance of a safe and dignified burial intervention during an Ebola epidemic in the eastern Democratic Republic of the Congo, 2018–2019". In: *BMC medicine* 21.1 (2023), p. 484.

[12] Carrie F Nielsen et al. "Improving burial practices and cemetery management during an Ebola virus disease epidemic—Sierra Leone, 2014". In: *MMWR Morb Mortal Wkly Rep* 64.1 (2015), pp. 20–27.

[13] *COVID-19 Update for the United States*. https://covid.cdc.gov/covid-data-tracker/. Accessed: 2023-01-30.

[14] *COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University*. https://github.com/CSSEGISandData/COVID-19. Accessed: 2023-01-30.

[15] Fuqing Wu et al. "SARS-CoV-2 RNA concentrations in wastewater foreshadow dynamics and clinical presentation of new COVID-19 cases". In: *Science of The Total Environment* 805 (2022), p. 150121.

[16] Fizza Manzoor and Donald A Redelmeier. "COVID-19 deaths on weekends". In: *BMC Public Health* 23.1 (2023), p. 1596.

[17] Elizabeth M White. "Underreporting of early nursing home COVID-19 cases and deaths in federal data". In: *JAMA network open* 4.9 (2021), e2123696–e2123696.

[18] Elaine O Nsoesie et al. "Monitoring disease trends using hospital traffic data from high resolution satellite imagery: a feasibility study". In: *Scientific reports* 5.1 (2015), p. 9112.

[19] Vittoria Colizza et al. "The role of the airline transportation network in the prediction and predictability of global epidemics". In: *Proceedings of the National Academy of Sciences* 103.7 (2006), pp. 2015–2020.

[20] Matteo Chinazzi et al. "The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak". In: *Science* 368.6489 (2020), pp. 395–400.

[21] Kyra H Grantz et al. "The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology". In: *Nature communications* 11.1 (2020), p. 4961.

[22] Amy Wesolowski et al. "Quantifying the impact of human mobility on malaria". In: *Science* 338.6104 (2012), pp. 267–270.

[23] Amy Wesolowski et al. "Impact of human mobility on the emergence of dengue epidemics in Pakistan". In: *Proceedings of the national academy of sciences* 112.38 (2015), pp. 11887–11892.

[24] Michele Tizzoni et al. "On the use of human mobility proxies for modeling epidemics". In: *PLoS computational biology* 10.7 (2014), e1003716.

[25] Dennis M Feehan and Ayesha S Mahmud. "Quantifying population contact patterns in the United States during the COVID-19 pandemic". In: *Nature communications* 12.1 (2021), p. 893.

[26] Yang Liu et al. "The impact of non-pharmaceutical interventions on SARS-CoV-2 transmission across 130 countries and territories". In: *BMC Medicine* 19.1 (2021), p. 40. ISSN: 1741-7015. DOI: 10.1186/s12916-020-01872-8. URL: https://doi.org/10.1186/s12916-020-01872-8.

[27] Shashank Vaid et al. "Risk of a second wave of Covid-19 infections: using artificial intelligence to investigate stringency of physical distancing policies in North America". In: *International Orthopaedics* 44.8 (2020), pp. 1581–1589. ISSN: 1432-5195. DOI: 10.1007/s00264-020-04653-3. URL: https://doi.org/10.1007/s00264-020-04653-3.

[28] Asmita P. Khatiwada et al. "Vaccination and non-pharmaceutical interventions during COVID-19: Impact on health and non-health outcomes in the US". In: *Health Policy and Technology* 13.1 (2024), p. 100792. ISSN: 2211-8837. DOI: https://doi.org/10.1016/j.hlpt.2023.100792. URL: https://www.sciencedirect.com/science/article/pii/S2211883723000680.

[29] Diogo Costa, Sven Rohleder, and Kayvan Bozorgmehr. "Impact of non-pharmaceutical interventions on COVID-19 incidence and deaths: cross-national natural experiment in 32 European countries". In: *BMC Public Health* 24.1 (2024), p. 2341. ISSN: 1471-2458. DOI: 10.1186/s12889-024-19799-7. URL: https://doi.org/10.1186/s12889-024-19799-7.

[30] Han Yan et al. "Better strategies for containing COVID-19 pandemic: a study of 25 countries via a vSIADR model". In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 477.2248 (2021). doi: 10.1098/rspa.2020.0440, p. 20200440. DOI: 10.1098/rspa.2020.0440. URL: https://doi.org/10.1098/rspa.2020.0440.

[31] Ann Osi and Navid Ghaffarzadegan. "A Simultaneous Simulation of Human Behavior Dynamics and Epidemic Spread: A Multi-Country Study Amidst the Covid-19 Pandemic". In: *Available at SSRN 4782272* ().

[32] Estee Y Cramer et al. "Evaluation of individual and ensemble probabilistic forecasts of COVID-19 mortality in the United States". In: *Proceedings of the National Academy of Sciences* 119.15 (2022), e2113561119.

[33] Thomas Hale et al. "A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)". In: *Nature Human Behaviour* 5.4 (2021), pp. 529–538.

[34] Thomas Hale et al. "Oxford COVID-19 government response tracker (OxCGRT)". In: *Last updated* 8 (2020), p. 30.

[35] Federico Delussu, Michele Tizzoni, and Laetitia Gauvin. "Evidence of pandemic fatigue associated with stricter tiered COVID-19 restrictions". In: *PLOS Digital Health* 1.5 (2022), e0000035. DOI: 10.1371/journal.pdig.0000035. URL: https://doi.org/10.1371/journal.pdig.0000035.

[36] World Health Organization. *Pandemic fatigue – reinvigorating the public to prevent COVID-19. Policy framework for supporting pandemic prevention and management.* Government Document. 2020. URL: https://iris.who.int/bitstream/handle/10665/335820/WHO-EURO-2020-1160-40906-55390-eng.pdf.

[37] *A timeline of the CDC's advice on face masks*. URL: https://www.yahoo.com/news/timeline-cdcs-advice-face-masks-234738419.html (visited on 07/27/2021).

[38] Jacob Wallace, Paul Goldsmith-Pinkham, and Jason L Schwartz. "Excess death rates for republican and democratic registered voters in Florida and Ohio during the COVID-19 pandemic". In: *JAMA Internal Medicine* 183.9 (2023), pp. 916–923.

[39] Brian Neelon et al. "Associations between governor political affiliation and COVID-19 cases, deaths, and testing in the US". In: *American journal of preventive medicine* 61.1 (2021), pp. 115–119.

[40] Binod Pant et al. "Mathematical Assessment of the Role of Human Behavior Changes on SARS-CoV-2 Transmission Dynamics in the United States". In: *Bulletin of Mathematical Biology* 86.8 (2024), p. 92.

[41] Caitlin Ward, Rob Deardon, and Alexandra M Schmidt. "Bayesian modeling of dynamic behavioral change during an epidemic". In: *Infectious Disease Modelling* 8.4 (2023), pp. 947–963.

[42] Justin Kaashoek et al. "The evolving roles of US political partisanship and social vulnerability in the COVID-19 pandemic from February 2020–February 2021". In: *PLOS global public health* 2.12 (2022), e0000557.

[43] *The COVID States Project*. URL: https://www.covidstates.org/ (visited on 05/01/2024).

[44] *Best Practices for Survey Research - AAPOR — aapor.org*. https://aapor.org/standards-and-ethics/best-practices/. [Accessed 17-06-2024].

[45] Courtney Kennedy et al. *Assessing the Risks to Online Polls From Bogus Respondents*. en-US. 2020. URL: https://www.pewresearch.org/methods/2020/02/18/assessing-the-risks-to-online-polls-from-bogus-respondents/ (visited on 07/29/2024).

[46] Andrew Mercer, Courtney Kennedy, and Scott Keeter. *Online opt-in polls can produce misleading results, especially for young people and Hispanic adults*. en-US. 2024. URL: https://www.pewresearch.org/short-reads/2024/03/05/online-opt-in-polls-can-produce-misleading-results-especially-for-young-people-and-hispanic-adults/ (visited on 07/29/2024).

[47] *GitHub - CSSEGISandData/COVID-19: Novel Coronavirus (COVID-19) Cases, provided by JHU CSSE — github.com*. https://github.com/CSSEGISandData/COVID-19. [Accessed 17-06-2024].

[48] *Coronavirus (COVID-19) Hospitalizations — ourworldindata.org*. https://ourworldindata.org/covid-hospitalizations. [Accessed 20-06-2024].

[49] Thomas Hale et al. "Variation in government responses to COVID-19". In: (2020).

[50] James A Fuller. "Mitigation policies and COVID-19–associated mortality—37 European countries, January 23–June 30, 2020". In: *MMWR. Morbidity and Mortality Weekly Report* 70 (2021).

[51] US Census Bureau. *Census.gov — census.gov*. https://www.census.gov/en.html. [Accessed 17-06-2024].

[52] *2020 presidential election results — cnn.com*. https://www.cnn.com/election/2020/results/president. [Accessed 02-07-2024].

[53] *Oxford Covid-19 Government Response Tracker (OxCGRT)*. URL: https://github.com/OxCGRT/covid-policy-dataset (visited on 10/29/2020).