Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

HUMAN-INFRASTRUCTURE INTERACTIONAL DYNAMICS: SIMULATING COVID-19 PANDEMIC REGIME SHIFTS

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ABSTRACT

When subject to disruptive events, the dynamics of human-infrastructure interactions can absorb, adapt, or, in a more abrupt manner, undergo substantial change. These changes are commonly studied when a disruptive event perturbs the physical infrastructure. Infrastructure breakdown is, thus, an indicator of the tipping point, and possible regime shift, in the human-infrastructure interactions. However, determining the likelihood of a regime shift during a global pandemic, where no infrastructure breakdown occurs, is unclear. In this study, we explore the dynamics of human-infrastructure interactions during the global COVID-19 pandemic for the entire United States and determine the likelihood of regime shifts in human interactions with six different categories of infrastructure. Our results highlight the impact of state-level characteristics, executive decisions, as well as the extent of impact by the pandemic as predictors of either undergoing or surviving regime shifts in human-infrastructure interactions.

1 INTRODUCTION

The capacity of urban built environment for sustainability and resilience is, to a large degree, driven by the vulnerability of its infrastructure to disruption. Vulnerability to disruption is often characterized by the susceptibility of the infrastructure to large, persistent changes caused by natural or man-made disruptions such as earthquakes, flooding, wildfires, transport accidents, aging infrastructure, terrorist attacks, etc. These phenomena commonly lead to infrastructure breakdown, interrupted supply, and can result in critical transitions and a regime shift in the structure and function of the infrastructure system. Paradoxically, in the event of a global pandemic, with minimal risk of infrastructure breakdown, interruptions do not directly target the structure and function of the infrastructure system, but simply impose a change in the essential service supply of the infrastructure that is disrupted by external drivers (i.e., possibly a critical decline in demand). Such perturbations, if significant, can lead to a regime shift in the infrastructure supply and demand equilibrium, and, by extension, a regime shift in the entirety of human-infrastructure system interactions.

The World Health Organization (WHO) declared the novel coronavirus (COVID-19) outbreak a global pandemic on March 11, 2020. The global human-infrastructure system abruptly received a very rare type of shock event that was severe enough to suspend a majority of human-infrastructure interactions for months. It is unclear whether the continued changes in the human-infrastructure interactions will cause a regime shift and whether the system will pass critical thresholds. This is crucial in the ability of the system to adapt, absorb, and recover from the disruption in the interactions between the physical infrastructure and the urban population who depend on essential infrastructure services. A regime shift corresponds to the phenomenon of substantial, and often abrupt, change and reorganization in the structure, function, and feedback of a system (Scheffer 2009; Walker et al. 2004; Brock et al. 2008). Regime shifts due to a shock event (e.g., pandemic) can overwhelm the dominant feedback loops of human-infrastructure systems and lead to passing a critical threshold in human-infrastructure interactions, where a new set of feedback loops begin to become dominant, resulting in the system self-organizing into a new regime (Scheffer et al. 2001). A possible example of such a phenomenon in US transit stations, due to the COVID-19 pandemic, can be observed in Figure 1; where there is a clear, abrupt drop in the human mobility of the transit infrastructure at the state-level. In this study, we investigate this phenomenon and explore the probability of a region suffering a regime shift in human-infrastructure interactions. In particular, we examine the likelihood of critical transitions in human-infrastructure interactions due to significant changes in the mobility of the population for all 50 US states and the District of Columbia (DC) considering the ecological resilience, which is concerned with the likelihood of a system to shift between multiple equilibria (Kinzig et al. 2006). We investigate the critical transitions and possible regime shifts (Carpenter et al. 2011; Scheffer et al. 2009) in the human-infrastructure interactions by developing a predictive model to determine possible thresholds at which point critical transitions in human-infrastructure interactions could move beyond a tipping point. We then determine the key parameters that have the highest probability of predicting such regime shifts in the future, exploring how the impact of each parameter unfolds across different states.

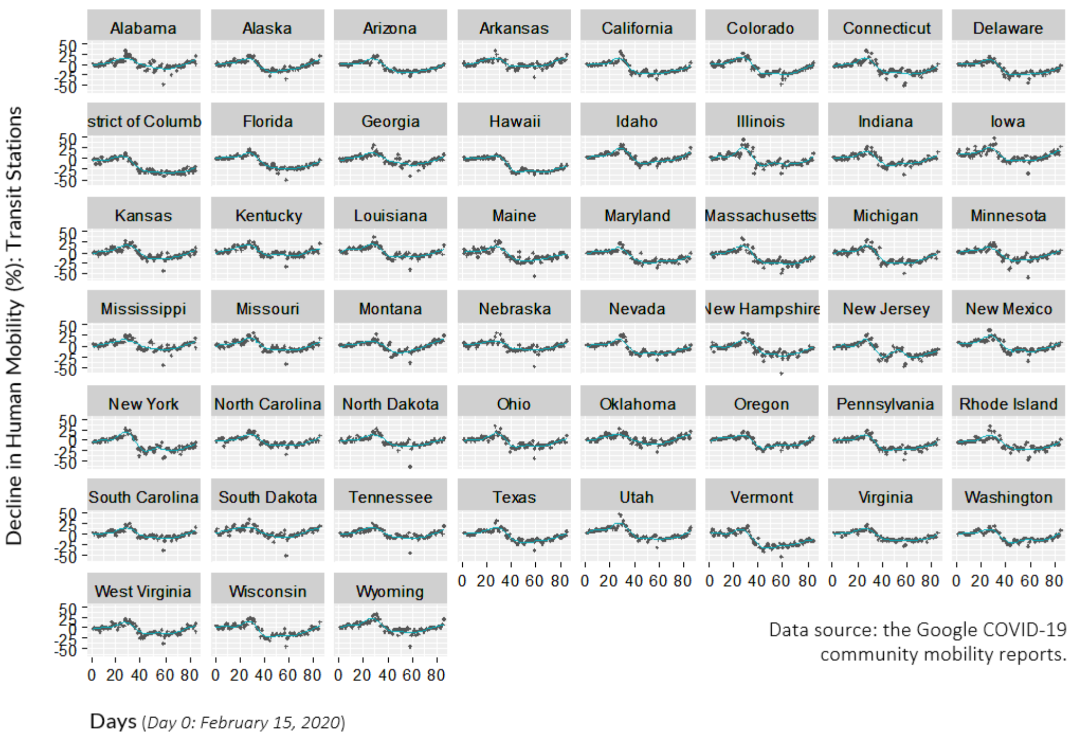


Figure 1: Critical state-level decline of human mobility in US transit stations due to COVID-19 pandemic.

2 METHODS

2.1 Data

The study was conducted for a total duration of 90 days (February 15, 2020 to May 15, 2020). The mobility dataset was retrieved from the Google COVID-19 community mobility reports (Google LLC 2020) and highlights the change in human mobility for the six categories shown in Table 1. These categories are recognized to provide access to the most essential underlying infrastructure services and are largely impacted by social distancing regulations. Changes in mobility are measured for each day by comparing to a baseline (median value) during Jan 3-Feb 6, 2020 for the corresponding day of the week (Google LLC

2020). Other state-level variables are retrieved from the COVID-19 US state policy database (Raifman et al. 2020), and the COVID tracking project (The Atlantic 2020) for state-level COVID-19 cases, including percentage of population at risk for serious illness due to COVID-19, number of individuals tested positive and negative for COVID-19, number of deaths, recovered, hospitalized and treated in intensive care units (ICU) due to COVID-19. Please refer to Table 2 for a complete list of variables examined in this study.

Table 1: Infrastructure categories of state-level community mobility (Google LLC 2020).

Category	Description
Grocery & Pharmacy	Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.
Parks	Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.
Transit Stations	Mobility trends for places like public transport hubs such as subway, bus, and train stations.
Retail & Recreation	Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
Residential	Mobility trends for places of residence.
Workplaces	Mobility trends for places of work.

2.2 Regime Shift

Figure 2 depicts the overall state-level trends and critical transitions that suggest the possibility of one or more regime shifts in each of the six aforementioned categories of infrastructure due to pandemic.

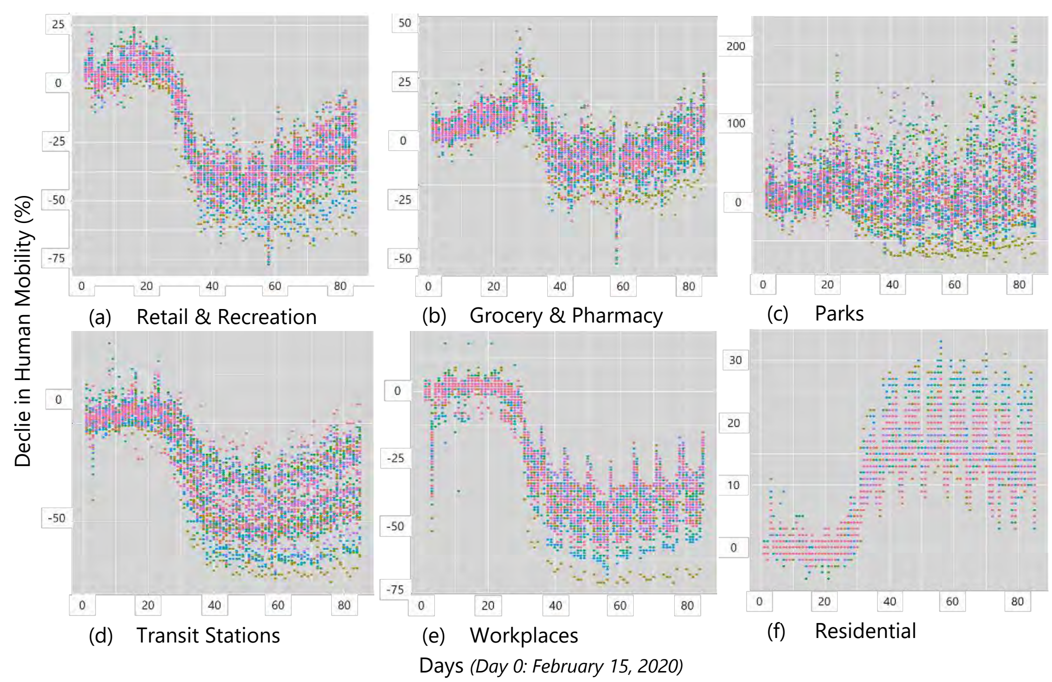


Figure 2: State-level regime shifts in human-infrastructure interactions (colors represent different states).

In order to distinguish and characterize these shifts or abrupt changes (i.e., either an abrupt shift in the rate of change or between two stable states) in the mobility patterns of individuals, we implemented model fitting over a series of change point models. These models include constant mean, linear trend, multiple change points in the mean, and trend with multiple change points in the regression parameters (all models fitted for both w/ and w/o first-order autocorrelation) (Beaulieu and Killick 2018); piecewise linear segmentation (Muggeo 2003), simultaneous multiple change point detection (Jin et al. 2016), non-parametric multiple change point analysis (James and Matteson 2013), and Bayesian analysis of change point to estimate means and probability of change point at each point in time (Erdman and Emerson 2007). In each case, we selected the most representative model fit that describes the mobility patterns.

2.3 Time-to-Event Prediction: Cox Proportional Hazards Model

Next we developed a Cox proportional hazards model (1) (Cox 1972) to investigate the association between several explanatory variables and the likelihood of a regime shift in human-infrastructure interactions (inferred from human mobility patterns) taking place between the time of (a) declaration of State of Emergency, and (b) stay at home/shelter in place order during the pandemic. Several conditions potentially affect the occurrence of a critical transition and regime shift. For example, each state has a different population density, different policies on mandating and/or suspending activities and businesses, a different number of deaths per day and percentage of individuals at risk for serious illness due to COVID-19, etc. Table 2 provides a complete list of the 28 predictors or explanatory variables (i.e., covariates) of interest examined in this study (Raifman et al. 2020; The Atlantic 2020). The model was used for multivariate analysis and simultaneously identifying the effect of predictors on regime shifts in all six categories of infrastructure. The proportional hazard ratios are given by the hazard function (Andersen and Gill 1982; Therneau and Grambsch 2000):

$$h(t)=h_0(t)\times exp(\beta_1 x_1+\beta_2 x_2+\ldots+\beta_p x_p) \quad (1)$$

where t equals survival time; $h(t)$ is the hazard function (probability that a state will experience a regime shift) for a state at risk at time t, determined by a set of p covariates x_k $(k = 1,\ldots,p)$; the coefficient β_k $(k = 1,\ldots,p)$ measures the effect size of the covariates; finally, $h_0(t)$, the baseline hazard, corresponds to the value of the hazard if all the x_k are equal to zero. The 't' in $h(t)$ reminds us that the hazard may vary over time.

A proportional hazard means that the change in a predictor results in a proportional change of the hazard on a log scale and the proportion is equal to the coefficient β. A function of the coefficient β, $exp(\beta)$, represent the hazard ration (HR). A HR greater than one (β_k greater than zero), indicates that increases in the covariate x_k , results in increases in the event hazard (probability) and, thus, decreases in the length of survival (HR = 1: No effect; HR < 1: Decreases in hazard; HR > 1: Increase in hazard).

3 RESULTS

A total of 50 US states, plus DC (due the high impact executive decisions of DC, we have considered this region independently in our analysis), and 243 regime shift events across the six infrastructure categories were examined in this study. Of these, 24 states declared a State of Emergency with a delay from the day WHO declared COVID-19 a global pandemic on March 11, 2020 (we have determined this date as the onset of the pandemic outbreak in this study), 8 declared on the same day, and 19 declared before the WHO announcement, as early as February 29, 2020 (State of Alabama). Finally, 11 states had not issued a Shelter in place/Stay at home executive order following the global pandemic declaration as of May 20, 2020 (See Supplementary Figure 1, Appendix A for additional details on the timeline of events occurred within the duration of this study). The median time of regime shift was 6 days from the WHO announcement (ranging from 1 to 58 days). This shows that most of the shifts occurred in the early days of the pandemic outbreak.

3.1 Regime Shifts following State Declarations of State of Emergency

Upon fitting several change point models and examining the relevance and accuracy of the change points detected by each model, we identified the best-fitting model and the corresponding largest single change point detected in each, per infrastructure category for each state. These measures were then incorporated into the Cox Proportional Hazards model for investigating the effect of predictors, as well as the likelihood of a regime shift in future pandemics. Figure 3 depicts the results of Bayesian analysis of change point to estimate means and probability of change point (Erdman and Emerson 2007) for the human interactions with the six infrastructure categories across time in the state of Georgia following the COVID-19 pandemic. Interestingly, the results suggest a major human-infrastructure regime shift, at a relatively similar point in time, for four of the six infrastructure categories.

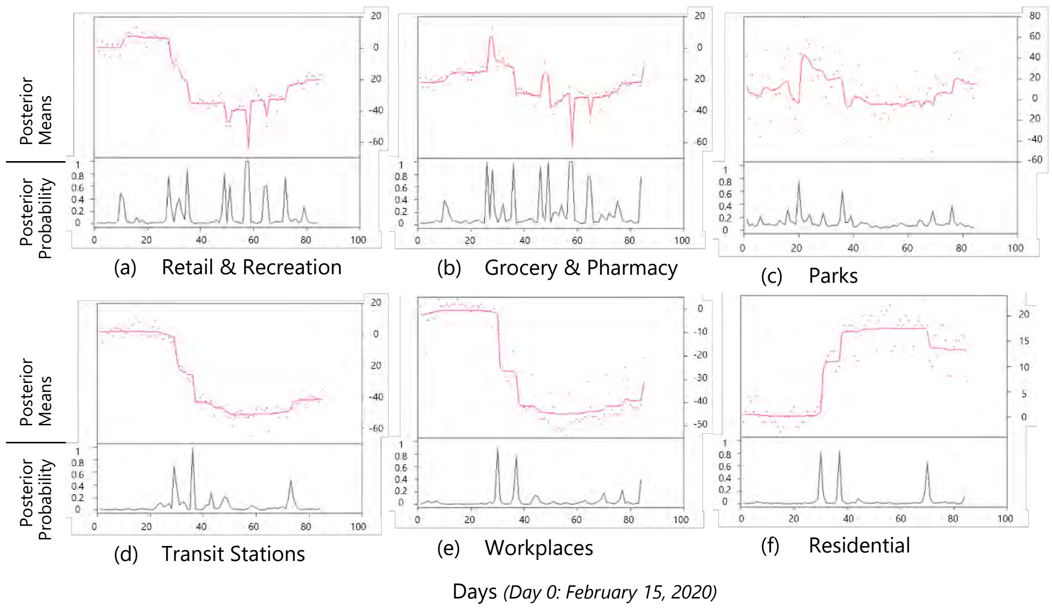


Figure 3: Regime shifts in human-infrastructure interactions in the state of Georgia following the COVID-19 pandemic.

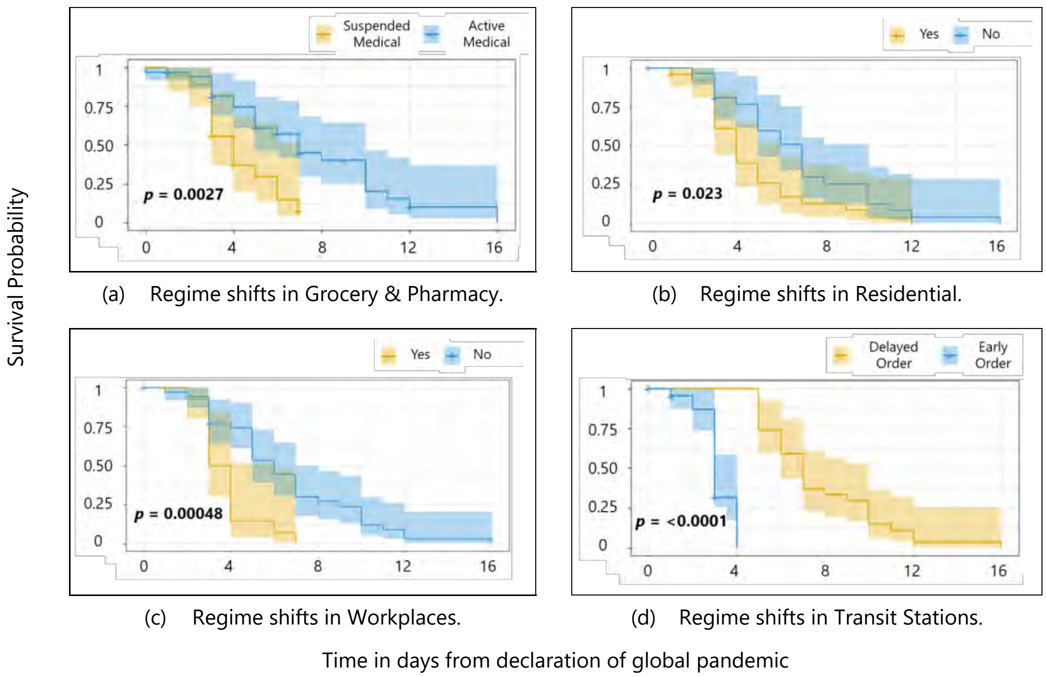
3.2 Predictors of Regime Shifts in Human-Infrastructure Interactions

We began the variable selection of the Cox Proportional Hazards model by implementing univariate analysis on an initial list of 28 variables. Fitting a univariate model for each covariate, we screened out those that are likely noise, and identified the predictors that are significant at 25 percent level ($p_1 > 0.25$) for each infrastructure category. We then fit a multivariate model with the 20 percent significant predictors and further eliminated non-significant variables at 10 percent level ($p_2 > 0.10$) through a combination of backward and forward selections. Finally, we further pruned the model by omitting variables that are non-significant, and adding those that are at the significance level of less than 5% ($p_3 < 0.05$). Table 2 summarizes the final predictors that were determined as the most appropriate subset predictors for the final Cox model in each infrastructure category.

The results can be interpreted in terms of hazard and hazard ratio (HR). The hazard can be understood as an immediate rate for the regime shift event. In other words, higher hazards have higher probability of experiencing the regime shift and lower hazards have a better chance of survival. As seen in the Kaplan-Meier (Kaplan and Meier 1958) time-to-event (survival) curves in Figure 4, there are differences in the probability of experiencing a regime shift in future pandemics among different states.

Overall, states with population densities lower than the national average (92.9 residents/sq.mi.) as well as those who declared State of Emergency with delays from the day WHO made the announcement have a higher probability of experiencing a regime shift in human-infrastructure interactions. States who suspend elective medical and dental services have a higher likelihood of undergoing a regime shift in most human-infrastructure interactions (all categories except for Parks). States in which day cares were closed, on the other hand, are more likely to experience a regime shift in human interactions with the park infrastructure. States with higher than national average rate of homelessness (0.17%), and unemployment (5.7%) are more likely to experience a regime shift in their human interactions with the transit stations infrastructure.

As depicted in Figure 4, (a) states with suspended medical services have a lower chance of surviving a regime shift during a pandemic; (b) states whose allowance of audio-only telehealth have a higher chance experiencing a pandemic regime shift in human interactions with residential infrastructure; (c) states who issued executive orders on face mask use in public-facing businesses have a higher chance of experiencing a pandemic regime shift in human interactions with the workplaces infrastructure; and (d) states with delayed State of Emergency declaration have a higher chance of experiencing a regime shift during a pandemic. However, there were no clear differences among states with reference to executive orders to close non-essential business.



(a) Regime shifts in Grocery & Pharmacy. (b) Regime shifts in Residential. (c) Regime shifts in Workplaces. (d) Regime shifts in Transit Stations.

Figure 4: Comparison of Kaplan-Meier survival curves of regime shifts in human-infrastructure interactions for state-level (a) grocery & pharmacy by suspension of elective medical/dental procedures; (b) residential by allowance of audio-only telehealth; (c) workplaces by executive orders on face mask use in public-facing businesses; and (d) transit Stations by delays in declaration of state of emergency.

4 CONCLUSIONS

Communities are impacted and respond differently to disruptive events. Similarly, they may adapt and recover in different manners. These differences, rooted in social norms and societal characteristics, can result in complete shifts in how they will interact with their surroundings, as new stable states emerge during or after shock events such as a pandemic. This study is an attempt to identify the factors that affect the likelihood of a regime shift in human-infrastructure interactions during and after a global pandemic event. We found that there is a significant difference in the likelihood of different states experiencing regime shifts in the interaction of their population with different infrastructure. Major contributors to these effects were state-level executive decisions such as suspension of elective medical services, mandating facemasks in public/public-facing businesses, allowing audio-only telehealth, closure of K-12 schools and day cares, and whether or not the state declared the State of Emergency with delays; state-level characteristics such as population density, whether or not the state is below national average rates of homelessness, and unemployment (prior to the pandemic); and, finally, how much the state has been impacted by the pandemic in terms of the number of deaths, recoveries, positive vs. negative cases of COVID-19 infection, and those

Table 2: Cox proportional hazards model (All days are measured from the day of state declaration of state of emergency up to May 15, 2020; and all covariates are state-level measures, conditions, or properties. A 95% confidence interval is used to estimate the hazard ratios (HR). Statistical significance is indicated as follows: *p<0.001***; p<0.01**; p<0.05*; p<0.1*$^{+}$).

	Retail & Recreation			Grocery & Pharmacy			Parks			Transit Stations			Workplaces			Residential		
Covariate	ß	HR[1]	SE(ß)	ß	HR[1]	SE(ß)	ß	HR[1]	SE(ß)	ß	HR[1]	SE(ß)	ß	HR[1]	SE(ß)	ß	HR[1]	SE(ß)
1 Days under stay at home/shelter in place order	1.1E-02	1.0E+00	0.015	2.1E-02	1.0E+00	0.0151	-7.1E-01 ***	4.9E-01	0.02	2.0E-02	1.0E+00	0.014	2.3E-02	1.0E+00	0.01613	1.4E-02	1.0E+00	1.3E-02
2 Days K-12 schools closed	-1.4E-01 *	8.7E-01	0.055	-1.5E-01 *	8.6E-01	0.0625	1.0E+00 ***	2.8E+00	0.08	-1.4E-01 **	8.7E-01	0.052	-1.6E-01 **	8.5E-01	0.05677	-1.5E-01 **	8.6E-01	5.2E-02
3 Days daycares closed	2.8E-02 *	1.0E+00	0.012	2.7E-02 *	1.0E+00	0.0125	-1.5E-01 ***	8.6E-01	0.02	1.1E-02	1.0E+00	0.011	3.1E-02 *	1.0E+00	0.01338	2.1E-02 +	1.0E+00	1.1E-02
4 Days nursing homes banned all visitors	9.1E-03	1.0E+00	0.009	-8.7E-04	1.0E+00	0.0102	3.1E-01 ***	1.4E+00	0.01									
5 Days restaurants closed/take out only	-8.8E-02 **	9.2E-01	0.031	-7.9E-02 *	9.2E-01	0.0322	4.1E-02 +	1.0E+00	0.02	-8.9E-02 **	9.2E-01	0.032	-9.1E-02 **	9.1E-01	0.03126	-5.4E-02 +	9.5E-01	3.2E-02
6 Days gyms closed							-6.8E-01 ***	5.1E-01	0.02	4.4E-02	1.0E+00	0.028						
7 Days movie theaters closed	9.9E-03	1.0E+00	0.017	1.6E-02	1.0E+00	0.0193	1.7E+00 ***	5.7E+00	0.02	-9.9E-03	9.9E-01	0.023	1.0E-02	1.0E+00	0.01636	4.7E-03	1.0E+00	1.8E-02
8 Days audio-only telehealth allowed	-6.5E-03	9.9E-01	0.011	-1.6E-02	9.8E-01	0.0104	-6.2E-01 ***	5.4E-01	0.01	-9.2E-03	9.9E-01	0.010	-4.6E-03	1.0E+00	0.01209	-1.5E-02	9.9E-01	1.1E-02
9 Days non-essential businesses closed	-3.4E-02 *	9.7E-01	0.016	-3.2E-02 *	9.7E-01	0.0163	-2.9E-01 ***	7.5E-01	0.02	-2.3E-02	9.8E-01	0.015	-3.3E-02 *	9.7E-01	0.01484	-3.0E-02 *	9.7E-01	1.4E-02
10 Days face mask use mandated (individuals)	-1.2E-01 **	8.9E-01	0.044	-1.4E-01 **	8.7E-01	0.0417	4.1E-01 ***	1.5E+00	0.03	-6.1E-02	9.4E-01	0.043	-9.9E-02 *	9.1E-01	0.04353	-9.0E-02 *	9.1E-01	4.1E-02
11 Days face mask use mandated (employees)	3.6E-02	1.0E+00	0.044	9.1E-02 *	1.1E+00	0.0447	-7.0E-01 ***	5.0E-01	0.04	2.3E-02	1.0E+00	0.039	3.1E-02	1.0E+00	0.04367	2.7E-02	1.0E+00	4.0E-02
12 Days elective medical/dentals suspended	-4.2E-02 **	9.6E-01	0.014	-4.7E-02 **	9.5E-01	0.0152	2.7E-01 ***	1.3E+00	0.02	-4.3E-02 ***	9.6E-01	0.013	-4.5E-02 ***	9.6E-01	0.01351	-4.0E-02 **	9.6E-01	1.3E-02
13 Religious gatherings exempt							-9.8E+00 ***	5.3E-05	0.66									
14 Alcohol/liquor stores open	-2.8E+00 *	6.0E-02	1.345	-1.6E+00	2.0E-01	1.4170	2.7E+01 ***	5.1E+11	1.12				-2.5E+00 +	7.9E-02	1.41900			
15 Keep firearms sellers open	1.4E-01	1.1E+00	0.989	1.8E+00	6.1E+00	1.3350	3.0E+01 ***	1.0E+13	0.81	4.8E-02	1.0E+00	1.039	7.6E-01	2.1E+00	1.05600	5.0E-01	1.7E+00	1.0E+00
16 Paid sick leave	-5.4E-01	5.8E-01	0.948	1.3E-01	1.1E+00	0.7807	4.3E+01 ***	2.9E+18	0.80	8.5E-02	1.1E+00	0.729	-4.1E-01	6.6E-01	0.83310	-7.7E-02	9.3E-01	8.8E-01
17 Population density per square miles	8.4E-04 **	1.0E+00	0.000	7.7E-04 *	1.0E+00	0.0003	-2.3E-03 ***	1.0E+00	0.00	4.8E-04 +	1.0E+00	0.000	8.4E-04 **	1.0E+00	0.00031	3.2E-04	1.0E+00	2.7E-04
18 Square miles area	-1.2E-06	1.0E+00	0.000	-1.7E-06	1.0E+00	0.0000	4.9E-05 ***	1.0E+00	0.00							-2.9E-06	1.0E+00	3.8E-06
19 Number homeless (2019)	-6.2E+02 *	3.5E-268	275.50	-6.4E+02 *	3.1E-278	297.10	-2.5E+03 ***	0.0E+00	141.20	-6.3E+02 +	2.4E-274	349.0	-7.1E+02 **	1.5E-307	260.000	-4.6E+02 +	7E-200	2.4E+02
20 Percent unemployed (2018)	6.8E-01	2.0E+00	0.590	1.8E-01	1.2E+00	0.4401	-1.4E+01 ***	7.5E-07	0.33	2.1E-01	1.2E+00	0.358	3.0E-01	1.3E+00	0.36790	6.4E-01	1.9E+00	6.2E-01
21 Percent living under the federal poverty line (2018)	-3.2E-01	7.2E-01	0.217				1.4E+01 ***	8.6E+05	0.13	6.4E-02	1.1E+00	0.177	-9.3E-02	9.1E-01	0.24130	3.1E-02	1.0E+00	2.4E-01
22 Percent at risk for serious illness due to COVID-19	2.0E-01	1.2E+00	0.147	3.7E-02	1.0E+00	0.1418	-7.4E+00 ***	5.9E-04	0.09	7.4E-02	1.1E+00	0.138	6.1E-02	1.1E+00	0.15640	-7.7E-02	9.3E-01	1.4E-01
23 Number tested COVID-19 positive	2.3E-06	1.0E+00	0.000	-3.8E-05	1.0E+00	0.0001	4.2E-04 ***	1.0E+00	0.00	-4.0E-05	1.0E+00	0.000	-4.2E-05	1.0E+00	0.00005	-2.8E-05	1.0E+00	4.3E-05
24 Number tested COVID-19 negative	-3.6E-06	1.0E+00	0.000	5.8E-07	1.0E+00	0.0000	-2.5E-05 ***	1.0E+00	0.00	-1.5E-08	1.0E+00	0.000	2.1E-07	1.0E+00	0.00000	-1.5E-06	1.0E+00	2.0E-06
25 Number in ICU due to CVID-19							-2.3E-02 ***	9.8E-01	0.00				-3.4E-04	1.0E+00	0.00070			
26 Number recovered COVID-19	1.3E-04 **	1.0E+00	0.000	1.4E-04 **	1.0E+00	0.0000	3.0E-05	1.0E+00	0.00				1.1E-04 *	1.0E+00	0.00005	8.1E-05 *	1.0E+00	4.1E-05
27 Number COVID-19 deaths	6.3E-05	1.0E+00	0.001	9.4E-05	1.0E+00	0.0008	-3.4E-03 ***	1.0E+00	0.00	4.9E-04	1.0E+00	0.001	5.3E-04	1.0E+00	0.00071	4.4E-04	1.0E+00	6.3E-04
28 Number hospitalized for COVID-19	-1.7E-05	1.0E+00	0.000	7.2E-05	1.0E+00	0.0001	-4.8E-04 ***	1.0E+00	0.00				2.1E-05	1.0E+00	0.00005			
N	48			48			15			46			48			47		
Concordance	0.868 (se = 0.029)			0.885 (se = 0.03)			1 (se = 0)			0.847 (se = 0.034)			0.862 (se = 0.031)			0.839 (se = 0.039)		
Likelihood Ratio Test	61.37 on 25 df, p=7e-05			58.69 on 24 df, p=1e-04			70.51 on 28 df, p=2e-05			56.08 on 21 df, p=5e-05			59.37 on 24 df, p=8e-05			52.65 on 22 df, p=3e-04		
Wald Test	36.40 on 25 df, p=0.07			33.79 on 24 df, p=0.09			40800 on 28 df, p=<2e-16			30.76 on 21 df, p=0.08			36.54 on 24 df, p=0.05			38.16 on 22 df, p=0.02		
Score (Logrank) Test	52.14 on 25 df, p=0.001			47.91 on 24 df, p=0.003			50.65 on 28 df, p=0.005			49.23 on 21 df, p=5e-04			54.56 on 24 df, p=4e-04			50.17 on 22 df, p=6e-04		

in serious risk of illness.

Limitations of this study are as follows. The data used in the study is not generated by the authors and has been retrieved semi-processed from external sources (i.e., may include incomplete, biased or censored information). Thus, the results of the study are only representative of the data provided by those referenced sources. Further research needs to determine the more precise impact of each covariate over a longer period of time to better characterize the regime shifts in human-infrastructure interactions as conditions in different states evolves over time. Understanding the evolution of the likelihood of regime shifts over time is of utmost importance in determining thresholds (size of a critical change in human-infrastructure interactions) that could specify the mechanisms that provoke such regime shifts and that could predict an upcoming event. Characterizing threshold responses to pandemics are critical in ensuring the sustainability and resilience of urban built environments as they result in sudden changes with no warning, and can lead to complete transition into new regimes that are difficult to reverse.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under Grants No. 1837021 and 1929928. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

A APPENDIX

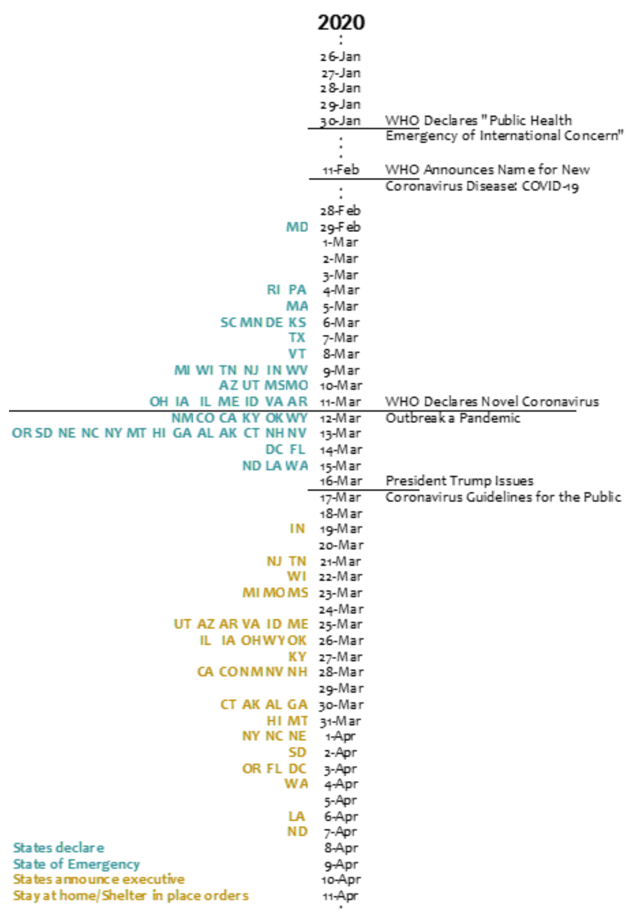


Figure 5: Timeline of events in the USA: COVID-19 global pandemic, 2019-2020 (FRASER 2020).

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