State-level variation of initial COVID-19 dynamics in the United States: The role of local government interventions

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Abstract

In the development of an epidemic, metrics such as R_0, doubling time, and case fatality rates are important in understanding and predicting the course of an epidemic. However, if collected over country or regional scales, these metrics hide important smaller-scale, local dynamics. We examine how commonly used epidemiological metrics differ for each individual state within the United States during the initial COVID-19 outbreak. We found that the case number, and trajectory of cases, differs considerably between states. We show that early non-pharmaceutical, government actions, were the most important determinant of epidemic dynamics. In particular, restricting restaurant operations was correlated with increased doubling times. Although individual states are clearly not independent, they can serve as mini, natural experiments in how different demographic patterns and government responses can impact the course of an epidemic. Thus, these results should be used to better understand what actions are working most effectively.

Keywords: SARS-CoV-2, COVID-19, spatial heterogeneity, doubling time

Daily updates to figures in this manuscript are available at: https://github.com/eastonwhite/COVID19_US_States

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Introduction

The global SARS-CoV-2 (COVID-19) pandemic began in Wuhan, China in late 2019 (WHO 2020). As of April 07^{th}, 1,426,096 cases have been reported across 184 countries and regions. There have been several sets of efforts to track the progression of the outbreak across the world and within countries. For example, John Hopkins University Center for Systems Science and Engineering (CSSE) has compiled data from various sources, including the US Center for Disease Control and the World Health Organization, to present a global picture of COVID-19 cases and deaths (Dong *et al.* 2020). These efforts have allowed for international scientific research and political decision-making. Although data are collected at local scales (e.g. within hospitals), in an emerging pandemic, data are typically reported at the country level. This allows for interesting comparisons between countries (Anderson *et al.* 2020) and for information from an earlier affected country to be used to slow the outbreak in other places. For instance, South Korea was able to flatten their outbreak curve through early and widespread testing as well as strict quarantine policies (citation). However, country-level analyses still hide more local dynamics that are important to the overall epidemic progression (Lin *et al.* 2020).

Spatial heterogeneity is important for population dynamics generally (Levin 1992) and in particular for understanding the progression of infectious disease dynamics (Grenfell *et al.* 1995). Spatial heterogeneity can include differences in local population density, movement patterns, suitability of environmental conditions for transmission, among other factors. For instance, Keeling *et al.* (2001) showed how spatial distribution and size of farms affected the 2001 UK Foot and Mouth Epidemic.

Here we examine the progression of COVID-19 at the state level within the United States. We examine how commonly-used metrics, including doubling time, can vary by state. Although not independent units, we can use state-level data to understand the progression of the outbreak across different replicates within a country (Adolph *et al.* 2020). We then show that across measures of demography, education, health, and wealth, only population density was correlated with doubling time. Instead, we show that doubling time was more tightly correlated with state-level governmental actions, including restricting businesses.

Results and Discussion

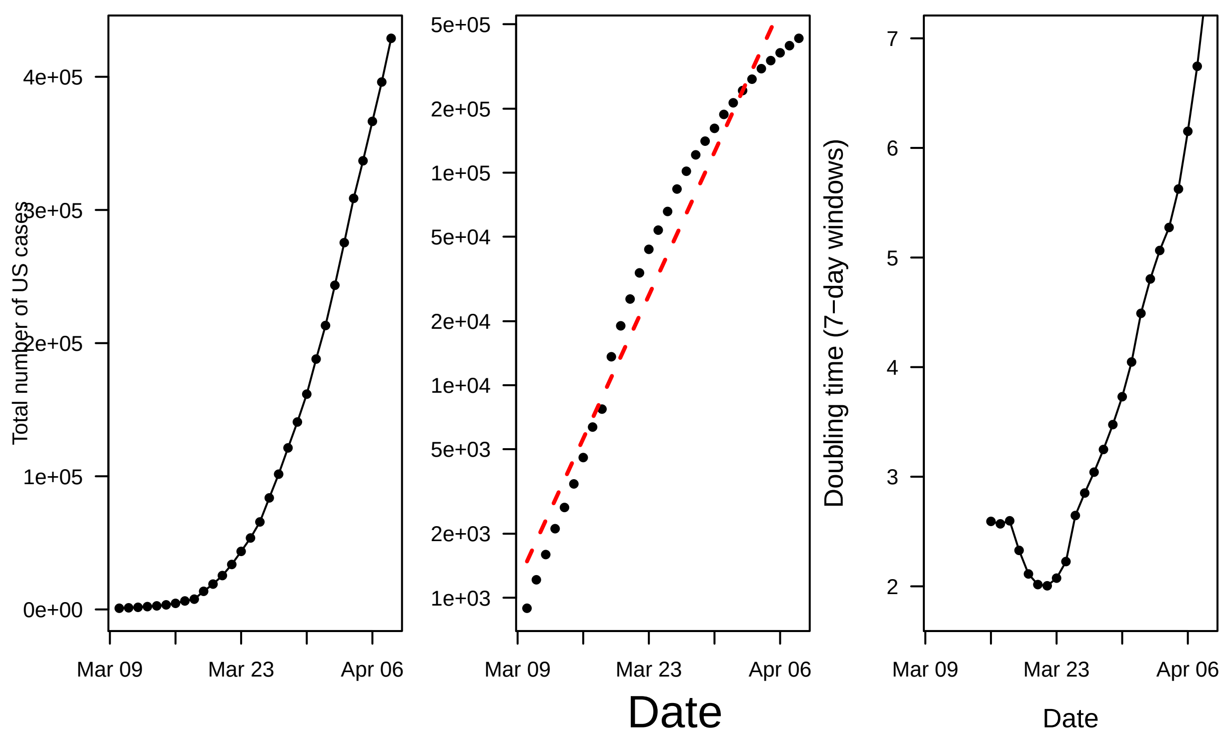

Figure 1: (Left panel) Cases versus time for the whole United States. (Right panel) Log number of cases versus time for the whole United States. The red, dashed line is the line of best fit for all the data and the blue, solid line is the line of best fit since Feburary 29th.

We used data compiled by John Hopkins University Center for Systems Science and Engineering (Dong *et al.* 2020). The United States has seen exponential growth in the number of cases, especially since February 29th (Fig. 1). Country-level results, however, hide underlying dynamics within each state.

Therefore, we examined how the number of cases changed over time within each state. To properly compare the progression of the epidemic across states, we looked at the log number of cases since the first day a state reported 25 cases (Fig. 2). On a log scale, a straight line of the cases over time indicates exponential growth where the slope of the line is the exponential growth parameter.

State-level variation in COVID-19 trajectories

We found considerable differences between states in how the outbreak has progressed (Fig. 2). States like New York, New Jersey, Michigan, and Indiana have experienced a doubling of cases every two or three days. Conversely, Washington has experienced a doubling time closer to six days. These doubling times are, of course, changing over time. We mapped doubling time across the US and found regional differences where the West Coast and Northeast have seen large doubling times, i.e. slower outbreak dynamics (Fig. 3).

Predictors of early (pre-intervention) state-level trajectories - NEED TO WORK ON THIS NEXT

Each US state varies considerably across a number of important axes: wealth, access to healthcare, number of international travelers, age distribution, population density, among other factors. In addition, much of the response to COVID-19 has been done at the state, as opposed to federal, government level in the US (citations). These responses have varied a lot with different laws and such... (citations).

We had two hypotheses to explain the state-level variation in COVID-19 trajectories before government intervention occurred: human demographics as well as wealth and education indicators.

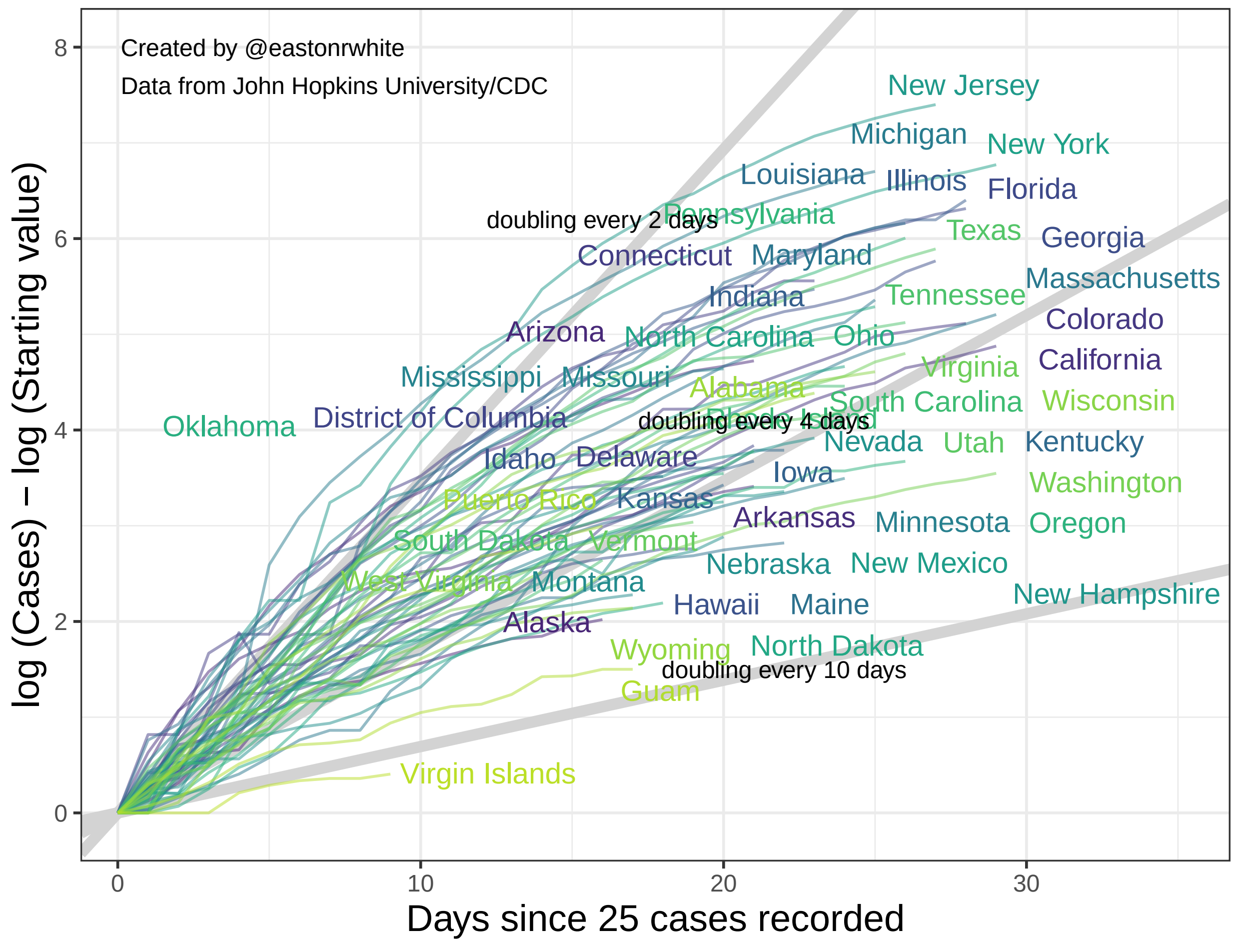

Figure 2: The log number of cases over time for each individual state that recorded more than 25 cases over at least three days. The light grey diagonal lines represent the growth trajectory for doubling times of 2, 4, and 10 days. The log number of the starting value (intial number of cases on first day when at least 25 cases were recorded) had to be subtracted on the y-axis to standarize the graph across states.

Doubling time (days) as of 2020−04−09

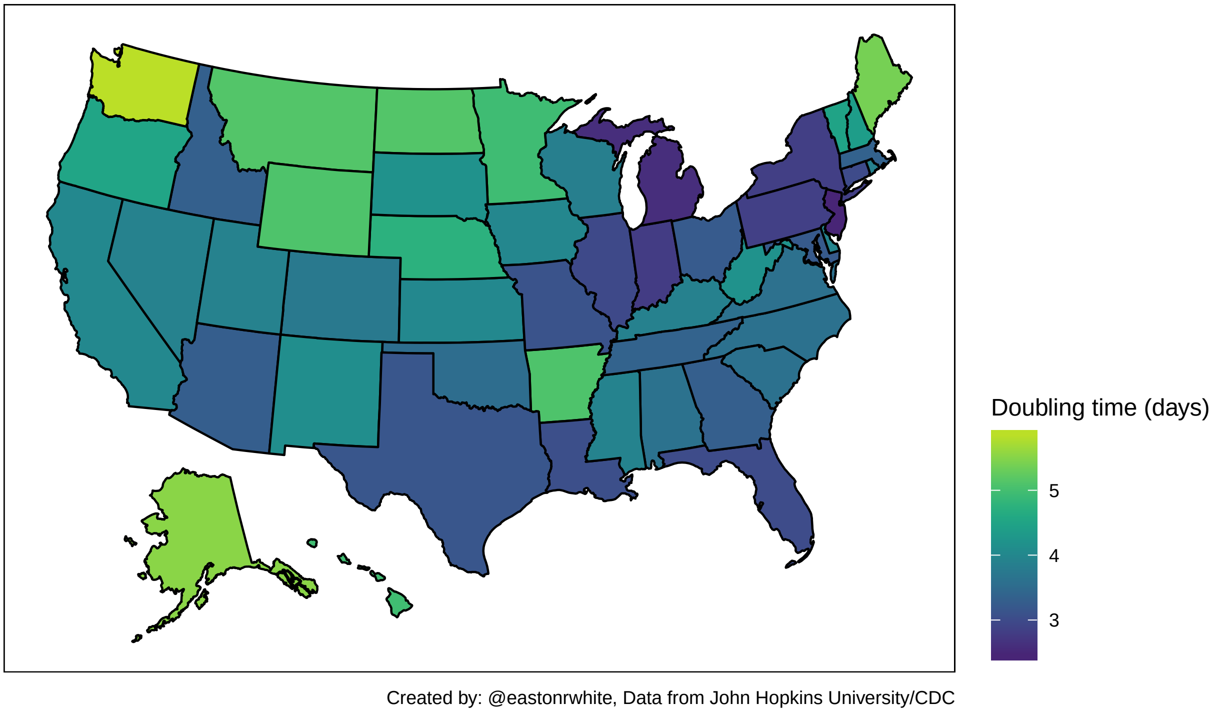

Figure 3: Doubling time (in number of days) across the US states that recorded more than 25 cases over at least three days.

Predictors of overall state-level trajectories

We had three hypotheses to explain the state-level variation in COVID-19 trajectories: human demographics, wealth and education indicators, and governmental actions.

Except for population density and percent of population living in rural areas, we found that demography, education, and wealth were poor predictors of the state-level doubling times (Fig. 4). Therefore, we also examined the correlation between doubling time and state government interventions, and timing of those interventions. We specifically looked at whether or not a state had implemented a specific action by the first day they had 25 or more cases. We adjusted this number to 100 cases for more severe restrictions like closing all non-essential business or stay at home mandates). We looked at closing of public schools, limiting large gatherings (usually of more than 10 people), restricting business, and stay at home orders. Of these factors, only restricting businesses, specifically resturants, was a

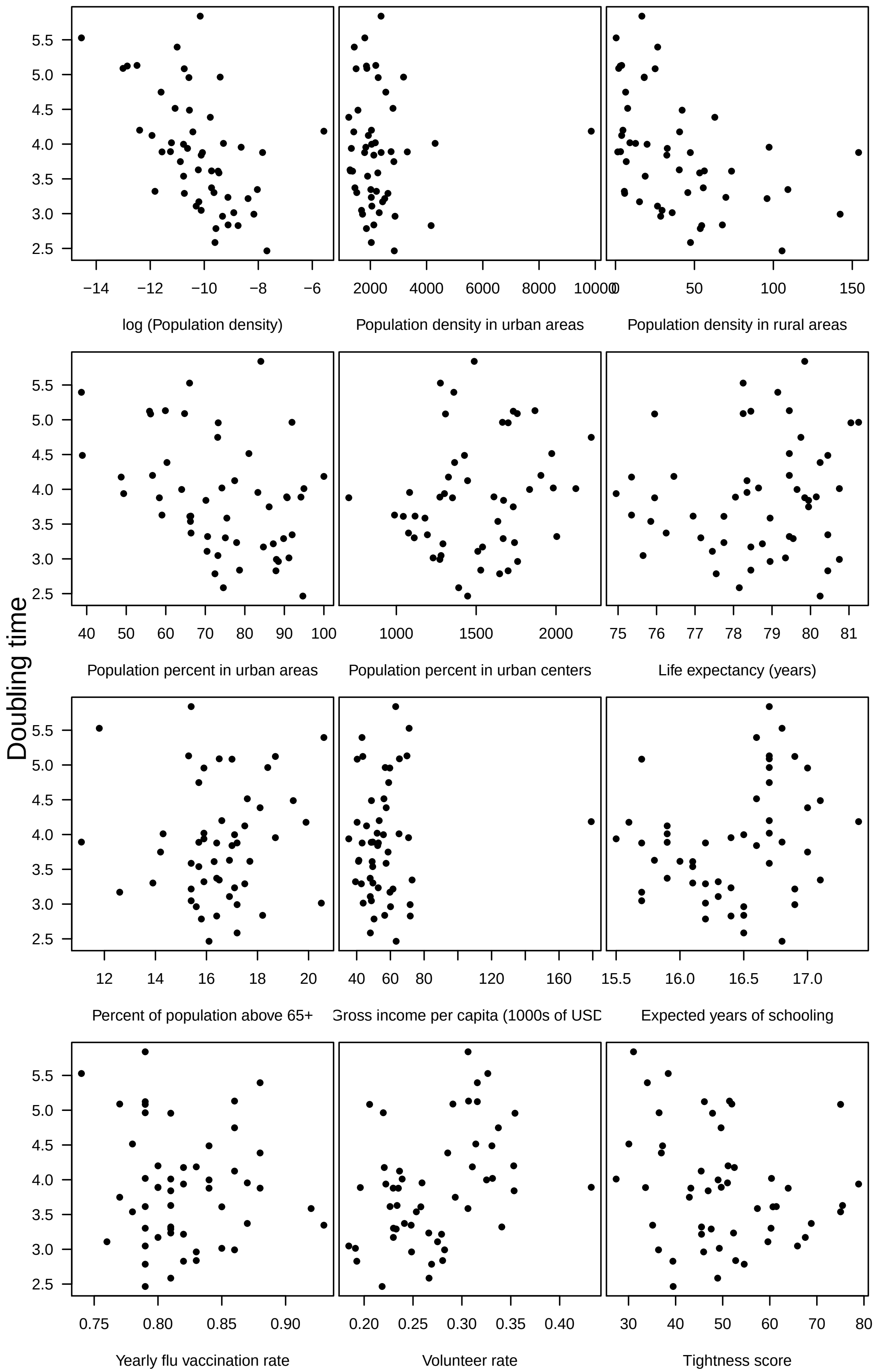

Figure 4: Doubling time (in number of days). . . .

significant predictor of doubling time (Fig. 5, Table 1). These restrictions were also additive, as states that implemented more actions early had higher doubling times (Fig. 5).

Lastly, after accounting for population density, a state's "tightness" score was also correlated with doubling time. A state with a high tightness score has "many strongly enforced rules and little tolerance for deviance" (Harrington & Gelfand 2014). We expected that states with highly enforced rules should have higher doubling times compared to "loose" states. Instead, we found that opposite where tight states had low doubling times and faster disease spread. We hypothesis this may be the result of people in tight cultures finding it more difficult to adjust their behavior when new rules are imposed. More work has to be done to understand this relationship though.

Call: lm(formula = doubling_time ~ RestrictRestaurants + POPDEN_log + POPPCT_RURAL + TightnessScore)

Residuals: Min 1Q Median 3Q Max -1.05261 -0.36277 -0.03713 0.18441 1.84351

Coefficients: Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.411989 0.737270 1.915 0.0618 .

RestrictRestaurants 0.435998 0.212455 2.052 0.0460 *

POPDEN_log -0.297037 0.066124 -4.492 4.88e-05 * **POPPCT_RURAL 0.013267 0.007409 1.791 0.0801 .**

TightnessScore -0.020680 0.007317 -2.826 0.0070 — Signif. codes: 0 '' ***0.001*** '' *0.01* " 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5665 on 45 degrees of freedom (1 observation deleted due to missingness) Multiple R-squared: 0.5669, Adjusted R-squared: 0.5284 F-statistic: 14.73 on 4 and 45 DF, p-value: 9.145e-08

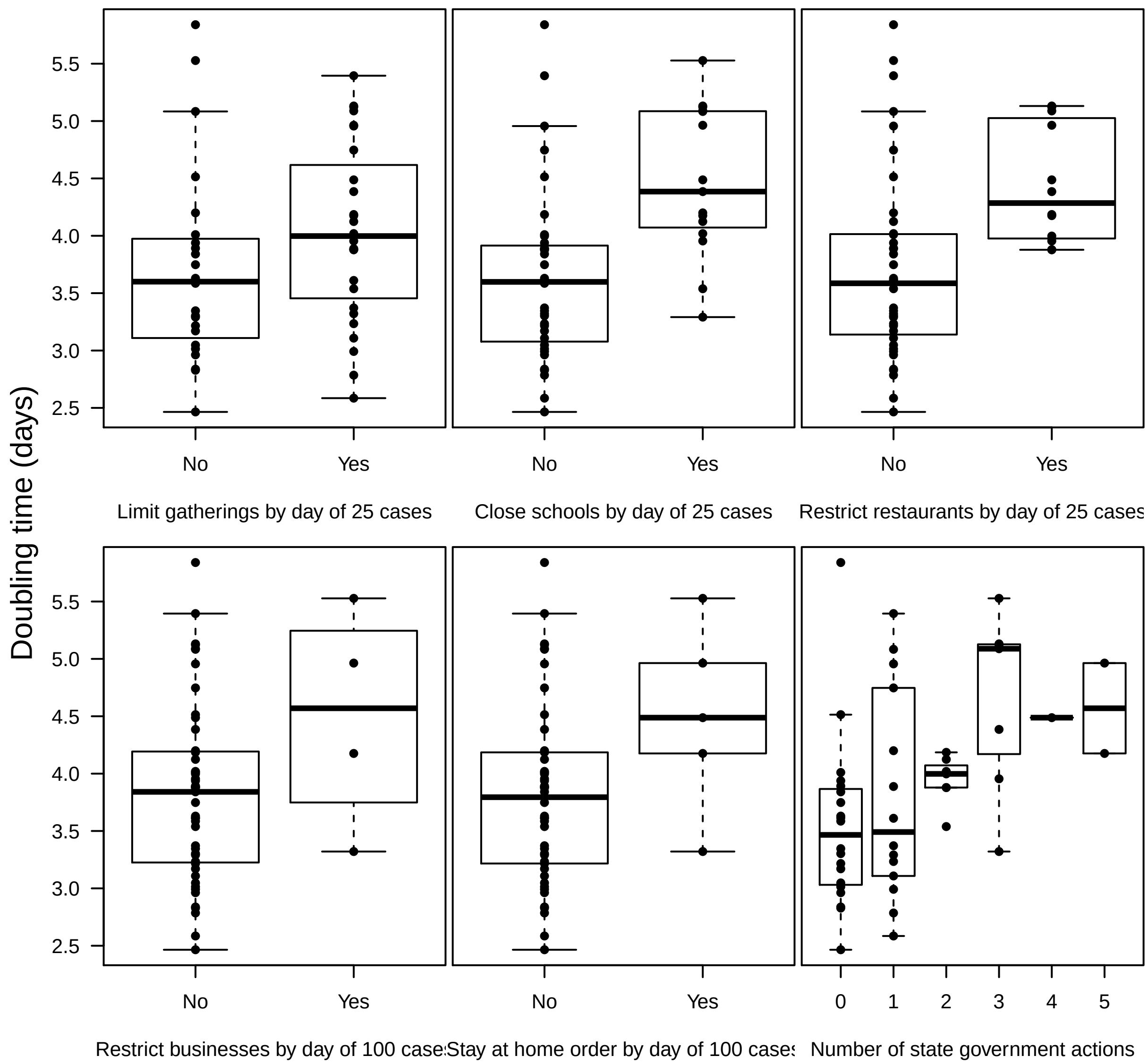

Figure 5: Doubling time (in number of days) across the US states that recorded more than 25 cases over at least three days.

Table 1: Best fit linear model estimates.

	Dependent variable:
	Doubling time
Restrict Restaurants	0.436**
	(0.020, 0.852)
log (Population density)	−0.297***
	(−0.427, −0.167)
Population percent in rural areas	0.013*
	(−0.001, 0.028)
Tightness score	−0.021***
	(−0.035, −0.006)
Constant	1.412*
	(−0.033, 2.857)
Observations	50
R^2	0.567
Adjusted R^2	0.528
Note:	*p<0.1; **p<0.05; ***p<0.01

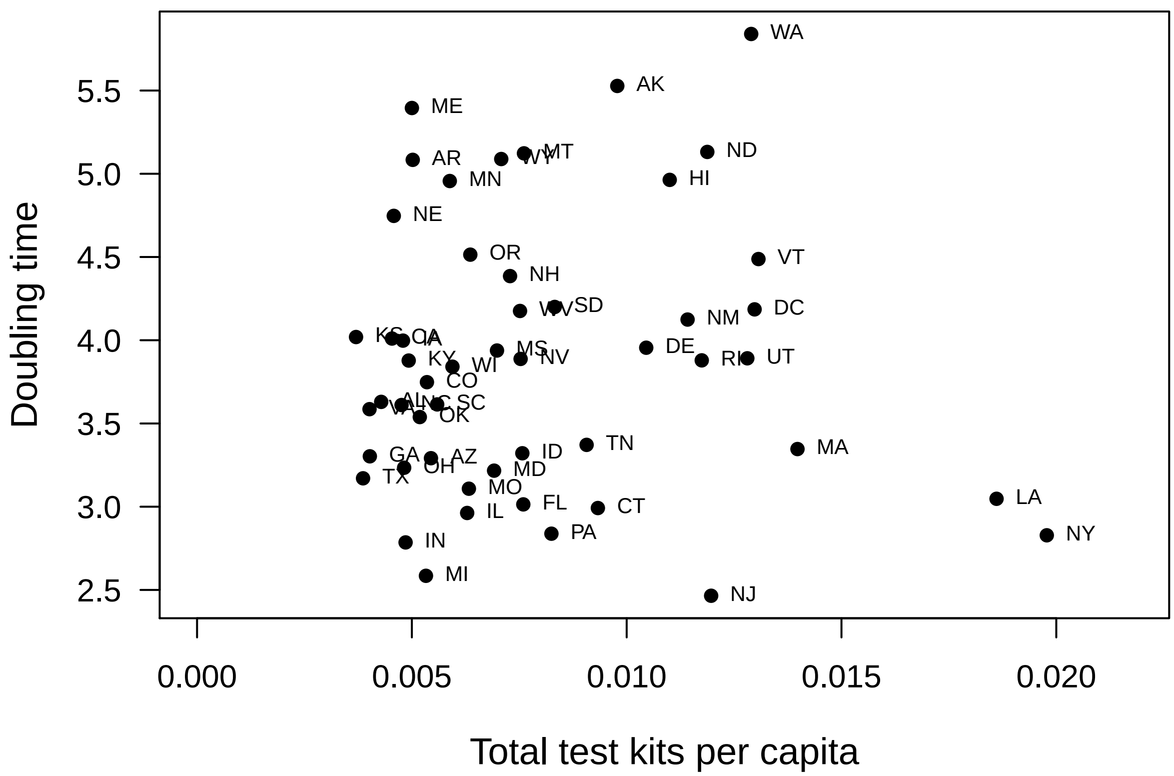

Figure 6: Doubling time (in number of days) across the US states that recorded more than 25 cases over at least three days.

Conclusions and Future Work

We found a large degree of heterogeneity in the number of cases over time across US states. After state-level government actions were implemented, doubling time was most strongly correlated to restrictions on businesses, in particular restaurants. More detailed work will be needed to understand how these dynamics differ within each state, especially as many government actions started on more local scales.

Code availability and acknowledgements

All code and corresponding data is freely available at https://github.com/eastonwhite/COVID19_US_States. The original raw data has been compiled by the Johns Hopkins University Center for Systems Science and Engineering at (https://github.com/CSSEGISandData/COVID-19). The authors received no specific funding for this work.

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