



Twitter Sentiments on the Stay-at-home Orders in the United States

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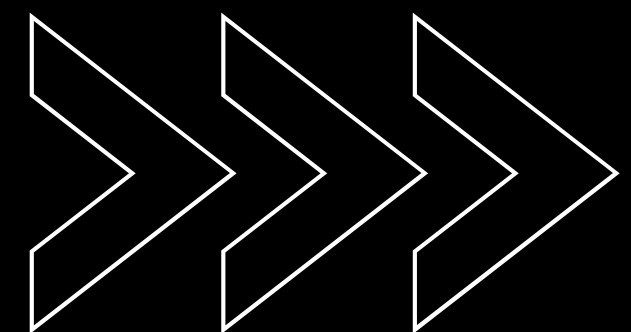
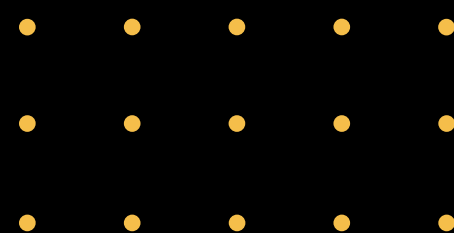
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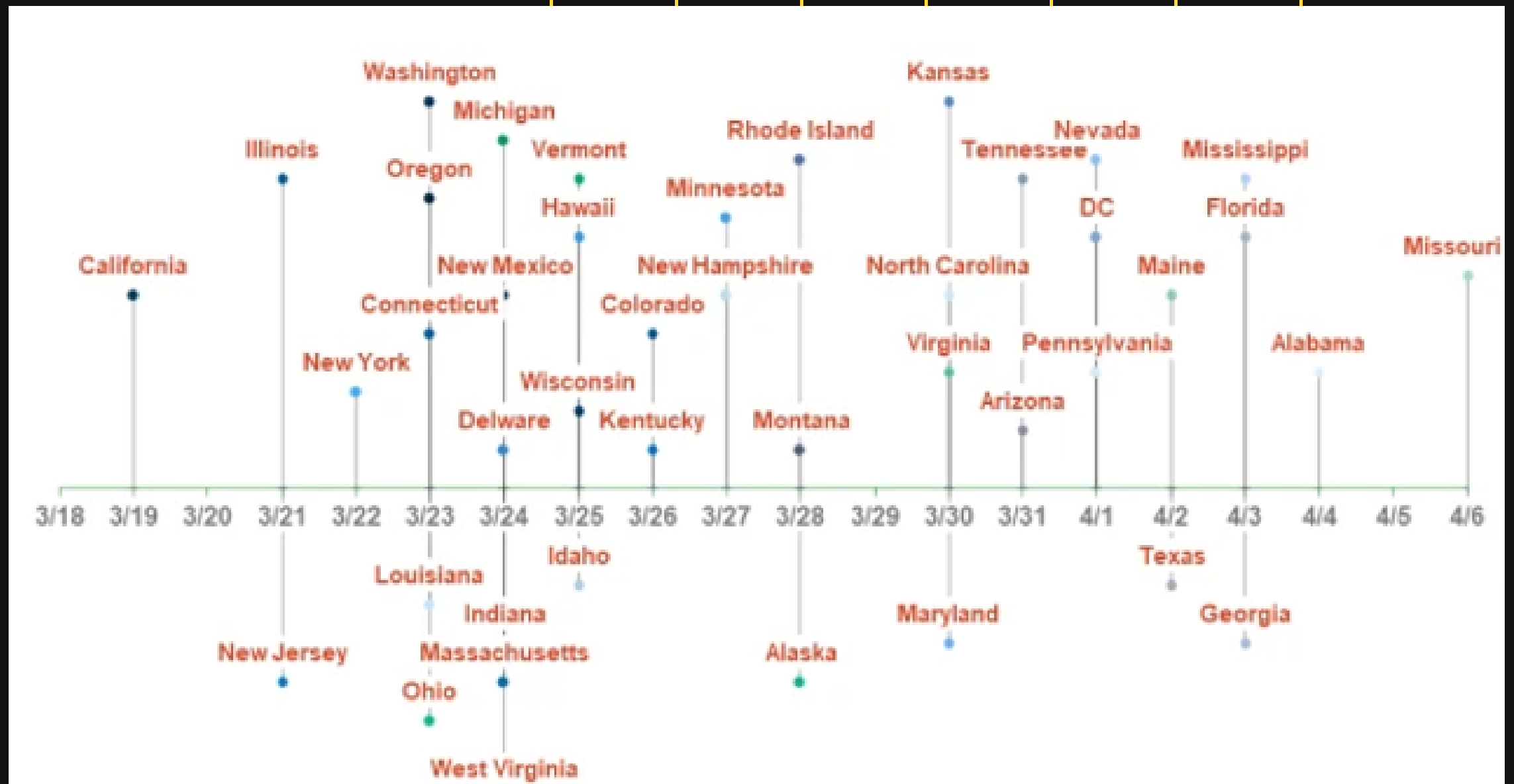
About

Stay-at-home orders were one of the controversial interventions to curb the spread of COVID-19 in the United States (US).



SARS-nCoV-2
isolate
COVID-19
flatten the curve
social d
CORONAVIRUS
quarantine
test
lockdown
stay home curfew wash h
virus self-isolate
shelter in place
test negative

About



The stay-at-home orders, implemented in 43 (out of 51) states and territories between 7 March to 30 June 2020, impacted the lives of individuals and communities and accelerated the heavy usage of online social networking sites.



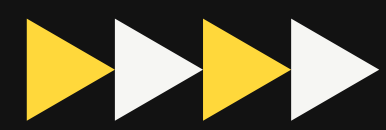


TWITTER INSIGHT

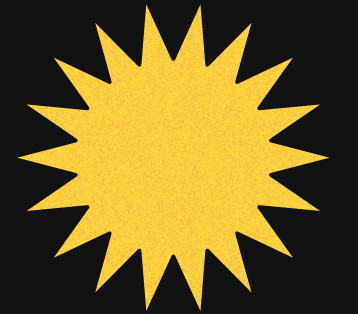
About



Twitter sentiment analysis can provide valuable insight into public health emergency response measures and allow for better formulation and timing of future public health measures to be released in response to future public health emergencies.



Objective



The purpose of the study was to evaluate how stay-at-home orders affect Twitter sentiment in the US. We particularly focused on vulnerable groups, including elderly groups, rural people, and low-income groups.



RURAL VS URBAN



ELDERLY



LOW INCOME

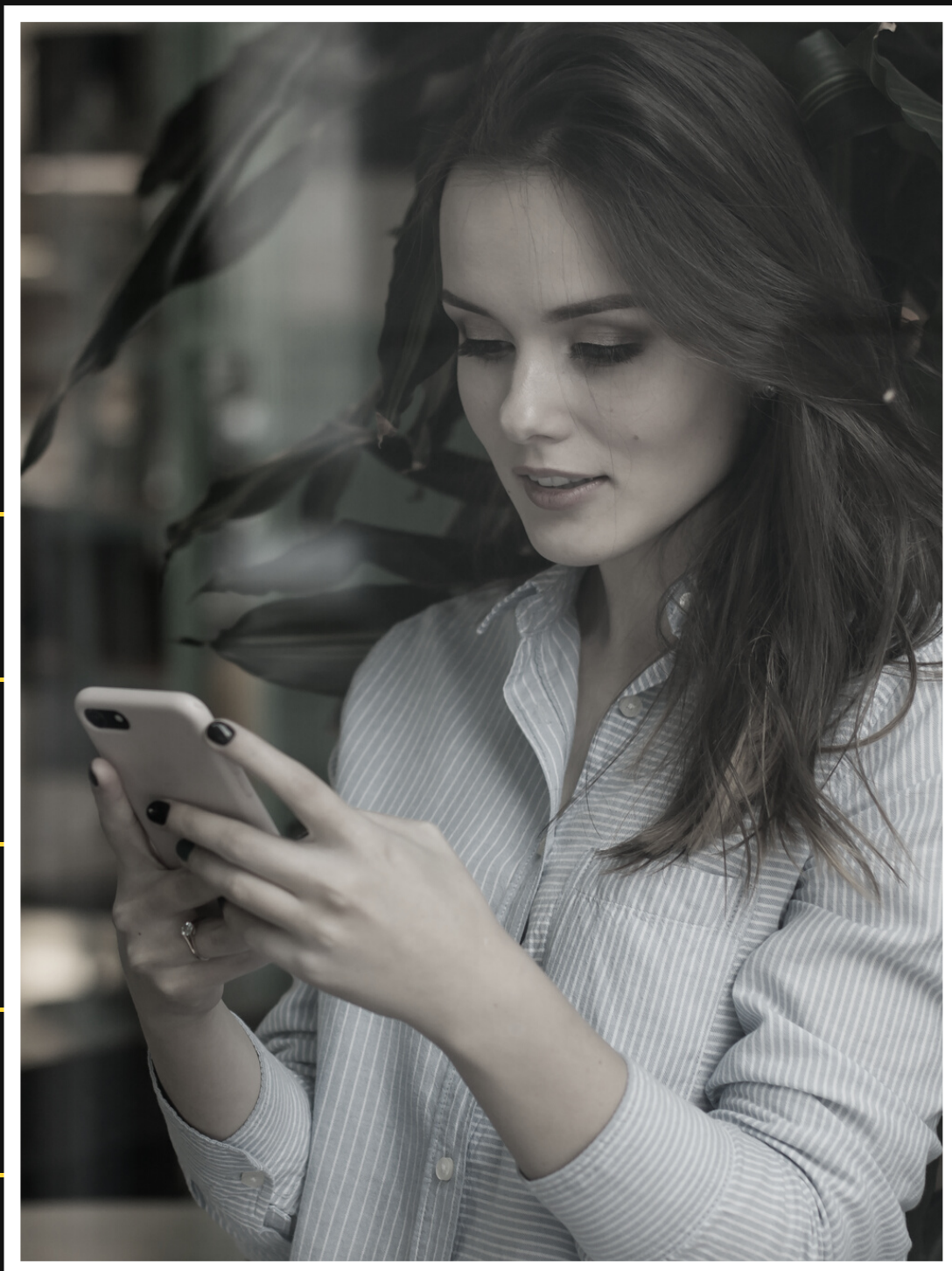




Data: Twitter sentiment geographical index (TSGI)



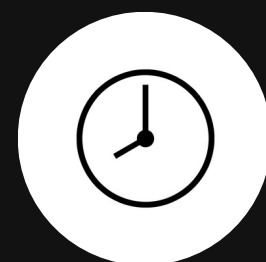
- A proxy for **subjective well-being**
- applying natural language processing techniques
- a comprehensive archive of **10** billion geotagged tweets
- spanning time, geography, and 104 languages maintained (by the Center of Geographic Analysis at Harvard University)



Data: Twitter sentiment geographical index (TSGI)



Country, State/Province, and County/City level in 164 countries



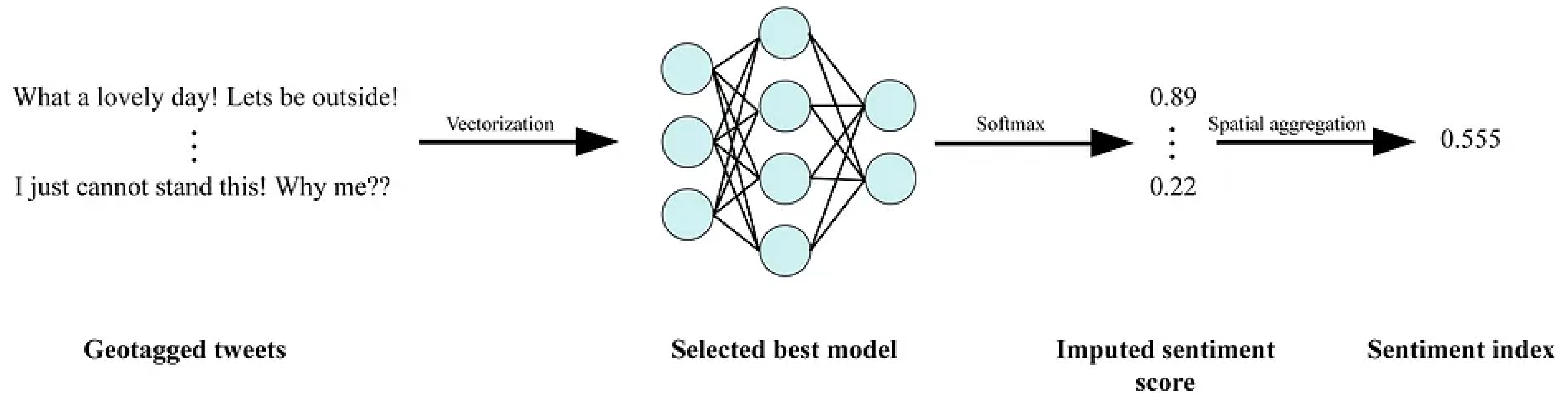
Daily sentiment scores in 10 year coverage (2012 to 2022)



83% sentiment classification accuracy by using neural network model

▶▶▶▶ Data: Twitter sentiment geographical index (TSGI)

Generate sentiment index



The sentiment index for global geotagged tweets was made in the following steps:

1. They vectorized the text into a 768 dimensions vector.
2. They fed the vector into a trained neural classifier to get the single sentiment score.
3. They aggregated the scores in different administrative areas to represent the local subjective well-being.

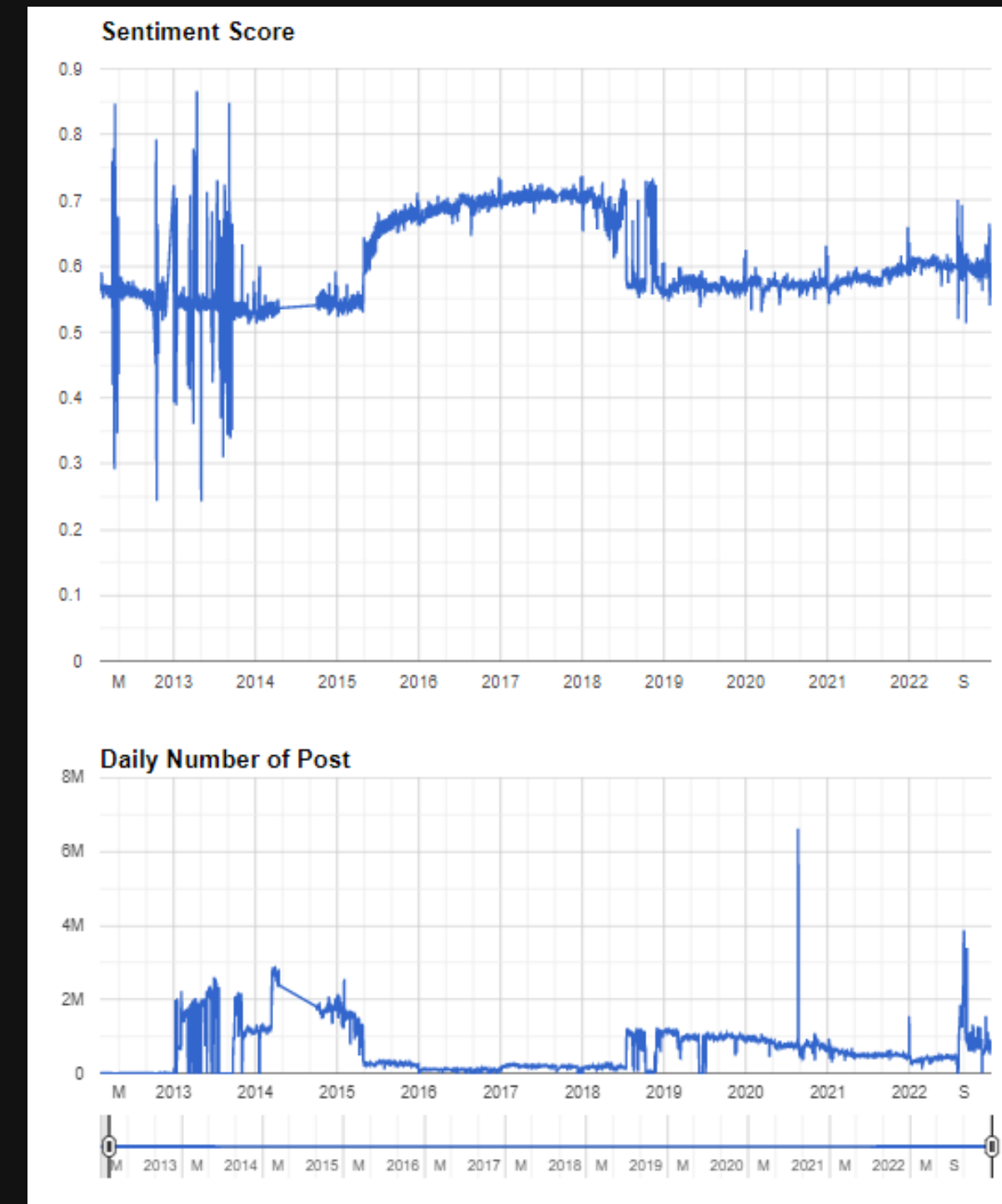
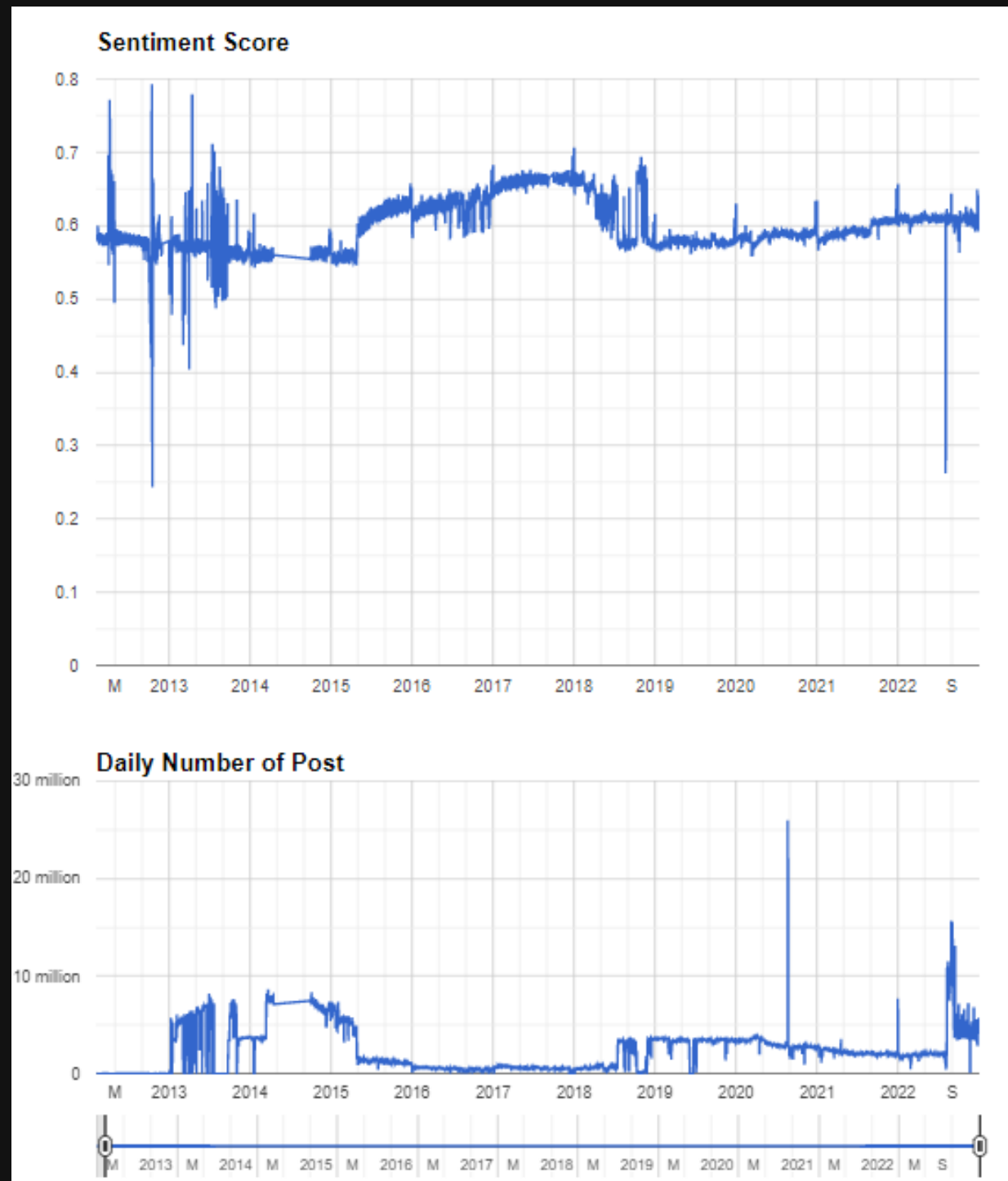


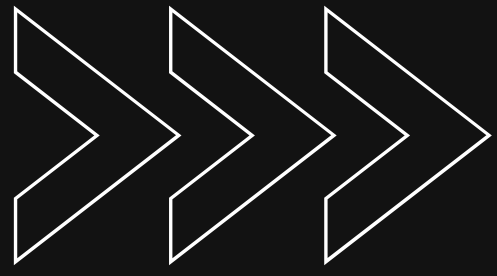
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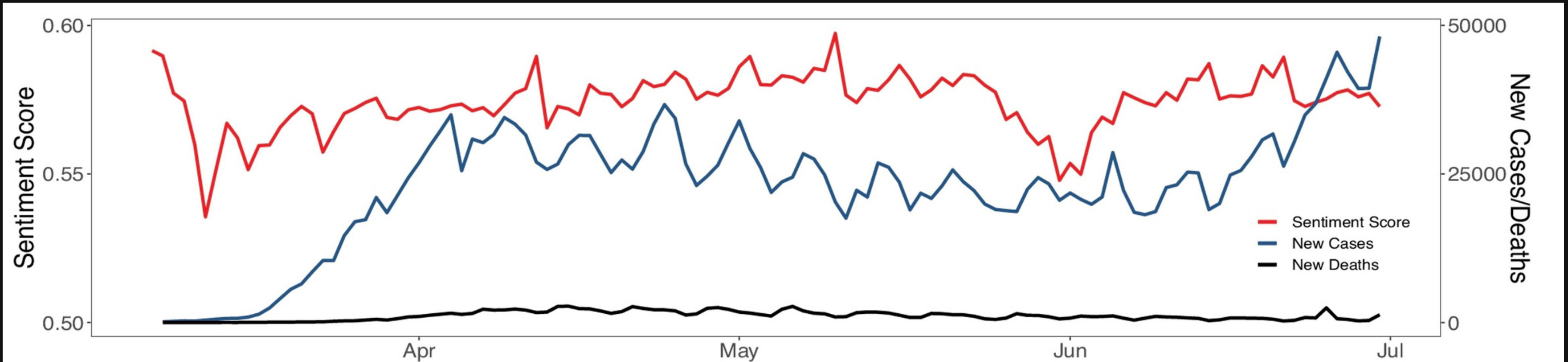
World

United States

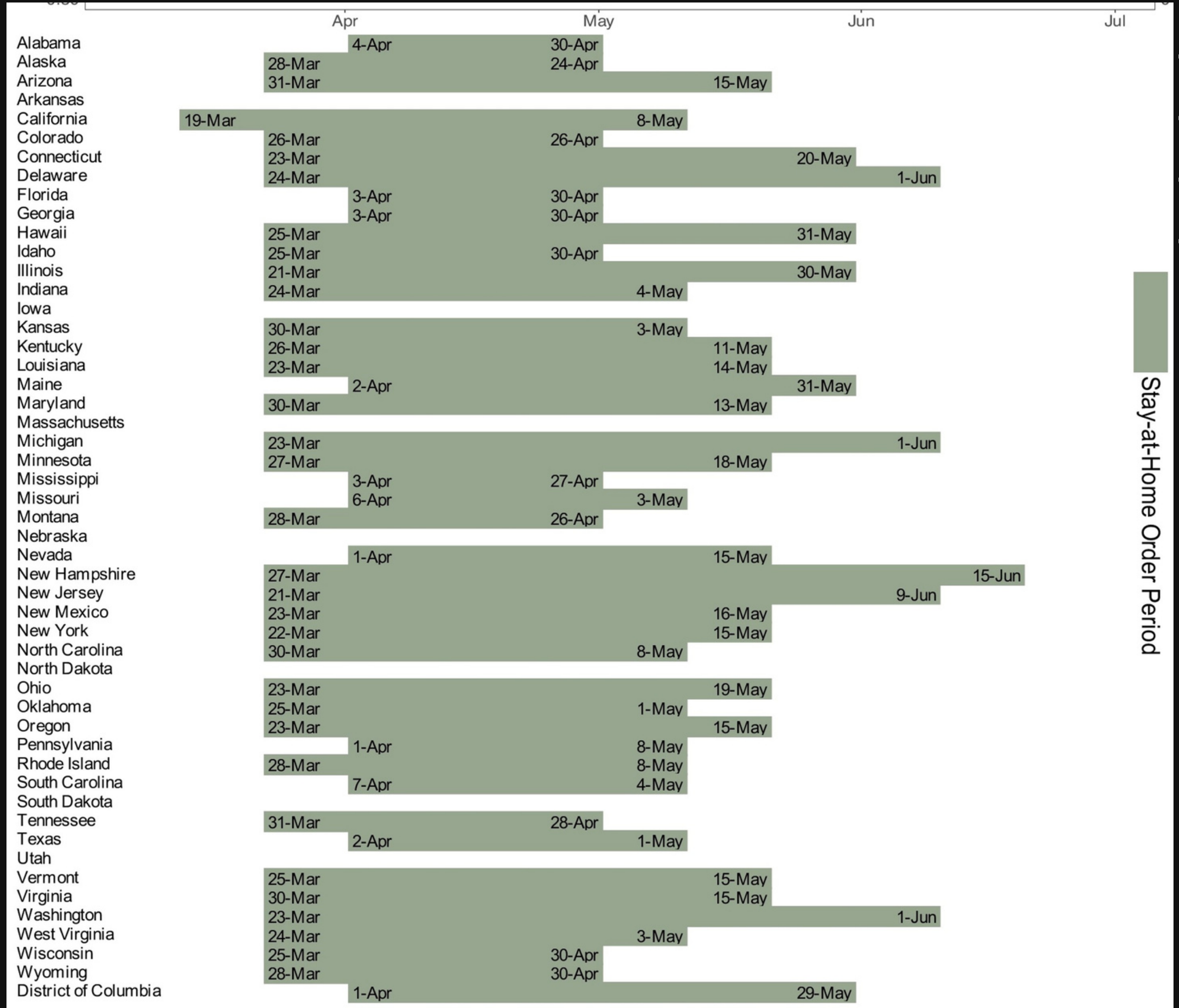
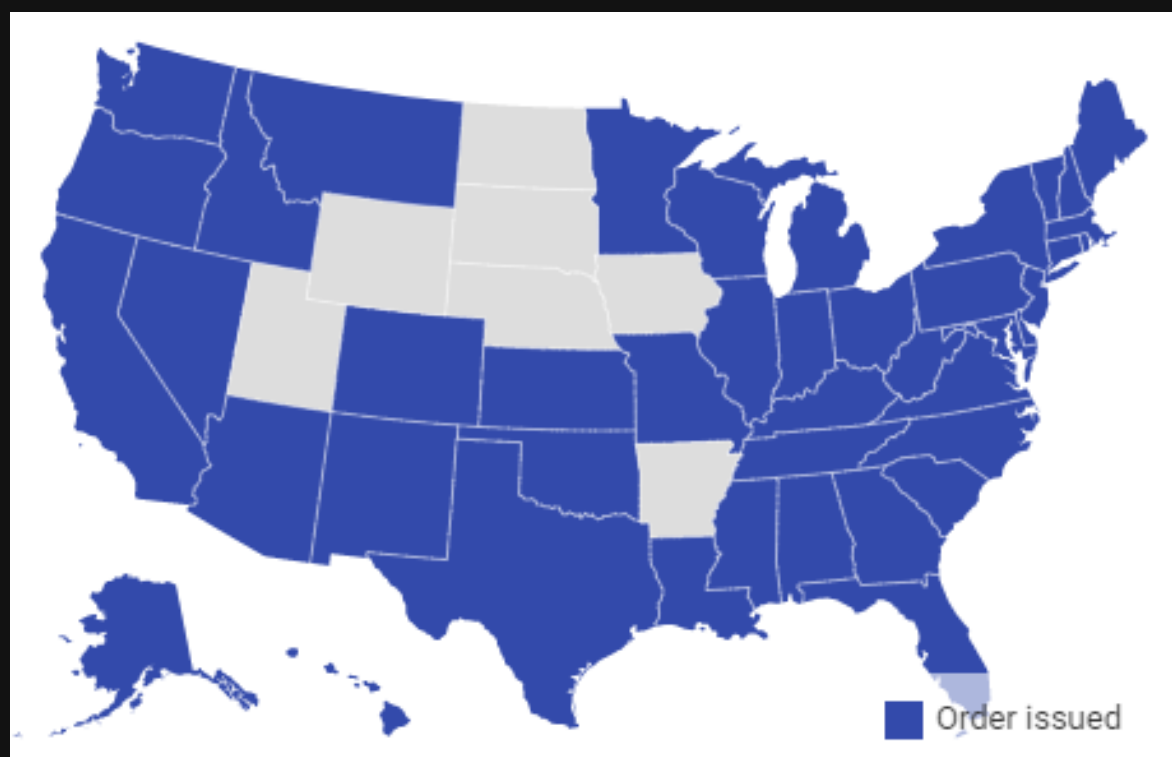




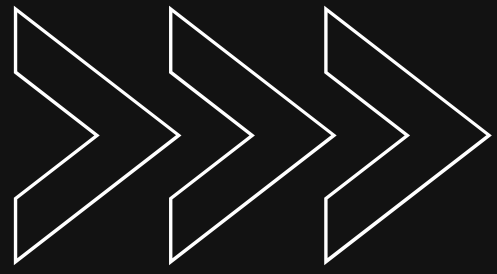
Preliminary results: Sentiment score vs. New cases/deaths



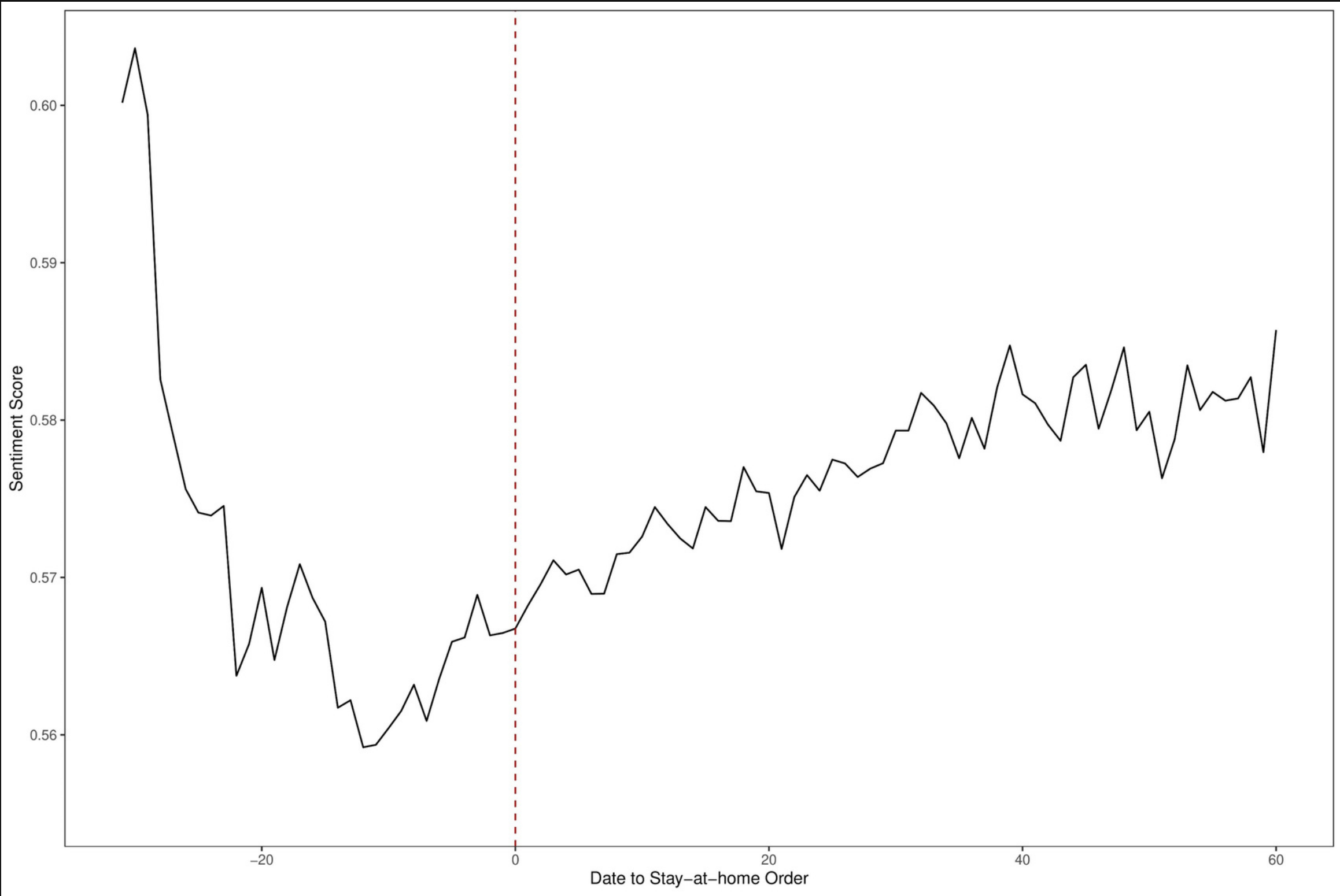
Stay-at-home related policy timeline

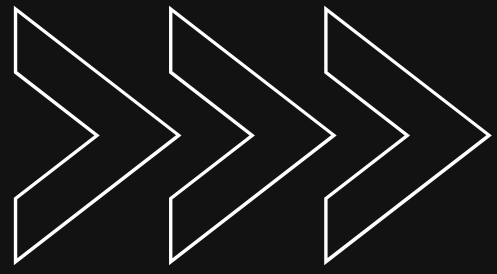


Stay-at-Home Order Period

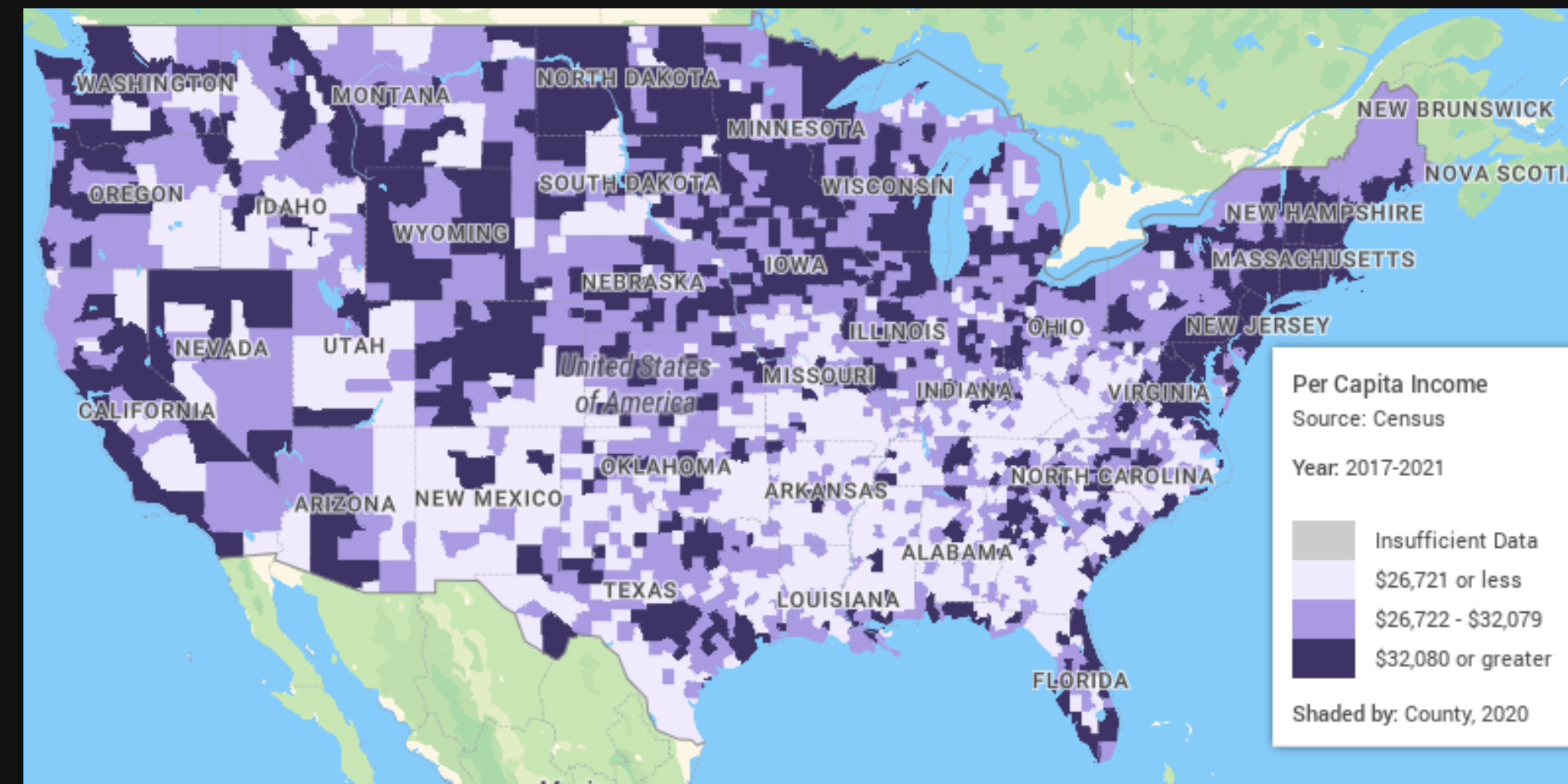
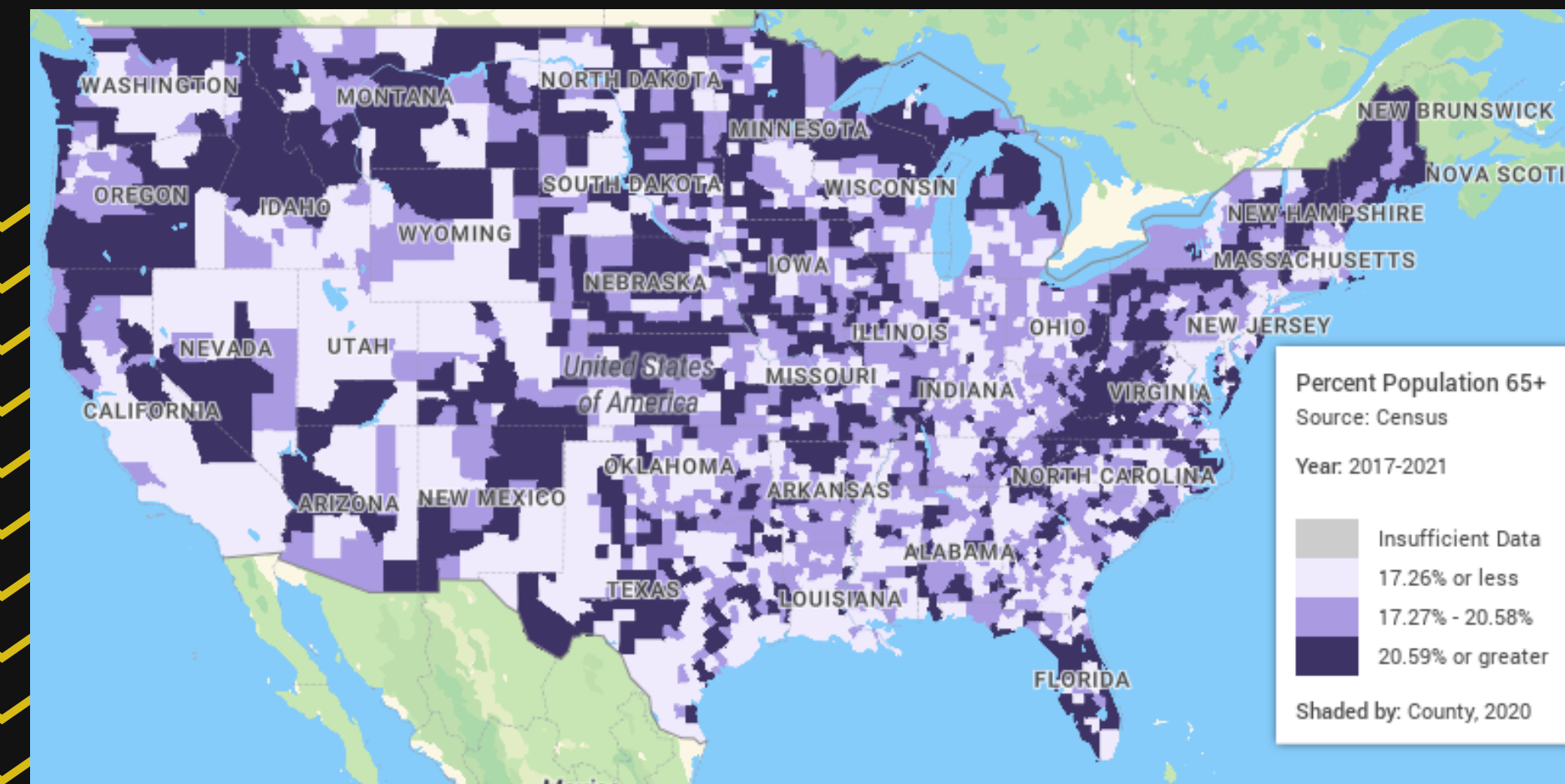
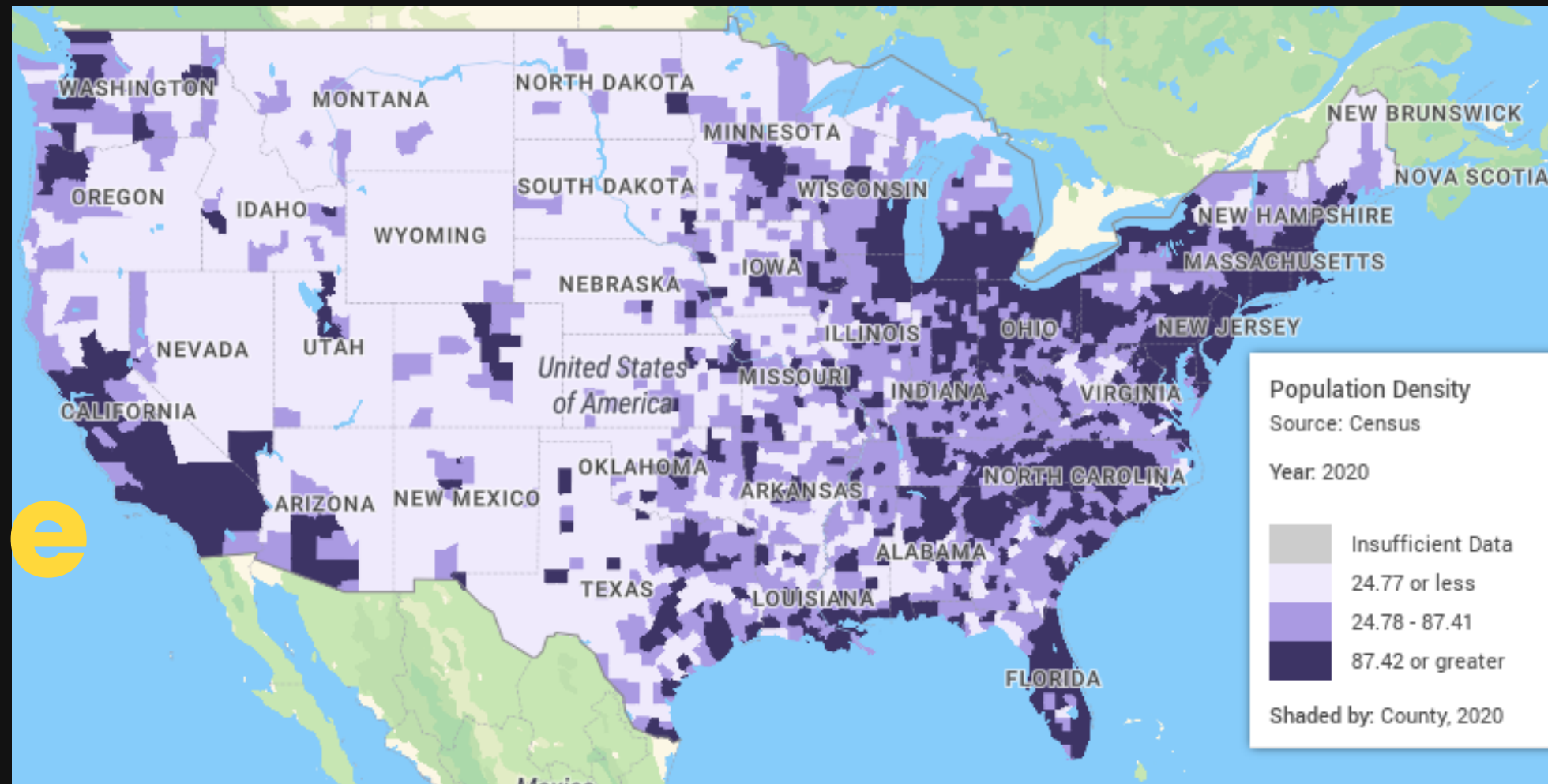


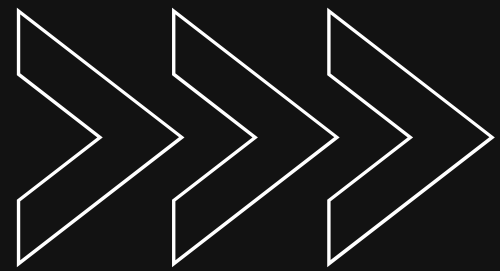
Sentiment scores before and after the stay-at-home orders



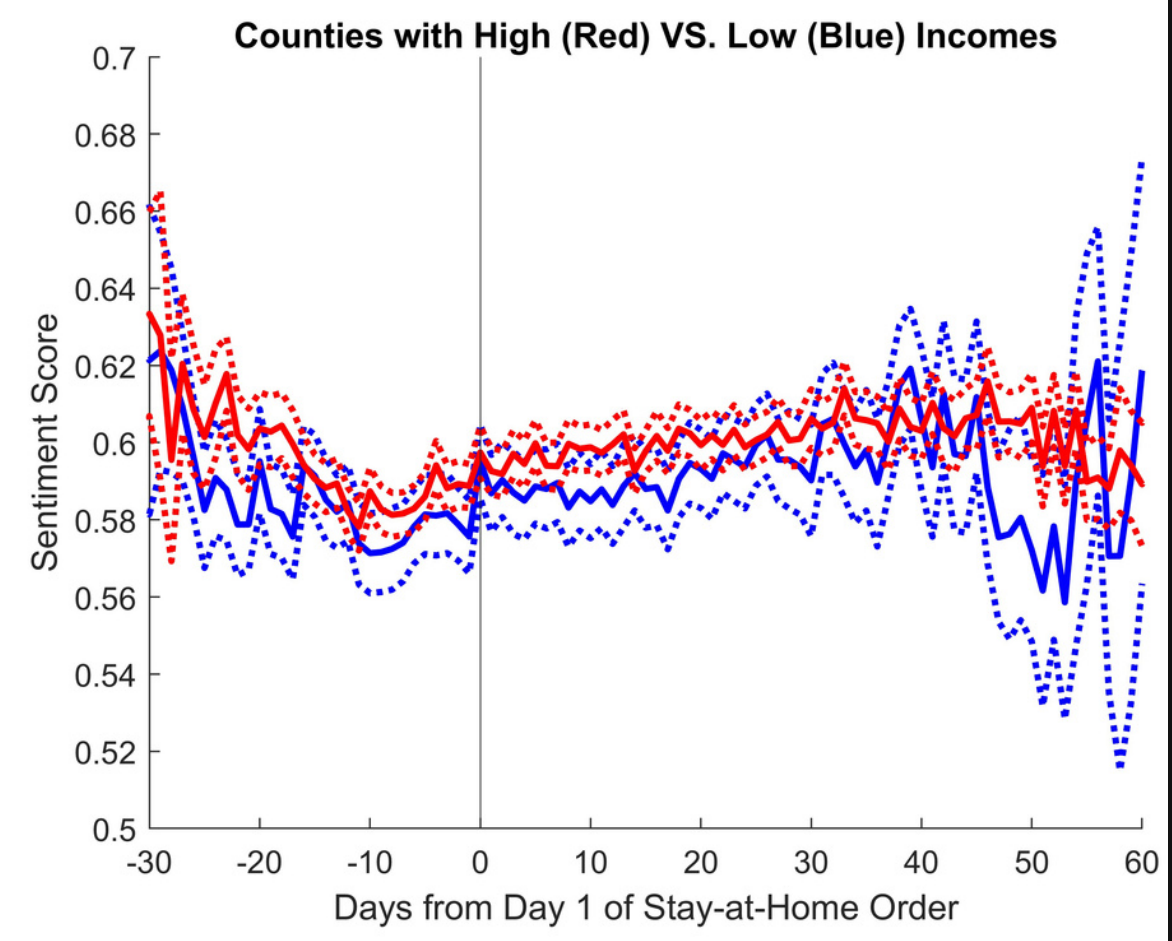
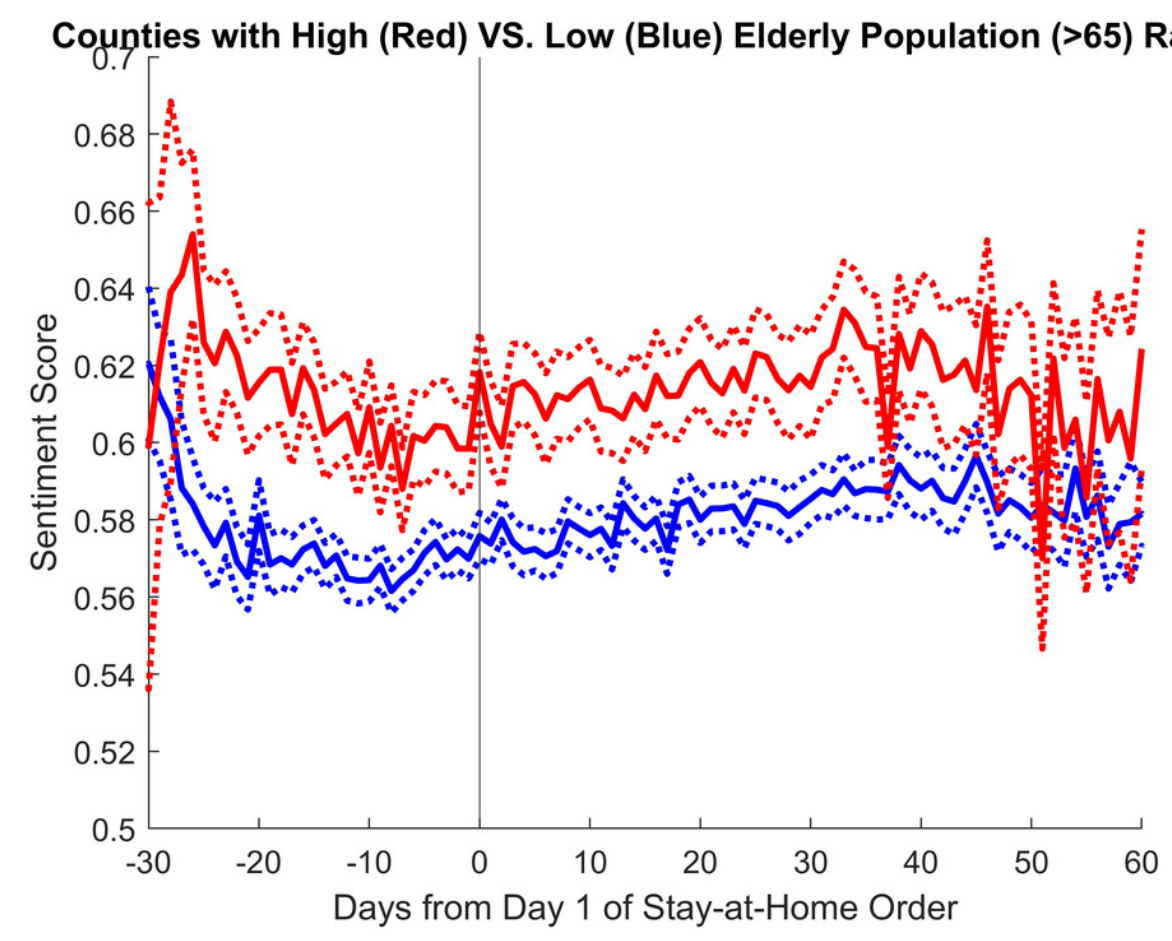
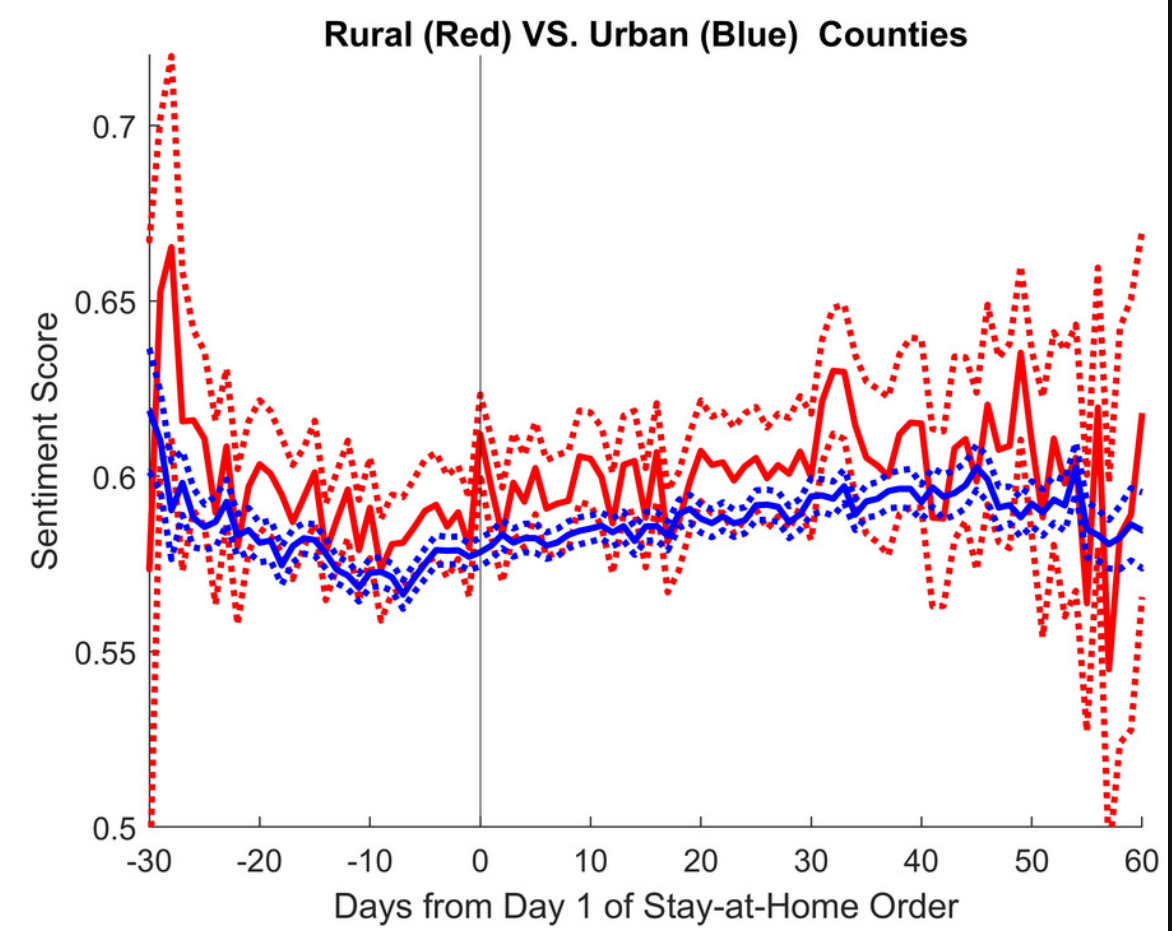
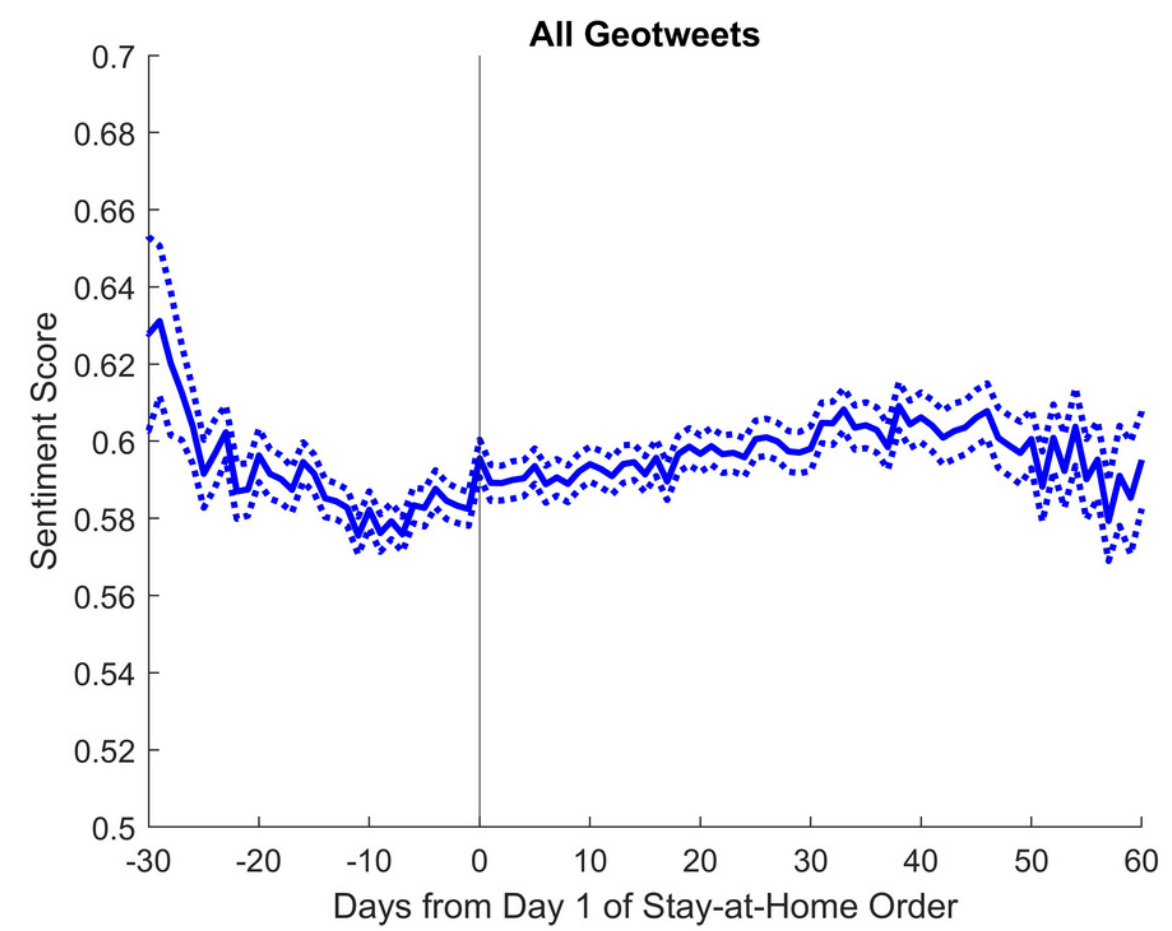


Vulnerable groups





Sentiment scores among vulnerable groups

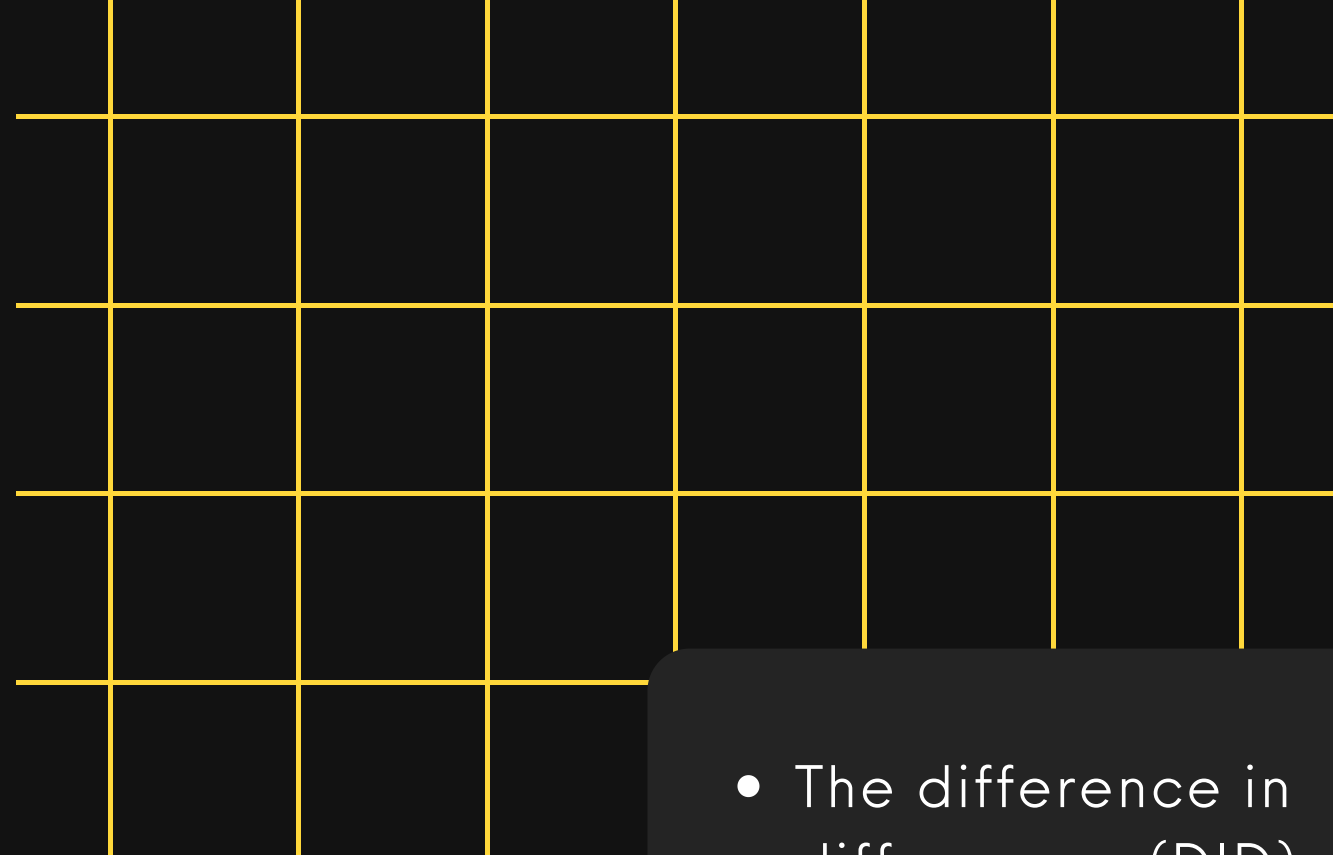


Summary



- Stay-at-home orders received a positive response and contributed to an improvement in Twitter sentiments.
- However, counties faced more significant difficulties in an urban (versus rural) setting, with a lower concentration of elderly individuals, or lower incomes during the pandemic.
- This study offers a sociological perspective, informed by large-scale Twitter data, for monitoring changes in public opinion, evaluating the impact of social events, and understanding the disaster management of pandemic shocks.

Next Steps

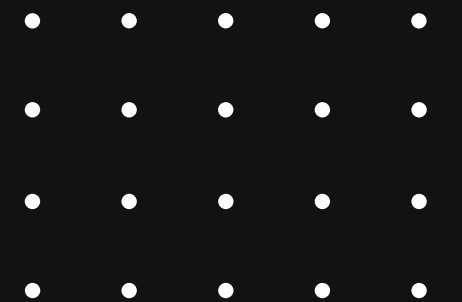


Methodology

- The difference in differences (DID) regression model
- Topic modeling

Research topics

- Natural disasters (e.g., hurricanes)
- The efficiency of policies (stay-at-home orders in the US vs lockdowns in China)



Thank You!

Contact me for more questions.

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