Psychological States' Impact on Pandemic: Indicating Power and Policy Moderation

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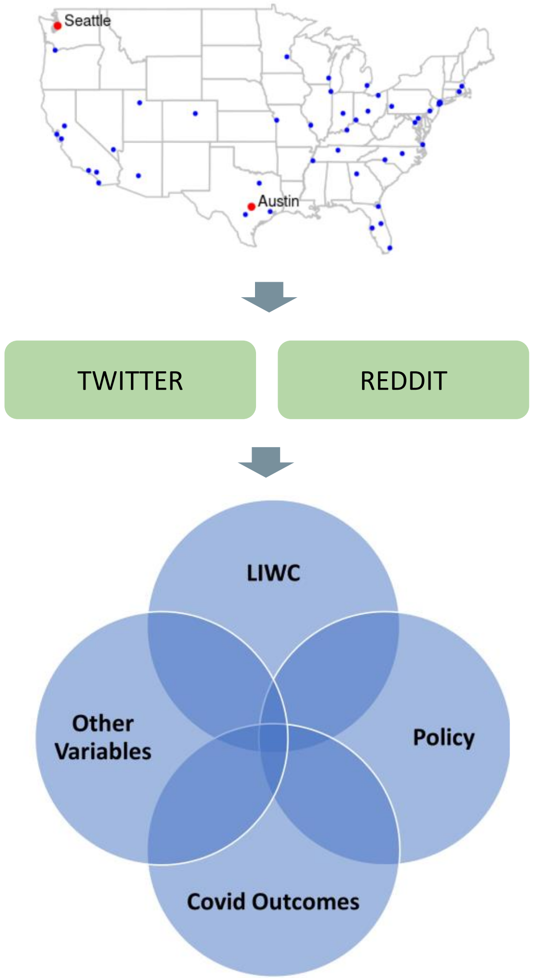
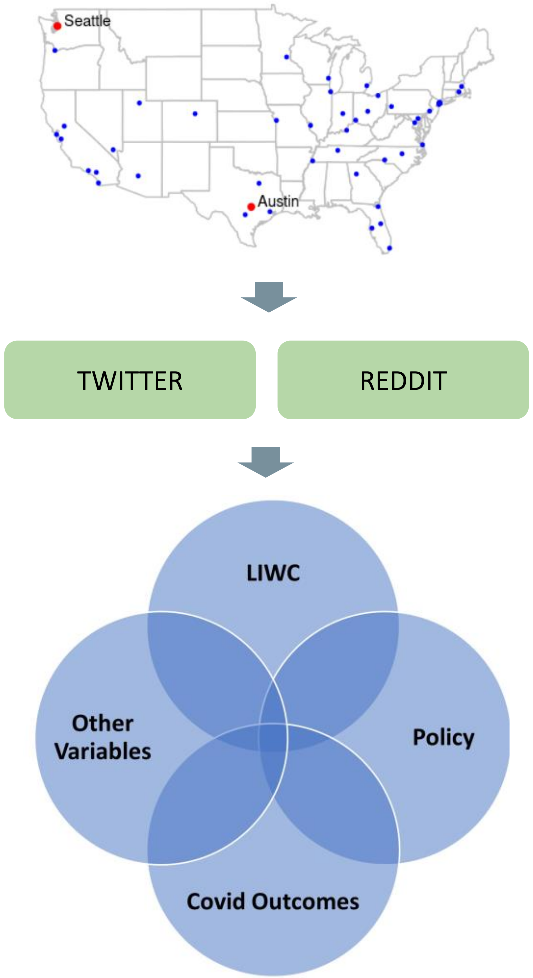
Problem Statement

- **Indicating Power:** Can psychological states on social media predict epidemiological outcomes and preventive health behaviors during an ongoing pandemic?
  - If yes, what psychological dimensions could be good predictors?
- **Policy Moderation:** Can psychological states on social media be used to assess how policies moderate epidemiological outcomes and preventive health behaviors?



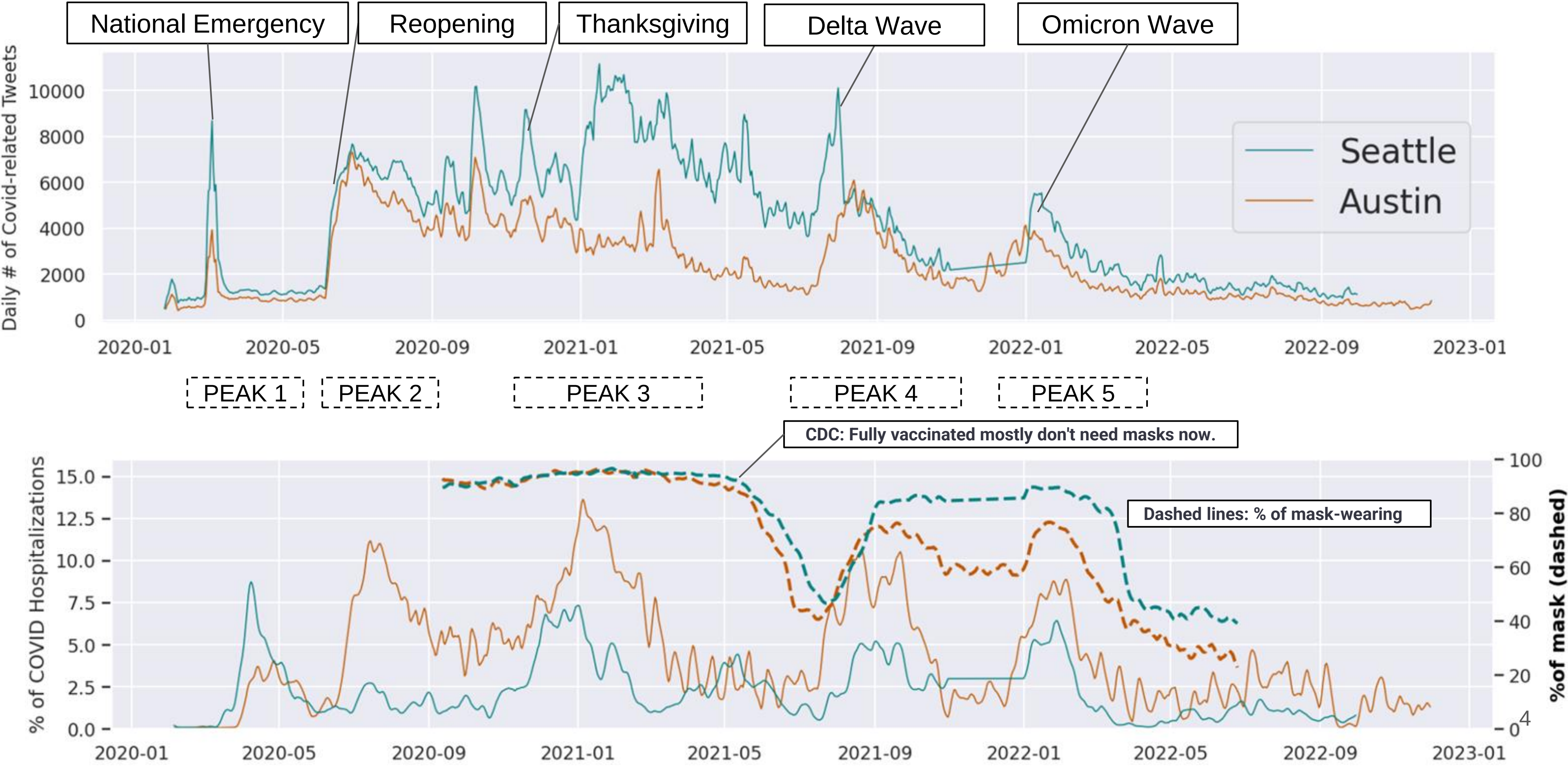
Modeling Strategy

1. **Explore social media data** across two cities, and by common policy breakpoints
2. **Examine differences in LIWC** scores across differing policy timepoints (DID)
3. **Evaluate modeling** techniques:
   - ARIMA
   - Incorporate how policy may moderate outcomes

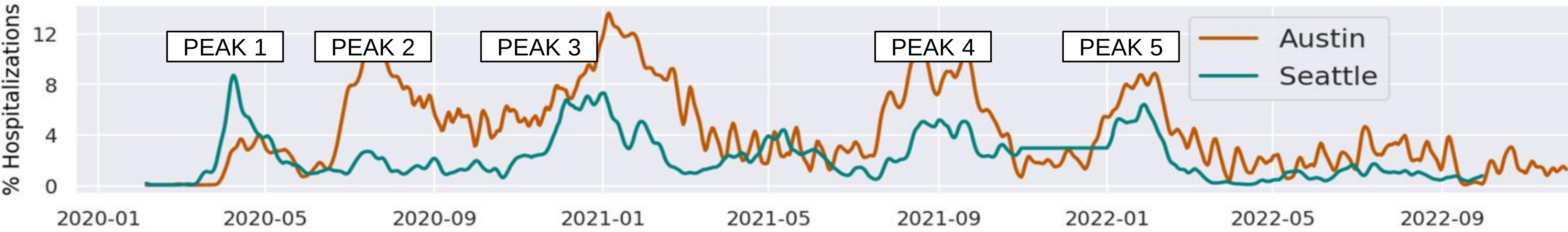


1. Explore Social Media Data

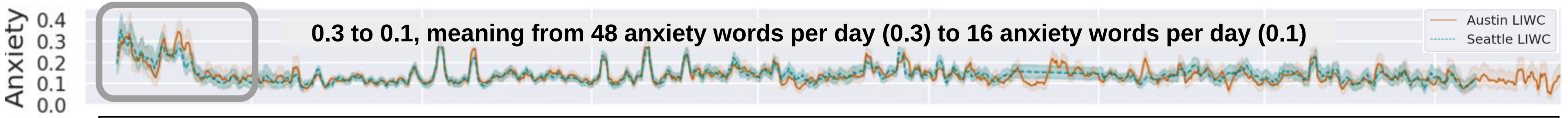
Austin & Seattle: Number of Covid related Tweets, hospitalizations, and mask wearing



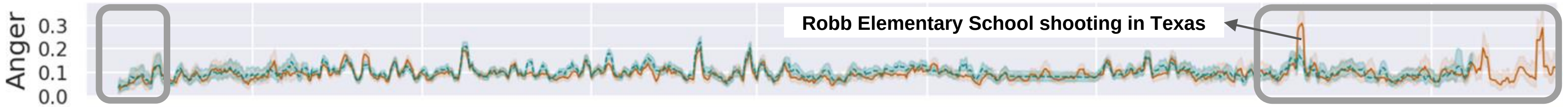
1. Explore Social Media Data: Anxiety, Anger, Positive Emotion in Austin & Seattle



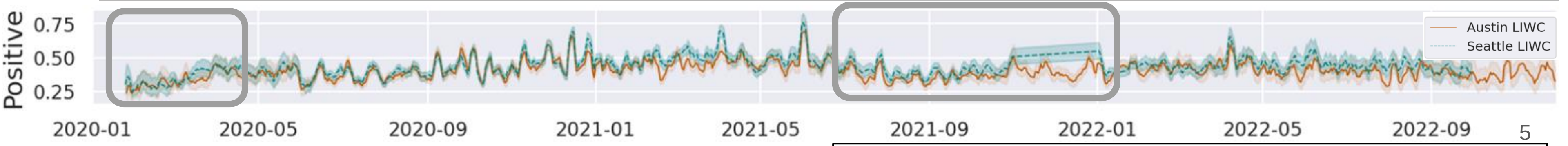
Anxiety was high and highly unstable before April. Then the anxiety level remained steady, showing a **fatigue** pattern.



Anger increased during the first two months of COVID.Then the anger level remained **persistent**, with some high peaks in **2022**.



Positive Emotion increased before June 2021. When the pandemic entered the second half (after July 2021), the level of positive emotions was low, indicating people's **fatigue** with COVID-19.

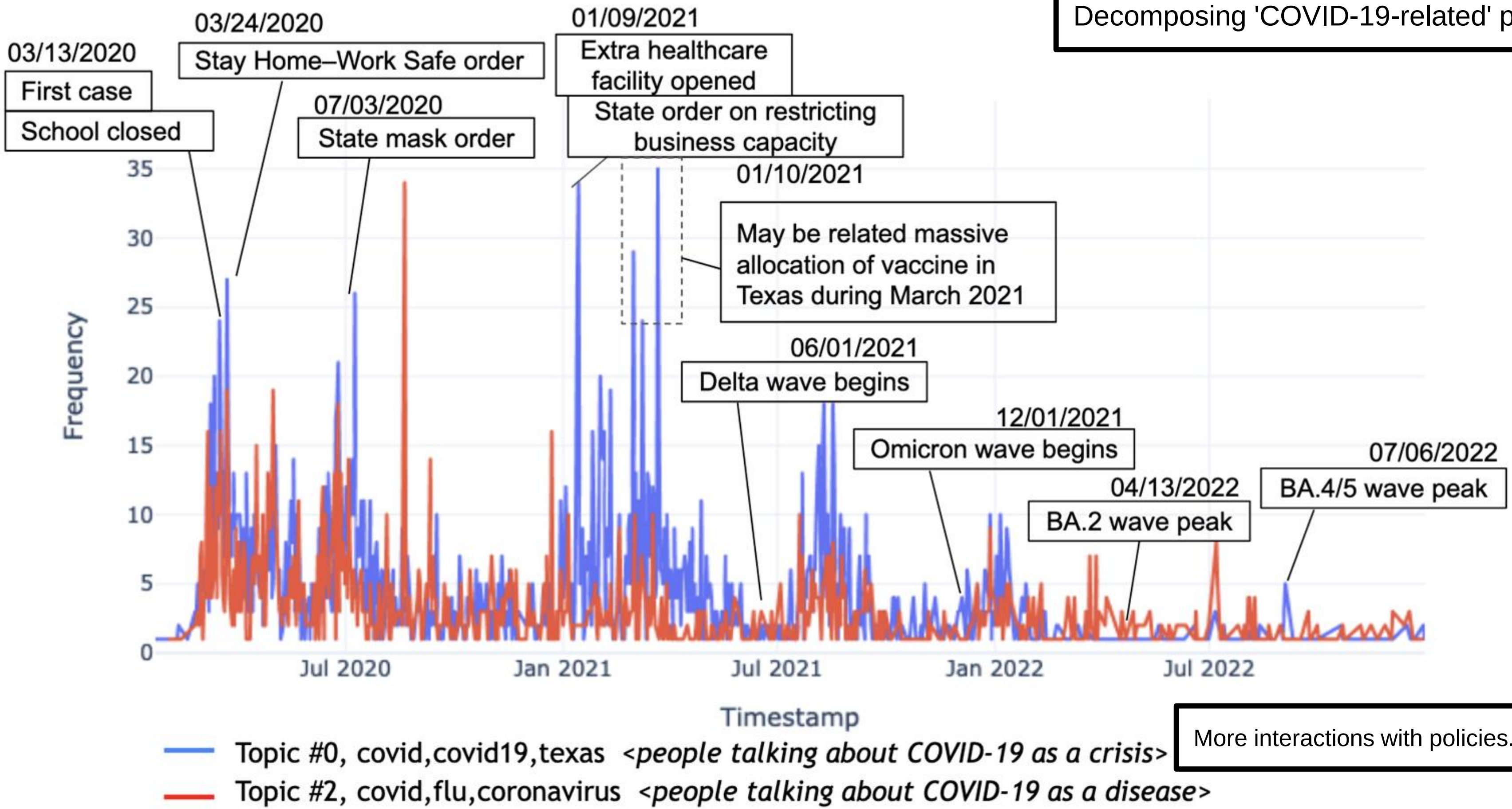


*people typically speak about 16,000 words per day in daily conversations.

Twitter 5 days rolling avg. 80% bootstrapped confidence interval

1. Explore Social Media Data: REDDIT Austin

Decomposing 'COVID-19-related' posts.



More interactions with policies.

2. Examine Differences in LIWC: an impactful policy can hugely influence what people are talking about (mask-wearing), and their emotions. And how they behave.

Policy
CDC ends indoor mask requirements.

↓

What people are talking about. (Mask increased)

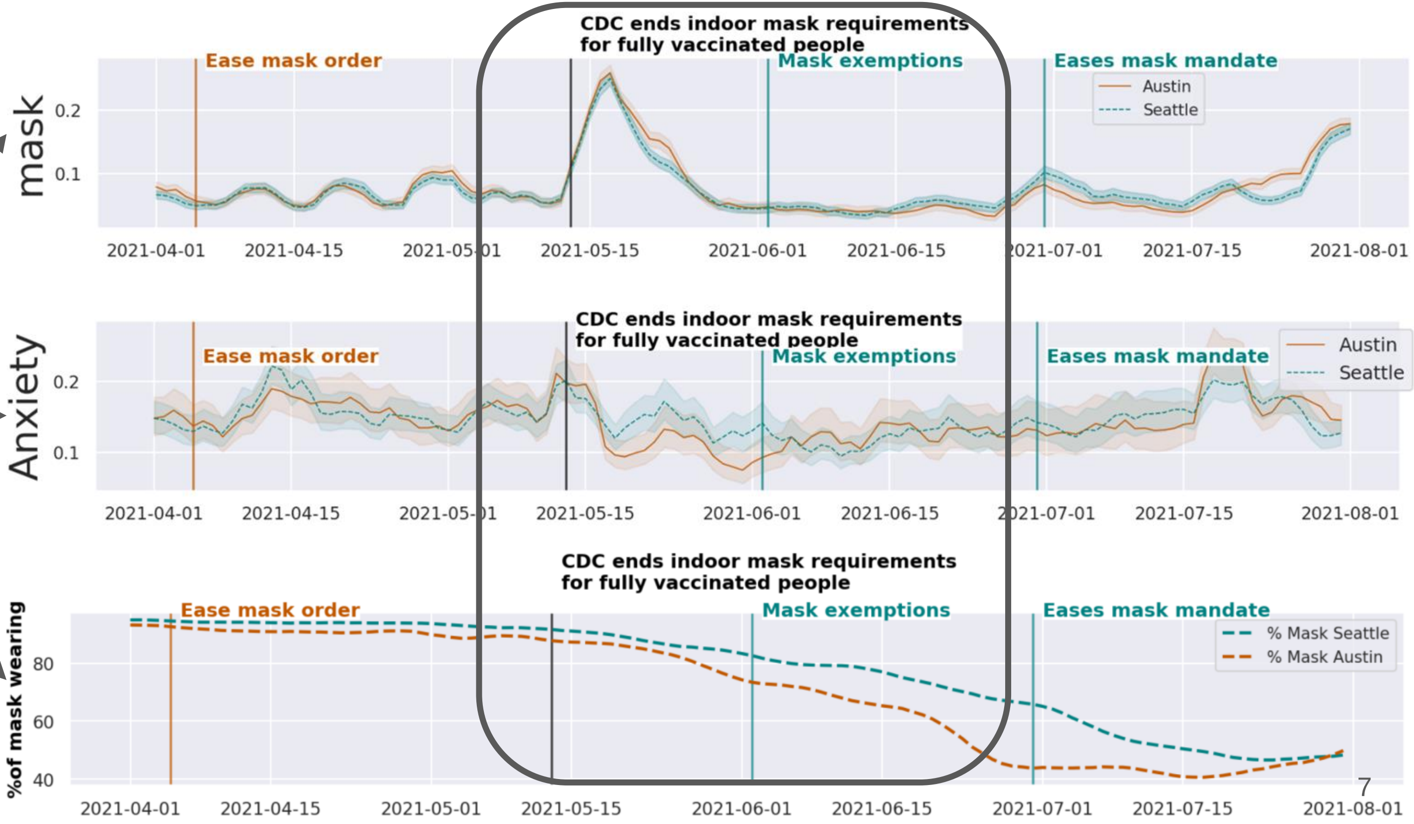
↓

People's Emotion. (Dropped Anxiety)

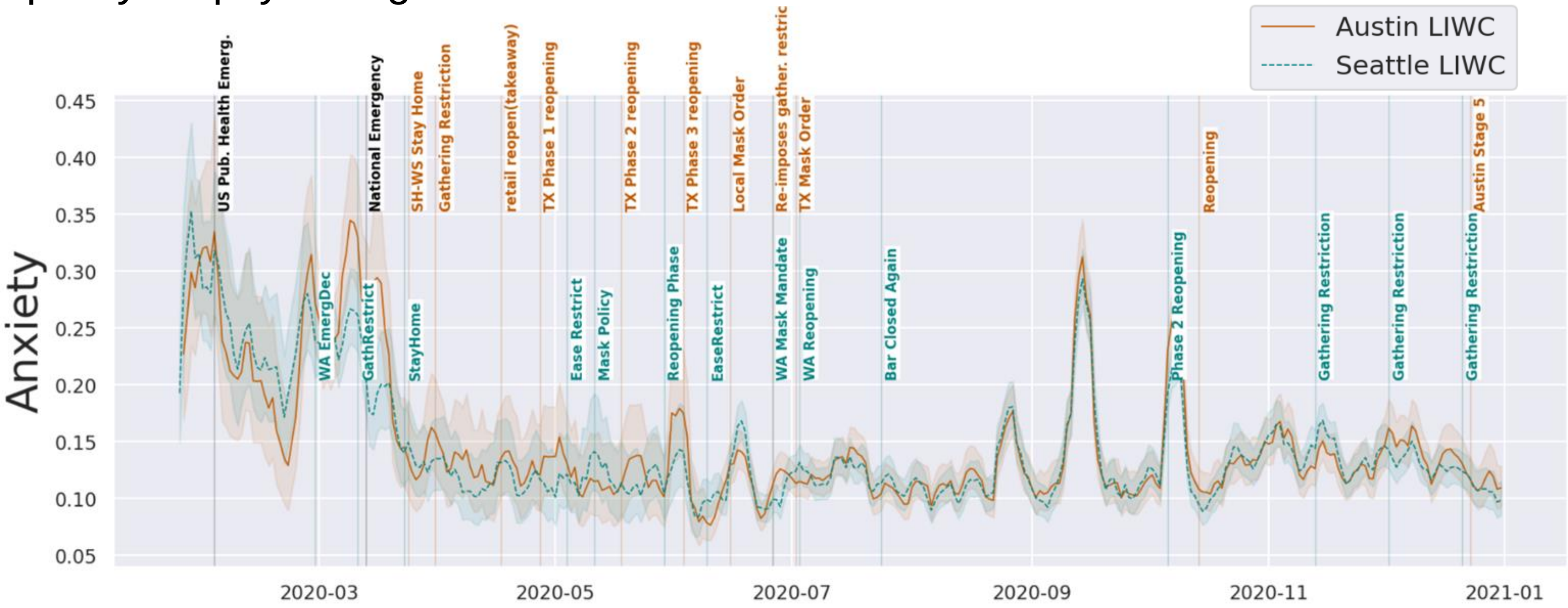
↓

People's Behavior. (Mask-wearing.)

Twitter 5 days rolling avg. 80% bootstrapped confidence interval



2. Examine Differences in LIWC: Austin & Seattle, seeking causality of policy on psychological trends



Twitter 5 days rolling avg. 80% bootstrapped confidence interval

*people typically speak about 16,000 words per day in daily conversations

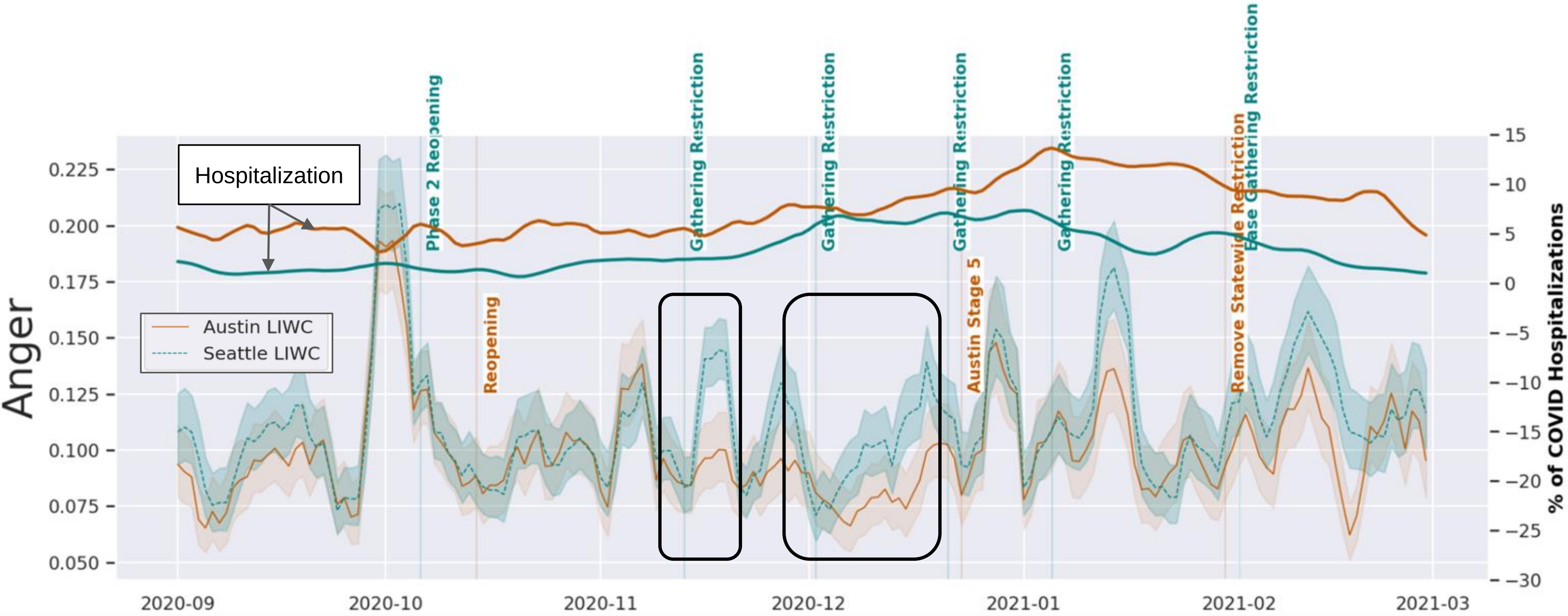
2. Examine Differences in LIWC: Austin & Seattle, weak signal

Mask exemption might **alleviate** people's **anxiety.**

Twitter 5 days rolling avg. 80% bootstrapped confidence interval

*people typically speak about 16,000 words per day in daily conversations

2. Examine Differences in LIWC: Austin & Seattle, weak signal

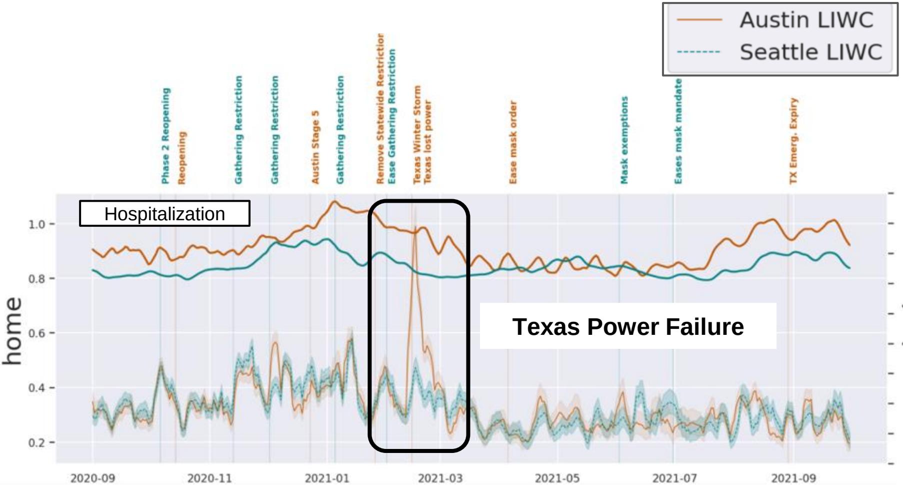


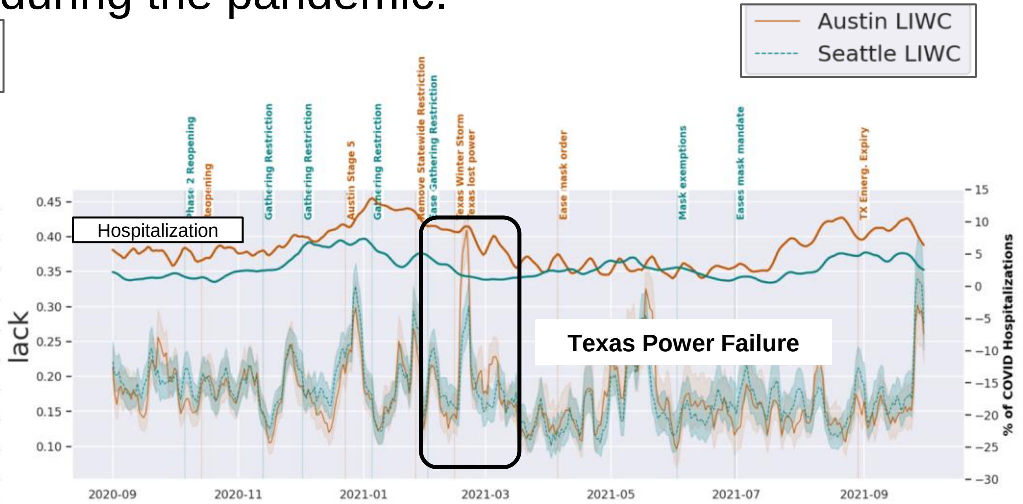
Gathering restriction might **increase** people's **anger.**

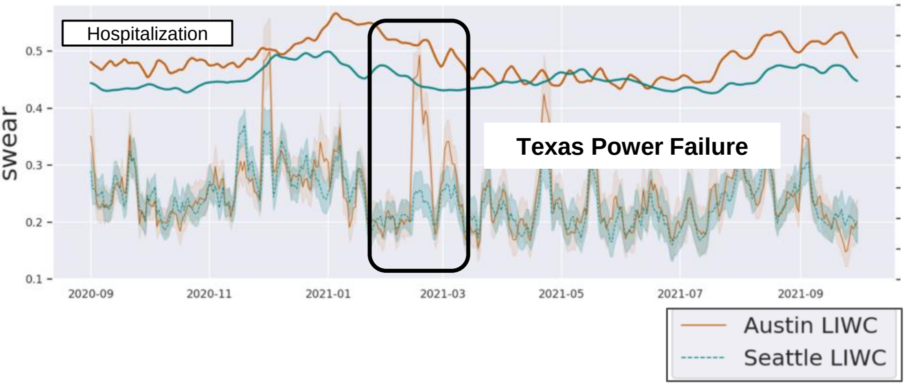
Twitter 5 days rolling avg. 80% bootstrapped confidence interval

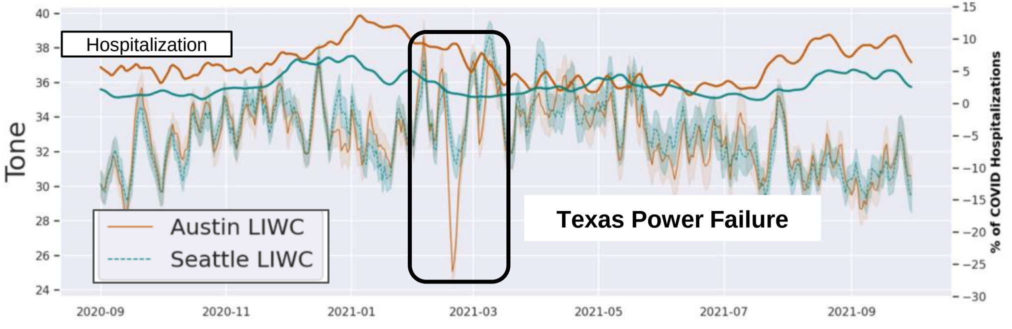
*people typically speak about 16,000 words per day in daily conversations

2. Examine Differences in LIWC. The black swan event that causes damage to **infrastructure**: the Texas winter storms during the pandemic.





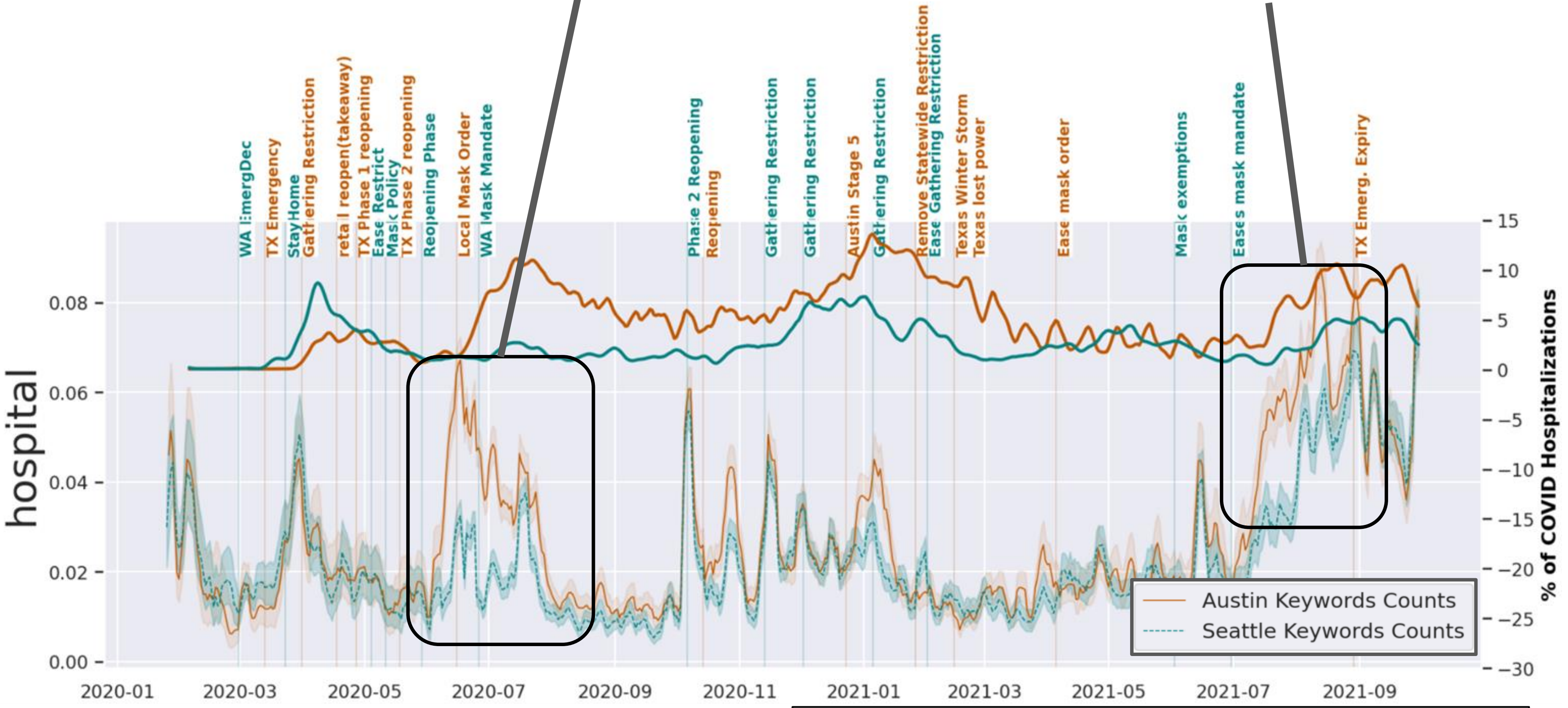




Twitter 5 days rolling avg. 80% bootstrapped confidence interval

2. Examine Differences in LIWC. Pandemic-related keywords indicate an increase in hospitalizations.

An increase in the use of the term 'hospital' results in a rise in hospitalizations.



Twitter 5 days rolling avg. 80% bootstrapped confidence interval

3. Evaluate Modeling Techniques: ARIMA

Using LIWC value to predict Hospitalizations

Input features

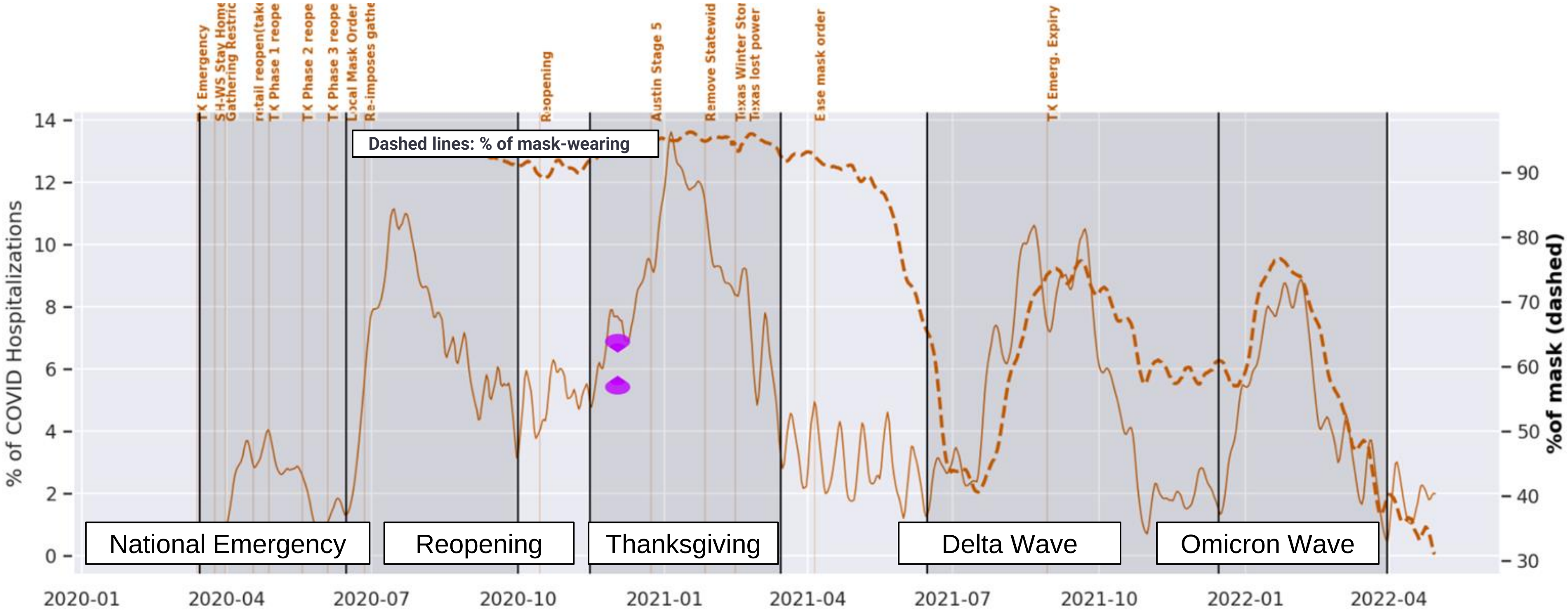
LIWC variables

- emo_pos, emo_anx, emo_sad, emo_anger
- Lifestyle
  - leisure, home, work, money, religion
- illness, wellness, mental health
- substances
- food
- death
- fatigue, lack, fulfill
- reward and risk
- politic
- prosocial, conflict, moral
- swear

Pandemic related variables

- mask
- covid
- vaccine
- Policy
- health
- hospital

3. Evaluate Modeling Techniques: Hospitalizations - Austin



P < 0.1
coef. > 0.3

PEAK 1
lack: 0.09
substances: -0.07
swear: 0.05
risk: -0.04

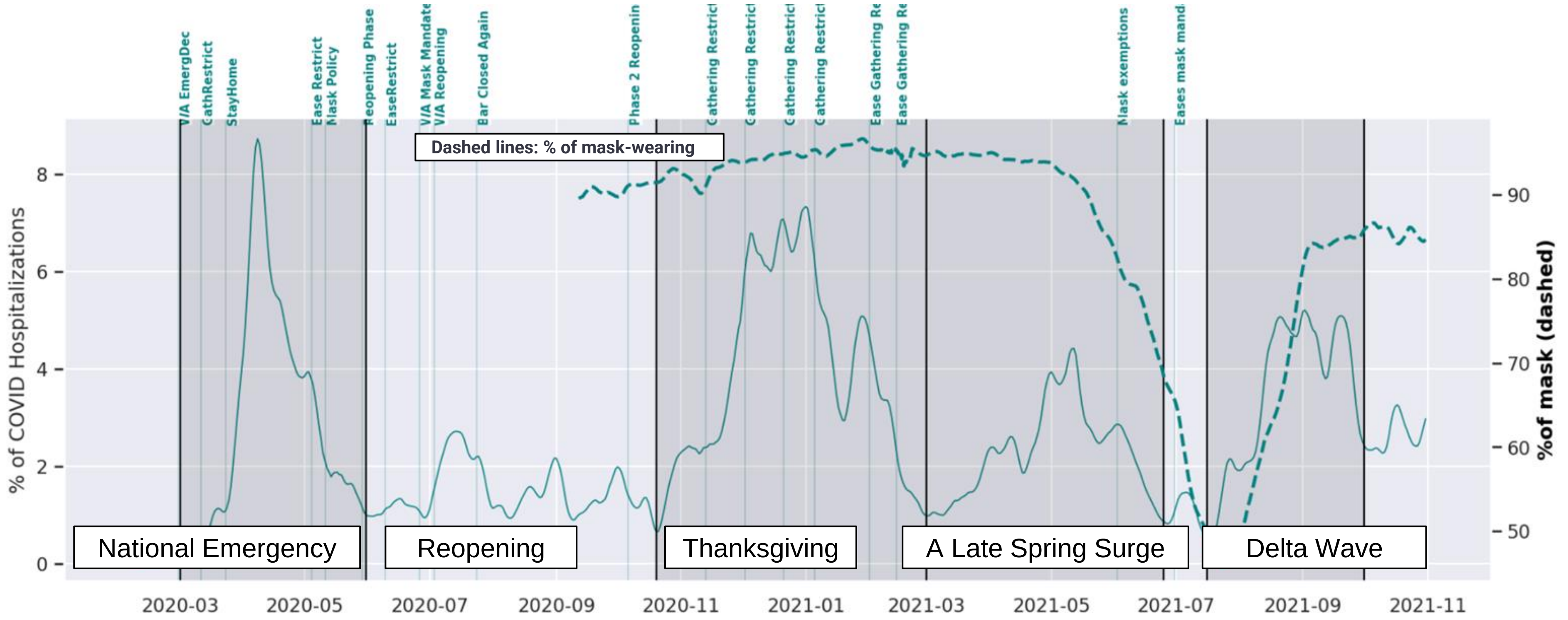
PEAK 2
emo_anger: -0.12
politic: 0.11
wellness: 0.10
conflict: 0.08
fatigue: 0.07
prosocial: -0.06

PEAK 3
vaccine: -0.15
illness: 0.12
moral: -0.08

PEAK 4
covid: 0.08
death: -0.05

PEAK 5
covid: 0.26
illness: -0.16
politic: 0.07
reward: 0.05

3. Evaluate Modeling Techniques: Hospitalizations - Seattle



P<0.2
coef. > 0.3

PEAK 1
emo_anger: -0.07
money: 0.07
prosocial: 0.06

PEAK 2
mask: -0.05
vaccine: -0.08
emo_anger: 0.03

PEAK 3
emo_sad: 0.04

PEAK 4
vaccine: 0.09
prosocial: -0.09
emo_pos: -0.06
moral: -0.05

3. Evaluate Modeling Techniques: Summary

- During the initial stages of the pandemic (before 2021), the most influential predictors of hospitalization were the LIWC values.
    - In four LIWC emotion variables (anxiety, anger, sadness, positive emotion), **anger** is the best predictor of hospitalization.
- post-2020, pandemic-related keywords demonstrated a stronger predictive capacity.
    - Pandemic related frequency of keywords, e.g., **vaccine, mask, covid** are all good predictors.
    - Around January 2021, when people began to receive the vaccine, the "number of vaccine mentions" was a good predictor of hospitalization.

Conclusions and Next Steps

- Expand the approach for comparison to other cities.
- Integrate other datasets which may improve model predictive power (demographics, economics, political ideology, mobility.)
- Consider other spatiotemporal modeling approaches.
- Evaluate how feature importance may vary across locations and pandemic phases.
- Expand policy moderation efforts in model development.

Some problems: state-level analysis

In our state-level analysis, the sample size of tweets with geo-tagged locations is small.
The bootstrapped confidence interval overlaps.