The Impact of the COVID-19 Pandemic on Suicidal Ideation Among Youth

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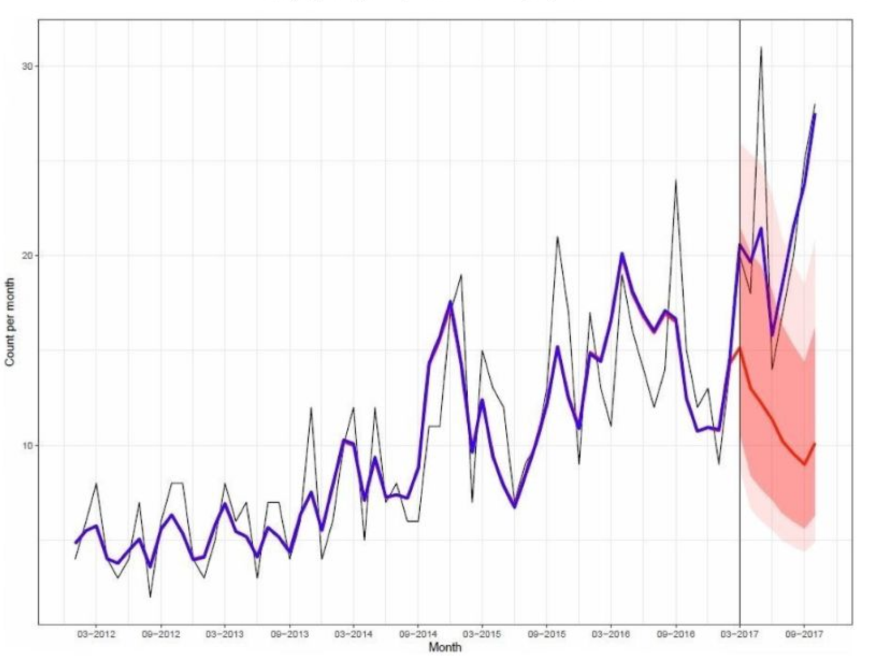
Outline

1. Previous work examining adolescent suicide presentations in response to culturual phenomena
2. Presentation differences following the COVID-19 pandemic
3. Identifying variables which predict presentation rates following the pandemic
4. Extending these analyses into the N3C enclave
   a. QA
   b. Analytic strategy

13 Reasons why summary

1. Trends in suicidal idetation presentation were examined following the release of the netflix series: “13 Reasons Why”

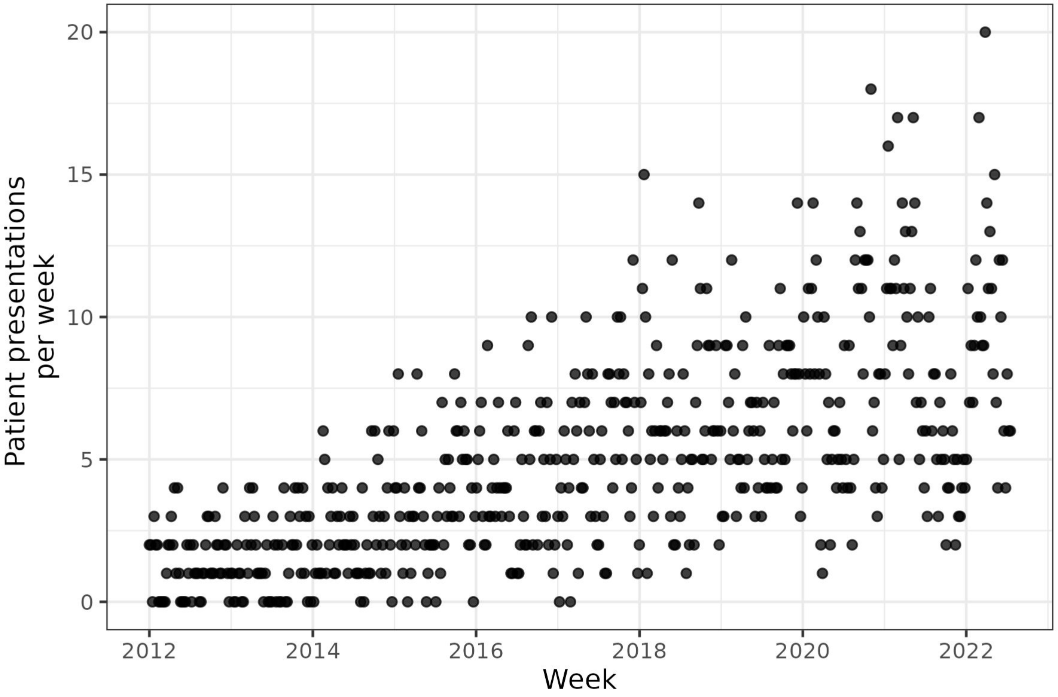


Black vertical line represents March 2017 when the Netflix episodes premiered.
Black jagged line (thin) represents observed data.
Blue line (thick) represents predicted values from the ‘best’ fitted model.
Red line captures forecast predictions from a model that only included pre-show data.
Red shaded regions reflect the 80% (darker) and 95% (lighter) confidence intervals for the forecast.

Townsend Cooper et al., 2018

Local Trends in Suicide Presentation

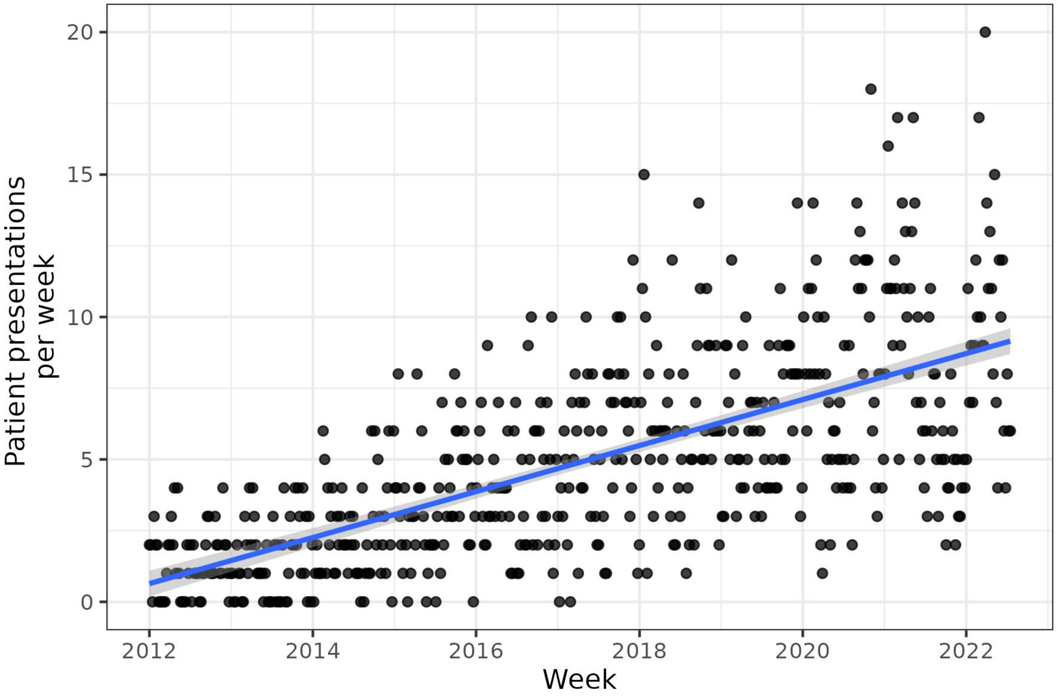
1. A chart review was performed at the Oklahoma CHildren's Hospital examining electronic charts for patients of ages 4-17
2. Patients were identified by ICD codes indicating a diagnosis of suicidal ideation or intentional acts of self-harm from January of 2012- July 2022; each visit was counted as a separate event, and no patients were excluded if they met these criteria.
3. In total 2698 patient encounters met inclusion criteria



DeLetter et al., Under Review

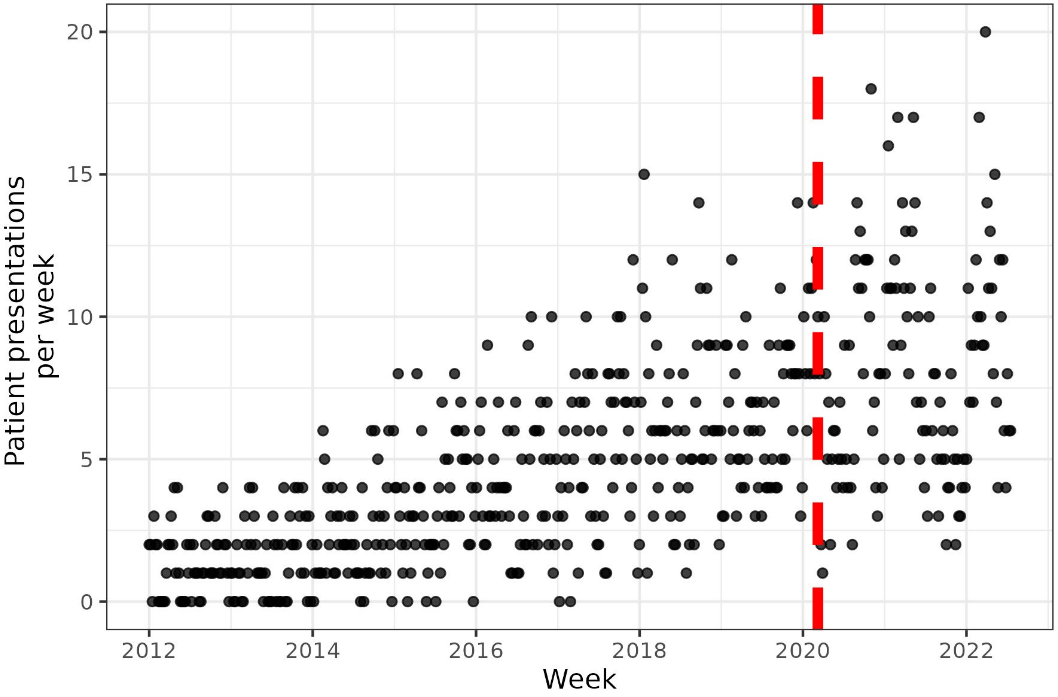
Local Trends in Suicide Presentation

1. Historical trends were examined from January 2012 through July 2022
2. A strong linear trends was observed across all available data: (β=0.02, $t(549)$=21.316, R^2=0.45)



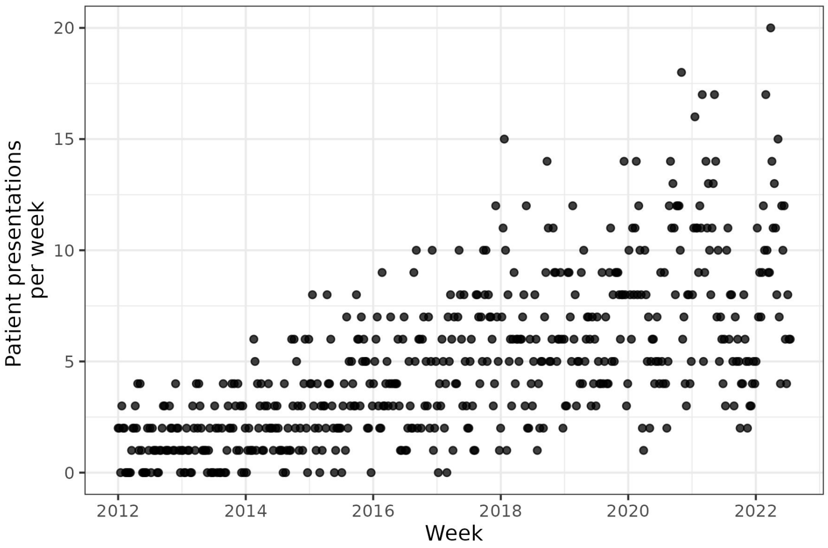
Local Trends in Suicide Presentation

1. Hypotheses seek to examine differences in presentation patterns succeeding the pandemic, <u>specifically for an increase in presentation rates</u> aligning with Pediatricians' qualitative reports
2. This hypothesis was examined using two separate techniques:
   a. Change point model
   b. Comparison of best fitting ARIMA coefficients

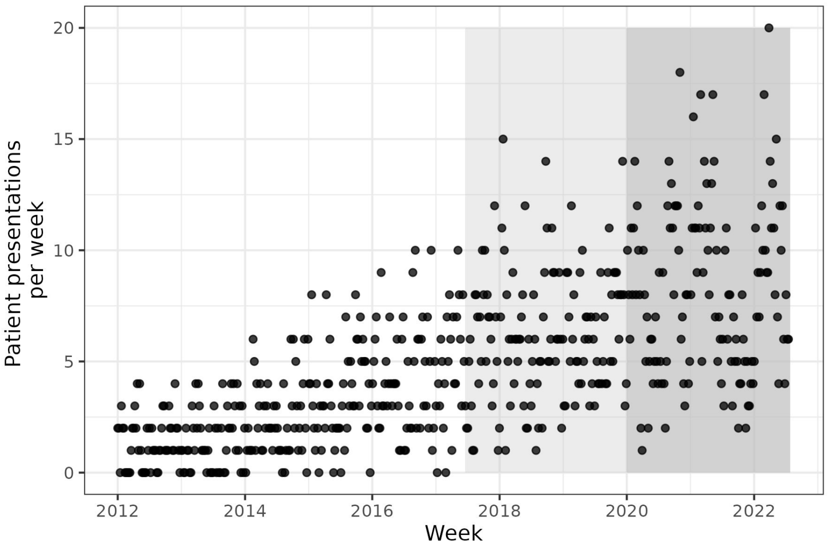


Local Trends in Suicide Presentation

The change point model uses **ALL** available data to identify historical points when best fitting models change

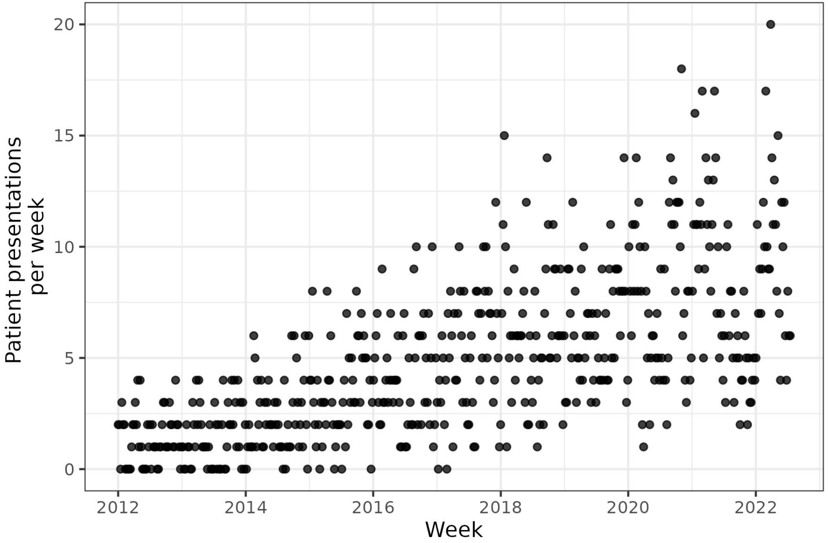


The best fitting ARIMA models uses two isolated identical length time periods preceding and succeeding the onset of the pandemic

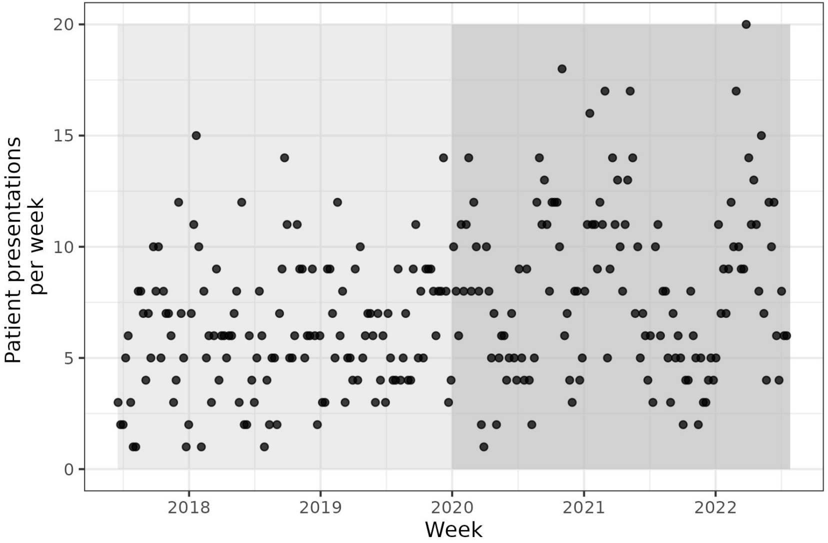


Local Trends in Suicide Presentation

The change point model uses **ALL** available data to identify historical points when best fitting models change (Jan 2012: July 2022)



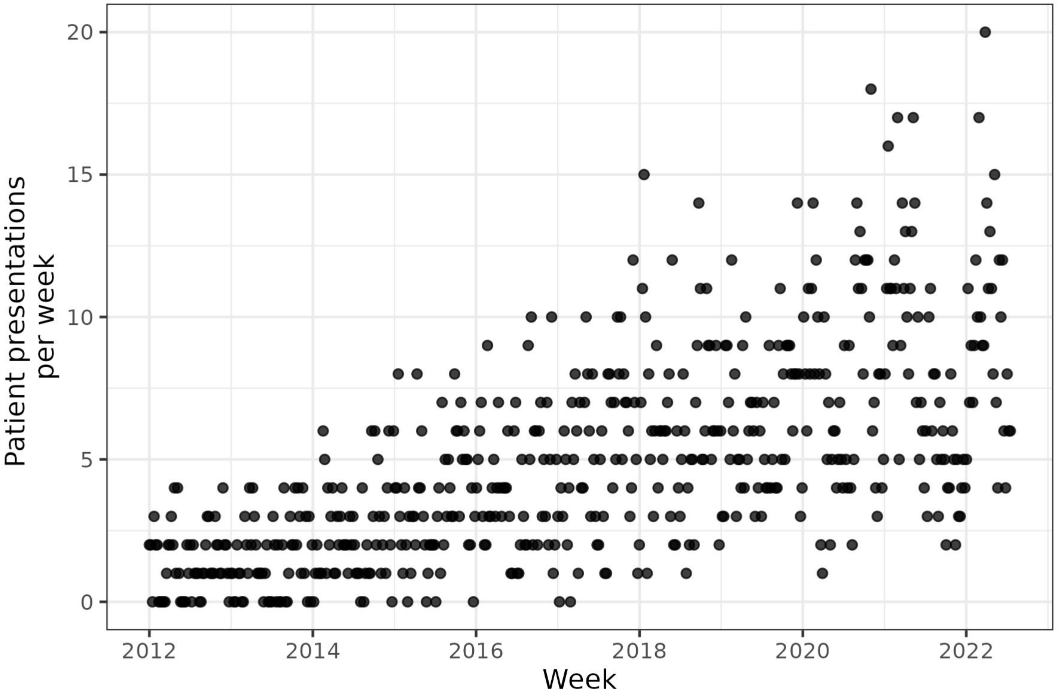
The best fitting ARIMA models uses two isolated identical length time periods preceding and succeeding the onset of the pandemic:
(Jan 2017: Jan 2020) & (Jan 2020:July 2022)



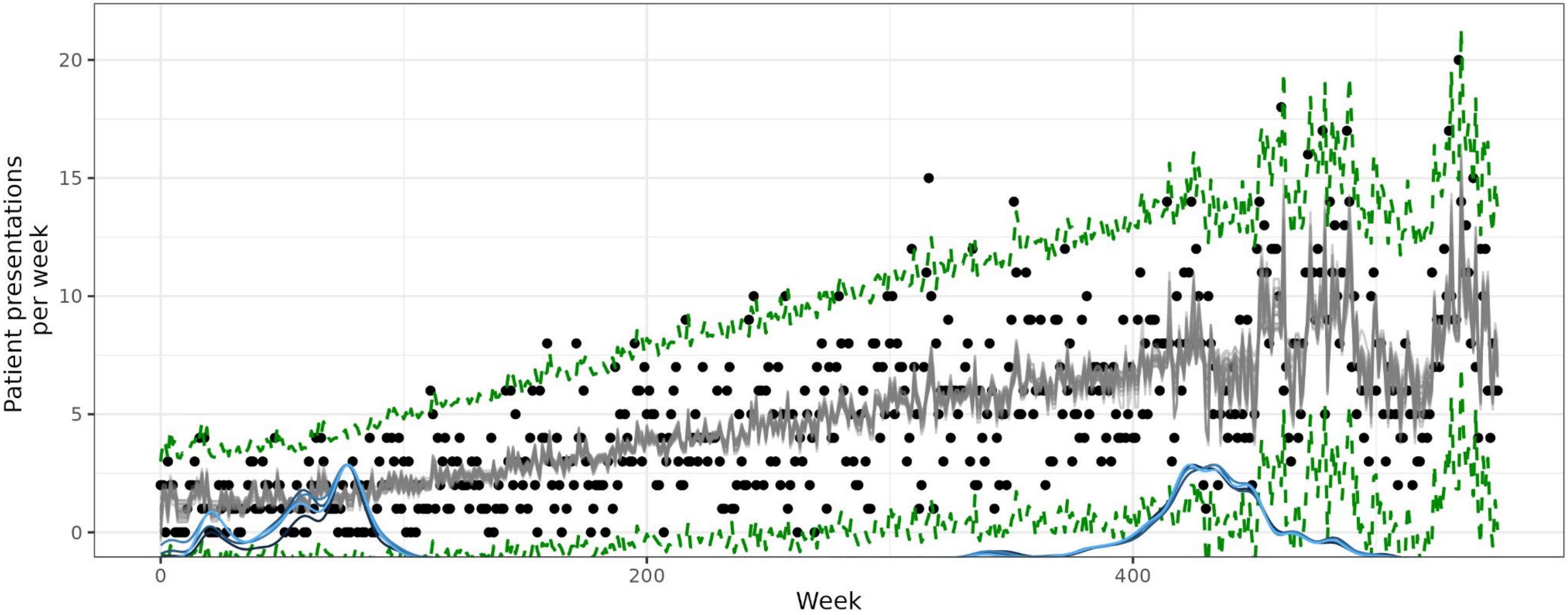
DeLetter et al., Under Review

Local CP model methods

1. A 2-change-point model was fit estimating 3 models, the three models included:
   a. Presentations ~ Slope + AR(1)
   b. ~ Slope + Var(Month) AR(1)
   c. ~ Slope AR(1)
2. All parameters were estimated in a bayesian framework **<u>using diffuse & naive priors</u>**
   a. 4 chains; 2000 burn-ins;
      4000 iterations
3. Our criterion variables included:
   a. The location of any changepoint specific to the pandemic
   b. Comparison of any pre- and post-pandemic parameter differences



Local CP model results

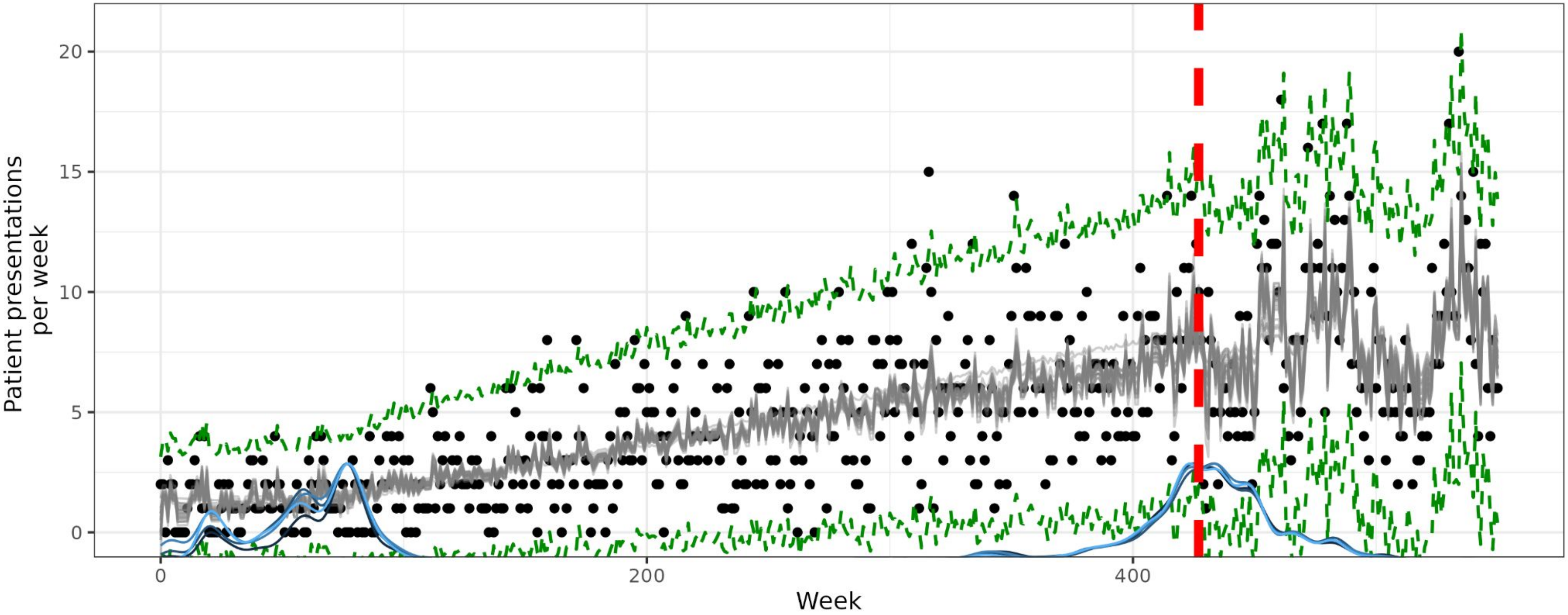


CP1(0): ~ 12 + .0002*Week + Ar(.31)

CP3(430): ~ 12 + .004*Week + Ar(.50)

CP2(60): ~ 12 + .017*Week + Ar(.14) + sigma(12 + week * .005)

Local CP model results



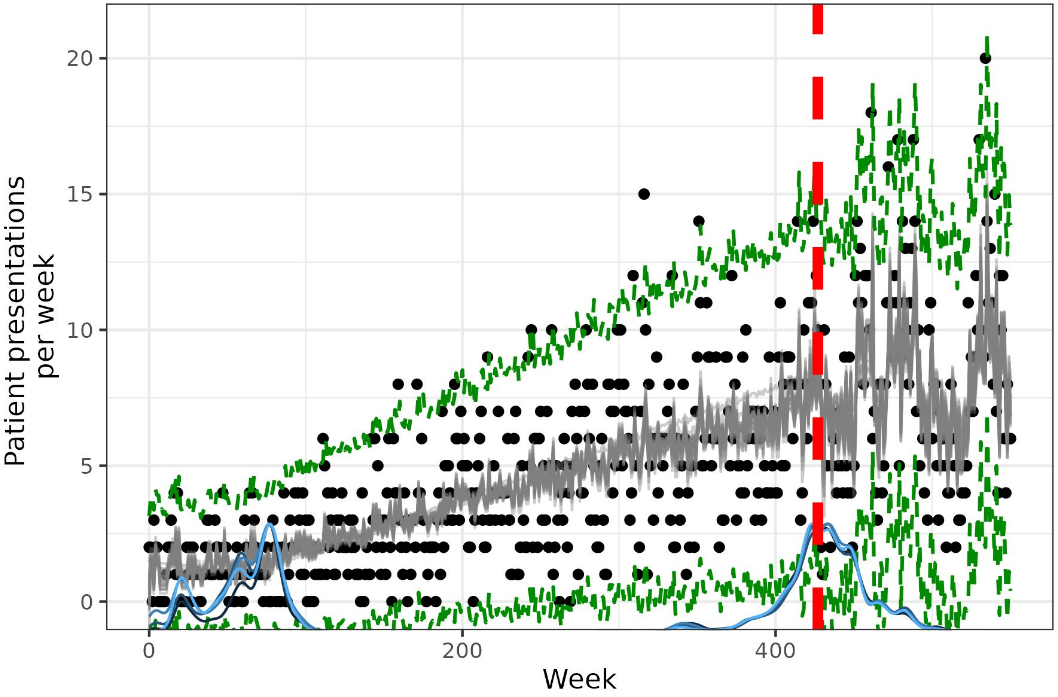
CP1(0): ~ 12 + .0002*Week + Ar(.31)

CP3(430): ~ 12 + .004*Week + Ar(.50)

CP2(60): ~ 12 + .017*Week + Ar(.14) + sigma(12 + week * .005)

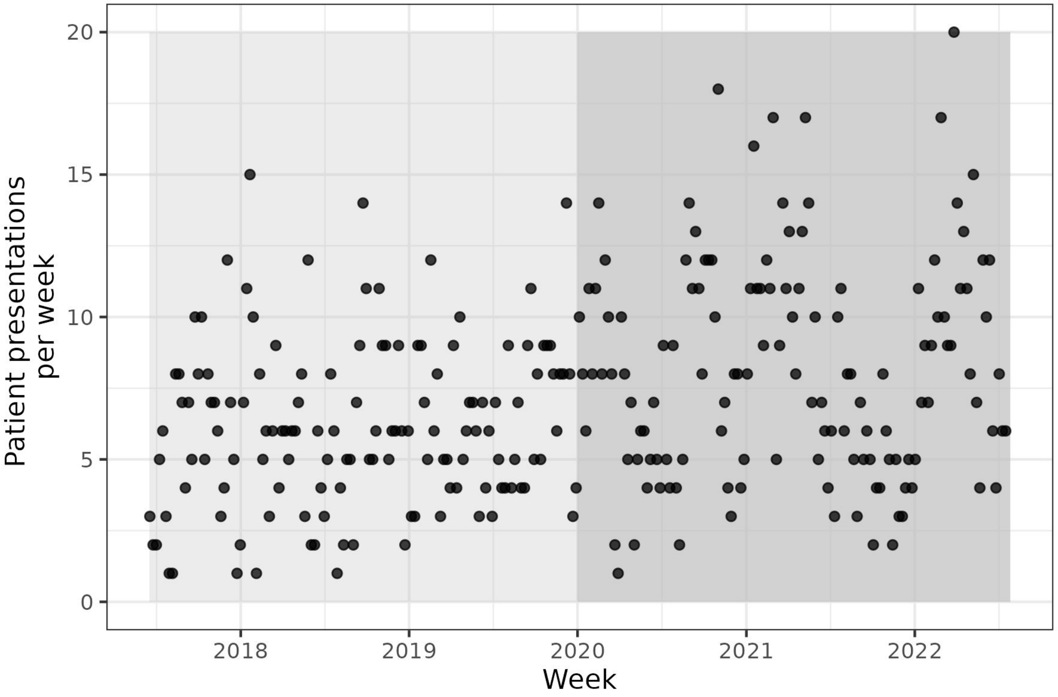
Local CP model summary

1. A change point was identified to have occurred almost concurrently with the stay-at-home orders
2. The model preceding the pandemic suggests a weaker autoregressive parameter (ar(1)=.14), but a stronger linear trend (β=.17); following the pandemic, the linear trend is negligible (β=.004) but a strong autoregressive relationship was observed (ar(1)=.50)



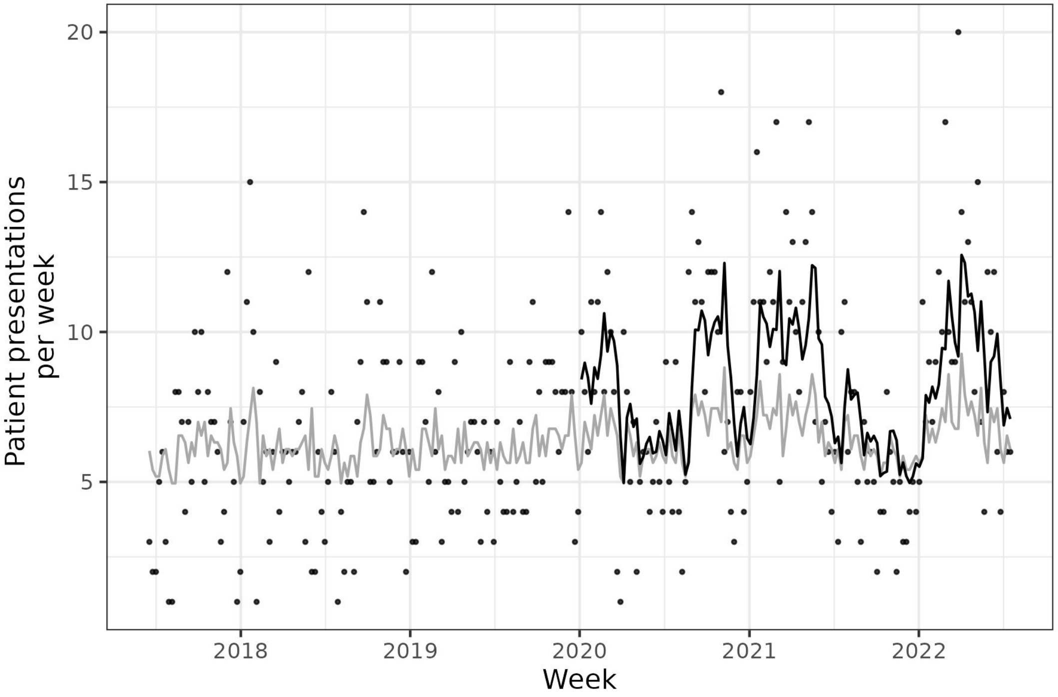
Local ARIMA model methods

1. Two ARIMA models were estimated across two equidistant time series; one period preceding and one succeeding the onset of the pandemic
2. Best fitting ARIMA models were identified through an informatics allowing for the most optimal number and parameter of AR(), MA(), and I() terms to be identified
3. The best fitting pre-pandemic model was then extended into the post-pandemic time series to identify differences in presentation patterns



Local ARIMA model results

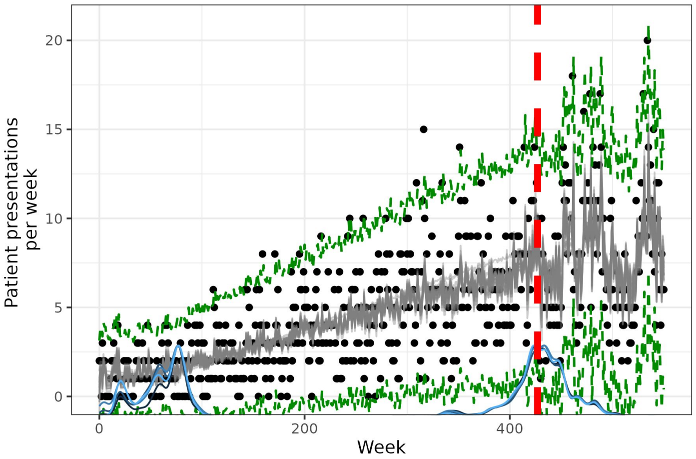
1. Pre-pandemic ARIMA results:
   a. Intercept = 6.12
   b. AR(1) = .23
   c. MA(0)
   d. I(0)
2. Post-pandemic ARMIA results:
   a. Intercept =8.16
   b. AR(1) = .83
   c. MA(1) = -.50
   d. I(0)

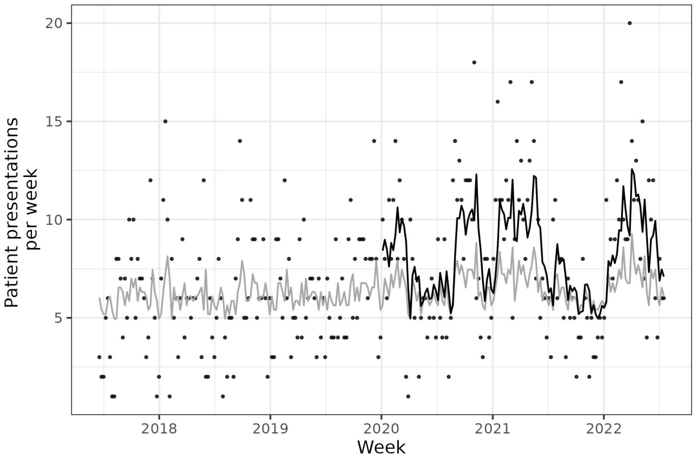


Local trends summary

1. The CP model details how a shift in autoregressive parameters and linear trends occurred almost at the onset of stay-at-home orders

1. The ARMIA models details how changes in presentation trends saw an increase in both inertia (AR parameter) & the kurtosis of the distribution (MA parameter)





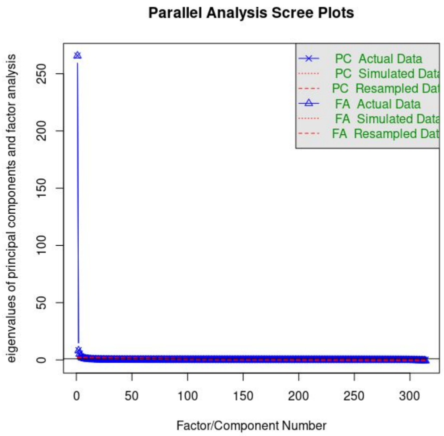
Local analyses next steps

1. Having identified differences in pre- and post-pandemic trends, the next set of analyses seeks to identify variables that can predict patterns in presentations
2. These exploratory analysis sought to identify variables that can identify linear trends in presentation patterns within the best fitting ARIMA model in the post-pandemic timeseries
    a. Oklahoma City metropolitan covid case counts (Center for Systems Science and Engineering (CSSE) JHU)
    b. Oklahoma City metropolitan covid death counts (Center for Systems Science and Engineering (CSSE) JHU)
    c. COVID-19 twitter engagement data (Banda et al., 2021)
    d. Google mobility data (https://www.google.com/covid19/mobility/)
    e. School opening & closing data (Burbio)
3. Each these is included as a linear predictor in the best fitting ARIMA model as well as the 1- and 2-week lagged variables – FDR correction is performed across all variables within each lagged distance (e.g. correction is performed across all 2-week lagged variables)

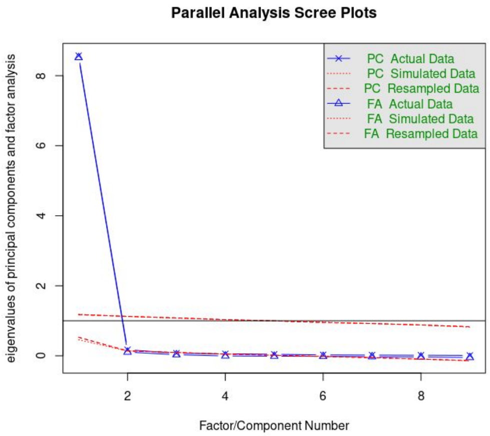
Local analyses next steps cont.

1. Some preprocessing must be performed given the complexity of the predictor variables, for example, there are 363 keywords from the twitter dataset that are used when discussing COVID-19 (e.g. “economy”, “recovery”)
    a. A factor analysis was performed for the twitter data, as well as the mobility data

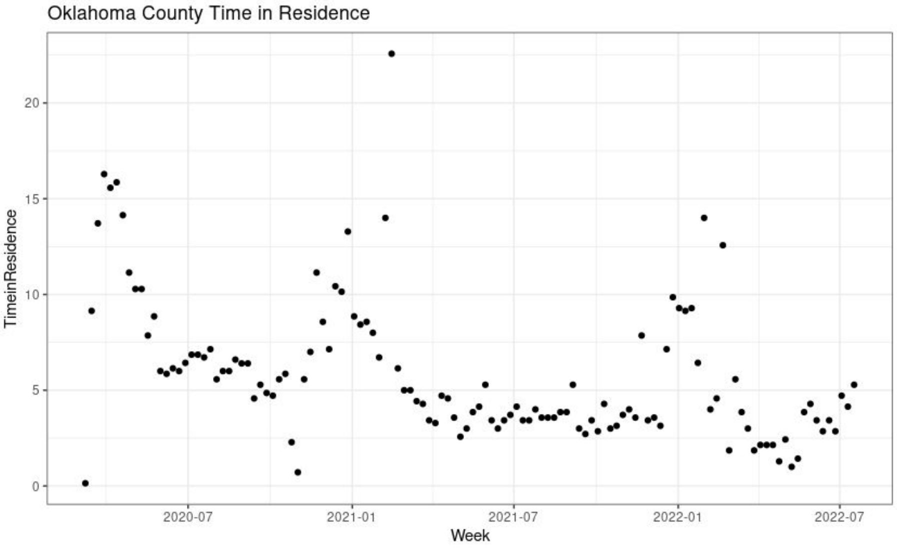
Twitter

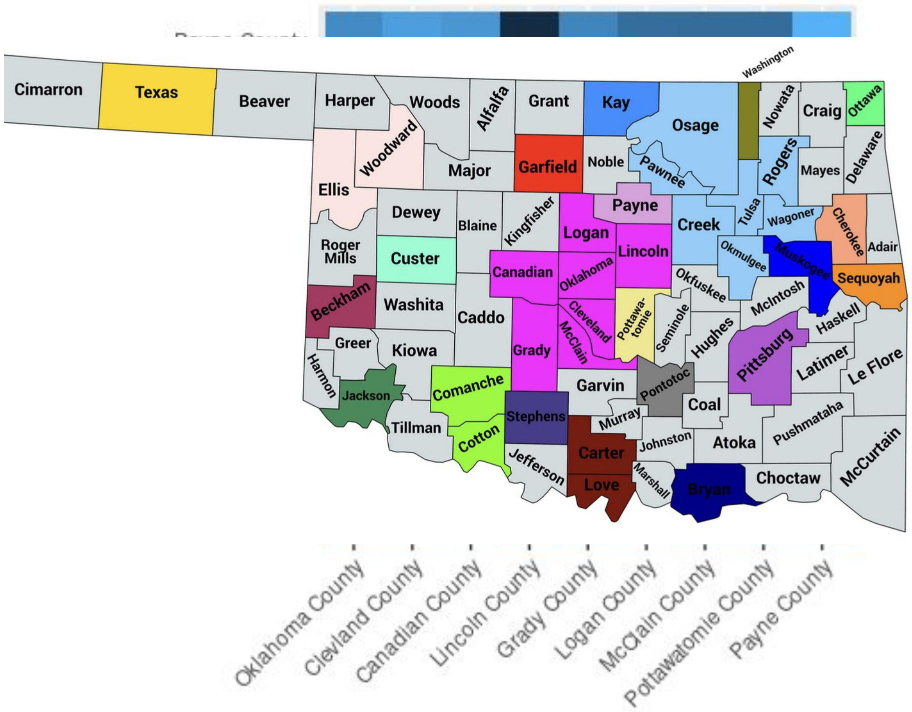


Mobility

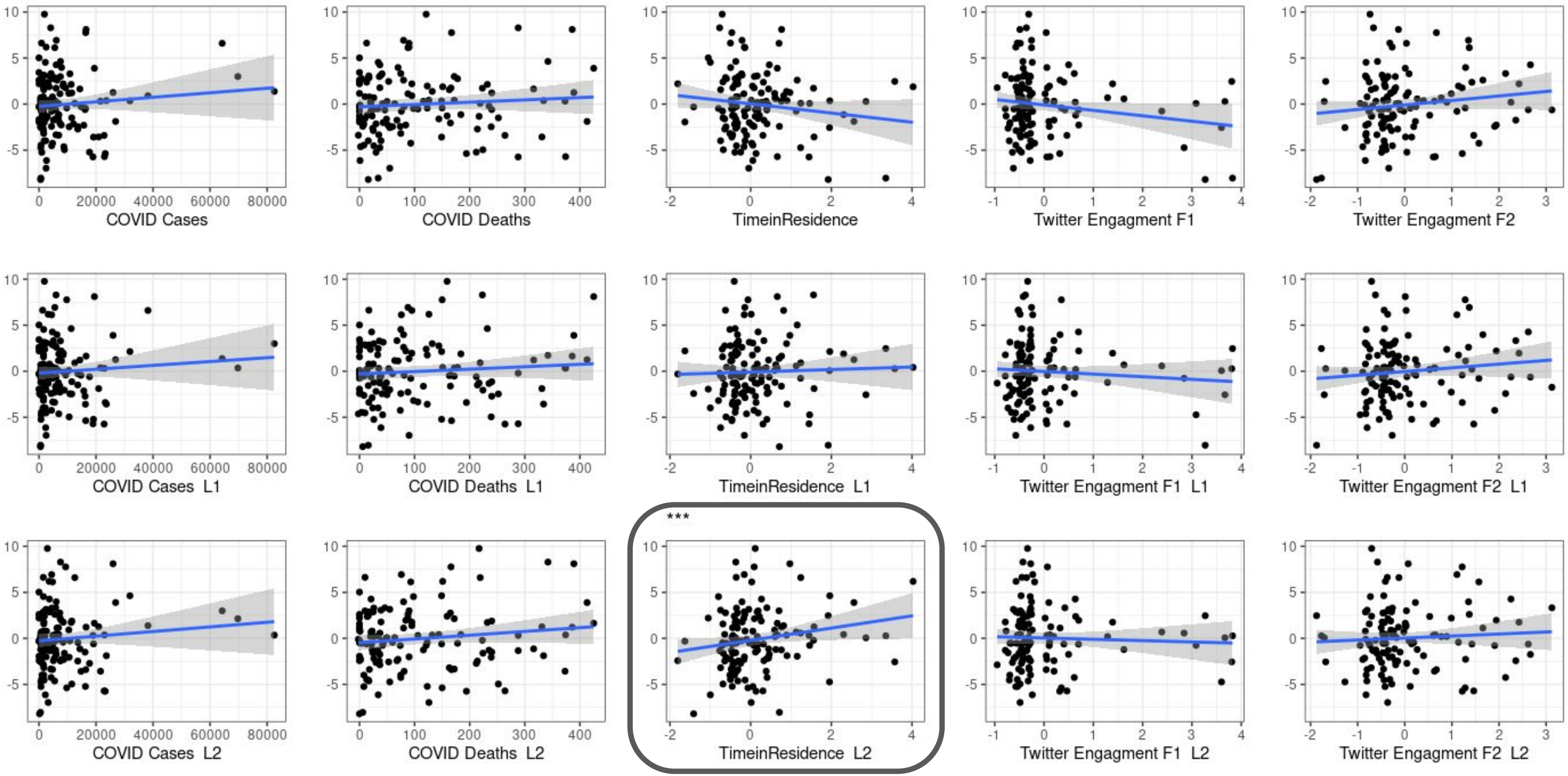


Local analyses next steps cont. (Mobility)



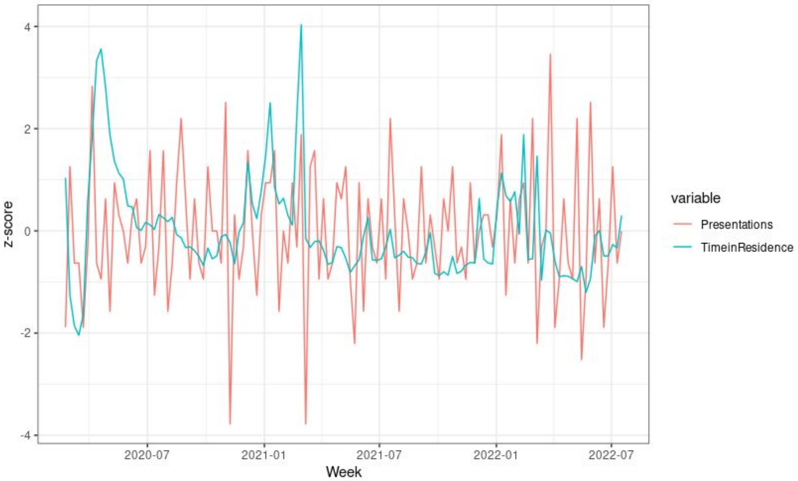


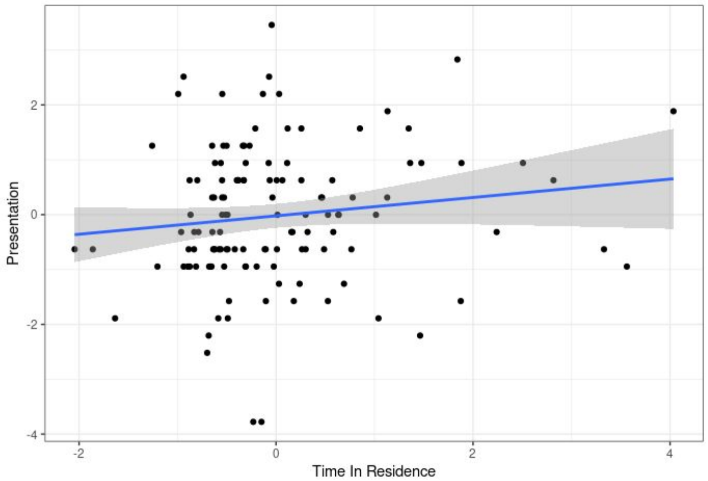
Local analyses next steps results



Local analyses results: movement

1. The only significant linear predictor was the 2-week lagged movement factor score
2. Model suggests a modest positive effect (β=0.32, t(124)=2.2; Q < 0.05)
3. As the two week prior time in residence increases, suicide presentations increase





Local analyses summary

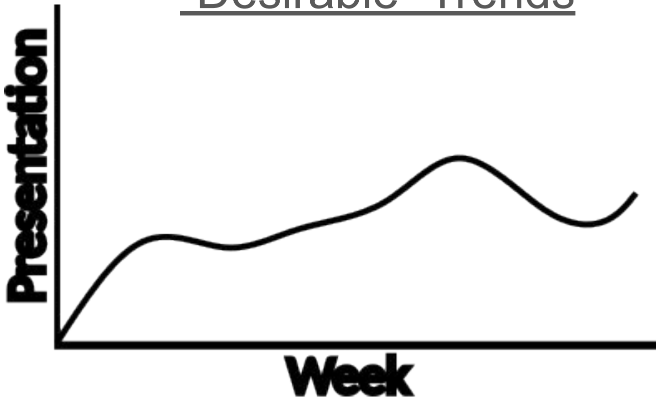
1. Study 1 examined historical trends in presentation rates and sought to identify differences that were co-occurant with the onset of the pandemic using a change point model and an ARIMA based approach. Convergent results suggested an increase in presentation patterns following the pandemic.
2. Study 2 examined variables that relate to these differences in presentation rate, examining relationships with COVID cases, deaths, social media engagement and mobility. The only significant predictor was time in residence suggesting greater time in residence lead to slight uptick in presentations two weeks after.

Scaling local results up to the N3C data

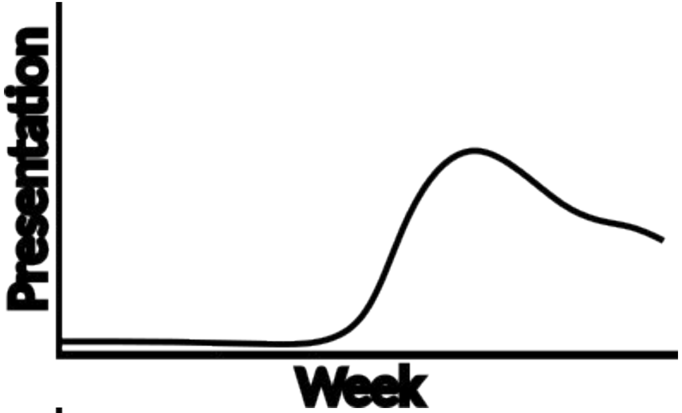
1. The next steps include expanding our analyses into the data available from the N3C
2. Currently performing two separate tasks including:
    a. QA trends:
        i. Suicidal ideation presentation
        ii. COVID cases & deaths
    b. Building a predictive model which can identify linear trends between presentation patterns & predictive variables
        i. GAM

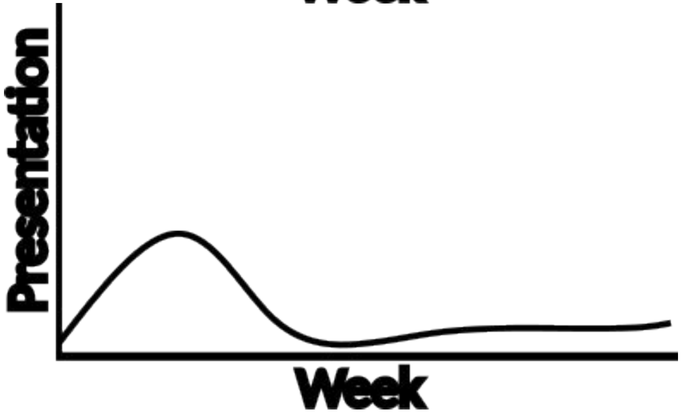
QA of presentation patterns: 0 strings?

"Desirable" Trends



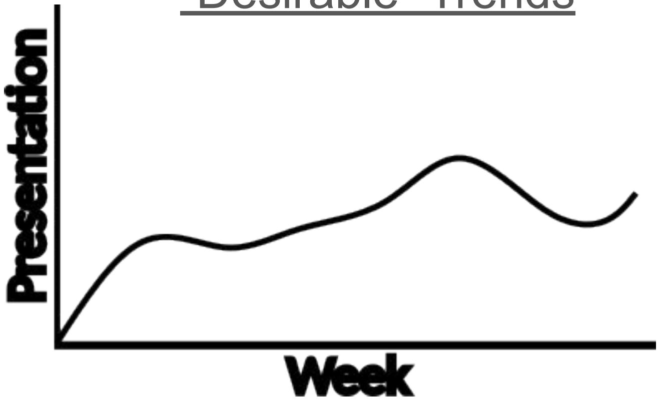
"Suspect" Trends



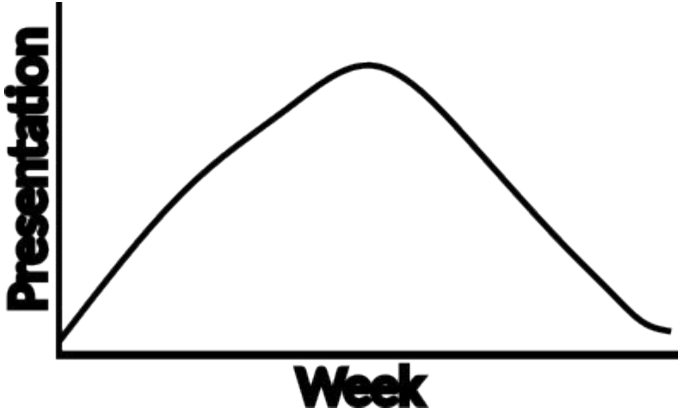


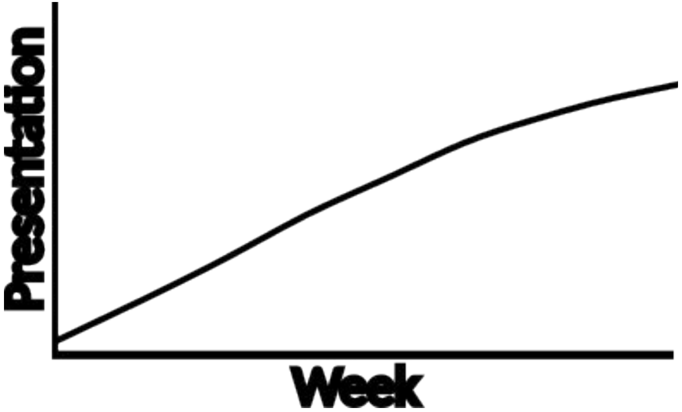
QA of presentation patterns: Reporting trends?

"Desirable" Trends



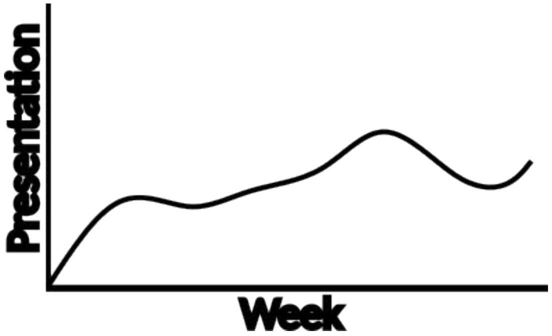
"Suspect" Trends

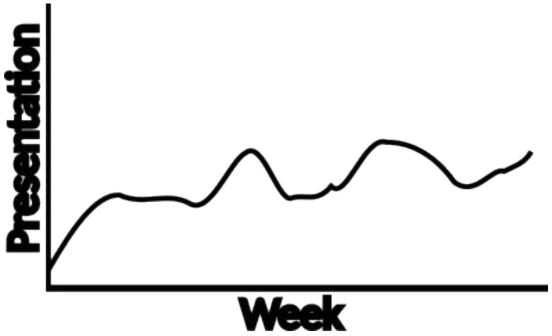


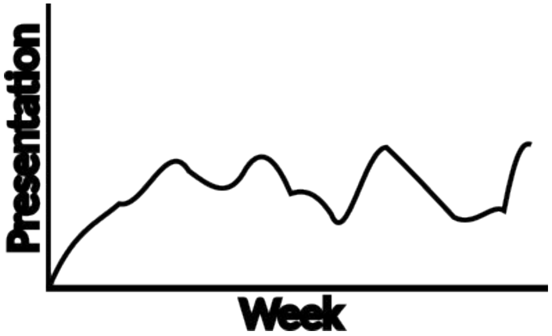


Modeling heterogeneity in time series

1. Trends across sites displayed noticeable differences and required more flexible analytic techniques
2. A generalized additive modeling (gam) framework was applied in order to address the site heterogeneity:
   a. Final model: presentations ~ s(time) + s(time:site) + ar(1) + covariateOfInterest + (1|site)







N3C analyses summary

1. The N3C data allow us to examine trends in suicidal ideation from 2018-present day
2. However, the veracity of these data requires careful examination as both strings of 0 counts and suspicious temporal trends may suggest data quality concerns
3. Modeling the data will require a very flexible technique which can handle nonlinearities across time and within sites

Acknowledgments

The UNIVERSITY of OKLAHOMA
Health Sciences Center

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Questions?