Changes in public response associated with various COVID-19 restrictions in Ontario, Canada: an observational study using social media time series data

Antony Chum, Andrew Nielsen, Zachary Bellows, Eddie Farrell, Pierre-Nicolas Durette, Juan M. Banda, Gerald Cupchik

Submitted to: Journal of Medical Internet Research
on: March 11, 2021

Table of Contents

Changes in public response associated with various COVID-19 restrictions in Ontario, Canada: an observational study using social media time series data

Antony Chum[1, 2*] PhD; Andrew Nielsen[1*] BPH; Zachary Bellows[1] BSc; Eddie Farrell[1] BSc; Pierre-Nicolas Durette[3] BSc; Juan M. Banda[4] PhD; Gerald Cupchik[3] PhD

[1]Department of Applied Health Sciences Brock University St. Catharines CA
[2]Unity Health Toronto Toronto CA
[3]University of Toronto Toronto CA
[4]Department of Computer Science College of Arts and Sciences Georgia State University Atlanta US
[*]these authors contributed equally

Corresponding Author:
Antony Chum PhD
Department of Applied Health Sciences
Brock University
1812 Sir Isaac Brock Way
St. Catharines
CA

Abstract

Background: News media coverage of anti-mask protests, COVID-19 conspiracies, and pandemic politicization has overemphasized extreme views, but does little to represent views of the general public. Investigating the public's response to various pandemic restrictions can provide a more balanced assessment of current views, allowing policymakers to craft better public health messages in anticipation of poor reactions to controversial restrictions.

Objective: Using data from social media, this study aims to understand the changes in public opinion associated with the implementation of COVID-19 restrictions (e.g. business and school closure, regional lockdown differences, additional public health restrictions such as social distancing and masking).

Methods: COVID-related tweets in Ontario (n=1,150,362) were collected based on keywords between March 12 to Oct 31 2020. Sentiment scores were calculated using the VADER algorithm for each tweet to represent its negative to positive emotion. Public health restrictions were identified using government and news media websites, and dynamic regression models with ARIMA errors were used to examine the association between public health restrictions and changes in public opinion over time (i.e. collective attention, aggregate positive sentiment, and level of disagreement) controlling for the effects of confounders (i.e. daily COVID-19 case counts, holidays, COVID-related official updates).

Results: In addition to expected direct effects (e.g. business closure led to decreased positive sentiment and increased disagreements), the impact of restriction on public opinion is contextually driven. For example, the negative sentiment associated with business closures was reduced with higher COVID-19 case counts. While school closure and other restrictions (e.g. masking, social distancing, and travel restrictions) generated increased collective attention, they did not have an effect on aggregate sentiment or the level of disagreement (i.e. sentiment polarization). Partial (region-targeted) lockdowns were associated with better public response (i.e. higher number of tweets with net positive sentiment and lower levels of disagreement) compared to province-wide lockdowns.

Conclusions: Our study demonstrates the feasibility of a rapid and flexible method of evaluating the public response to pandemic restrictions using near real-time social media data. This information can help public health practitioners and policymakers anticipate public response to future pandemic restrictions, and ensure adequate resources are dedicated to addressing increases in negative sentiment and levels of disagreement in the face of scientifically informed, but controversial, restrictions.

(JMIR Preprints 11/03/2021:28716)

DOI: https://doi.org/10.2196/preprints.28716

Preprint Settings

1) Would you like to publish your submitted manuscript as preprint?

✔ **Please make my preprint PDF available to anyone at any time (recommended).**

Please make my preprint PDF available only to logged-in users; I understand that my title and abstract will remain visible to all users.

Only make the preprint title and abstract visible.

No, I do not wish to publish my submitted manuscript as a preprint.

2) If accepted for publication in a JMIR journal, would you like the PDF to be visible to the public?

✔ **Yes, please make my accepted manuscript PDF available to anyone at any time (Recommended).**

Yes, but please make my accepted manuscript PDF available only to logged-in users; I understand that the title and abstract will remain v

Yes, but only make the title and abstract visible (see Important note, above). I understand that if I later pay to participate in <a href="http

Original Manuscript

Original Paper

Antony Chum, PhD[1,2*], Andrew Nielsen[1], Zachary Bellows[1], Eddie Farrell[1], Pierre-Nick Durette[3], Juan M. Banda[4], PhD, Gerald Cupchik[3], PhD

[1]Department of Health Sciences, Brock University, Ontario, Canada
[2]Unity Health Toronto, Ontario, Canada
[3]University of Toronto, Ontario, Canada
[4]Department of Computer Science, College of Arts and Sciences, Georgia State University, Atlanta, GA, USA

*Corresponding author:
Email: antony.chum@gmail.com

Manuscript title: Changes in public response associated with various COVID-19 restrictions in Ontario, Canada: an observational study using social media time series data

Abstract

Background: News media coverage of anti-mask protests, COVID-19 conspiracies, and pandemic politicization has overemphasized extreme views, but does little to represent views of the general public. Investigating the public's response to various pandemic restrictions can provide a more balanced assessment of current views, allowing policymakers to craft better public health messages in anticipation of poor reactions to controversial restrictions.

Objective: Using data from social media, this study aims to understand the changes in public opinion associated with the implementation of COVID-19 restrictions (e.g. business and school closure, regional lockdown differences, additional public health restrictions such as social distancing and masking).

Methods: COVID-related tweets in Ontario (n=1,150,362) were collected based on keywords between March 12 to Oct 31 2020. Sentiment scores were calculated using the VADER algorithm for each tweet to represent its negative to positive emotion. Public health restrictions were identified using government and news media websites, and dynamic regression models with ARIMA errors were used to examine the association between public health restrictions and changes in public opinion over time (i.e. collective attention, aggregate positive sentiment, and level of disagreement) controlling for the effects of confounders (i.e. daily COVID-19 case counts, holidays, COVID-related official updates).

Results: In addition to expected direct effects (e.g. business closure led to decreased positive sentiment and increased disagreements), the impact of restriction on public opinion is contextually driven. For example, the negative sentiment associated with business closures was reduced with higher COVID-19 case counts. While school closure and other restrictions (e.g. masking, social distancing, and travel restrictions) generated increased collective attention, they did not have an effect on aggregate sentiment or the level of disagreement (i.e. sentiment polarization). Partial (region-targeted) lockdowns were associated with better public response (i.e. higher number of tweets with net positive sentiment and lower levels of disagreement) compared to province-wide lockdowns.

Conclusions: Our study demonstrates the feasibility of a rapid and flexible method of evaluating the public response to pandemic restrictions using near real-time social media data. This information can help public health practitioners and policymakers anticipate public response to future pandemic restrictions, and ensure adequate resources are dedicated to addressing increases in negative sentiment and levels of disagreement in the face of scientifically informed, but controversial, restrictions.

Keywords: COVID-19; public opinion; social media; sentiment analysis; public health restrictions; infodemiology; coronavirus; evaluation;

Introduction

Since the identification of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in late 2019 until Feb 7, 2021, there have been 106 million cases of COVID-19 infections worldwide along with 2.32 million deaths. To contain the spread of infection, many national and regional governments have implemented a series of public health restrictions, including travel restrictions, closing of non-essential businesses, school closures, mandatory masking, social distancing rules, and other restrictions on the movement of populations.

While news media coverage of the public response to these COVID-19 restrictions have highlighted the growing number of anti-mask protests, COVID conspiracies, and pandemic politicization with extreme views, these characterizations may not necessarily represent the general public opinion and sentiment about pandemic restrictions. The objective of this study is to investigate the association between pandemic restrictions and COVID-related public sentiment (i.e. collective attention, aggregate sentiment, and sentiment polarization/disagreement) using Twitter data. The development of novel methods to incorporate sentiment analysis into the evaluation of public health restrictions is important since traditional methods of monitoring public reactions are often expensive and inefficient (e.g. random representative surveys) and may suffer from limited coverage and significant delays.

Prior relevant studies

In a recent scoping review of studies related to COVID-19 and social media concerning the first outbreak from November, 2019 to November, 2020 [1], the authors noted a growing number of studies that document social media reaction to the COVID pandemic to track and identify prevalent themes and concerns. While there is a larger literature that has identified changes in public opinions and perceptions over time using sentiment, topics and content analysis of COVID-related social media content [2–7], the authors of the review noted that there is a scarcity of studies (at the time of publication in Jan 2021) that evaluate the impact of public health restrictions on public opinions (e.g. level of positive/negative emotions, level of disagreement, etc). However, some studies have begun to examine how COVID-related events (i.e. COVID case incidence, interventions, news media) coincide with the frequency of COVID-related social media discussion (i.e. collective attention).

In a study of COVID-related tweets between Feb 25 to Mar 30, 2020 in Belgium [8], researchers plotted tweet frequency alongside major COVID-related events, and they found that spikes in tweet frequency coincided with COVID infections, stock market crashes, school closure, and infection of notable persons. A similar descriptive study of COVID-related tweets from Australian states and territories detailed changes in aggregate sentiment trends in relation to COVID-related deaths and major COVID-related policy events [9] (e.g. blocking arrivals from specific countries, expansion of testing criteria, and limits on outdoor gatherings), and concluded that this information can usefully inform public health interventions and communication. However, due to the lack of statistical multivariate time series modelling in both studies, it was not possible to disentangle the independent contribution of these events on tweet frequency or aggregate sentiment and investigate their relative importance in the shaping of public opinion.

Other studies have employed statistical models to understand factors that contribute to social media collective attention on COVID-19. In a study of the effects of COVID-related news coverage on collective attention [10] (measured by posts and comments on the r/coronavirus subreddit on reddit.com) between February 15 and May 15, 2020, researchers found, using linear regression, that the collective attention across the United Kingdom, United States, Canada, and Italy was associated with daily COVID-19 incidence and COVID-related news articles. However, it is worth mentioning that the study did not include other factors that might also influence collective attention in their models such as duration of business closure, the influence of holidays, and the introduction of restrictions including social distancing and mandatory face masks. The study focused mainly on collective attention (comment and post frequency), but did not evaluate other indicators that might be more relevant to policymakers such as the level of disagreement (e.g. sentiment polarity) and aggregate sentiment (e.g. positive to negative sentiment ratio) [3,4].

The limited number of studies that examined the association between COVID-related events, restrictions and public opinion have typically approached the question from a descriptive manner, such as by graphically plotting major events and COVID-19 incidence on a timeline against COVID-related tweet frequency [8]. However, without considering the contribution of multiple factors simultaneously (i.e. business closure, school closure, holidays, other restrictions, etc.), such as through the use of multivariate time-series analysis, these studies may over- or understate the unique contribution of any given factor due to statistical confounding. Additionally, they are unable to quantify the strength of the relationships between exposure (e.g. days of business closure) and relevant public opinion outcomes (e.g. level of negative sentiment). Our study will bridge this gap in the literature by using a dynamic regression approach to understand the unique contribution of restriction specifications (i.e. business closure, school closure, announcement of masking and social distancing measures, regional lockdown differences) on public opinion, while also taking into the account the influence of contextual factors including case counts, holidays, and COVID-related official updates. Our research question is as follows: What is the association between COVID-19 public health restrictions and measures of public opinion (i.e. collective attention, positive-to-negative sentiment ratio, and level of disagreement) while accounting for potential confounding factors?

Methods

Twitter data collection

Data from our study is drawn from the largest COVID-related twitter dataset [11]. It was constructed using the following data-driven selection of keywords: COVD19, CoronavirusPandemic, COVID-19, 2019nCoV, CoronaOutbreak, coronavirus, WuhanVirus, covid19, coronaviruspandemic, covid-19, 2019ncov, and coronaoutbreak. The Social Media Mining Toolkit [12] was used to collect all tweets worldwide with the keywords mentioned above starting on March 12, 2020. Further details about the data collection process can be found in a previous paper [11]. We used the cleaned dataset of English-only tweets with retweets filtered out. A retweet is the sharing of a tweet without any added comments; however, quoted tweets (i.e. sharing a previous tweet along with one's own comment) are included in the data.

To identify a subset of tweets originating from Ontario, Canada, geographic coordinates were used for tweets with geo-location enabled. For tweets that did not have geo-location enabled, our team created an algorithm that matched the text of the user-defined location to a standard gazetteer at www.geonames.org. The gazetteer data contains alternative spellings for cities across different languages and includes various airport codes used for matching (e.g., YTO and YYZ for Toronto). We used a list of locations that had a population of 1,000 or greater. When inferring location based on user input, our algorithm will match to a city with a unique name. For cities that share the same name with other cities, the algorithm will attempt to find a match based on country and/or state identifiers in the text. If there is no state or country data in the text (e.g. "London" only), the tweet is matched to the place with the highest population (in this case it would be London, England, UK). Matching to the largest population centre (in cases where no further information is available) was based on the assumption that people from the largest cities are more likely to leave out further country or regional identifiers, while those in smaller cities (that share the same name with larger cities) are more likely to include further regional information. If no match is made at the city or town level, the text is then matched to a higher-level geographical unit (i.e., state, region, or province), and then to a country. Out of the subset of all tweets with user entered location text, our program matched 89.9% to a GeoName ID. A link to our Github for the algorithm is available [13]. Our program also examined any Unicode data(e.g. a flag emoji) entered by users in lieu of country level information. We randomly sampled 250 matches to ensure that the matches were made according to the algorithm described above. In total, we identified 2,649,317 tweets originating from Canada between March 12 and Oct 31, 2020, 43% of which (1,149,804 tweets) were from Ontario.

Sentiment analysis

Once we collected the COVID-19 Twitter data, we conducted the VADER Sentiment Analysis (Valence Aware Dictionary and sEntiment Reasoner), which assigned a sentiment score (-1 to +1) to each tweet that represents a polarity (negative and positive) and a strength of emotion for the tweets. A prior validation study has found that the VADER method to be particularly well-suited to text from social media: scoring by the program had a r=0.88 correlation with gold standard ground truth (i.e., the mean sentiment rating from 20 prescreened and appropriately trained human raters) [14].

Study outcomes

To study public opinion on COVID-related public restriction using Twitter data in a comprehensive manner, we considered 1) the collective attention on COVID-19 measured by the level of COVID-related discussion (i.e. COVID-related tweet frequency), 2) the aggregated sentiment level (measured using a positive-to-negative sentiment ratio), and 3) the level of disagreement, or sentiment polarity (measured by the GINI index).

COVID-related discussion (tweet frequency)

We used tweet frequency to represent the level of participation in COVID-related discussion on Twitter on a specific day. Prior studies have utilized social media activity data (i.e. Twitter and Weibo post frequency) to identify collective attention with regards to COVID-19 interventions and events [4,10]. We have included tweet frequency to estimate how public health restriction can influence COVID-related collective attention, which may provide a useful metric that policymakers can use to identify potential areas of concern at the population level.

Aggregate sentiment

To determine the aggregate sentiment of a particular day, a value was derived for each day that represents the ratio of positive to negative sentiment, expressed by the following:

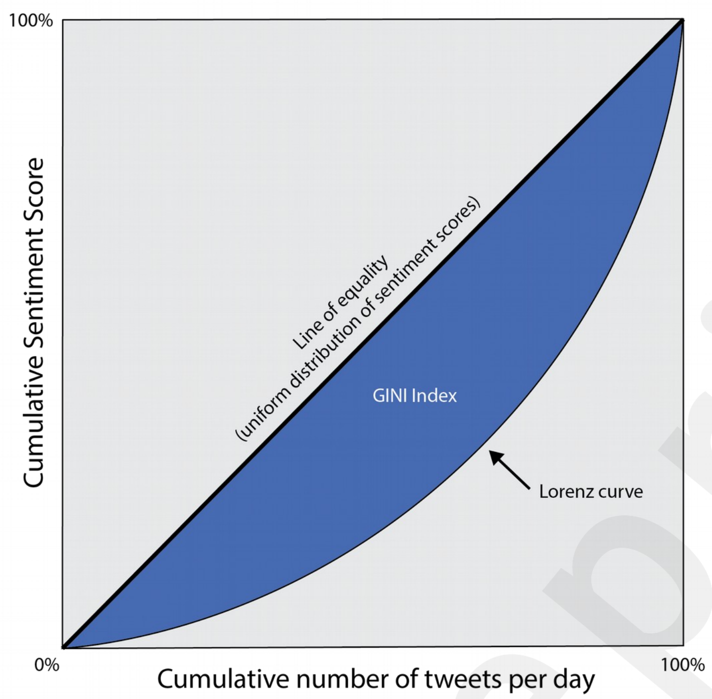
$$AG_t = \ln ¿¿$$

where $M_{t,pos}$ is the total count of positive tweets with sentiment scores greater than 0.05, and $M_{t,neg}$ is the count of negative tweets with sentiment scores lower than -0.05. The natural log transformation is used to avoid excessively large ratios. This specific formula for sentiment aggregation (to measure the net positive sentiment) is commonly used in prior literature of twitter sentiment analysis since it takes into account the number of twitter users on a given day [15,16].

GINI Index

A GINI coefficient was derived to measure the level of disagreement (or sentiment polarization) in COVID-related tweets. Although the GINI coefficient is typically used in literature to describe income inequality, this index has been used to measure inequality in other areas of social interest, such as opportunity for social mobility [17], educational attainment [18], public transit availability [19], and movie preferences [20]. A GINI coefficient of zero represents the lowest level of disagreement (perfect equality of scores), and a higher GINI coefficient represents greater differences in the sentiments scores across tweets on a particular day. For example, a GINI coefficient of 0.30 means that 30% of the sentiment scores would have to be redistributed in order for everyone's score to be the same. The GINI coefficient is calculated based on the area between 1) the line of equality and 2) the Lorenz curve as shown in figure one.

Figure 1. Graphical representation of using GINI coefficient to measure sentiment disparity



The 45° line of equality, where x=y, is the hypothetical situation of uniform distribution where each tweet (in the same day) exhibits the same sentiment score. By plotting the cumulative sentiment score on a given day against the cumulative number of tweets, the Lorenz curve can be used to characterize sentiment score disparity (i.e. visually represent how a range of tweets, from those with the lowest to highest sentiment scores, contribute to the relative increases in the cumulative score, where a more concave Lorenz curve represents greater disparity). To create a daily Lorenz curve, we started by rescaling each tweet-level sentiment score (-1 to +1) to a range from 1 to 100, because the standard calculations cannot include negative values. We then ordered tweets from the lowest to the highest sentiment scores, and plotted the cumulative number of tweets against the cumulative tweet sentiment score. Next, the GINI coefficient is calculated by finding the area under the line of equality and above the Lorenz curve (e.g. shaded blue area in fig. 1). This method of calculating a Lorenz curve and GINI coefficient is repeated for each day in our dataset. Our GINI coefficient (G) is calculated using the following equation:

$$G=\left|1-\sum_{k=1}^{n}\left(X-X_{k-1}\right)\left(Y_k-Y_{k-1}\right)\right|$$

where X_k is the cumulative proportion of tweets over n number of tweets in a given day (from k = 0,...n,), and Y_k is the cumulative proportion of sentiment in a given day.

Creating the Ontario COVID-19 timeline

We created a comprehensive timeline of COVID-related restrictions and events in Ontario by consulting with the COVID-19 intervention timeline created by the Canadian Institute for Health Information [21], timeline of COVID-19 events created by Public Health Ontario [22], and timelines that were created by news media [23,24]. This full timeline used for the study is available via supplementary materials (Multimedia Appendix 1). In Ontario, key events on the timeline include 1) the declaration of state of emergency on March 17, 2020, which led to the closing of all non-essential businesses and schools, 2) the closure of the US-Canada border to non-essential travelers on March 21st, 3) the partial reopening of selected regions in Ontario began on June 12, 4) the reopening of nearly all businesses and public places across Ontario (with restrictions) by August 12, 5) the restrictions to reduced private gatherings were reinstated on September 19, and 6) the restrictions on restaurants, bars, banquet halls, and gyms were reinstated on October 3 in selected urban regions. For the purpose of our study, we focused on four dimensions of the public health restrictions, including 1) business closures, 2) school closures, 3) regional lockdown differences (i.e. partial vs province-wide lockdown), and 4) additional public health measures (e.g. travel, social distancing, and masking).

Business closures

Ontario implemented closure and limitations on non-essential businesses to help control the spread of COVID-19. With the exception of essential businesses (including stores that sell food, big box retailers, pharmacies, and alcohol stores) that stayed open, many businesses were closed or offered limited services (e.g. restaurants were limited to providing delivery or take-out services only). Given the importance of business and retail services to Ontario residents, we considered the cumulative effect of business closure. First, we created a binary variable to indicate, for each day on the timeline, whether non-essential businesses were closed due to restrictions. For each consecutive day of closure, we created a cumulative variable to consider effects associated with the duration of closure (e.g. 1 for the first day of closure, 10 for the 10th day of closure). Additionally, we hypothesized that each additional day of closure has an additive but diminishing effect (logarithmic growth) because each additional day of the closure can have a normalizing effect due to adaptation; therefore, we derived the natural log cumulative business closure variable to be used in our regression models.

School closures

We considered primary and secondary school closures to be a significant restriction that impacts a large number of Ontario families. Moreover, the closure of primary and secondary schools would lead to the need for parents to make accommodations to provide childcare. Days for school closure due to COVID-19 restrictions were represented through a binary variable. Universities and colleges were not considered as students are older and able to care for themselves, therefore causing less disruption. We hypothesized a logarithmic growth effect to the experience of school closure because each additional day of the closure can have a normalizing effect (where each additional day of closure has an additive but diminishing effect) due to adaptation and adjustment to new childcare arrangements and work accommodations.

Regional lockdown differences

Over the course of the study period, Ontario implemented province-wide lockdowns and partial lockdowns, where the latter focused on dense urban areas (e.g. Toronto, Peel, and Ottawa) to implement a targeted approach to pandemic restrictions. We categorized days in our time series into 3 groups: 1) province-wide lockdown 2) partial lockdown, and 3) no lockdowns. We expect these variations in lockdown conditions to have an effect on social media discussion and sentiment. Decisions around the implementation of partial vs province-wide lockdowns were controversial [25], with diverging beliefs around the benefits of a province-wide lockdown (e.g. under partial lockdown, some people may travel to an adjacent region with no lockdown to visit the gym) and the benefits of partial lockdowns (e.g. partial lockdown allows for a flexible approach tailored to local COVID-19 infection rates to minimize economic impacts).

Additional public health measures

Between March 12 to October 31, 2020, there were a number of additional restrictions put in place by the Ontario and federal government to reduce the spread of COVID-19. These include measures such as non-essential travel restrictions (e.g. US-Canada border), mandatory quarantine for travelers, limits on indoor and outdoor gatherings, health and safety bylaws for businesses such as sanitizer and plexiglass, and social distancing/mask policies for the general population. Given the overlapping nature of multiple public health measures which often target specific concerns (i.e. travel, distancing, hygiene), we only considered the day a restriction was announced. Unlike business and school closures, these additional public health measures remained enforced for the duration of our dataset. We characterized each day as either having 1) a new/updated restriction announced or 2) no restrictions announced.

Control variables

In order to adjust for other contextual factors that may also influence COVID-related public opinion, we included the following variables as control factors: 1) COVID-related official updates, 2) statutory holidays, 3) COVID-19 daily incidence for Ontario, and 4) COVID-19 daily incidence for Canada (excluding Ontario).

COVID-related official updates

Multiple official COVID-19 development announcements have been released over the course of the pandemic, including press conferences for major events (i.e. case counts and mortality milestones), new screening guidelines, and provincial reopening plans, as well as notable COVID-19 developments (e.g. new evidence on the effectiveness of non-medical masks) from the World Health Organization, Ontario Hospital Administration, and government officials. While additional public health measures detail restrictions enforced on the population, COVID-related official updates are meant only to provide useful information about COVID-19 events. For example, after the announcement that Canada had passed 100,000 COVID-19 cases, we might expect that people would take to social media to express their emotions about this information.

Statutory holidays

There is prior evidence that public sentiment and frequency of posts on holidays systematically differ from non-holidays [26]. There were also public concerns that travel and social gathering plans over holidays (and long weekends) may promote COVID-19 infections [27], and in turn, public sentiment concerning COVID-19. Therefore, we included Canadian statutory holidays in our models as an adjustment variable. In our study period, seven holidays were identified: Good Friday (April 10), Easter (April 12), Victoria Day (May 18), Canada Day (July 1), Civic Holiday (August

3), Labour Day (September 7) and Thanksgiving (October 12). If the holiday was part of a long weekend, the entire weekend was coded as holiday. For example, Labour day was on Monday September 7th; therefore, Saturday September 5th and Sunday September 6th were also coded as a holiday.

COVID-19 daily incidence

COVID-19 new daily case count at the provincial and national levels were a major focus in news media, and a significant factor that can influence public opinion and collective attention on COVID-19. Case information is based on the Public Health Case and Contact Management Solution (CCM) [22], which is Ontario's primary disease reporting system. Case counts for Canada were drawn from the COVID-19 Data Repository at Johns Hopkins University [28]. We subtracted the Ontario case counts from the Canada case counts so the national numbers were deduplicated.

Statistical Analysis

Our study combined an ARIMA approach to time series modeling with regression methods in order to examine the associations between public health restrictions and changes in sentiment measures over time [29]. These are generally known as dynamic regression models, and they are typically used to generate forecasts [30], but are also useful for the purpose of explanatory modelling (i.e. understanding the relationship between multiple time series variables) as is the purpose of our study. They take on the form where the outcome time series y_t is modeled as a function of k explanatory variables ($x_{1,t},\ldots x_{k,t}$), where n_t is allowed to be autocorrelated (using ARIMA errors):

$$y=\beta_0+\beta_1 x_{1,t}+\ldots+\beta_k x_{k,t}+n_t$$

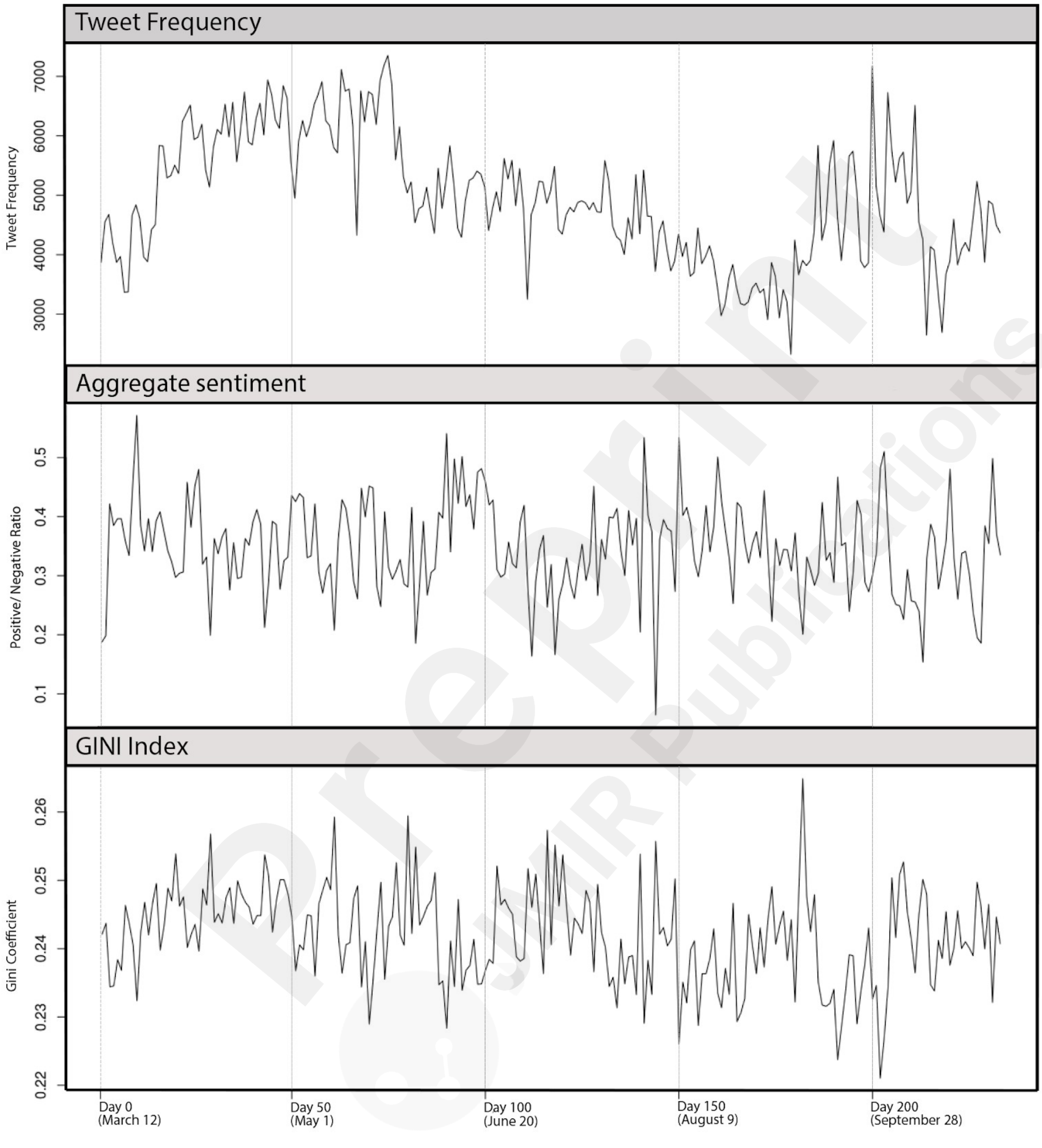
The ARIMA error n_t may contain 1) autoregressive (AR) terms used to determine the relationship between the current observation and previous observations, 2) moving average (MA) terms to determine the relationship between current observation and previous error, and 3) differencing term to stationarize the time series outcome if necessary. For parameter estimations of ARIMA error terms (the content of n_t), the auto.arima() function was used in the R package *forecast*. The purpose of using this function is to fit the most appropriate ARIMA model according to Akaike Information Criterion (AIC) values. The function searches across a number of candidate models, and selects the appropriate number of AR and MA terms based on minimization of the AIC, and applies the appropriate number of differencing terms to stationarize the outcome time series[31].

We constructed three models with model 1 for the frequency of tweets concerning COVID-19 each day (i.e. collective attention), model 2 for the aggregate sentiment score representing the ratio of positive to negative tweets each day, and model 3 for the level of sentiment disparity within each day (using the GINI coefficient). The outcomes were deseasonalized using the ts() function in R, since there is a tendency for more Twitter activities on weekdays over weekends. Following the deseasonalizing procedure, we used the Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for stationarity. If the trend was not stationary, differencing for stationarity would be handled by the auto.arima() function. Each outcome was regressed on all seven predictors mentioned above, and regressors that were not significantly associated with the outcome (at $p<0.05$) were subsequently removed. All statistical analyses were completed on R Studio Cloud (updated to Jan 20, 2021).

Results

We collected 1,149,804 COVID-related tweets that originated from Ontario, Canada between the period of Mar 12 and Oct 31, 2020, which consisted of 235 days. The mean daily tweet frequency was 4933 (SD=1065). The mean GINI index was 24.19 (SD=0.85), meaning that, on average, 24.18% of the scores would have to be redistributed for every tweet to have the same level of sentiment. The aggregate positive-to-negative tweet ratio was 34.57 (SD=7.92), meaning that more tweets were considered positive than negative based on the sentiment analysis. The univariate time series for frequency of tweets, the aggregate sentiment score, and the GINI index are displayed in figure 2.

Figure 2. Daily tweet frequency, aggregate sentiment, and GINI index time series



After deseasonalizing the 3 outcome variables, Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) returned large p-values ($p>0.1$) across all three variables, which provides evidence that they are stationary. This is further confirmed through visual inspection, and the fact that the auto.arima() did not require the inclusion of differencing (I) terms in any subsequent models.

Table 1. Descriptive statistics and bivariate associations for outcomes and regressors

	Frequency of days with event (n=235 days, March 12-Oct 31)	Tweet frequency (mean for days with condition)	GINI index (mean for days with condition)	Positive-to-Negative ratio (mean for days with condition)
Business closure				
Non-essential businesses closed	143	5384.90 (1136.55)	24.33 (0.78)	35.28 (10.22)
Non-essential businesses open	92	4127.85 (1285.98)	23.95 (0.92)	33.46 (10.98)
p-value for Kruskal-Wallis test for difference in mean across levels		p <0.001	p <0.001	p = 0.251
School closure				
Schools open	126	4302.24 (1222.53)	24.03 (0.90)	33.27 (10.84)
Schools closed due to covid	109	5575.42 (1141.91)	24.36 (0.76)	36.06 (10.03)
p-value for Kruskal-Wallis test for difference in mean across levels	---	p <0.001	p = 0.003	p = 0.045
Additional restrictions				
No restriction announcements	223	4876.51 (1354.63)	24.22 (0.84)	34.23 (10.62)
New/updated restriction announced	12	5195.16 (1122.22)	23.46 (0.75)	40.83 (6.40)
p-value for Kruskal-Wallis test for difference in mean across levels		p = 0.453	p = 0.003	p = 0.036
Regional differences in lockdown				
Province-wide lockdown	169	5137.50 (1334.11)	24.23 (0.85)	34.44 (9.85)
Partial lockdown	61	4347.68 (1094.77)	24.08 (0.85)	35.66 (12.07)
No regions under lockdown	5	3271.60 (1587.16)	23.76 (0.93)	25.34 (10.76)
p-value for Kruskal-Wallis test for difference in mean across levels		p < 0.001	p = 0.175	p = 0.084
Statutory holidays				
Holidays (with attached weekends)	17	4016.06 (1249.85)	24.86 (0.52)	24.41 (9.34)
Not holidays	218	4961.15 (1329.05)	24.13 (0.85)	35.36 (10.23)
p-value for Kruskal-Wallis test for difference in mean across levels		p = 0.005	p < 0.001	p < 0.001
New COVID case counts (in hundreds of cases)				

Low (0-1.57)	77	4158.34 (963.00)	24.05 (0.73)	35.01 (10.15)
Medium (1.58-4.04)	76	5275.28 (1282.49)	24.21 (0.89)	35.51 (10.21)
High (4.05+)	81	5241.12 (1434.39)	24.28 (0.92)	33.25 (11.20)
p-value for Kruskal-Wallis test for difference in mean across levels	---	$p < 0.001$	$p = 0.181$	$p = 0.405$
New COVID case counts in Canada (in hundreds of cases)				
Low (0-4.53)	78	4185.12 (1143.35)	24.22 (0.75)	33.70 (10.67)
Medium (4.54-12.36)	77	5174.81 (1211.07)	24.08 (0.95)	36.06 (10.23)
High (12.37+)	80	5311.31 (1382.81)	24.26 (0.86)	33.99 (10.70)
p-value for Kruskal-Wallis test for difference in mean across levels	---	$p < 0.001$	$p = 0.169$	$p = 0.242$
Official announcements of COVID developments (e.g. WHO declarations, release of reopening plans, etc.)				
No announcement	218	4848.34 (1342.49)	24.22 (24.22)	34.35 (10.31)
Announcement	17	5462.65 (1258.50)	23.69 (0.92)	37.34 (13.27)
p-value for Kruskal-Wallis test for difference in mean across levels	---	$p = 0.102$	$p = 0.012$	$p = 0.214$

COVID-related tweet frequency

Auto.arima selected ARIMA (2, 0, 0) for the final model predicting COVID-related tweet frequency. Inclusion of predictor terms in the model improved the value of AIC by 5%. The ACF plot (fig. 4) for the model shows no significant autocorrelations indicating that the residuals are behaving like white noise. Additional days of business and school closures were associated with more tweets in a non-linear manner, where one additional day of closure had a stronger effect in the earlier part of the closure compared to the later parts (Table 2). In other words, the effect of closure had a diminishing effect on tweet frequency with each additional day of closure. Each 10 % increase in the duration of business closure (i.e. 196*LN(1.1)=18.6) is associated with an increase of 18.6 tweets (95% CI 11.5, 25.8). Each 10 % increase in the duration of school closure (i.e. 130*LN(1.1)=12.3) is associated with an increase of 12.3 tweets (95% CI 5.7, 18.9). Figure 3 and 4 below plots the rate of increase of tweet frequency associated with business and school closure. The announcement of additional public health restrictions was associated with 544 additional tweets (95% CI 178, 910). Based on the statistically significant interaction between daily new COVID cases in Ontario and lockdown condition (i.e. Ontario case-counts by province-wide vs. partial lockdown, $p < 0.001$) , new COVID cases had a different effect on tweet frequency depending on the lockdown condition. Under province-wide lockdown, each 100 new COVID cases were associated with 391 additional tweets, and under partial lockdown, each 100 new cases were associated with 134 additional tweets. The effect of new COVID cases under the no lockdown condition was not different compared to the province-wide lockdown condition (p=0.489). Compared to non-holidays, statutory holidays and their connected weekends saw a decrease of 385 tweets (95% CI -761, -7.8). Each additional 100 new cases across Canada (excluding Ontario) was associated with 46.2 additional tweets (95% CI 20.9, 71.6). Days with an official COVID-related update saw an additional 373 tweets (95% CI 95.4, 650) compared to days without any updates.

Figure 3. Estimated marginal increases in tweet frequency associated with increases in number of days of business closures, holding all other factors constant

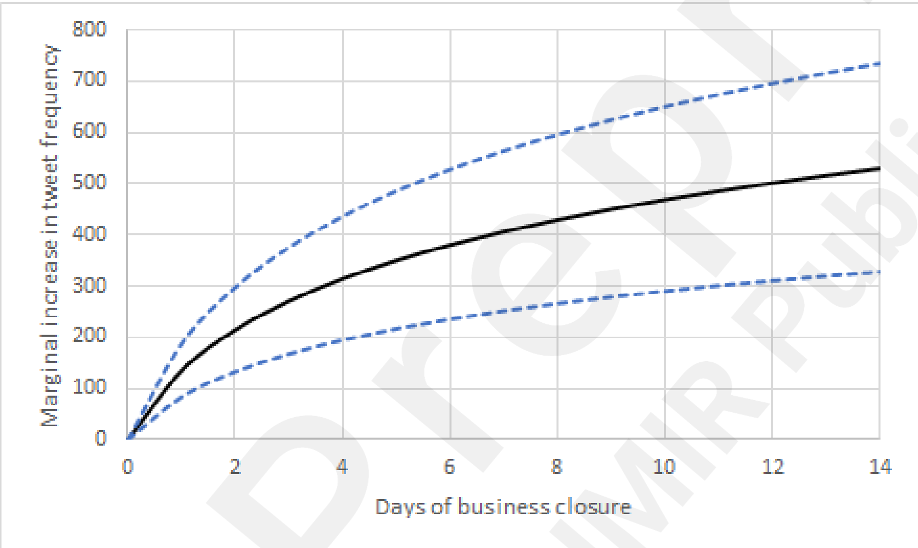


Figure 4. Estimated marginal increases in tweet frequency associated with increases in number of days of school closure, holding all other factors constant

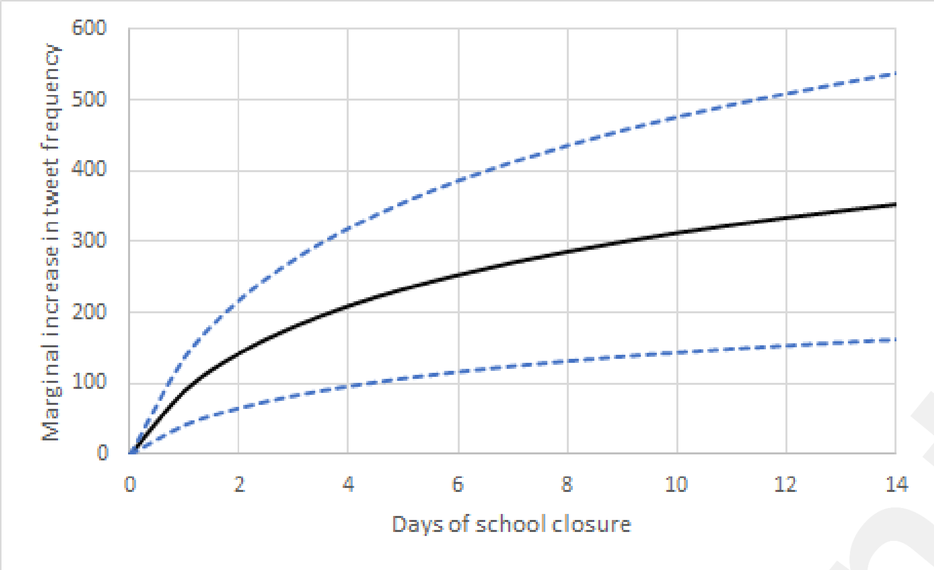
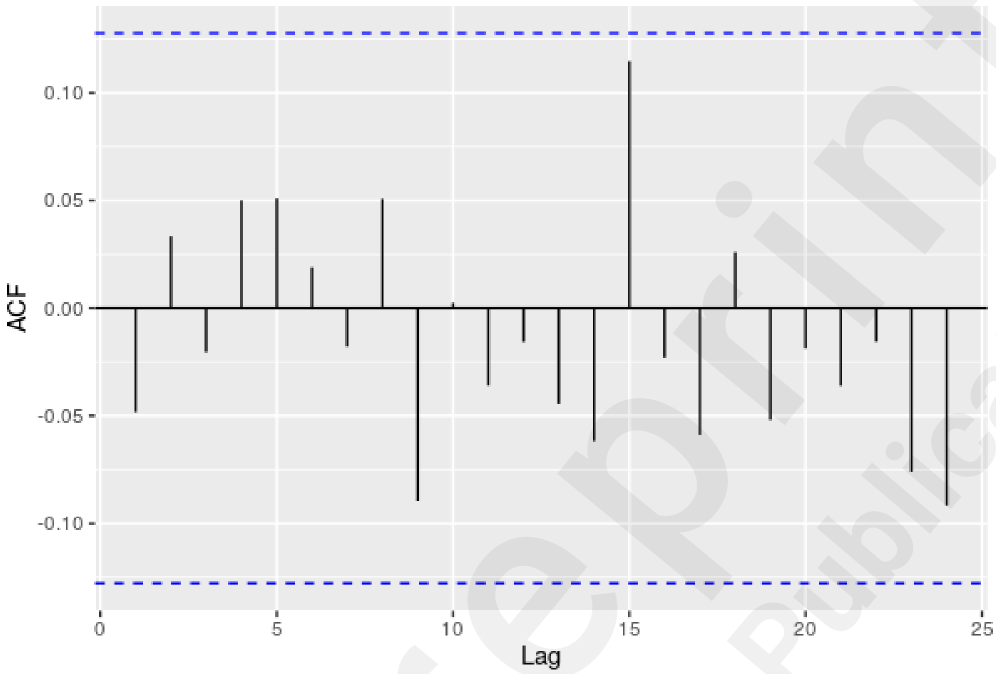


Table 2. Model 1: Dynamic regression model predicting daily tweet frequency with ARIMA error term (2, 0, 0)

	Model 1: Tweet Frequency
	Estimate of effect (95% Confidence Interval), p-value
Intercept	3143 (2837, 3450), p < 0.001
Statutory holidays (1 for holidays, 0 for non-holidays)	-385 (-761, -7.8), p = 0.044
Business closure (increase in 1 log day)	196 (121, 271), p < 0.001
School closure	130 (60.1, 199), p < 0.001
Additional measures	544 (178, 910), p = 0.003
New COVID case counts (in hundreds of cases)	391 (311, 470), p < 0.001
New COVID case counts in Canada, excluding Ontario (in hundreds of cases)	46.20 (20.9, 71.6), p < 0.001
Official COVID-related updates	373 (95.4, 650), p = 0.008
Regional differences in lockdown	
(Province-wide lockdown) Regions are in the same stage of lockdown	Reference group
(Partial lockdown) Regions are in different stages of lockdown	140 (-343, 624), p = 0.582
(No lockdown) Regions are not under lockdown	-440 (-1513, 632), p = 0.429
Regions are in different stages of lockdown * new cases (AB)	-257 (-361, -153), p < 0.001

Regions are not in lockdown * new cases	1219 (-2161, 4599), p = 0.489
Goodness of FIt (with covariates)	
AIC	3693.89
Goodness of Fit (without covariates)	
AIC	3873.2

Figure 5: ACF plot for COVID-related tweet frequency



Positive to negative tweet sentiment ratio

ARIMA (1, 0, 0) was chosen for the model predicting tweet sentiment ratio. Compared to the empty model, the inclusion of predictor variables improved model AIC by 6.5%. The ACF plot for the model shows no significant autocorrelations indicating that the residuals do not exhibit temporal autocorrelation (Figure 7). While higher COVID-19 case counts in Ontario had the effect of reducing the positive-to-negative ratio of tweet sentiment, where each 100 new cases were associated with -0.98 in the aggregate sentiment ratio (95% -1.81, -0.16) during the period where no business closures were in effect, the impact of new Ontario COVID-19 cases on the sentiment ratio changed once business closures were introduced - as indicated by the significant interaction term in table 3 (i.e. business close * Ontario new cases, p=0.024). To facilitate interpretation of the 3-way non-linear relationship, we plotted the change in predicted aggregate sentiment ratio from day 0 to day 10 of a business closure period given 4 case count scenarios (where case counts were held constant at 50, 100, 150, and 200 over the closure period - see figure 6). In short, given everything else being equal, while higher case counts reduced sentiment ratio in a direct manner, higher case counts also reduced the negative effect associated with an additional day of business closure. Compared to days where Ontario was in province-wide lockdown, a partial lockdown was associated with an increase in sentiment ratio of 5.75. The sentiment ratio was lower on statutory holidays compared to non-holidays (-6.22, 95% CI -10.3, -2.12). New COVID cases across Canada (excluding Ontario) were not associated with a change in sentiment ratio.

Figure 6. Predicted tweet sentiment ratio (positive-to-negative): change in ratio from day 0 to day 10 of a business closure period, varying by Ontario new COVID case counts (holding all other factors constant)

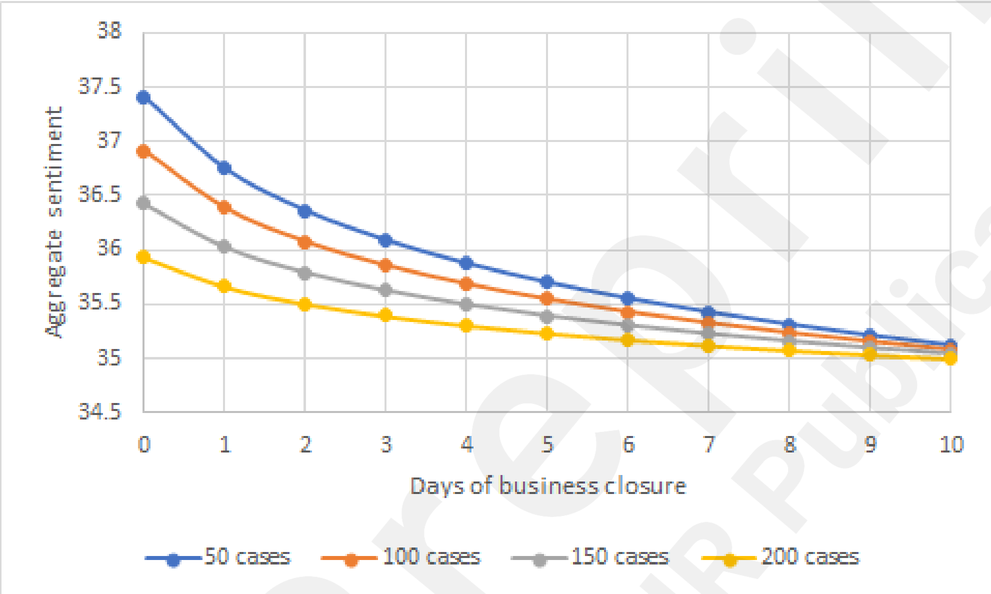
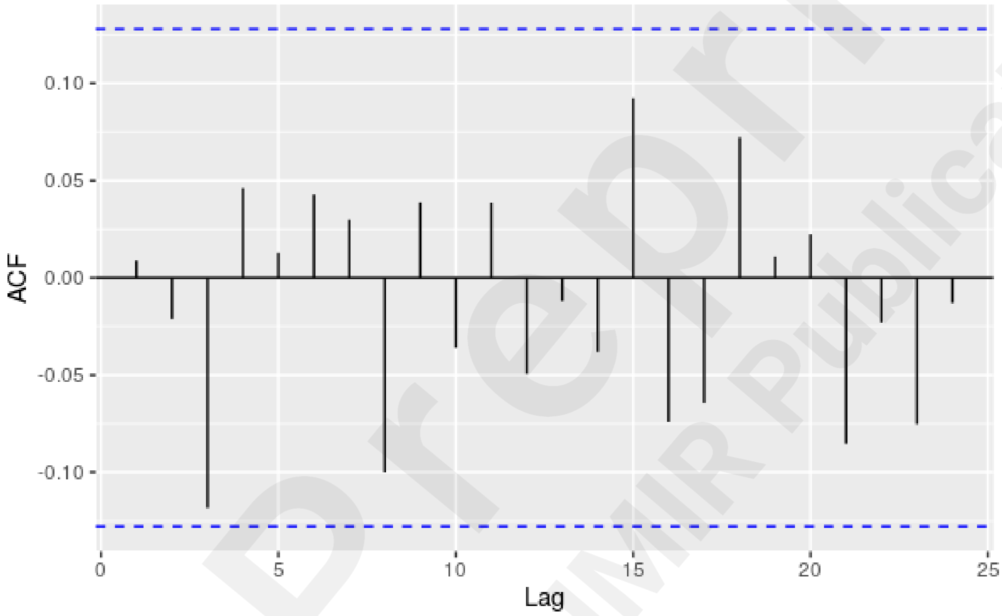


Table 3. Model 2: Positive-to-negative ratio

	Model 3: Positive-to-negative ratio
	Estimate of effect (95% Confidence Interval), p-value
Intercept	37.90 (34.60, 41.20), p < 0.001
Statutory holidays (1 for holidays, 0 for non-holidays)	-6.22 (-10.30, -2.12), p = 0.002
Business closure (log transformed)	-1.14 (-2.26, -0.01), p = 0.046
Regional differences in lockdown	
Regions are in the same stage of lockdown	Reference group
Regions are in different stages of lockdown	5.75 (2.16, 9.33), p = 0.001

Regions are not under lockdown	-10.50 (-18.70, -2.29), p = 0.011
New COVID case counts in Canada, excluding Ontario (in hundreds of cases)	0.17 (-0.14, 0.48), p = 0.286
New COVID case counts (in hundreds of cases)	-0.98 (-1.81, -0.16), p = 0.018
Business closed * new cases (increase of 1 log unit in business closure + 100 new cases)	0.37 (0.04, 0.70), p = 0.024
Goodness of FIt (with covariates)	
AIC	1612.43
Goodness of Fit (without covariates)	
AIC	1723.89

Figure 7: ACF plot for positive-to-negative sentiment ratios



Sentiment disparity measured by the GINI index

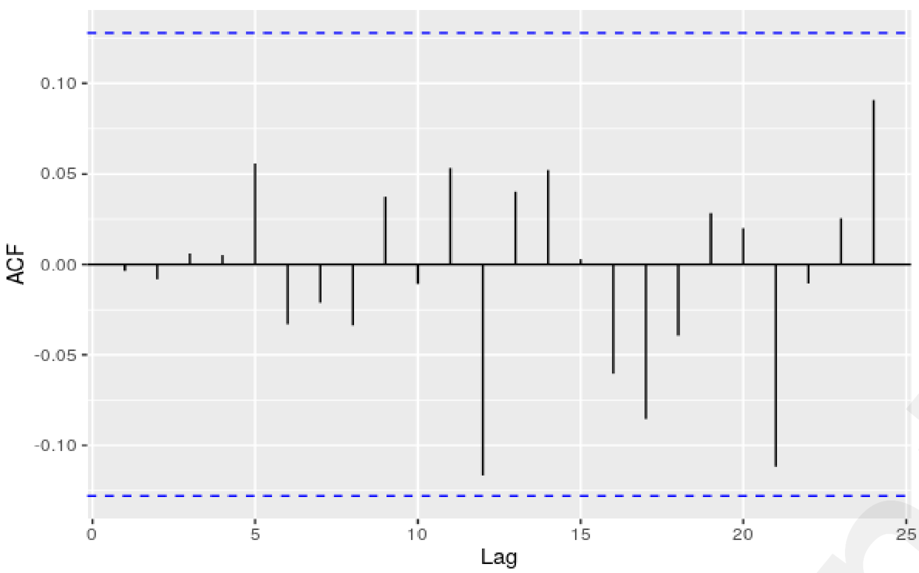
ARIMA (1, 0, 2) was used in the model predicting sentiment disparity. Compared to the empty model (with no predictors), the inclusion of predictors improved the model's AIC value by 20%. The ACF plot for the model shows no significant autocorrelations indicating that the residuals are behaving like white noise (Figure 8). A higher GINI index represents a more polarized range of sentiments across COVID-related tweets in a given day (i.e. more disparities in the sentiment scores). Each 10 % increase in the duration of business closure (i.e. 0.113*LN(1.1)=0.0107) was associated with an increased GINI index of 0.01 (95% CI 0.005, 0.01). Compared to days with province-wide lockdown, days with partial lockdown were associated with a 0.738 reduction in the

GINI index (95% CI -1.19, -0.283). We also found evidence that lockdown conditions can modify the effect of Ontario new COVID-19 case counts on the GINI index, where each 100 new cases were associated with a decrease of 0.11 in the GINI index (95% CI 0.01, 0.21) while Ontario was under partial lockdown, but the GINI index remained unchanged with additional COVID-19 cases under province-wide lockdown (0.00, 95% CI -0.07, 0.07). The GINI index was higher on statutory holidays compared to non-holidays (0.44, 95% CI 0.08, 0.81). New COVID-19 cases in Canada (excluding Ontario) were not associated with the Gini index (95% CI -0.04, 0.01).

Table 4. Model 3: Dynamic regression model predicting GINI Index with ARIMA error term (1, 0, 2)

	Model 2: GINI Index
	Estimate of effect (95% Confidence Interval), p-value
Intercept	23.90 (23.60, 24.20), p < 0.001
Statutory holidays (1 for holidays, 0 for non-holidays)	0.44 (0.08, 0.81), p = 0.016
Business closure	0.11 (0.05, 0.17), p < 0.001
Regional differences in lockdown	
Regions are in the same stage of lockdown	Reference group
Regions are in different stages of lockdown	-0.738 (-1.19, -0.28), p = 0.001
Regions are not under lockdown	0.16 (-0.89, 1.22), p = 0.772
New COVID case counts in Canada, excluding Ontario (in hundreds of cases)	-0.01 (-0.04, 0.01), p = 0.307
New COVID case counts (in hundreds of cases)	0.00 (-0.07, 0.07), p = 0.996
Regions are in different stages of lockdown * new cases	0.11 (0.01, 0.21), p = 0.025
Regions are not under lockdown * new cases	-1.98 (-5.06, 1.10), p = 0.208
Goodness of FIt (with covariates)	
AIC	461.82
Goodness of Fit (without covariates)	
AIC	573.98

Figure 8: ACF plot of GINI indices



Discussion

Our study found significant associations between COVID-19 restrictions and public opinion. In summary, additional days of business closure were associated with collective attention (i.e. COVID-related tweet frequency) and increased levels of disagreement (i.e. sentiment polarity). While business closure reduced aggregate sentiment (i.e. the net number of tweets with positive sentiment), additional COVID-19 cases reduced the impact of business closure on overall sentiment. In other words, the model shows that people were more accepting of additional business closure days if the cases were high. While additional days of school closure were associated with collective attention (with diminishing effects for each additional day), school closure was not associated with aggregate sentiment or levels of disagreement.

Compared to province-wide lockdowns, partial lockdowns were associated with increased aggregate sentiment (i.e. net number of tweets with positive sentiment) and decreased levels of disagreement. Partial lockdown, compared to province-wide lockdown, was associated with decreased collective attention, and also reduced the effect of additional COVID-19 case counts on collective attention. In other words, while new COVID-19 case counts increased collective attention, this effect was reduced under partial lockdown compared to province-wide lockdown. Finally, we found that the announcement of other restrictions (e.g. social distancing, masking, and travel restriction) led to increased collective attention, but were not associated with changes in aggregate sentiment or level of disagreement.

Comparison with prior literature

While our study is focused on investigating the unique impact of multiple pandemic restrictions on changes in public opinion over time, which has not been examined in prior literature, we found that the association between new COVID-19 case counts and collective attention (one of our ancillary findings) to be consistent with prior studies including the impact of daily new cases on Australian tweets [9], and the impact of daily COVID-19 incidence on Reddit posts/comments across the United Kingdom, United States, Canada, and Italy [10].

Limitations and strengths

Twitter users may not be representative of the Canadian general population; therefore, our results may not be generalizable to the average Canadian. However, as of 2018, more than 15 million Canadians are classified as regular Twitter users (i.e. use at least once per month) and represent a significant proportion of the 37 million Canadian population [32]. One study found that North American Twitter users are younger, more educated, and have higher income compared to the general population, but noted that their views were largely similar to the general population, except for their tendency to believe in the existence of gender and racial inequalities (which are lower in the general population) [33]. In light of this information, we can interpret our findings as generalizable to a large portion of Canadians (especially for those who are younger, more educated, have higher SES, and tend to be more socially progressive).

Since our collection of Tweets are based on keywords, there may be tweets that only contain less popular COVID-related keywords such as ‘covidiots’ or ‘antimask’ but do not have common words such as COVID19 or coronavirus. While VADER has been specifically validated to analyze the sentiment in social media text, it is restricted to English only tweets, and tweets written in other languages were not analyzed in our study. Finally, our study was not able to disentangle the separate effects of masking, social distancing, and travel restrictions since a) they all had similar start dates, b) they were in effect for most of the study period, and c) these restrictions were not lifted before the end of the study period. The overlapping nature of these restrictions limited our ability to investigate the unique contribution of their respective effects on public opinion.

Strengths of our study include: 1) the use of a multivariate statistical method to disentangle the effects of different pandemic restrictions, which provided stronger evidence for inference compared to prior literature that were largely descriptive in nature, which focused on documenting the tweet frequency and sentiment that coincided with COVID-related events [2,3,9]; 2) Our study demonstrated the feasibility of using sentiment analysis to evaluate the impact of public health restrictions on public opinion, which can provide a relatively rapid and low cost method to evaluate the impact of public health interventions compared to survey research; 3) We developed a novel approach of using the GINI index to measure sentiment polarization (where the index has been previously limited in its use as a measure of income disparity). Future studies may rely on the GINI index as a measure of sentiment polarization or level of disagreement; 4) Compared to prior studies that tend to focus only on the association between COVID-related events and collective attention (measure by tweet frequency), our study examined the effect of restrictions on multiple dimensions of public opinion including collective attention, aggregate sentiment, and level of disagreement, which provides a more holistic perspective of public opinion compared to single measure studies.

Conclusions

Our study demonstrates the feasibility of combining sentiment analysis of social media text with dynamic regression models to understand the relationship between the introduction of COVID-19 restrictions and changes in public opinion over time, which provides a rapid and flexible method of evaluating the public response to large scale restrictions. Our study also offers useful insights on the public opinion of COVID-19 restrictions: specifically, we show that the impact of restriction on public opinion is contextually driven (e.g. business closures were better tolerated with higher COVID-19 case counts), and while school closure and other restrictions generates increased collective attention, they did not have an effect on aggregate sentiment or the level of disagreement. Partial lockdowns were associated with better public response (higher number of tweets with net positive sentiment and lower levels of disagreement) compared to province-wide lockdowns. This information can help public health practitioners anticipate public response to future pandemic restrictions, and ensure adequate resources are dedicated to addressing increases in negative sentiment and levels of disagreement in the face of scientifically informed, but controversial, restrictions.

Conflicts of Interest

The authors do not have any personal financial interests related to the subject matters discussed in this manuscript.

References

1. Tsao S-F, Chen H, Tisseverasinghe T, Yang Y, Li L, Butt ZA. What social media told us in the time of COVID-19: a scoping review. Lancet Digit Health Elsevier; 2021 Mar 1;3(3):e175–e194. PMID:33518503
2. Valdez D, Ten Thij M, Bathina K, Rutter LA, Bollen J. Social Media Insights Into US Mental Health During the COVID-19 Pandemic: Longitudinal Analysis of Twitter Data. J Med Internet Res 2020 Dec 14;22(12):e21418. PMID:33284783
3. Chandrasekaran R, Mehta V, Valkunde T, Moustakas E. Topics, Trends, and Sentiments of Tweets About the COVID-19 Pandemic: Temporal Infoveillance Study. J Med Internet Res 2020 Oct 23;22(10):e22624. PMID:33006937
4. Hou K, Hou T, Cai L. Public attention about COVID-19 on social media: An investigation based on data mining and text analysis. Personal Individ Differ 2021 Jun;175:110701. [doi: 10.1016/j.paid.2021.110701]
5. Zhu B, Zheng X, Liu H, Li J, Wang P. Analysis of spatiotemporal characteristics of big data on social media sentiment with COVID-19 epidemic topics. Chaos Solitons Fractals 2020 Jul 17;140:110123–110123. PMID:32834635
6. Nguyen TT, Criss S, Dwivedi P, Huang D, Keralis J, Hsu E, et al. Exploring U.S. Shifts in Anti-Asian Sentiment with the Emergence of COVID-19. Int J Environ Res Public Health Multidisciplinary Digital Publishing Institute; 2020 Jan;17(19):7032. [doi: 10.3390/ijerph17197032]
7. Lwin MO, Lu J, Sheldenkar A, Schulz PJ, Shin W, Gupta R, et al. Global Sentiments Surrounding the COVID-19 Pandemic on Twitter: Analysis of Twitter Trends. JMIR Public Health Surveill 2020 May 22;6(2):e19447. [doi: 10.2196/19447]
8. Kurten S, Beullens K. #Coronavirus: Monitoring the Belgian Twitter Discourse on the Severe

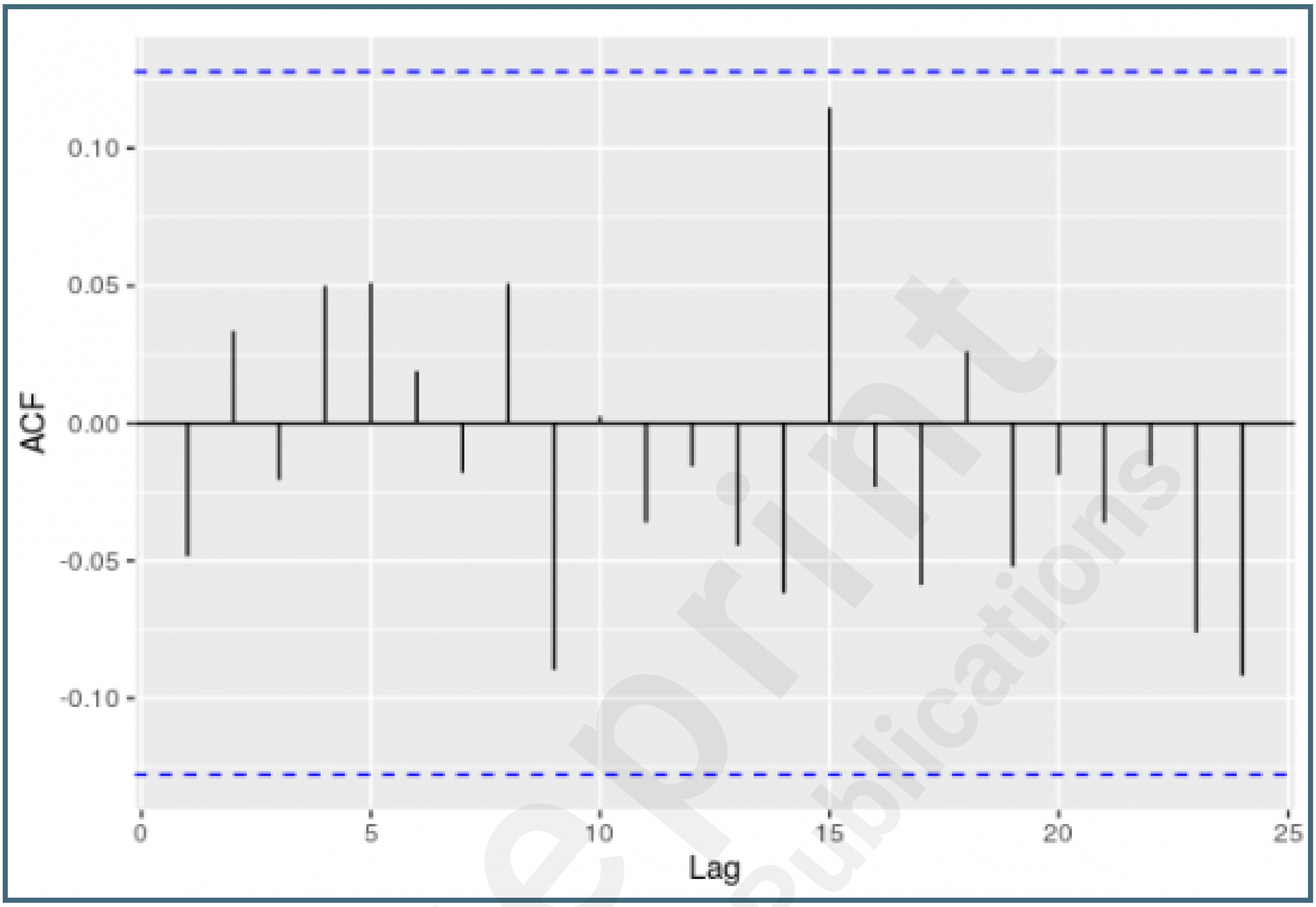
Acute Respiratory Syndrome Coronavirus 2 Pandemic. Cyberpsychology Behav Soc Netw Mary Ann Liebert, Inc., publishers; 2020 Aug 27;24(2):117–122. [doi: 10.1089/cyber.2020.0341]
9. Yigitcanlar T, Kankanamge N, Preston A, Gill PS, Rezayee M, Ostadnia M, et al. How can social media analytics assist authorities in pandemic-related policy decisions? Insights from Australian states and territories. Health Inf Sci Syst 2020 Oct 15;8(1):37. [doi: 10.1007/s13755-020-00121-9]
10. Gozzi N, Tizzani M, Starnini M, Ciulla F, Paolotti D, Panisson A, et al. Collective Response to Media Coverage of the COVID-19 Pandemic on Reddit and Wikipedia: Mixed-Methods Analysis. J Med Internet Res 2020 Oct 12;22(10):e21597. PMID:32960775
11. Banda JM, Tekumalla R, Wang G, Yu J, Liu T, Ding Y, et al. A large-scale COVID-19 Twitter chatter dataset for open scientific research -- an international collaboration. ArXiv200403688 Cs [Internet] 2020 Nov 13 [cited 2021 Mar 3]; Available from: http://arxiv.org/abs/2004.03688
12. Tekumalla R, Banda JM. Social Media Mining Toolkit (SMMT). Genomics Inform [Internet] 2020 Jun 15 [cited 2021 Mar 11];18(2). PMID:32634870
13. chumlab. chumlab/covid19project [Internet]. 2021 [cited 2021 Mar 3]. Available from: https://github.com/chumlab/covid19project
14. Elbagir S, Yang J. Twitter Sentiment Analysis Using Natural Language Toolkit and VADER Sentiment. Hong Kong 2019;5.
15. Sprenger TO, Tumasjan A, Sandner PG, Welpe IM. Tweets and Trades: the Information Content of Stock Microblogs. Eur Financ Manag 2014;20(5):926–957. [doi: https://doi.org/10.1111/j.1468-036X.2013.12007.x]
16. Mao H, Counts S, Bollen J. Quantifying the effects of online bullishness on international financial markets [Internet]. Stat Pap Ser. European Central Bank; 2015 Jul. Report No.: 9. Available from: https://ideas.repec.org/p/ecb/ecbsps/20159.html
17. Measurement of Inequality in Human Development – A Review | Human Development Reports [Internet]. [cited 2021 Mar 3]. Available from: http://hdr.undp.org/en/content/measurement-inequality-human-development-%E2%80%93-review
18. Thomas V, Wang Y, Fan X. Measuring Education Inequality: Gini Coefficients of Education [Internet]. The World Bank; 1999 [cited 2021 Mar 3]. [doi: 10.1596/1813-9450-2525]
19. Hörcher D, Graham DJ. The Gini index of demand imbalances in public transport. Transportation [Internet] 2020 Sep 24 [cited 2021 Mar 3]; [doi: 10.1007/s11116-020-10138-4]
20. Manek AS, Shenoy PD, Mohan MC, R VK. Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier. World Wide Web 2017 Mar 1;20(2):135–154. [doi: 10.1007/s11280-015-0381-x]
21. COVID-19 Intervention Timeline in Canada [Internet]. CIHI; 2020. Available from: https://www.cihi.ca/en/covid-19-intervention-timeline-in-canada
22. COVID-19 in Ontario: A Summary of Wave 1 Transmission Patterns and Case Identification [Internet]. p. 13. Available from: https://www.publichealthontario.ca/-/media/documents/ncov/epi/covid-19-daily-epi-summary-report.pdf?la=en
23. A timeline of COVID-19 in Ontario | Globalnews.ca [Internet]. [cited 2021 Mar 3]. Available from: https://globalnews.ca/news/6859636/ontario-coronavirus-timeline/
24. A timeline of events in Canada’s fight against COVID-19 [Internet]. CP24. 2020 [cited 2021 Mar 3]. Available from: https://www.cp24.com/news/a-timeline-of-events-in-canada-s-fight-against-covid-19-1.5231865
25. Canadians prefer strict lockdowns over partial shutdowns for hard-hit regions: Nanos survey

[Internet]. Coronavirus. 2020 [cited 2021 Mar 3]. Available from: https://www.ctvnews.ca/health/coronavirus/canadians-prefer-strict-lockdowns-over-partial-shutdowns-for-hard-hit-regions-nanos-survey-1.5231626
26. Hu W. Real-Time Twitter Sentiment toward Thanksgiving and Christmas Holidays. Scientific Research Publishing; 2013 Apr 30 [cited 2021 Mar 3];2013. [doi: 10.4236/sn.2013.22009]
27. Canada could see 'grotesque' spike in coronavirus cases after holidays: expert [Internet]. Glob News. [cited 2021 Mar 3]. Available from: https://globalnews.ca/news/7540186/canada-coronavirus-christmas-spike/
28. CSSEGISandData. CSSEGISandData/COVID-19 [Internet]. 2021 [cited 2021 Mar 3]. Available from: https://github.com/CSSEGISandData/COVID-19
29. Jebb AT, Tay L, Wang W, Huang Q. Time series analysis for psychological research: examining and forecasting change. Front Psychol [Internet] Frontiers; 2015 [cited 2021 Jan 27];6. [doi: 10.3389/fpsyg.2015.00727]
30. Pankratz A. Forecasting with Dynamic Regression Models. John Wiley & Sons; 2012. ISBN:978-1-118-15078-8
31. Woodward WA, Gray HL, Elliott AC. Applied time series analysis, with R. Second edition. Boca Raton: CRC Press, Taylor & Francis Group; 2017. ISBN:978-1-4987-3422-6
32. By the numbers: Twitter Canada at Dx3 2018 [Internet]. [cited 2021 Mar 3]. Available from: https://blog.twitter.com/en_ca/topics/insights/2018/TwitterCanada_at_Dx3.html
33. Sizing Up Twitter Users [Internet]. Pew Research Center; 2020 Apr. Available from: https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2019/04/twitter_opinions_4_18_final_clean.pdf

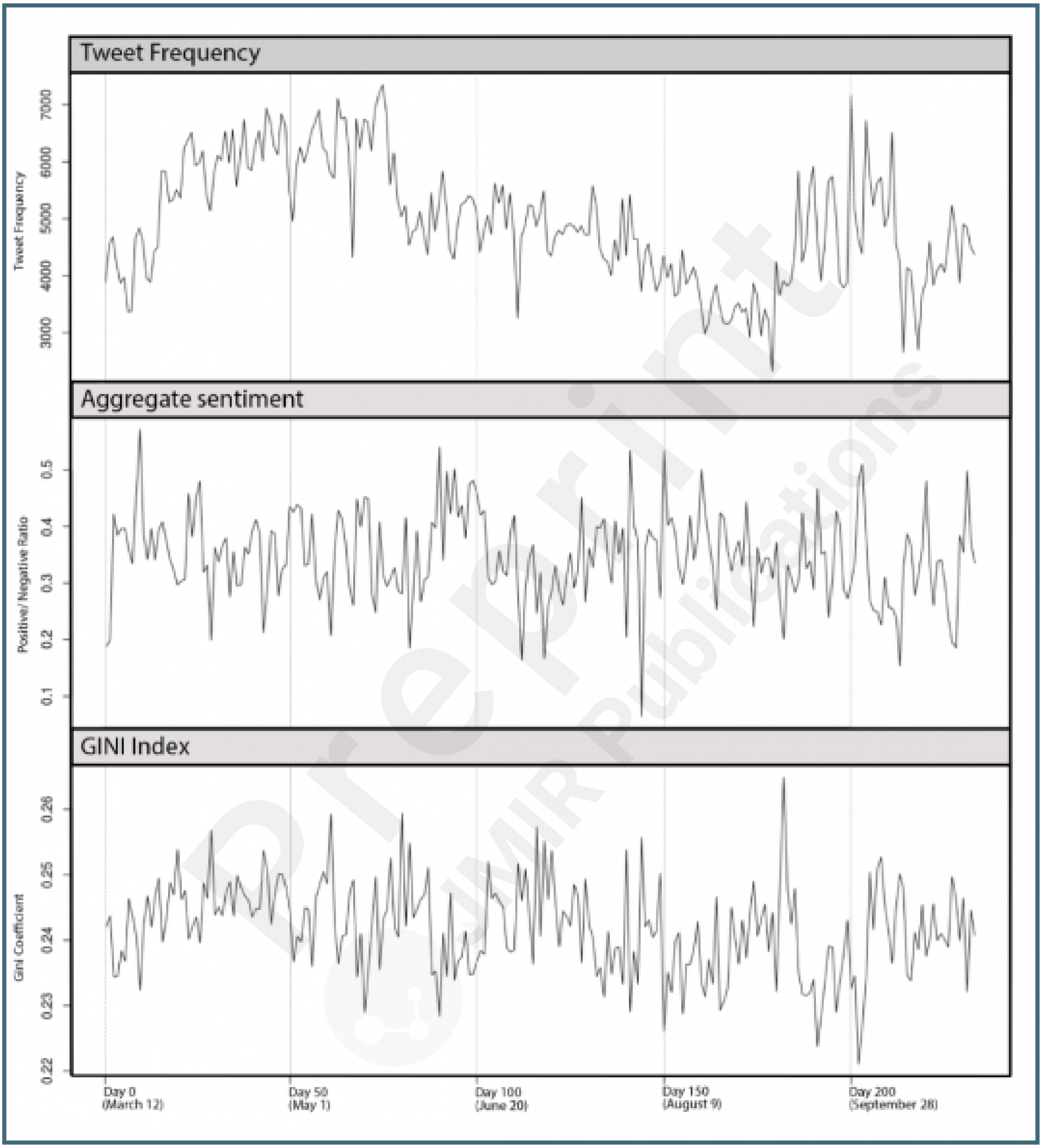
Supplementary Files

Figures

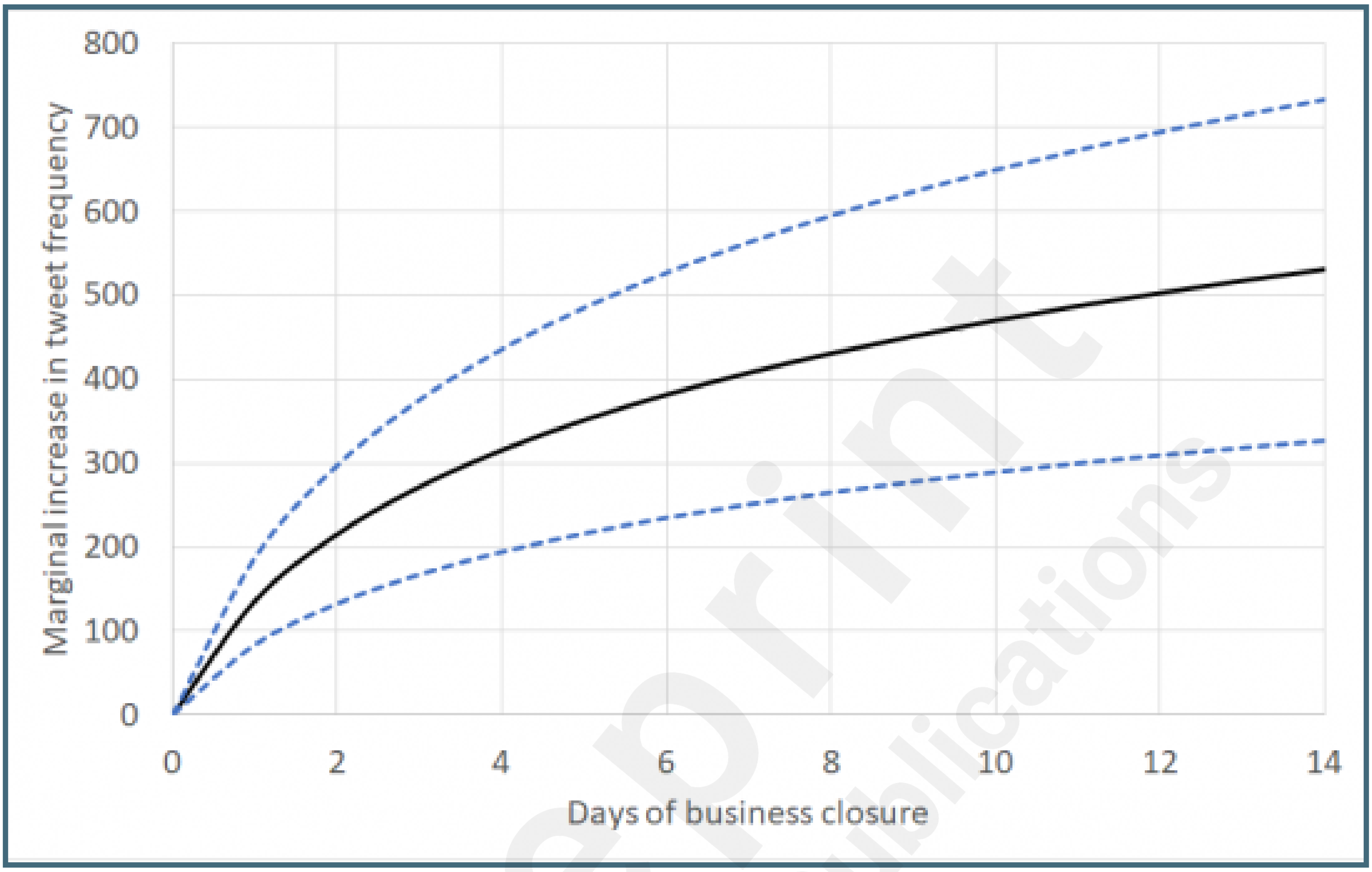
Graphical representation of using GINI coefficient to measure sentiment disparity.



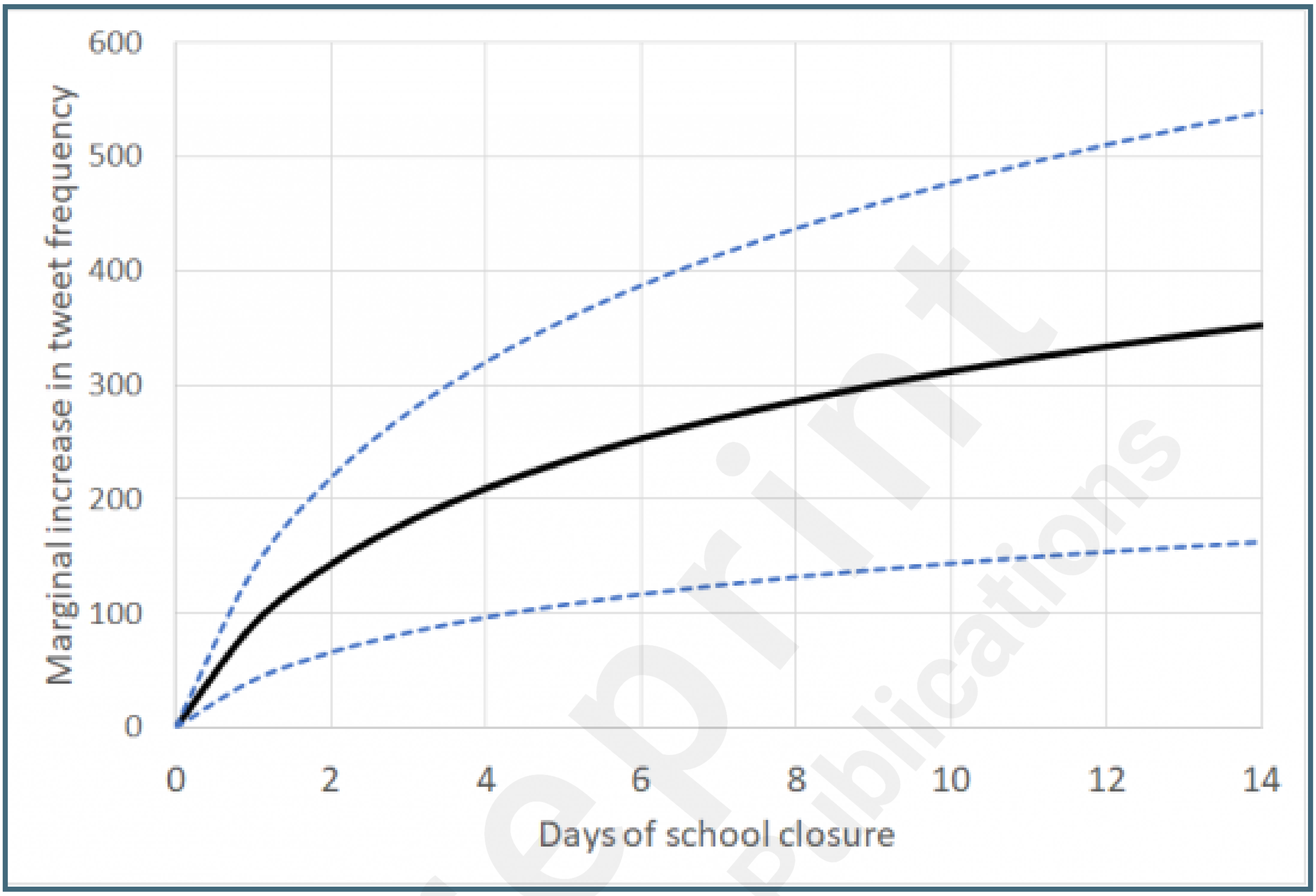
Daily tweet frequency, aggregate sentiment, and GINI index time series.



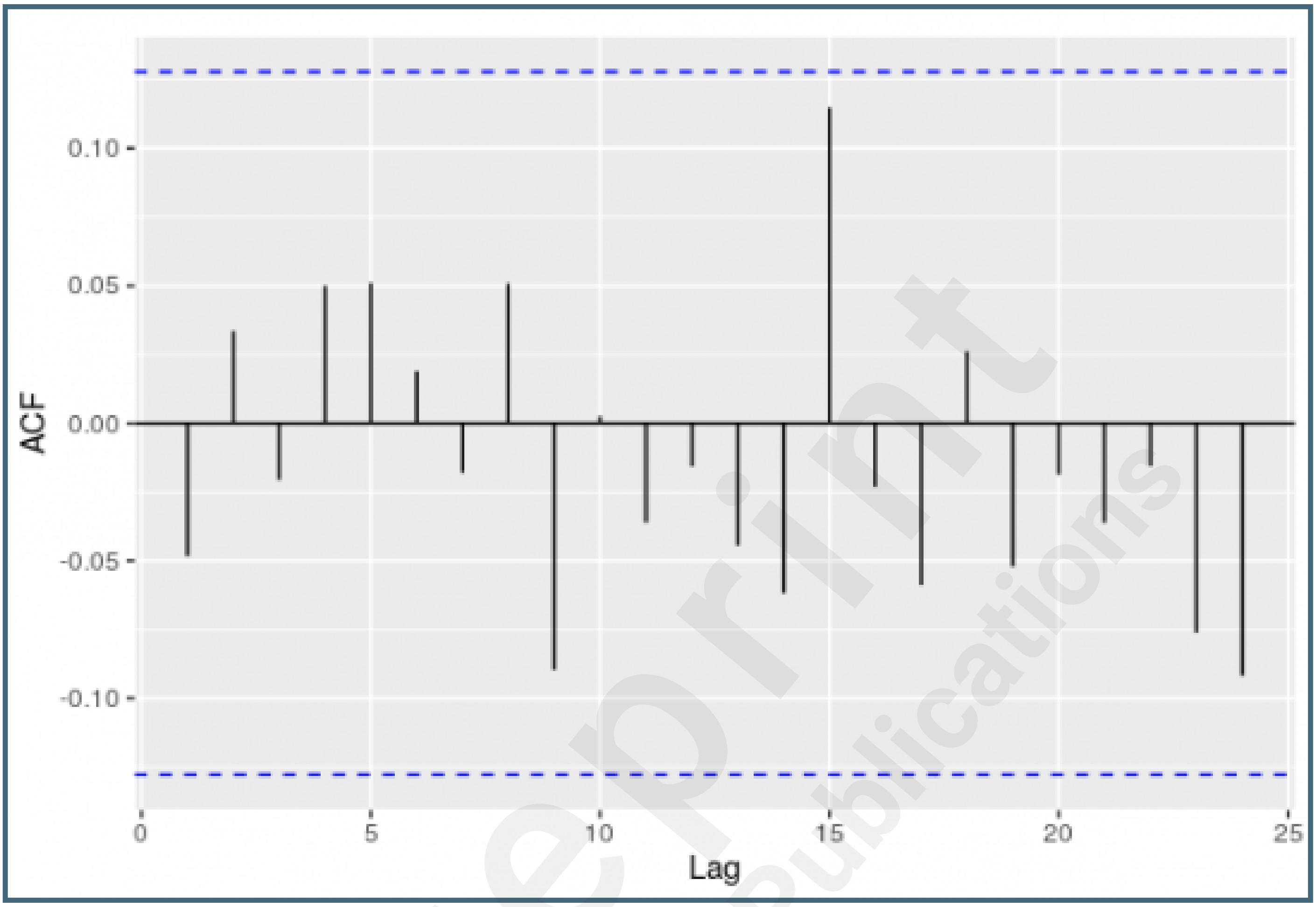
Estimated marginal increases in tweet frequency associated with increases in number of days of business closures, holding all other factors constant.



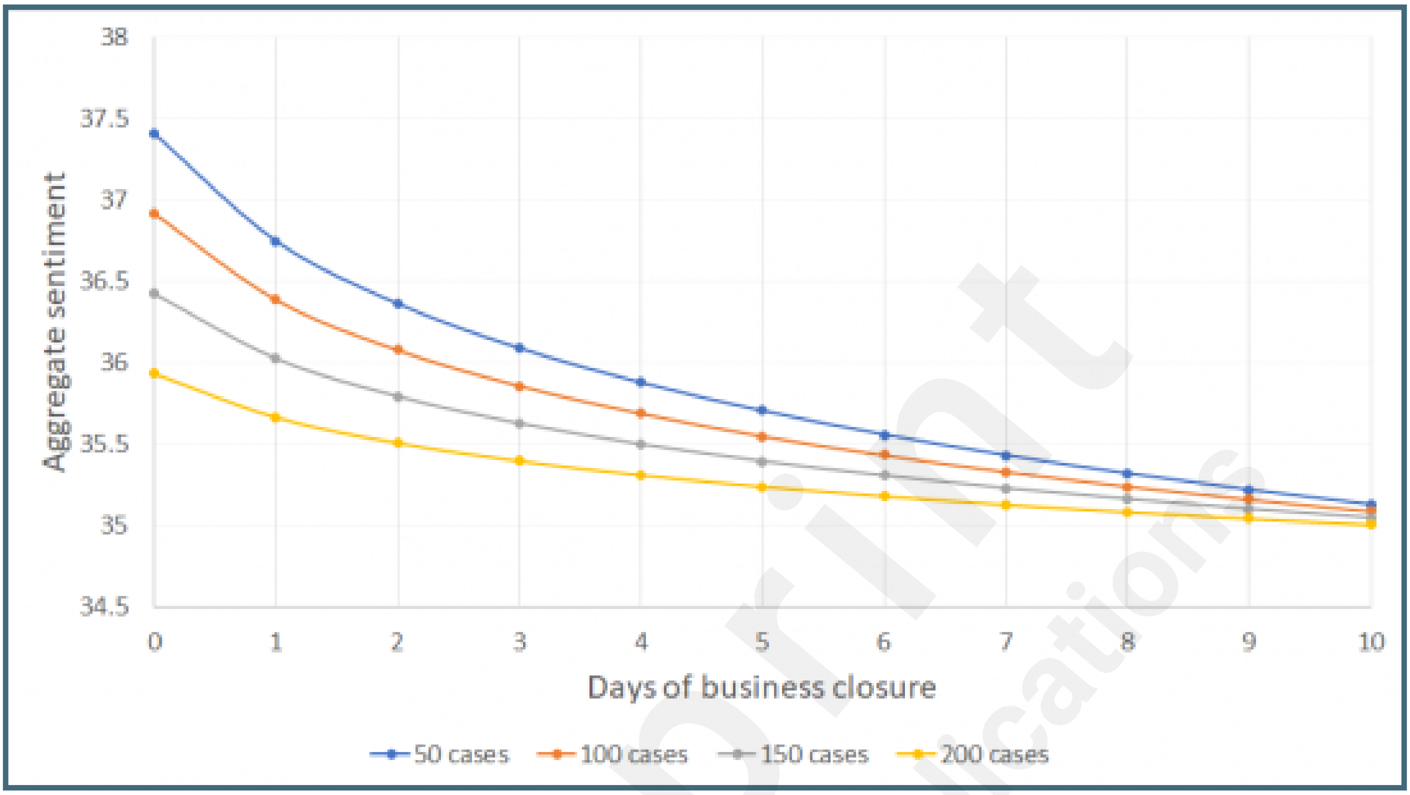
Estimated marginal increases in tweet frequency associated with increases in number of days of school closure, holding all other factors constant.



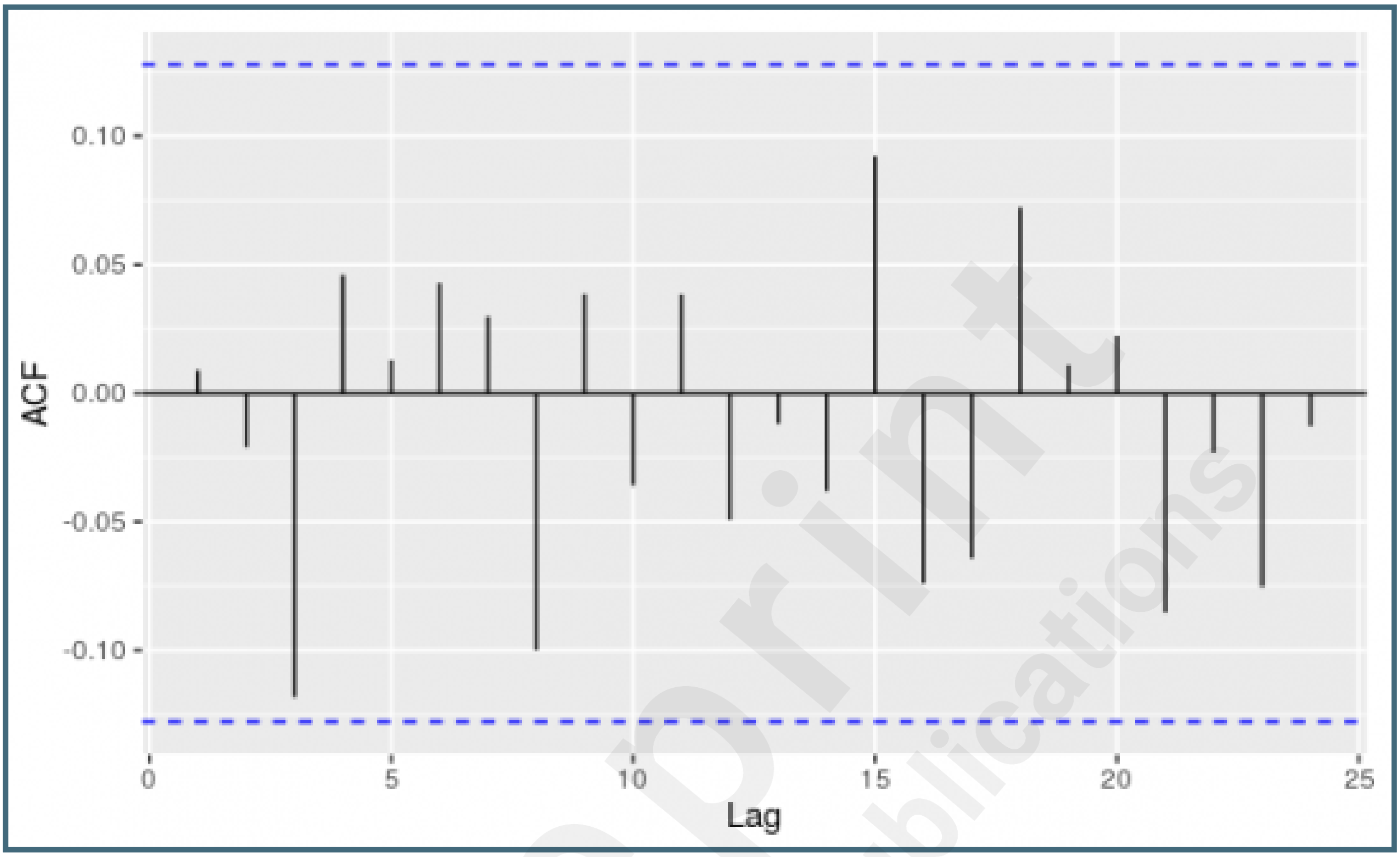
ACF plot for COVID-related tweet frequency.



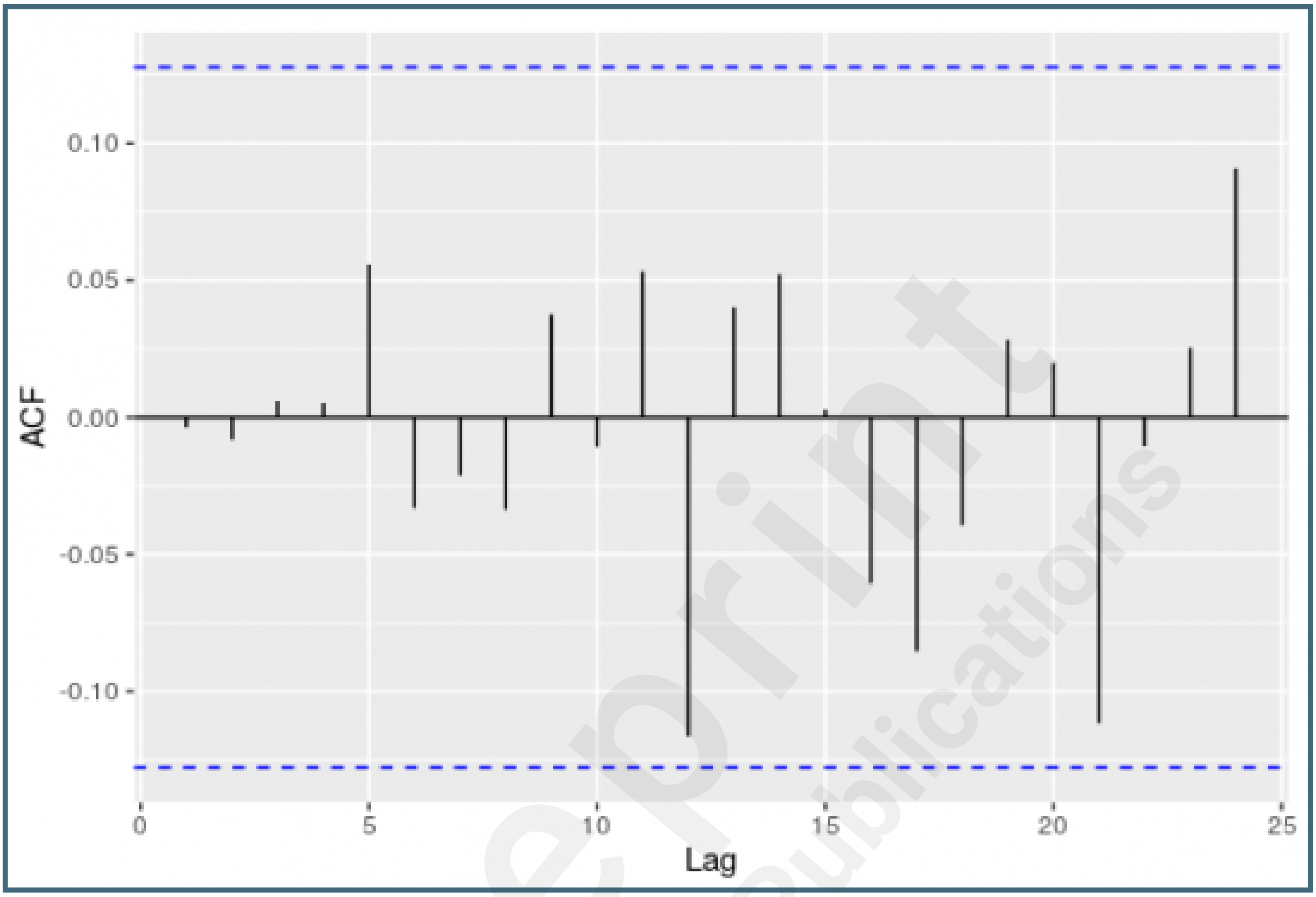
Predicted tweet sentiment ratio (positive-to-negative): change in ratio from day 0 to day 10 of a business closure period, varying by Ontario new COVID case counts (holding all other factors constant).



Predicted tweet sentiment ratio (positive-to-negative): change in ratio from day 0 to day 10 of a business closure period, varying by Ontario new COVID case counts (holding all other factors constant).



ACF plot of GINI indices.



Multimedia Appendixes

Timeline of key COVID-related events in Ontario from March to October 2020.
URL: http://asset.jmir.pub/assets/ae5ba55eedee81862f16b1f6521bad1d.docx