Examine the Impact of COVID-19 Policies and Restrictions on the Sentiment Score of Tweets

Jenny Chan '22.5 | Data Science Capstone Project

Research Question:

Do U.S. COVID-19 policies and restrictions affect the average sentiment score for COVID-19-related tweets from the U.S. on Twitter?

Hypothesis:

Stricter travel restrictions and health policies lower the average sentiment score for COVID-19-related tweets on Twitter.

Background:

On March 13, 2020, the Travel Ban issued by President Donald Trump prohibited foreign nationals from entering the U.S. if they have been in the Schengen Area within 14 days before their entry. Soon afterwards, the continued rise of COVID-19 cases led to a series of health policies and travel restrictions being issued by the federal government, including a nation-wide travel restrictions, states-wide stay-at-home orders and mask mandates.

During the pandemic, there were many tweets related to COVID-19. This research focuses on policies and restrictions in the U.S.

Data Collection:

COVID-19 Tweets ID and Sentiment Score (Source: IEEE):

ID of COVID-19 related tweets that are geotagged (have a location) and their sentiment score.

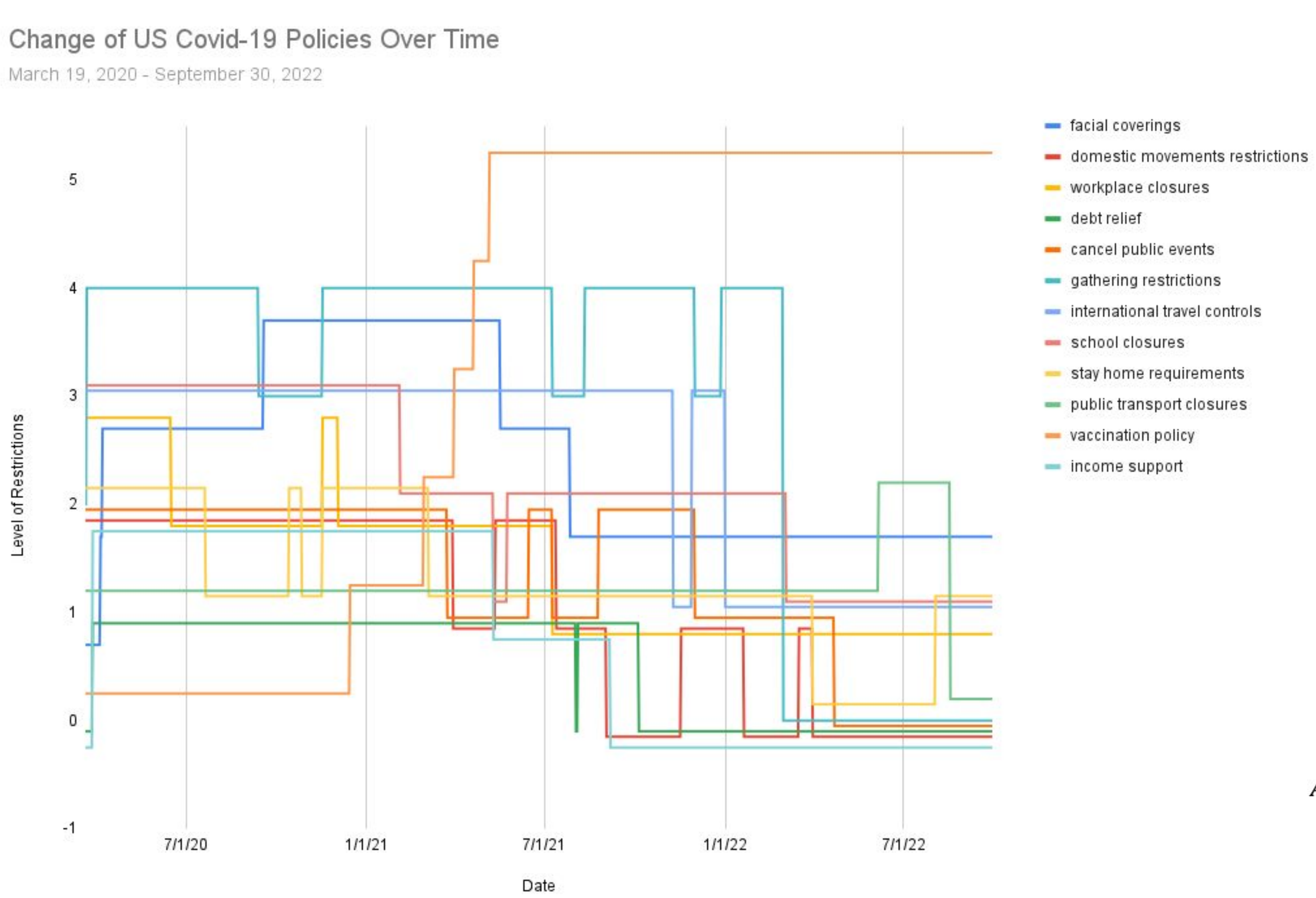
Using a Twitter Hydrator, I extracted the complete information (including the text, date, and location) of the Tweet from the Tweet ID. From there, I converted the location (ie. cities or states/provinces) into country names, and filtered only tweets from the U.S.

There were a total of 178049 tweets from the U.S. during the 926 days from 2020-03-19 to 2022-09-30.

COVID-19 Policies and Restrictions (Source: Oxford):

15 different datasets of panel data on the COVID-19 policies and restrictions across different countries between March 2020 till now. Data includes travel restrictions, mask policies, and stay-at-home policies. All datas are ordinal data, ranked from 0 to 5, from no restrictions to the tightest restrictions.

I kept the data of 15 policies from the U.S and between 2020-03-19 and 2022-09-30.



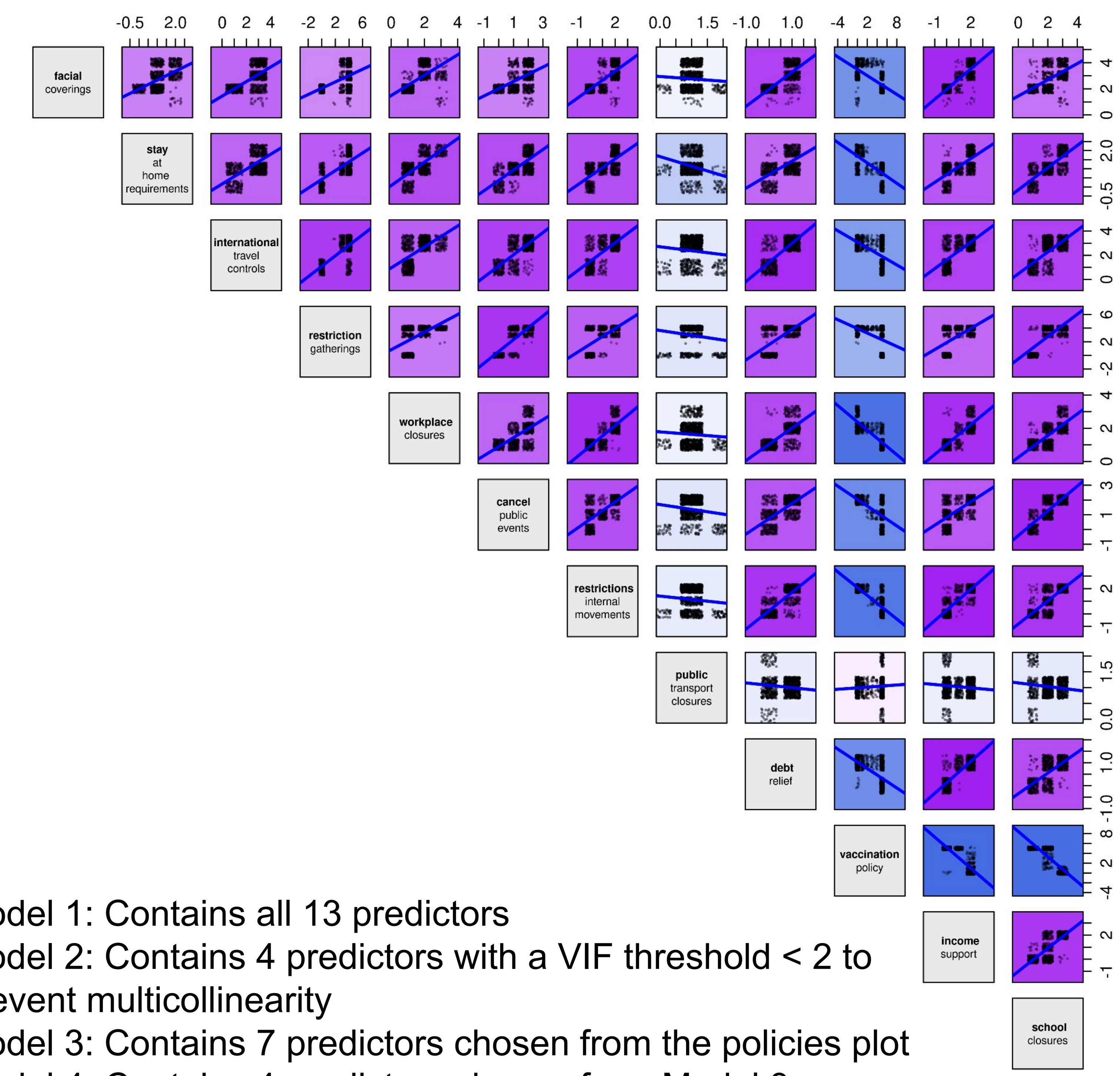
Data Modeling:

Using an autoregressive model, we identify the relationship between COVID-19 policies and restrictions (Independent Variables) and the average daily sentiment score (Dependent Variable) of COVID-19-related tweets.

$$Average\ sentiment\ score_t = \beta_0 + \beta_1 * X_{1,t-1} + \beta_2 * X_{2,t-1} + \dots + \beta_n * X_{n,t-1}$$

For IV: There are 15 different possible predictors in time-series format. We removed 3 predictors that have no changes over time (testing policy, contact tracing, and public campaigns).

For DV: There were a total of 178,049 tweets, we removed the 2843 tweets that didn't contain a sentiment score. A significant number of tweets (n=54,411) have a neutral sentiment score, which were also removed. The final dependent variable is the daily average sentiment score in time-series format.



Model 1: Contains all 13 predictors

Model 2: Contains 4 predictors with a VIF threshold < 2 to prevent multicollinearity

Model 3: Contains 7 predictors chosen from the policies plot

Model 4: Contains 4 predictors chosen from Model 3

Preliminary Result (Model 4):

	Estimate Coefficient	P-value
Intercept	0.136	<2e-16***
Facial_coverings	0.00969	0.000579***
Workplace_closures	0.0105	0.0172*
Cancel_public_events	0.0112	0.0134*
School_closures	-0.0108	0.0415*

$$Average\ sentiment\ score_t = \beta_0 + \beta_1 facial\ covering_{t-1} + \beta_2 workplace\ closures_{t-1} + \beta_3 cancel\ public\ events_{t-1} + \beta_4 school\ closures_{t-1}$$
$$= \beta_0 + 0.0097 * facial\ covering_{t-1} + 0.010 * workplace\ closures_{t-1} + 0.011 * cancel\ public\ events_{t-1} - 0.011 school\ closures_{t-1}$$

Model Evaluation:

	Model 1	Model 2	Model 3	Model 4
Adjusted R^2	0.0658	0.0531	0.0649	0.0645
AIC	-2343	-2340	-2347	-2350
BIC	-2278	-2312	-2305	-2322
P-value (vs M1)	NA	0.0198	0.335	0.336
P-value (vs M3)	NA	NA	NA	0.0246

Model 1 has the highest Adjusted R^2 scores. However, model 1 does include variables that violate the multicollinearity assumption.

Model 4 has the lowest AIC and BIC values, indicating a better fitting model compared to the others. Even though it doesn't have the highest Adjusted R^2 value, it is still relatively close to Model 1.

We also build a model using the Canadian sentiment scores but with the U.S. policies and restrictions and a model using the U.S. sentiment scores but with Canadian policies and restrictions.

	Model 4	CAN senti.	CAN policies
Intercept	0.136***	0.1066***	0.167***
Facial_coverings	0.00969***	-0.00725	-0.0007
Workplace_closures	0.0105*	0.0234***	0.0106
Cancel_public_events	0.0112*	-0.0103	-0.0007
School_closures	-0.0108*	0.0151	0.00149

The coefficients and p-values are different. This indicate that our initial model does show how U.S. policies and restrictions can affect the sentiment scores of tweets from the U.S, but may not be as good for Canada.

Discussion:

Public tends to have different opinions regarding policies and restrictions. My original hypothesis predicts that more stringent restrictions will negatively impact the average sentiment score for tweets. My result however shows opposite effect for all predictors in the model where stricter policies led to higher sentiment score s(more positive feelings), except for school closures.

This is understandable, especially during the height of the pandemic, when the public was generally more concerned about health and safety for society and wanted to enforce stricter rules. My model also doesn't explain everything that can affect the sentiment score of tweets on Twitter. There are other possible predictors, such as unemployment rate or number of COVID-19 cases.

Data Limitations:

TextBlob - NLP library that generated the sentiment score in the dataset doesn't recognize Covid-related phrases. "Positive test result" would be classified as a positive phrase, referring to "positive" as an attitude rather than actually referring to a "positive" test result for COVID-19.