Social Media, Public Sentiment, and Social Distancing: Evidence from 10 Million Tweets

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January 13, 2021

Abstract

Does social media predict risk-taking behaviour? I investigate this question in the context of COVID-19 by exploiting a large panel of tweets. Using inferred and explicit geolocation data embedded in the tweets, I study the extent to which public expressions of sentiment such fear, anger, and optimism influence social distancing, as measured by GPS-located smartphone data. In this 2000-word excerpt, I motivate the research design, conduct a literature review, and present descriptive statistics on a portion of the dataset.

1 Introduction

1.1 Overview

The early stages of the COVID-19 pandemic saw an unprecedented shift in behaviour for most citizens of the United States. In a short period of time, a large number changed their habits of working, socialising, and travelling. They did so both as a result of government restrictions in the form of non-pharmaceutical interventions (NPIs) and as a private response to the spread of the pandemic. Economists have taken interest in how citizens formed these behaviour changes, and the role that beliefs and risk attitudes played in determining the response to public policy. A new way to measure belief formation and public sentiment is with social media, an increasingly common platform for expression of opinion. It is plausible that those who express less risk-averse sentiment towards COVID online will be inclined to respond in a more lax fashion to social distancing and other public health regulation. In this dissertation, I investigate the role of online expressions of risk attitude on public behaviour in the early months of the pandemic. Specifically, I study whether a measure of risk-seeking sentiment on Twitter is linked to decreased social distancing behaviour, agreggated at the county/week level.

A key vector for expressing sentiment is social media, with Twitter and Facebook's suite of products[1] being the most widely-adopted, each platform having over 80 million monthly active users in the US. A survey by the Pew Research Foundation indicates that 22% of US adults use Twitter, with 42% of these using it on a daily basis (Perrin & Anderson, 2019). On Twitter, users can share their own text, with the option to link to a website; alternatively, they can 'retweet' another user's text or link. Users can also use 'hashtags' in their tweet, which connects their tweet to a particular topic. If the user has allowed it, Twitter also records the location of the tweet; and it is also possible for the user to set their location on their profile. In this way, it is possible to create a panel of geographically-located tweets about a particular topic.

I exploit GeoCov19, a dataset of 524 million geolocated tweets, to measure the local public sentiment on COVID in the US. The tweets cover the period from 1st February to 1st May, the period I focus on. The particular subset of the data I use contains X tweets in total; X are exactly geolocated (the user has provided a GPS location), and X are inferred from the location tab in the user's profile. The tweets were collected using the Twitter API, querying for a random sample of 1% of the tweets containing any of a list of 800 COVID-related keywords. I also use anonymous smartphone location data, collected by the company SafeGraph, as a measure of the extent of social distancing in an area. I present two measures

[1] Facebook, Facebook Messenger, Instagram, and WhatsApp

of social distancing at county level: first, the median minutes spent at home during 8am-6pm; second, the proportion of measured devices that stayed at home all day (SafeGraph, Inc., 2020).Demographic controls are also acquired and presented from the American Community Survey and the 2010 US census.

I use dictionary-based text analysis to assess the level of risk sentiment in a tweet. More sophisticated methods of text analysis like latent factor modelling are discussed in the Methods section. In the absence of a lexicon of risk preference, the NRC Emotion Lexicon (Mohammad & Turney, 2013) is used. This is a widely-used mapping of English words to eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust). Starting from a set of tweets that mention COVID, I assign tweets containing fear-associated words to a risk-averse sentiment. The base unit of analysis is the county-week; as such, I measure the proportion of tweets that contain fearful language in each county and week.

It is plausible that social media is a valid measure for risk appetite. The intuition is that the textual content of a social media post broadly reflects the poster's current opinion of a topic: for example, in response to the first confirmed US COVID death on February 26th, a user may express fearful, or uncertain, sentiment: for example, 'i think i have 70 panic attacks every day because of how scared i am for my mom to catch corona', a Tweet in the dataset – or a neutral sentiment. This opinion of the topic, particularly their level of fear, maps to a user's broader expectations about the course of the pandemic: while other emotions like joy, anticipation, and trust may rely on the context of the discussion, expressions of fear are plausibly consistent in mapping to risk-averse sentiment. When restrictions are implemented, users who initially formed pessimistic expectations may be more inclined to adhere more to them than a user who formed optimistic or netural expectations.

The primary econometric specification is a panel model with county and week fixed effects;

$$Y_{it} = \alpha + \beta r_{it} + \mu c_{it} + \tau_i + \delta_t + X_{it}\gamma + \epsilon_{it}$$

where Y_{it} is a vector of social distancing metrics, βr_{it} is the risk perception measure, (i.e. the proportion of total tweets containing fearful language), μc_{it} the number of COVID cases, $\tau_i + \delta_t$ county and week-level fixed effects, and $X_{it}\gamma$ demographic controls.

This research contributes to the recent economics literature seeking to explain the disparities in social distancing in the early stages of the pandemic in the US. In particular, partisanship has been shown to be a significant factor on the practice of social distancing: Allcott et al. (2020), Barrios and Hochberg (2020), and Painter and Qiu (2020) show that areas with more Republicans engaged in less social distancing, are associated with lower perceptions of risk of the pandemic, and exhibited less remote transactions. Ananyev et al. (2020) and Simonov et al. (2020) also measure the causal effect of the right-wing Fox News network on social distancing during the pandemic. This paper builds on Barrios and Hochberg (2020) in particular, which shows that online risk perception is predicted by Trump voter share: by measuring risk perception with a high-frequency geolocated dataset, my approach controls for political alignment and assesses the effect of risk perceptions on their own. In essence, the above papers argue that political beliefs affect complicance with Social Distancing orders; I measure expressions of sentiment regarding COVID risk, and given this data I ask two questions: first, does local risk sentiment predict social distancing behaviour beyond political affilitation; second, do differing interpretations of political messages – like Trump's messages in March and April downplaying the virus – colour local risk sentiment?

This dissertation also contributes to the rapidly-expanding field of text analysis in economics, and presents an example of how the rich sentiment data encoded in social media communication can inform insights into public behaviour. This topic is particularly mature in finance – where sentiment data from public company documents, news media, and social media have been shown to predict stock market reactions (Bollen et al., 2011) – and monetary economics, where central bank statements, coded according to their dovishness or hawkishness, predict fluctuations in Treasury securities (Gentzkow et al., 2019; Lucca & Trebbi, 2009). On the topic of empirical economics, this paper takes a similar approach – by using online data to predict local sentiment – as Stephens-Davidowitz (2014), which uses Google search data to proxy an area's racial animus, and uses this to estimate the Obama vote share. I use geolocated Twitter sentiment to proxy the local attitude to COVID in a given week, and test to see if this predicts social distancing practice.

The argument of the dissertation rests on the following assumptions: first, that social media data is a valid proxy for local risk appetite, and that fear-associated language in COVID-related tweets is an effective estimator of the risk appetite encoded in the tweet. It is also important to note a possible selection effect in the dataset: tweets about COVID may attract a greater level of fear-related language and not reflect an individual's true opinion about social distancing and other preventative measures. I address these assumptions and drawbacks and discuss methods to alleviate them in the Results section.

2 Literature Review

2.1 Misinformation and media bias

2.2 Digital trace datasets

2.3 COVID-19 policies and social distancing

3 Data

4 Methods

5 Results

6 Discussion

`1361 words in main body, excluding headers and bibliography.`

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