Social Media, Risk Perception, and Social Distancing: Evidence from 33 Million Geolocated Tweets

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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 influence social distancing, as measured by GPS-located smartphone data. In this short excerpt, I motivate the research design and briefly describe the Twitter dataset.

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Motivation

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 more risk-averse sentiment towards COVID online will be inclined to respond in a stricter fashion to social distancing and other public health regulations. In this dissertation, I study the impact of local expressions of risk attitude on public behaviour in the early months of the pandemic. Specifically, I study whether a measure of risk-averse sentiment on Twitter is linked to increased social distancing behaviour at the county/week level.

This dissertation contributes to two strands of the recent economics literature on the COVID-19 pandemic. First, it investigates the relationship between partisanship and risk preference. Previous papers posit that political preference influences social distancing through risk preference; I contend that *local* risk preference is a separate factor to political partisanship, and has an independent impact on social distancing. More broadly, the paper investigates the relationship between risk preference and economic behaviour, and presents a novel example of economic inference from social media using text analysis.

A key vector for expressing sentiment is social media, with Twitter and Facebook's suite of products 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 (Qazi et al., 2020), 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 33.36 million tweets in total; a small subset are exactly geolocated (the user has provided a GPS location), while most are inferred from the location tab in the user's profile. The tweets were collected using the Twitter Streaming API, querying

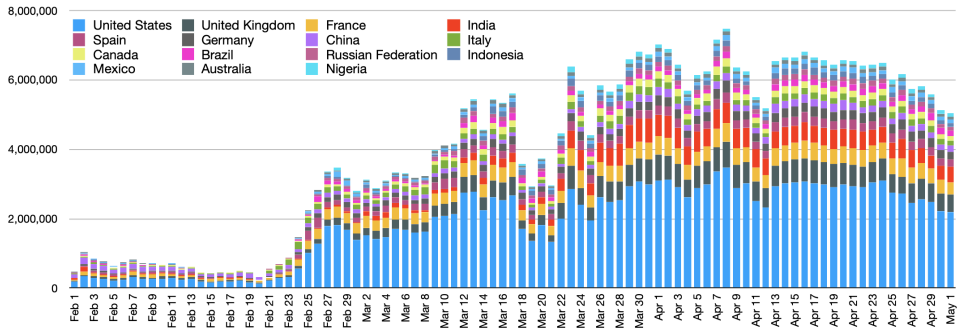


Figure 1: Daily distribution by country of GeoCoV19 tweets, Feb 1st to May 1st, 2020 (Qazi et al., 2020)

for 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 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 might express fearful sentiment, 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 key aspect to the data is that the Twitter conversations provide a real-time insight into local sentiment as NPIs are implemented; this sentiment changes both in response to current, local experience *and* broader partisan interpretations of current events.

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, also including the Trump vote share.

The argument of the specification rests on the two assumptions 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.

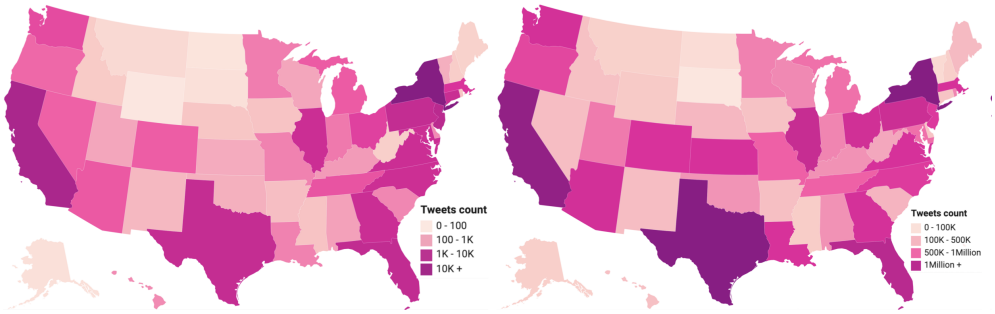
This research contributes to the recent economics literature seeking to explain the disparities in social distancing in the early stages of the pandemic in the US. In particular, partisanship has been shown to be a significant factor on the practice of social distancing: Allcott et al. (2020), Barrios 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, I measure expressions of sentiment regarding COVID risk, and given this data I ask whether local risk sentiment predicts social distancing behaviour beyond political affilitation. Second, this research relates to the recent economics literature around heterogeneous-agent epidemiological models, which endogenise individual behaviour – including social distancing – into the effective reproductive number $R(t)$. These recent models, such as Acemoglu et al. (2020), Brotherhood et al. (2020), and Eichenbaum et al. (2020), assume that preferences over risk are predictive of social distancing behaviour; this paper looks to empirically confirm this key assumption.

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 attitude to inflation, 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.

GeoCoV19 and geolocation inference of Twitter datasets

The primary dataset of tweets I present is a subset of GeoCoV19, a project which collected tweets relating to COVID-19 between February 1 and May 1 2020. The Twitter Streaming API provides a live filter function for a number of keywords and hashtags, and returns all tweets matching any of the search terms. The terms were chosen to cover a broad base of COVID-related talk in addition to central discussion topics like 'coronavirus'. In total, 524 million tweets were collected during the time period; during the first three weeks of February this number was lower, reflecting lower general interest, and increasing to around 6.4 million per day during March and April. We filter for tweets that are in English and are geotagged to originate from the United States; the final number of tweets is 33.36 million, all geolocated to the county level.



(a) USA: Organic geotagged tweets (b) USA: User distribution

Figure 2: Geographic distribution of GeoCoV19 tweets and users (Qazi et al., 2020)

Of the final dataset, around 150,000 have exact geolocation embedded in the tweet. A different method of geolocating tweets is used to identify most of the locations: when activating a Twitter account the user is strongly encouraged to set their location in their profile. Although it is a free field, most users set this to their current location; this metadata is included with every tweet. The maintainers of the dataset then employ a toponym extraction approach to elicit the location of the location field. Cross-checking the

procedure with GPS-geolocated tweets, the dataset shows good coverage and accuracy across US counties, and so makes a panel approach viable. A possible drawback to this approach is that, since users can set their profile location freely, users from other countries or states could masquerade as Americans in particular locations, or the classification process could mis-classify a foreign (particularly English) place as a US location due to sharing a name – for example, York County, Maine. In order to account for this we remove counties from consideration that have a share of total tweets significantly higher than their population share of the US. Other than misclassification, deliberate setting of the profile location to a US location is possible. This may be a concern for large, well-known cities like Los Angeles and New York, but it is less likely that a given user will set their location to a less well-known American county. Finally, users may move county and not change their profile location.

Since the tweets are delivered from the servers at download time, the download procedure entails that a proportion of Tweets – particularly those identified as containing misinformation or those sent by users whose accounts have since been suspended or deleted – will be unavailable on request from the service when the dataset is 'rehydrated'. This presents a selection problem for topics like misinformation, where Twitter enacts a stringent and continuous policy; however, this policy would not bias the chosen variable, local expressions of opinion. The deletion rate ultimately encountered during the rehydration process was around 20%, reflecting the normal removal of machine-generated content.

References

Acemoglu, D., Makhdoumi, A., Malekian, A., & Ozdaglar, A. (2020, July). *Testing, Voluntary Social Distancing and the Spread of an Infection* (w27483). National Bureau of Economic Research. Cambridge, MA. Retrieved January 20, 2021, from http://www.nber.org/papers/w27483.pdf. (Cit. on p. 3)

Allcott, H., Boxell, L., Conway, J., Gentzkow, M., Thaler, M., & Yang, D. (2020, April). *Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic* (Working Paper No. 26946). National Bureau of Economic Research. Cambridge, MA. (Cit. on p. 2).

Ananyev, M., Poyker, M., & Tian, Y. (2020). The safest time to fly: Pandemic response in the era of Fox News. *Covid Economics*, (49) (cit. on p. 3).

Barrios, J., & Hochberg, Y. (2020, April). *Risk Perception Through the Lens of Politics in the Time of the COVID-19 Pandemic* (Working Paper No. 27008). National Bureau of Economic Research. Cambridge, MA. Retrieved January 8, 2021, from https://www.nber.org/system/files/working_papers/w27008/w27008.pdf. (Cit. on pp. 2, 3)

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. Retrieved January 13, 2021, from https://linkinghub.elsevier.com/retrieve/pii/S187775031100007X (cit. on p. 3)

Brotherhood, L., Kircher, P., Santos, C., & Tertilt, M. (2020). *An Economic Model of the COVID-19 Epidemic: The Importance of Testing and Age-Specific Policies* (Discussion Paper No. 13265). IZA Institute of Labor Economics. Bonn. (Cit. on p. 3).

Eichenbaum, M., Rebelo, S., & Trabandt, M. (2020, March). *The Macroeconomics of Epidemics* (w26882). National Bureau of Economic Research. Cambridge, MA. Retrieved January 20, 2021, from http://www.nber.org/papers/w26882.pdf. (Cit. on p. 3)

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as Data. *Journal of Economic Literature*, *57*(3), 535–574. Retrieved January 13, 2021, from https://pubs.aeaweb.org/doi/10.1257/jel.20181020 (cit. on p. 3)

Lucca, D. O., & Trebbi, F. (2009, September 17). *Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements* (w15367). National Bureau of Economic Research. Retrieved January 13, 2021, from https://www.nber.org/papers/w15367. (Cit. on p. 3)

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a Word–Emotion Association Lexicon. *Computational Intelligence*, *29*(3), 436–465. Retrieved January 13, 2021, from https:

//onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8640.2012.00460.x (cit. on p. 2)
_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1467-8640.2012.00460.x

Painter, M., & Qiu, T. (2020). Political Beliefs affect Compliance with COVID-19 Social Distancing Orders. *SSRN Electronic Journal*. Retrieved January 8, 2021, from https://www.ssrn.com/abstract=3569098 (cit. on p. 2)

Perrin, A., & Anderson, M. (2019, April 10). *Share of U.S. adults using social media, including Facebook, is mostly unchanged since 2018*. Pew Research Center. Washington, DC. Retrieved January 6, 2021, from https://www.pewresearch.org/wp-content/uploads/2019/04/FT_19.04.10_SocialMedia2019_topline_methodology.pdf. (Cit. on p. 1)

Qazi, U., Imran, M., & Ofli, F. (2020). GeoCoV19: A dataset of hundreds of millions of multilingual COVID-19 tweets with location information. *ACM SIGSPATIAL Special*, *12*(1), 6–15. Retrieved January 13, 2021, from https://dl.acm.org/doi/10.1145/3404820.3404823 (cit. on pp. 1–3)

SafeGraph, Inc. (2020). *Social Distancing Metrics*. SafeGraph. Retrieved January 7, 2021, from https://docs.safegraph.com/docs/social-distancing-metrics. (Cit. on p. 2)

Simonov, A., Sacher, S., Dubé, J.-P., & Biswas, S. (2020). *The Persuasive Effect of Fox News: Non-Compliance with Social Distancing During the COVID-19 Pandemic* (Working Paper No. 27237). National Bureau of Economic Research. Cambridge, MA. Retrieved January 7, 2021, from http://media.mediapost.com.s3.amazonaws.com/uploads/FoxNewsPaper.pdf. (Cit. on p. 3)

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics*, *118*, 26–40. Retrieved January 12, 2021, from https://linkinghub.elsevier.com/retrieve/pii/S0047272714000929 (cit. on p. 3)