Reasons behind Mobility Decline in the US during Covid-19- Evidence from Twitter and Local Policy Data

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1 Research Object

Covid-19 became the global event in 2020. It influenced many aspects of individual lives. The government policy also played a dramatic role during the process, especially in March, when the local governments issued Stay-at-home order while the central government introduced CARES action. The situation requires researchers to understand how human behaviors change and their effect on the economy.

This study focused on a currently focused question-- Which is the major force of citizen’s mobility decrease during the Covid-19? Is that due to the lockdown policy or social awareness? If it was led by social awareness, what kind of emotional reaction will influence mobility mostly?

There are generally two directions for Covid-19 studies: The first one looks at how the disease or some policies (lockdown or CARES, for example) influence people's behaviors, while the second orientation suggests their direct economic impact. My research is closer to the first type.

There have been some papers discussing the impact of social awareness and lockdown policy: Goolsbee and Syverson (2020) argued that the lockdown policy can only explain a 7 percent decline in consumption flow, while the majority decrease should be due to the increasing social awareness. Goldfarb and Tucker (2020) applied retail activity data to evaluate citizen’s mobility. What’s more, studies on the social network also support that social awareness is playing a big role in human behaviors. For example, Bailey, Cao, Kuchler & Stroebel (2018a) found that the social network will influence people’s decisions on housing. That suggests researchers find other reasons and to measure their impacts on the mobility decrease. Because if the mobility decline was not only due to the lockdown policy, the economy flow may not increase only by removing the lockdown policy.

Besides studies in the economic area, researchers already notice the social media data have been a great tool to analysis people’s response towards a particular issue. Because it can capture the effect directly and promptly. With the help of machine learning methods and other tools, researchers are able to build models to help identify emotions of large set literal content. Many researchers have summarized the commonly used tools in sentiment study for social media studies, like Kharde & Chapman (2018). Giachanou & Crestani (2016), Sahayak, Shete, Pathan (2015). They found that machine learning and Lexicon-Based models are most employed. There are also many studies that applied the sentiment study on Twitter. For instance, Roberts, Sadler & Moore (2019) used Twitter data to determine people’s emotional response to urban green spaces. Allen et al. (2016) trained machine learning model to monitor influenza outbreaks with Twitter data.

In this research, I want to measure the real impact on citizen’s mobility by the sudden lockdown policy and the gradual awareness employing time-series datasets. Although the lockdown policy also generated a social awareness impact, the impact will show after it announced, which is normally earlier than its delivered.

2 Data Description

In this research, I combined three main panel data: The mobility dataset, the Twitter data, and the Lockdown dataset. The first one is the response variable and the latter two are the explanatory variables.

2.1 Mobility Dataset

The mobility data collected by Descartes Labs.[[1]](#footnote-1) They collected anonymous locations data from the mobile device using cloud computing strategies, then computed the daily mobility of citizens living in each county in the US. It is worth noticing that the data at the county level is important as the detailed lockdown dates are varied between counties. Some counties began lockdown before the state government’s decision. The time range of the mobility dataset is from March first to the current, and they keep updating.

The citizen’s mobility is calculated in the following way: According to their explanation, the mobile device will automatically report a new position by its latitude, longitude, and an estimate of accuracy with other identified information like time and its id. The researchers will collect the data once a day, which generally around 100GB, and use an algorithm to normalize the data. After the data clearing, they obtained the max-distance mobility per individual within the given county and select the median of the max-distance mobility-- m50 as the county’s mobility. What’s more, they use a normalization function to normalize m50. The normalization function is as follows:

Where m50 stands for the median value of the max-distance mobility in a given region and m50\_norm is the standard level of mobility in that region, defined as the median m50 from an earlier period of the region.

Table 1 shows an example of the mobility data, and Table 2 is the distribution of the m50 and m50\_index. The two distributions have significant differences as the function denotes, m50 is in kilometers while the index is in percentage.

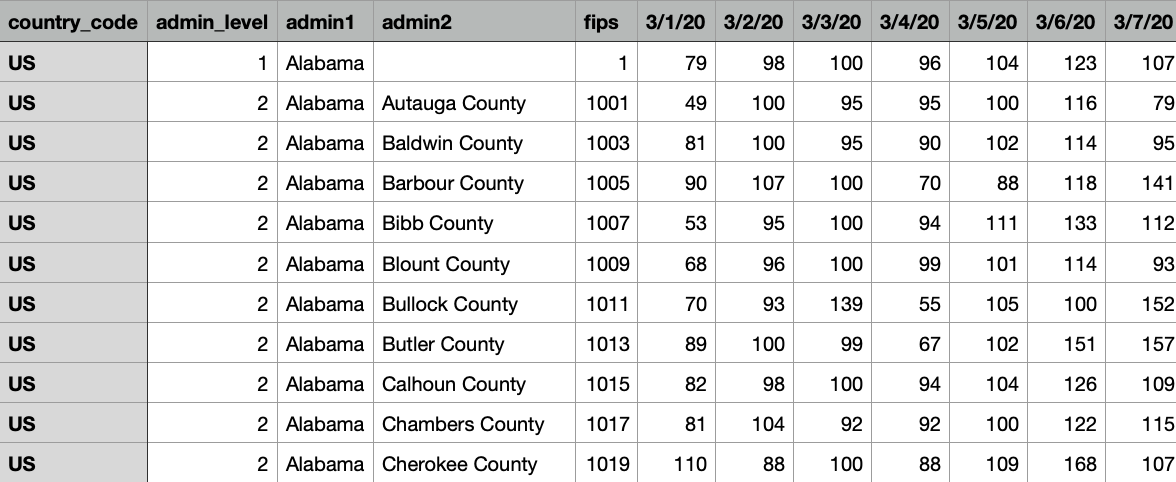


Table 1 Sample of Mobility Data

Fig. 1 and 2 are two sample graphs of the mobility dataset. Fig.1 is the change of mobility of six different states, and the Fig.2 shows the trend of mobility of different counties in Wisconsin state during March. We can see on the state level, the change pattern is very similar. Moreover, there is a decline at the beginning of April, when most of states begin the stay at home policy. However, we can still find the gap in the county level.

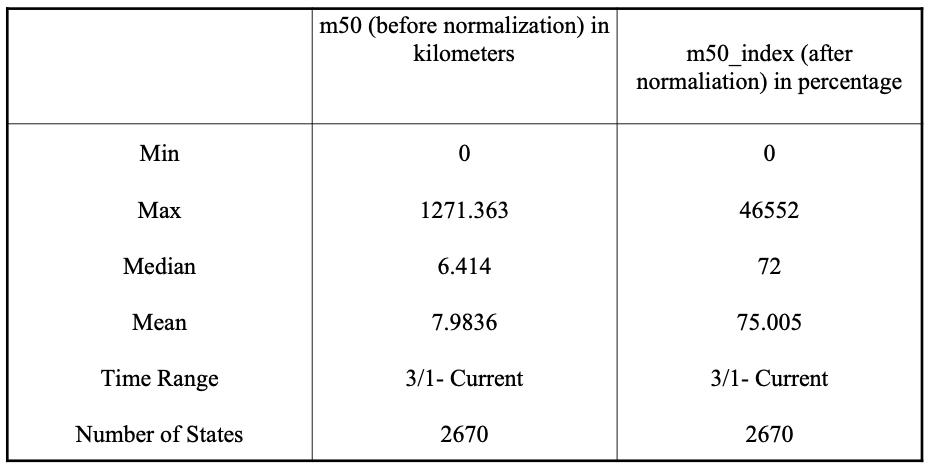
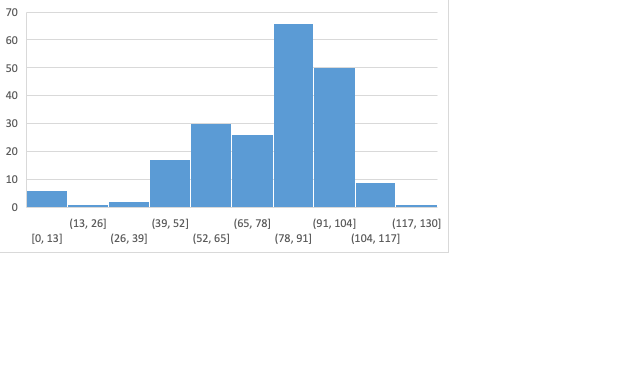


Table 2 Distributions of m50 and m50\_index

Fig 3 is a histogram of one state, Alabama, we can see that after the normalization process, the most frequent value of m50\_index is around [80,90].

2.2 Twitter Chatter Dataset

The second dataset is the Covid-19 Twitter chatter dataset maintained by Georgia State University’s Panacea Lab.[[2]](#footnote-2) This dataset tracked all the tweets and re-tweets that are relevant to Covid-19 from January, including all languages and nations. It included two versions of data, the first type is the whole dataset, and the second one is the “clean set” without all the retweeting. Table 3 shows the summary statistics for the clean versions. The researchers also collected the top 1000 words used each day from all twitters, which is more helpful with the natural language processing (NLP) task. Due to the privacy restrictions of Twitter, they can only share the Twitter ID instead of the real content of Twitters. However, researchers can trace back the original content through the hydrating process with some open-source packages and use it for non-profit study. [[3]](#footnote-3)

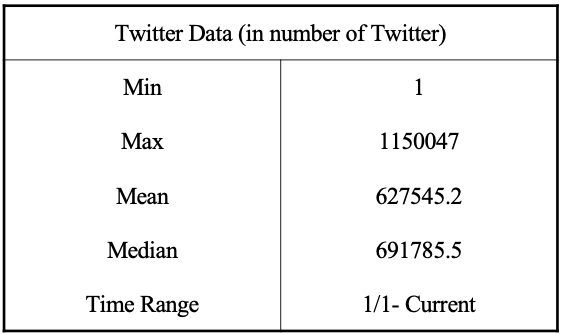


Table 3. Distribution of Twitter Data

Fig. 4 shows the trend of the number of tweets, and Fig.5 is the trend of the clean set.

2.3 The Local Policy Dataset

The third dataset is the Lockdown Policy Dataset collected by Goolsbee, Austan(2020). It included the Stay-at-home order beginning and end date of all the counties in the United States. As the authors of the dataset mentioned, the county-level data is useful as some counties take action before the states, especially in the states with a larger number of cases.

Fig 6 shows a combination of the three datasets. The orange line is the mobility change of Wisconsin during March, and the blue line is the number of Twitter during that period. We can see there is a pattern that increaes in the number of Twitter leads to a decline in mobility. Moreover, the mobility already decreased a lot when the State began lockdown on March 25th.[[4]](#footnote-4)

2.4 Other Datasets

There are other county-level datasets added as control variables. Currently, I use Local Area Unemployment data from the United States Bureau of Labor Statistics, and Number of Cases Data summarized by the New York Times.

Other time-invariant variables like poverty rate, age distribution, gender ratio are not included.

3 Methodology

The reasons behind mobility decrease can be generated by two major parts. The first one is due to policy restriction, as it states what an individual cannot do. The second reason is social education. Because through social education, individuals learn what they should or should not do. However, individuals may have different understandings of the same information. In that sense, to measure the impact of social awareness, the researchers could not only rely on the media reports but also need to analyze individual reactions to the reports. Different from traditional newspapers, social network platforms like Twitter can provide a relatively big picture of how the information is created, processed, and learned. In this way, it may serve as a great data source to evaluate the impact of social awareness on mobility decrease. Fig 7 displays the flow of how the two approaches work on mobility decline.

With this setting, the model will be generated by two parts separately, the first part is to use Regression Discontinuity (RD) to analysis the effect of Lockdown Policy, and the second part is to identify the effect of the number of Tweets and their emotions on Mobility with a Fixed Effect (FE) model.

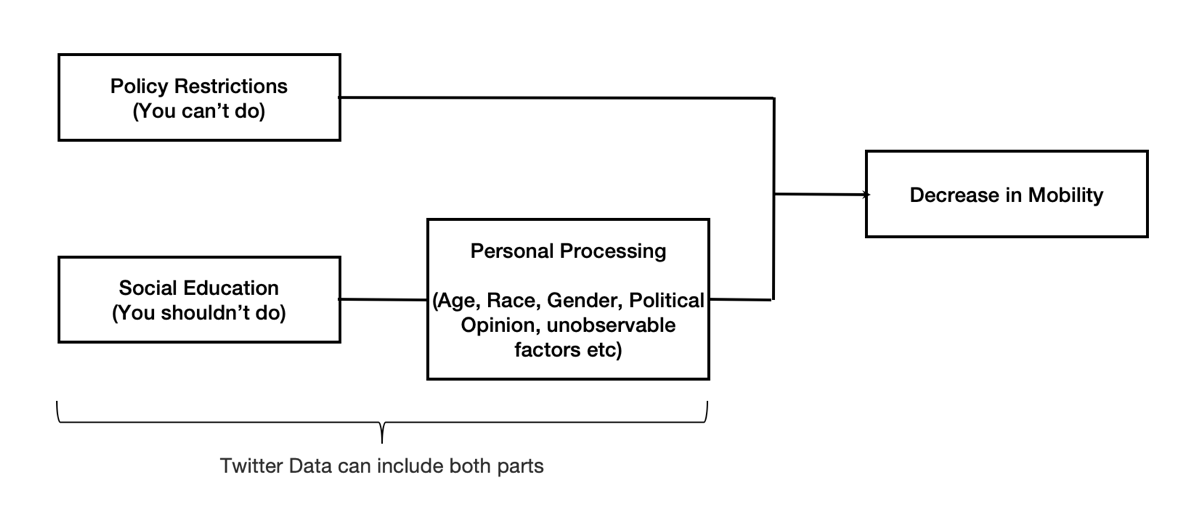


Fig 7. Reasons behind Mobility Decrease

Moreover, the two-part model is aimed to test the following three hypotheses:

Hypothesis 1: The Lockdown Policy has a negative effect on mobility.

Hypothesis 2: The Number of Tweets related has a negative effect on mobility.

Hypothesis 3: The Negative Emotional Tweets have a more significant impact on mobility.

3.1 The Model on Lockdown Policy

RD in time series can be employed for the Lockdown policy analysis as the policy stated a specific time on the beginning and ending time in each county. In addition, as the policy was generally introduced before a few days of its practice, we assume there are no other significant changes like media shock at the day of the policy became effective.

The formula below shows how RD works there. Prior to the stay-at-home order, the mobility in a particular day can be explained by county fixed effects, time fixed effect, other control variables and error. After its practice, the mobility is explained by county fixed effects, time fixed effect, the lockdown policy, other control variables and error. When use equation (1) subtracts (2), we can find the county fixed effect is cancelled out. What’s more, if there is no other big policy happen in the time range, which is highly possible as the model only employs two days[[5]](#footnote-5) before and after the Lockdown, the time fixed effects are relatively minor for equation (3).

Where is the control variables, is the time fixed effect of time t, is the county fixed effect of a county I, is a dummy variable of whether the Lockdown policy is effective at county i at time t.

The time fixed effect including other big events in national level, the weather, or whether this day is workday or not, etc. The county fixed effect covers all generally statistics at a county level, like average education, gender ratio, age distribution, income distribution, family size. Other control variables are both time-variant and county-variant, they are the local policy, unemployment rate, death, and infected numbers.

3.2 The Model on Social Awareness

The model of social awareness use data after Lockdown policy has been effective. It has two parts: The first part is to evaluate the effect of the number of Tweets on mobility. The second part is to regress the emotions of Tweets on mobility.

3.2.1 Number of Tweets of Mobility Decline

This one is the baseline model to determine how the number of Tweets influences citizen’s awareness on the Covid-19, then changes their mobility.

Where is the control variables, is the county fixed effect of a county I, is the number of Tweets at time t.

The time fixed effect is not included as it will absorb the impact of independent variables, however, it will be partly included in the control variables part. The county fixed effect covers all generally statistics at a county level, like average education, gender ratio, age distribution, income distribution, family size. Other control variables are county-variant, they are the national and local policy, unemployment rate, death, and infected numbers.

3.2.2 Sentiment Analysis of Mobility Decline

According to the Sentiment Analysis studies on Twitter data, a Tweet can be described by three categories: Negative, Positive, and Neural.[[6]](#footnote-6)That means we can calculate the proportion of Tweets that are negative, positive and neural, then determine which one takes the major part in mobility decline.

Where is the control variables, is the county fixed effect of a county I,  is a percentage of Tweets are positive at time t, while is a percentage of Tweets are negative at time t. is the number of Tweets at time t. Other controls are the same as the formula (4).

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1. Link of their project: <https://github.com/descarteslabs/DL-COVID-19> [↑](#footnote-ref-1)
2. Link to their project: <http://www.panacealab.org/covid19/> [↑](#footnote-ref-2)
3. Link of the hydrator software: <https://github.com/docnow/hydrator> [↑](#footnote-ref-3)
4. Different from some states, all the counties in Wisconsin use the same day of lockdown. [↑](#footnote-ref-4)
5. To be decided. [↑](#footnote-ref-5)
6. I am still working on this part. There are three choices: Use some existing tools/open-source models for sentiment analysis, however, it may not work for this content; Write my machine learning model (or Lexicon-Based model); Use existing emotional classifier package, which can identify six different emotions rather than positive/negative/neutral. <https://github.com/nikicc/twitter-emotion-recognition> [↑](#footnote-ref-6)