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

Mengshan Zhao[1]

University of Wisconsin, Madison

October 2020

Table of Contents

Table of Contents

Background

Covid-19 became the global event in 2020. It influenced every aspect of our lives. The government policy also played a dramatic role during the process (The lockdown policy, CARES Action etc). The situation requires researchers to work hard and understand how human behaviors change and its effect on economy.

- This is a timeline of US government response on Covid-19.

Background

The mobility change in five states in March.
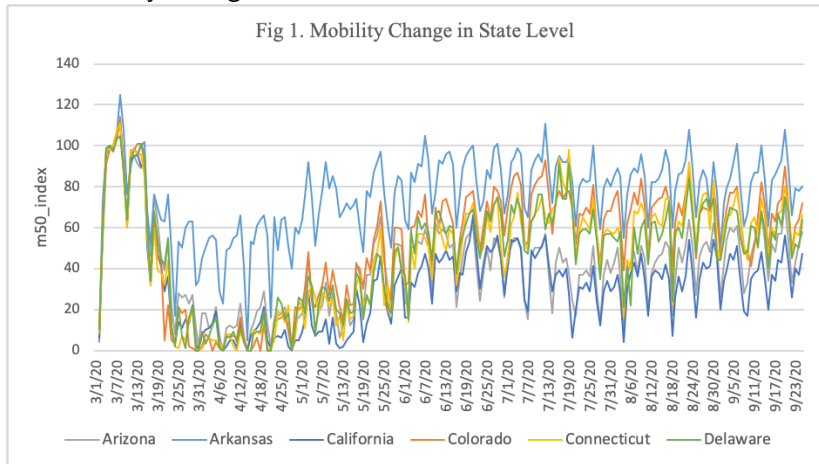
Fig 1. Mobility Change in State Level

Literature Review

There are two types of studies: The first one focus on the direct economic impact, and the second type emphasizes the behavior economics side.

- Goolsbee and Syverson (2020) argued that lockdown policy can only explain 7 percent decline in consumption flow, and the flow/ mobility is critical for the economy.

Literature Review

There are two types of studies: The first one focus on the direct economic impact, and the second type emphasizes the behavior economics side.

- Goolsbee and Syverson (2020) argued that lockdown policy can only explain 7 percent decline in consumption flow, and the flow/ mobility is critical for the economy.

- That means we need to find other reasons and measure their effects on the mobility decrease. Because if the mobility decline is not due to the lockdown policy, the economy may not recover with just removing the policy.
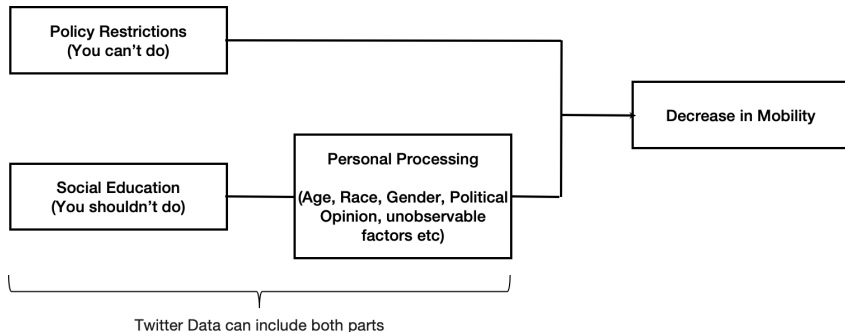
Basic Framework

Table of Contents

Data

I combine multiply panel datasets in this study. The most important three are: The Mobility data collected by Descartes Labs; The Covid-19 Twitter chatter dataset maintained by Panacea Lab, and the County-Level Policy data by Goolsbee and Syverson (2020).

- The Mobility data show the normalized daily median move distance of citizens in a county.

$$m50_{index} = 100 \frac{m50}{m50\_norm}$$

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.

Mobility Data

country_code	admin_level	admin1	admin2	fips	3/1/20	3/2/20	3/3/20	3/4/20	3/5/20	3/6/20	3/7/20
US	1	Alabama		1	79	98	100	96	104	123	107
US	2	Alabama	Autauga County	1001	49	100	95	95	100	116	79
US	2	Alabama	Baldwin County	1003	81	100	95	90	102	114	95
US	2	Alabama	Barbour County	1005	90	107	100	70	88	118	141
US	2	Alabama	Bibb County	1007	53	95	100	94	111	133	112
US	2	Alabama	Blount County	1009	68	96	100	99	101	114	93
US	2	Alabama	Bullock County	1011	70	93	139	55	105	100	152
US	2	Alabama	Butler County	1013	89	100	99	67	102	151	157
US	2	Alabama	Calhoun County	1015	82	98	100	94	104	126	109
US	2	Alabama	Chambers County	1017	81	104	92	92	100	122	115
US	2	Alabama	Cherokee County	1019	110	88	100	88	109	168	107

(a) Sample of Mobility Data

	m50 (before normalization) in kilometers	m50_index (after normaliation) in percentage
Min	0	0
Max	1271.363	46552
Median	6.414	72
Mean	7.9836	75.005
Time Range	3/1- Current	3/1- Current
Number of States	2670	2670

(b) Distribution of m50 and m50 index

Mobility Data

Fig 2. Mobility Change in County Level, Wisconsin
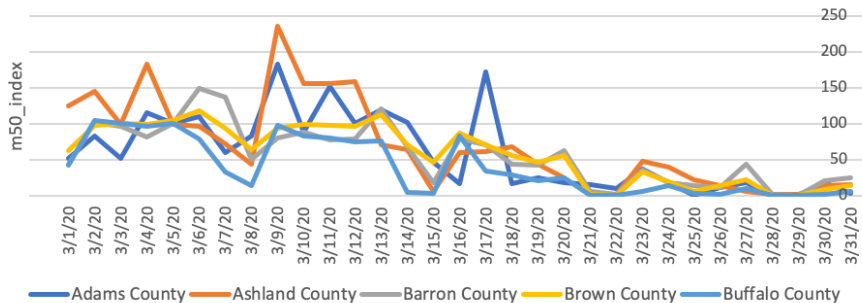
Twitter Data

Twitter Data show the number of twitter related to Covid-19, and the 1000 top one-word/ two-words/ three-words mentioned per day.

Twitter Data (in number of Twitter)	
Min	1
Max	1150047
Mean	627545.2
Median	691785.5
Time Range	1/1- Current

Twitter Data

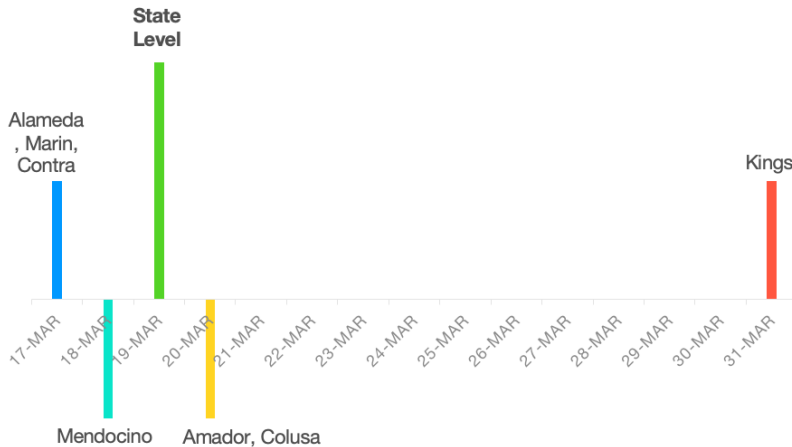Fig 4. Number of Twitter, Whole Set

Fig 5. Number of Twitter, Clean Set
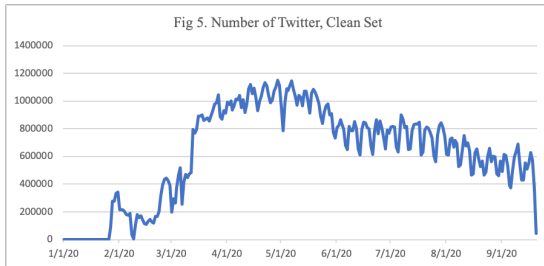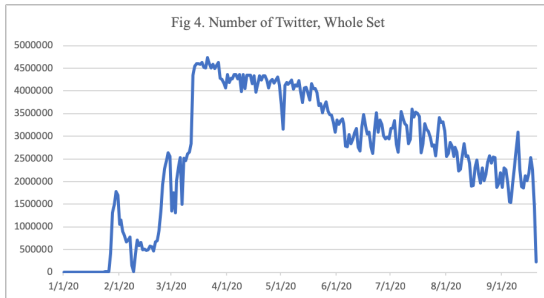
Lockdown Policy Data

A county-level Lockdown policy data is employed as some counties take action before the state. Take California as example.

Combine the Three Datasets

Take the state of Wisconsin as example, we can find that the mobility dropped before the Lockdown in March 25th, and seemed to have a strong relationship with number of twitter.

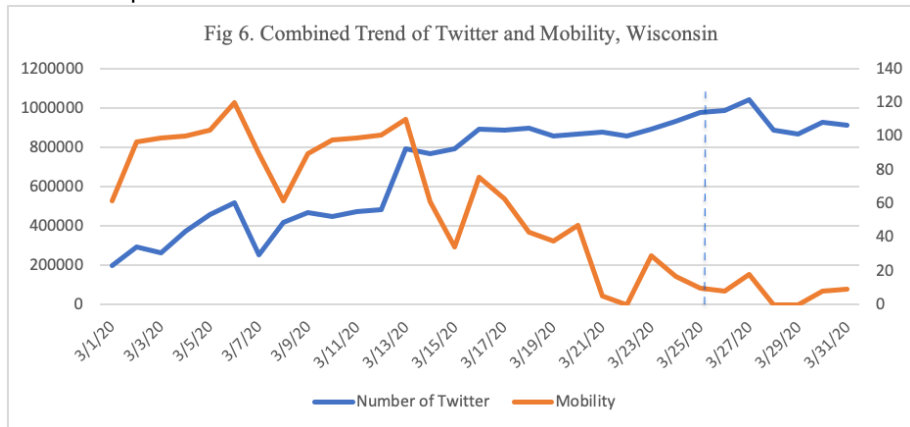Fig 6. Combined Trend of Twitter and Mobility, Wisconsin

Table of Contents

Next Step

- 1, Collect my own twitter data by scraping to identify the emotional and location of individuals, instead of using only the number of twitter.

Next Step

- 1, Collect my own twitter data by scraping to identify the emotional and location of individuals, instead of using only the number of twitter.
- 2, Use RD method to test the effect of Lockdown policy.

Table of Contents

Reference

Bailey, Michael, et al. "The economic effects of social networks: Evidence from the housing market." Journal of Political Economy 126.6 (2018): 2224-2276.

Baker, Scott R., et al. Income, liquidity, and the consumption response to the 2020 economic stimulus payments. No. w27097. National Bureau of Economic Research, 2020.

Goolsbee, Austan, and Chad Syverson. Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. No. w27432. National Bureau of Economic Research, 2020.

Bartik, Alexander W., et al. How are small businesses adjusting to covid-19? early evidence from a survey. No. w26989. National Bureau of Economic Research, 2020.

Jordà, Òscar, Sanjay R. Singh, and Alan M. Taylor. Longer-run economic consequences of pandemics. No. w26934. National Bureau of Economic Research, 2020.

Reference

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante. The Great Lockdown and the Big Stimulus: Tracing the Pandemic Possibility Frontier for the US. No. w27794. National Bureau of Economic Research, 2020.

Baker, Scott R., et al. How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic. No. w26949. National Bureau of Economic Research, 2020.

Hausman, Catherine, and David S. Rapson. "Regression discontinuity in time: Considerations for empirical applications." Annual Review of Resource Economics 10 (2018): 533-552.

Goldfarb, Avi, and Catherine Tucker. Which Retail Outlets Generate the Most Physical Interactions?. No. w27042. National Bureau of Economic Research, 2020.