The Association between Partisanship and Human Mobility Change during the First Wave of the COVID-19 Pandemic in the United States

Tao Peng
Department of Geography, University of Zurich, Switzerland
tao.peng@uzh.ch

Anjing Zhang
Department of Geography, University of Zurich, Switzerland
anjing.zhang@uzh.ch

Cheng Fu
Department of Geography, University of Zurich, Switzerland
cheng.fu@uzh.ch

Abstract

Facing the outbreak of COVID-19, various travel restrictions were imposed in the US. Previous research indicated a correlation between political partisanship and people's behavior, including whether to avoid traveling. This study investigates the changes in human mobility and their association with political partisanship during the first wave of the pandemic. The partisanship index is synthesized from the US presidential election voting data. Daily mobility volume is measured from dynamic origin-destination mobility matrices at county level. We identify the breakpoint of each county, a day when the daily mobility volume has an abrupt change. The changes in mobility are measured by three indicators: 1) Mobility Volume Difference before and after the breakpoint, 2) Before-break Trend, 3) After-break Trend. We find that people reduced traveling simultaneously even though the travel restrictions were imposed on different dates across the states. However, Democratic counties experienced the largest drop in mobility volume. People living there continued to avoid traveling towards the end of the first wave, when those in Swing and Republican counties ceased to do so.

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Category Short Paper

1 Introduction

A majority of the states adopted non-pharmaceutical interventions, such as travel restrictions and social distancing to curb the spread of COVID-19 [1]. The effectiveness of these policies is subject to public compliance. The willingness to comply with the policies varies among people. Political partisanship may influence individuals on how they perceive the risk of the virus and whether they choose to reduce traveling [9]. The political affiliation affects the information one collects, processes, and responds to [14, 17]. Hill et al. [8, 16] asserted that Trump voters are more resistant to public health recommendations and stay-at-home orders. Barbalat et al. [2] further discovered that Republican states exhibit increasing mobility over time.

In the US, political polarization has exacerbated over the past two decades [6, 10]. The COVID-19 pandemic in the United States is as much a political problem as it is a public

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health problem [5]. Most studies did not consider populations without consistent political partisanship. To fill this gap, we consider three types of partisanship, the Democratic, the Swing and the Republican. Furthermore, previous work mainly focused on the summary statistics, such as monthly average of mobility. We look at daily mobility of each county, as a finer temporal granularity carries more information

2 Research Question

What is the association between mobility change and partisanship during the first wave of the COVID-19 pandemic in the US?

To answer the research question, we investigate the mobility patterns and compare them with political partisanship.

3 Data

Political partisanship The 2016 and 2020 US presidential election voting data of each county are retrieved from MIT Election Data Lab[1]. The dataset contains the total number of votes, the number of votes received by each candidate and his political affiliation.

Human mobility volume Our source data is the dynamic origin-destination matrices at county level [11]. We process the raw data to derive the daily mobility volume indices of 3101 counties (7 out of 3108 contiguous counties are excluded due to missing data). The daily mobility volume indices of each county are then normalized by the county's average. The normalized indices fall between 0.45 to 1.95. A normalized mobility volume smaller than 1 indicates people living in a county travel less than the average. The mobility volume mentioned below is the normalized daily indices.

Timing of the first wave and the mandatory stay-at-home orders Our study covers February 1^{st} to April 30^{th}, 2020. The first case in the US was reported on January 20^{th}. The stay-at-home orders were issued as early as on March 19^{th} in California and as late as on April 7^{th} in South Carolina. On April 24^{th}, Montana was the first state to lift its order [15].

4 Methodology

4.1 Modeling political partisanship

We subtract the Republican vote share from the Democratic vote share of an election to derive a partisanship index [10, 12]. The indices of 2016 and 2020 capture the shift of the partisanship. 302 counties did not consistently vote for the same party. Their two-election average indices fall between -0.1195 to 0.1378. We define a county as Swing when its average index is between -0.15 to 0.15. A county with an average index larger than 0.15 is considered as Democratic, otherwise Republican.

4.2 Identifying structural breaks and characterizing mobility changes

A structural break in time series is a significant change in the parameters of linear regression models [4, 18]. Having observed abrupt changes in the mobility volumes of nearly all the

[1] `https://electionlab.mit.edu/data`

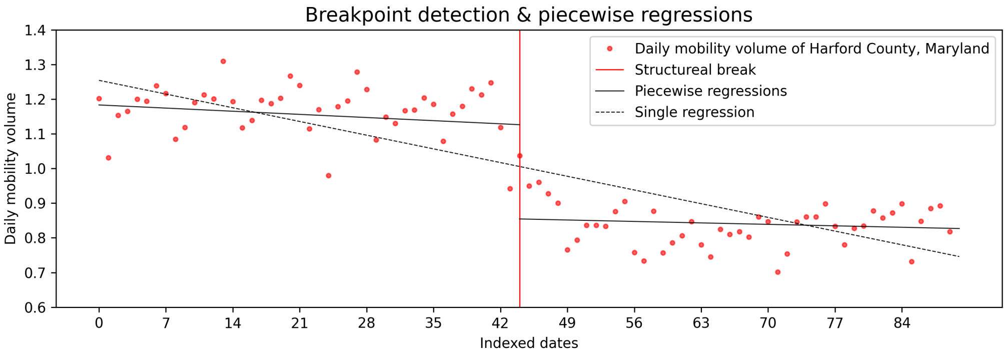

Figure 1 Harford County, Maryland as an example in the structural break analysis.

counties, we apply radial basis function [7] to detect breakpoints. With the detected breaks, we perform piecewise time series analysis on the daily mobility volume. The Harford county is the example to show the difference between a single regression and piecewise regressions (Figure 1). The piecewise regressions consider two intervals, from day 0 (February 1^{st}) to day 44 (March 16^{th}) and from day 44 (March 16^{th}) to day 90 (April 30^{th}). We gauge change in the mobility level by comparing the average mobility volumes before and after the breakpoint. A mobility trend is measured by the slope coefficient of a piecewise regression. We thus synthesize three indicators of each county: *Mobility Volume Difference*, *Before-break Trend*, and *After-break Trend*. We perform the Analysis of Variance (ANOVA) and t-test to compare Democratic, Republican, and Swing counties with respect to each mobility indicator.

Our study covers three months from February 1^{st} to April 30^{th}, 2020. We used 7 days as a unit as weekly pattern is observed in daily mobility volume. The mobility indicators are first calculated with tumbling windows of 7, 14, 21, 28, 35, 42, 49 days (e.g., 49 days before the breakpoint and 49 days after). Since small windows are subject to outliers, we utilize a 42-day window and conduct sensitivity analysis with 35-day and 49-day windows.

5 Results

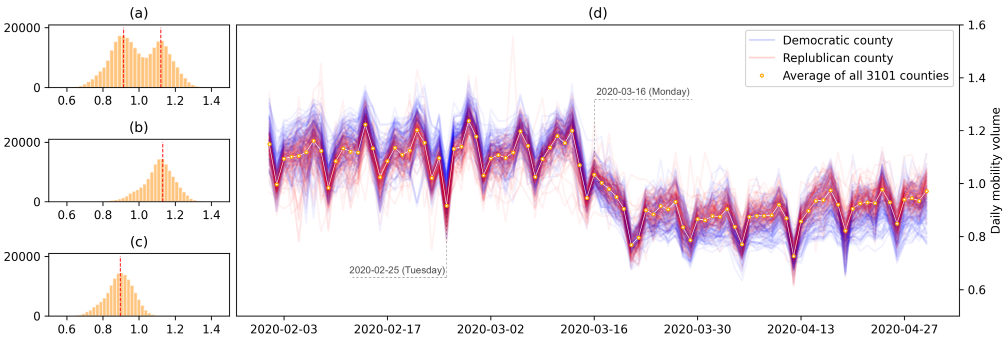

Figure 2 ***Left***: Histograms of the daily mobility volumes of all counties (a) over the entire study period, (b) before the breakpoint, (c) after the breakpoint. ***Right***: (d) Time series of sampled Democratic and Republican counties.

The daily mobility volume displays a weekly pattern, with the peak on Friday and the valley on Sunday. However, it deviates from the pattern in the week of February 24^{th} and the week of March 16^{th} (Figure 2). On February 25^{th} (Tuesday), the mobility volume declined significantly but recovered the next day. Whereas, the mobility volume kept decreasing from March 16^{th} (Monday) to March 22^{nd} (Saturday) monotonically. In the week of March 23^{rd} (Monday), the weekly pattern was restored but the volume was much lower than before. Break detection finds one break in 2972 out of 3101 counties. 2784 counties have the same breakpoint on March 16^{th}. Most of the counties changed mobility patterns simultaneously even though mandatory stay-at-home orders were issued on different dates.

ANOVA and t-test results suggest that Democratic, Swing and Republican counties are significantly different in each of the three mobility indicators, Mobility Volume Difference, Before-break Trend, and After-break Trend (Table 2). Almost all the counties exhibit a reduced mobility, with negative mobility volume difference in 42-day windows (Table 1). Comparing two 42-day windows, Democratic counties experienced the steepest decrease, followed by Swing counties. Within each 42-day window, Republican counties displayed increasing trends. The sensitivity analysis with 35-day and 49-day windows proves the robustness of the results.

Table 1 Descriptive statistics of mobility indicators: Mobility Volume Difference (MVD), Before-break Trend (BBT), and After-break Trend (ABT), in Democratic (Dem., N=276), Republican (Rep., N=2156), and Swing counties (Swi., N=508) with three different windows (Δt = 35, 42, 49 days).

Variables	Δt	Mean MVD	BBT	ABT
Dem.		-0.2810	-0.0011	-0.0017
Swi.	35	-0.2572	-0.0006	-0.0014
Rep.		-0.2188	-0.0003	-0.0011
Dem.		-0.2771	-0.0006	-0.0006
Swi.	42	-0.2507	-0.0002	-0.0002
Rep.		-0.2098	0.0001	0.0001
Dem.		-0.2771	-0.0012	-0.0005
Swi.	49	-0.2496	-0.0010	0.0008
Rep.		-0.2058	0.0007	0.0012

Table 2 Pairwise t-test results. (* $p < 0.05$; *** $p < 0.001$)

Variable pairs	$\Delta t = 35$			$\Delta t = 42$			$\Delta t = 49$		
	MVD	BBT	ABT	MVD	BBT	ABT	MVD	BBT	ABT
Dem. - Swi.	***	***	***	***	***	*	***	*	***
Dem. - Rep.	***	***	***	***	***	***	***	***	***
Swi. - Rep.	***	***	***	***	***	***	***	***	***

6 Discussion

Our study examines the characteristics of people's travel behavior and its relevance to partisanship during the first wave of the COVID-19 pandemic. Most counties saw a significant decrease in mobility level on March 16^{th}, three days earlier than March 19^{th}, when the first state-wide stay-at-home order was issued. This indicates a lag in public administration. People reacted early, as the avoidance of traveling is a voluntary behavior triggered by the fear of the virus. The fear might be associated with partisanship. Our study verifies this hypothesis and finds that people living in Democratic counties reduced traveling most severely and the decreasing trend lasted for the longest time. Swing and Republican counties started to increase traveling before April 24^{th}, when Montana became the first to lift the orders. It undermines the effectiveness of the policies in restricting mobility but highlights the importance of partisanship.

Data covering a longer period will allow future investigation beyond the scope of COVID-19 outbreak. Besides, data representation is biased as the origin-destination matrices were collected from mobile phone users. But the impact is expected to be minimal given the popularity of mobile devices [13].

7 Conclusion

Almost every county (2784/3101) had an abrupt drop in mobility volume on the same day (March 16^{th}, 2020) even though the travel restrictions were imposed on different dates across the states. It suggests that people took actions simultaneously regardless of the policies. However, people in Democratic counties reduced traveling most severely. A constant decreasing mobility trend is observed in most Democratic counties throughout the first wave of the pandemic. Swing counties experienced a reduction in the early stage but an increase later. Republican counties had a moderate drop in mobility volume then started to recover. Our study highlights the importance of bipartisan effort. The lesson we learn from the US applies to other countries, such as Canada and Denmark, which are also experiencing political polarisation [3]. Future work may analyze the interplay between human travel behavior and other sociopolitical factors within or outside the scope of COVID-19 pandemic. The study of human mobility may shed light on transportation planning, economic development and environment protection.

References

1. Christopher Adolph, Kenya Amano, Bree Bang-Jensen, Nancy Fullman, and John Wilkerson. Pandemic Politics: Timing State-Level Social Distancing Responses to COVID-19. *Journal of Health Politics, Policy and Law*, 46(2):211–233, 04 2021. `doi:10.1215/03616878-8802162`.
2. Guillaume Barbalat and Nicolas Franck. Association of republican partisanship with us citizens' mobility during the first period of the covid crisis. *Scientific Reports*, 12(1):8994, 2022.
3. Levi Boxell, Matthew Gentzkow, and Jesse M Shapiro. Cross-country trends in affective polarization. *Review of Economics and Statistics*, pages 1–60, 2022.
4. Gregory C Chow. Tests of equality between sets of coefficients in two linear regressions. *Econometrica: Journal of the Econometric Society*, pages 591–605, 1960.
5. Joshua Clinton, Jon Cohen, John Lapinski, and Marc Trussler. Partisan pandemic: How partisanship and public health concerns affect individuals' social mobility during covid-19. *Science advances*, 7(2):eabd7204, 2021.
6. Morris P. Fiorina and Samuel J. Abrams. Political polarization in the american public. *Annual Review of Political Science*, 11(1):563–588, 2008. `doi:10.1146/annurev.polisci.11.053106.153836`.
7. Zaid Harchaoui and Olivier Cappé. Retrospective mutiple change-point estimation with kernels. In *2007 IEEE/SP 14th Workshop on Statistical Signal Processing*, pages 768–772. IEEE, 2007.
8. Terrence Hill, Kelsey Gonzalez, and Andrew Davis. The nastiest question: Does population mobility vary by state political ideology during the novel coronavirus (covid-19) pandemic? *Sociological Perspectives*, 64:786–803, 11 2021. `doi:10.1177/0731121420979700`.
9. David Hsiehchen, Magdalena Espinoza, and Paul Slovic. Political partisanship and mobility restriction during the covid-19 pandemic. *Public Health*, 187:111–114, 2020. `doi:https://doi.org/10.1016/j.puhe.2020.08.009`.

10 Kiju Jung, Ellen Garbarino, Donnel A Briley, and Jesse Wynhausen. Blue and Red Voices: Effects of Political Ideology on Consumers' Complaining and Disputing Behavior. *Journal of Consumer Research*, 44(3):477–499, 01 2017. doi:10.1093/jcr/ucx037.

11 Yuhao Kang, Song Gao, Yunlei Liang, Mingxiao Li, and Jake Kruse. Multiscale dynamic human mobility flow dataset in the u.s. during the covid-19 epidemic. *Scientific Data*, pages 1–13, 2020.

12 Junghwan Kim and Mei-Po Kwan. The impact of the covid-19 pandemic on people's mobility: A longitudinal study of the us from march to september of 2020. *Journal of Transport Geography*, 93:103039, 2021.

13 Chris Kolmar. 25+ incredible us smartphone industry statistics [2023]: How many americans have smart phoness. URL: https://www.zippia.com/advice/us-smartphone-industry-statistics/.

14 Gabriel S Lenz. *Follow the Leader?* University of Chicago Press, 01 2013.

15 Amanda Moreland, Christine Herlihy, Michael A Tynan, Gregory Sunshine, Russell F McCord, Charity Hilton, Jason Poovey, Angela K Werner, Christopher D Jones, Erika B Fulmer, et al. Timing of state and territorial covid-19 stay-at-home orders and changes in population movement—united states, march 1–may 31, 2020. *Morbidity and Mortality Weekly Report*, 69(35):1198, 2020.

16 Michael Sances and Joshua Clinton. Who participated in the aca? gains in insurance coverage by political partisanship. *Journal of Health Politics, Policy and Law*, 44, 02 2019. doi:10.1215/03616878-7366988.

17 John R. Zaller. *The Nature and Origins of Mass Opinion.* Cambridge Studies in Public Opinion and Political Psychology. Cambridge University Press, 1992. doi:10.1017/CBO9780511818691.

18 Zümre Özdemir Güler and Mehmet Akif Bakır. Performance of methods determining structural break in linear regression models. *International Econometric Review*, 11(2):70 – 83, 2019. doi:10.33818/ier.450804.