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Did the political climate exacerbate the pandemic in the U.S.?

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Did the political climate exacerbate the pandemic in the U.S.?

Exploring partisanship, public sentiment, adherence to safety protocols, and COVID-19 Cases

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Abstract

The global pandemic that began in the United States in early 2020 continues to be a topic of controversy. The added aspect of affect polarization in the country's political realm may have exacerbated the effects of COVID-19. In their published article in *Nature Human Behaviour*, Gollwitzer et. al. found that it was possible to link voting partisanship, physical distancing, and COVID-19 outcomes showing that a county's partisanship might be used to predict the degree to which that county would socially distance and then, therefore, the rate of cases and fatalities in that error on a lagged timescale. This researcher attempted to replicate and validate the findings of an analysis conducted in the earliest months of the pandemic using approximately the same variables, models, and covariates, but over a longer span of time in the pandemic.

Three possible mediator variables (physical distancing data, mask mandate data, and online sentiment data) were gathered and tested for usability in the main mediation analysis. Preliminary analysis of the data gathered did not support the assertion of sentiment or masking data would be useful to the mediation analysis due to insufficient data. Though the distancing data was significantly linked to partisanship to become a proxy, mixed models showed that pandemic dates after the period of the original analysis could not support physical distancing as a mediator for partisanship. Only the segment of the final dataset which matched the dates of the original work were processed through the same mediation analysis in STATA. Significant effects of partisanship on case growth rates were discovered, but not to the same degree as the original work.

Background

The distinct separation of citizens based on party affiliation, as party becomes more of a social identity, causes an in-group and out-group situation that often leads to biases in non-political arenas and can be a driver for behavior (Iyengar, Lelkes, Levendusky, Malhotra, & Westwood, 2019). Research surrounding COVID has brought this polarization to the fore with several studies completed in the past few years. In November 2020, a study utilized phone GPS tracking and the voting gap in the 2016 presidential election as proxies to compare social distancing and partisanship at the county level and the authors found there was a strong association between partisanship and physical distancing that could not be explained by other factors and also showed COVID rates were higher in counties that voted for Donald Trump (Gollwitzer, et al., 2020). These results are worth further investigation as the studies conducted have a dearth of data spanning only a few months early in the pandemic and focused mainly on physical distancing. More research is needed to understand the nuances of what is taking place with regards to partisanship and associated behaviors. There now exists far more data as the pandemic continues into 2022 and there are more aspects of COVID behaviors to explore.

The main question to be addressed is whether affective polarization has negatively affected COVID outcomes in the U.S. by increasing cases and/or deaths. While many of the previous studies mentioned above have found a significant relationship between partisanship lines and pandemic cases, the data has grown exponentially since their analyses were published and this can assist in seeking out whether those trends continue. Authors also have stated that their sample sizes are rather small and may not accurately represent the entire population (Pollak, Dayan, Shoham, & Berger, 2020) and analysis should go deeper than state-level (Fischer, et al., 2021). These shortcomings of brief time windows, small sample sizes, and representing the population in question can be resolved by looking at county-level data that includes all available counties over a longer term. The analysis for this proposal was largely inspired by the analysis performed by Gollwitzer et al. Their analysis covered March to May of 2020 and showed robust findings within that window. A major improvement to further their research would be to look at a much larger time series of pandemic data with similar data sources and methodology to attempt to seek similar significance.

Initial Hypothesis

Using Gollwitzer's analysis as a framework for this work, the analysis was structured to mediate variables to infer a connection between a county's party affiliation, their physical distancing behavior, and the rates of COVID cases and deaths in that same region. This was achieved using three-level, mixed models where individual movement was nested within their county and that county nested within its appropriate state. This accounted for the possible lack of independence in the sample as clusters of individuals in constant contact with one another can cause high correlation among them. With millions of data points per day in the eighty-two-day study, a large number of covariate data for over three-thousand counties, the original study proved successful and robust for linking these predictor variables to COVID outcomes and showing that during the time of the pandemic observed, a county's party affiliation was strongly linked to their amount of social distancing.

This analysis attempts to go a little farther by exploring new possibilities for mediating variables other than distancing and expanding the timeframe from just eighty-two days to three-hundred and ninety-five days. While not every covariate could be collected to strictly follow the original work, many of the same covariates were gathered from most of the same sources with updated years of information. It was initially postulated that in addition to retesting the significant mediation of distancing, that mask use data might also be analogous to the task. Another avenue explored was online sentiment through mini-blogging sites such as Twitter or Reddit. Data was gathered on all three of these variable types for exploration as to whether they could lend themselves to the main analysis, which would also be a mixed model with random slopes and intercepts. Thus, the hypothesis of this study was that one or more of the predictor variables selected could achieve a similar significance level to that of the original work and mediate the relationship between partisanship and COVID rates. Significance was measured at more than 95% confidence or a p-value less than 0.05.

Data Sources

Partisanship

The data for assigning partisanship at the county level was derived from the same source as the Gollwitzer paper. Specifically, the dataset was found on the MIT Election Lab website and the information was obtained from the 'County Presidential Election Returns 2000-2020' dataset. It provides the exact record of popular votes for each presidential candidate in the 2016 presidential election and a vote gap by percentage points was extracted from this information to create a scale of partisanship at the county level.

COVID Rates

Information on case and death rates was sourced from the *New York Times*' COVID-19 dashboard website via the freely available GitHub repository. The repository contains case information and specific variable descriptions for all counties from the beginning of the pandemic in the United States.

Distancing

Carnegie Mellon University and the Delphi Group support an API for data gathered from various sources on COVID-19. This COVIDcast API was accessed to extract a dataset originally from SafeGraph, now discontinued by SafeGraph, that tracked cell phone GPS movement before and during the pandemic timeframe. Such data measured movement as it relates to median minutes spent at home per week.

Masking

Two sources were utilized for examining data relating to mask use. The first was a *New York Times* survey from July 2020 that asked individuals what percentage of time they wore a mask in public.

Sentiment

Sentiment data was gathered using Twitter posts. Tweets were queried from Twitter's Academic API using Python's Tweepy library. Tweets were specifically filtered to be located in the United States, be in English, and mentioned COVID either in text or with a hashtag from within the dates being studied.

Covariates

The following data was collected to represent covariate data that might explain the model better than the chosen predictor variables at the county level. Much was sourced from the U.S. Census Bureau, the U.S. Department of Agriculture, and the Centers for Disease Control. All sources can be found in the reference section of this document.

Control Variables:

- COVID cases per capita
- Median age
- Percentage of population under 18 years
- Percentage of population between 65 and 84 years
- Percentage of population over 85 years
- Percentage of population identifying as African descent
- Percentage of population identifying as Asian descent
- Percentage of population identifying as Hispanic descent
- Median income
- Percentage of the population considered religiously adherent
- Percentage of the population employed
- Wealthy equality via the Gini coefficient
- Population density
- Whether the date was a weekend day

- Whether a county stay at home mandate was in effect
- Time as a linear variable
- Time as a quadratic variable

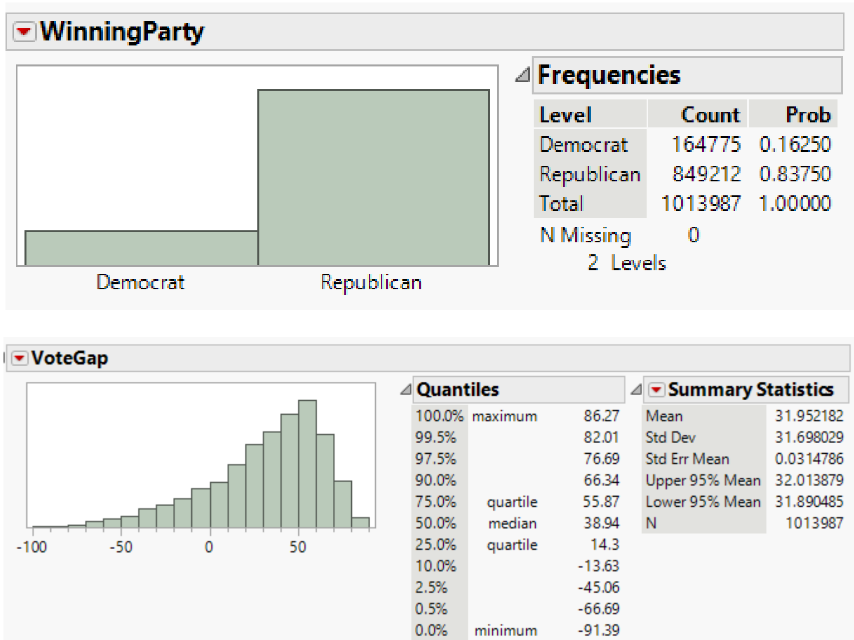
Exploratory Analysis

All variables were investigated for completeness and accuracy of representation. Methods for exploration include charting distributions, bivariate comparisons, time series, and mapped locations. More advanced methods include clustering with Euclidean distance, topic modelling, and sentiment analysis. Due to the large number of variables in the analysis, all distribution graphics are located at in the supplementary section of this document.

Partisanship

Partisanship data was collected from exactly the same source as the original paper and the measurement for partisanship was defined in the same manner. This was to ensure that any comparisons done between the new work and the former would be as analogous as possible, which is especially vital for partisanship as the experimental predictor. There was a total of 3,149 counties in the dataset with 2,648 Republican counties and 501 Democratic counties labelled from the results of the 2016 presidential election outcome.

This information was converted into one of the central variables of the analysis. By taking the difference in votes per county and scaling to a percentage scale, it became possible to see how partisan a county was in the election and broke the uneven distribution of counties by party into a more nuanced distribution. A near zero score represented a county that voted nearly evenly for both Trump and Clinton. Positive values represent counties that voted more for Trump and the higher the value, the more they favored him. The inverse is true for the negative values voting more heavily for Clinton. The final range (mean=31.95, s.d.=31.69) after removing counties with less than two thousand residents showed a maximum vote for Trump at 86% in Cimarron County, Oklahoma. Conversely, Washington D.C. voted 91.4% for Clinton.



Frequencies

Level	Count	Prob
Democrat	164775	0.16250
Republican	849212	0.83750
Total	1013987	1.00000

N Missing 0
2 Levels

Quantiles

100.0%	maximum	86.27
99.5%		82.01
97.5%		76.69
90.0%		66.34
75.0%	quartile	55.87
50.0%	median	38.94
25.0%	quartile	14.3
10.0%		-13.63
2.5%		-45.06
0.5%		-66.69
0.0%	minimum	-91.39

Summary Statistics

Mean	31.952182
Std Dev	31.698029
Std Err Mean	0.0314786
Upper 95% Mean	32.013879
Lower 95% Mean	31.890485
N	1013987

Figure 1: The original distribution of how counties voted in the 2016 presidential election. Then the same counties broken out by percentage gap in votes.

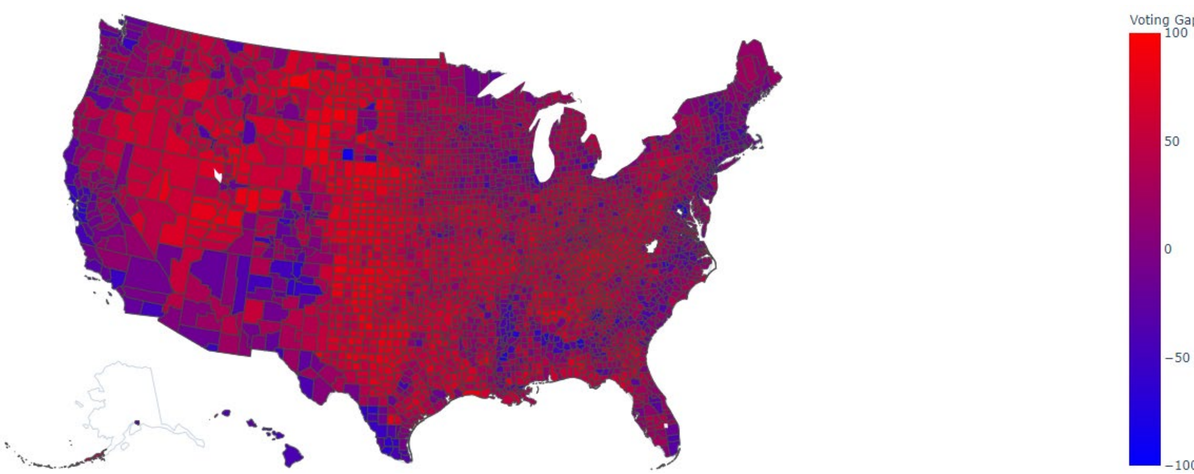


Figure 2: A choropleth map depicting the voting gap for each county by color.

COVID Rates

The data acquired from the *New York Times* repository listed 1,037,648 entries from 2,905 after cleaning and filtering counties with less than two thousand in population in order to better replicate the original work. While the raw case and death numbers were included, the information proved unusable in this analysis as, at times, there were negative values, which the NYT denotes as being error handling for previous entries with inaccurate numbers. Cases and deaths per capita (100,000) were also available and capita cases were used as a covariate in the final analysis. However, average cases and deaths based on a trailing seven-day average proved to be the superior aspect of the dataset and most closely resembled the original paper. When plotted on a histogram, average cases (mean=26.4, s.d.=2.4) showed a national range from zero to approximately 152,000 cases. This high number belonged to Los Angeles County on January 13, 2021. This would be expected for a county with more than ten million residents. Average deaths (mean=0.47, s.d.=2.43) showed a range of zero to 241.29. This high number belonged to Los Angeles County as well and was reported on January 14, 2021. This dataset would continue to confirm the assumption that case rates are strongly related to death rates.

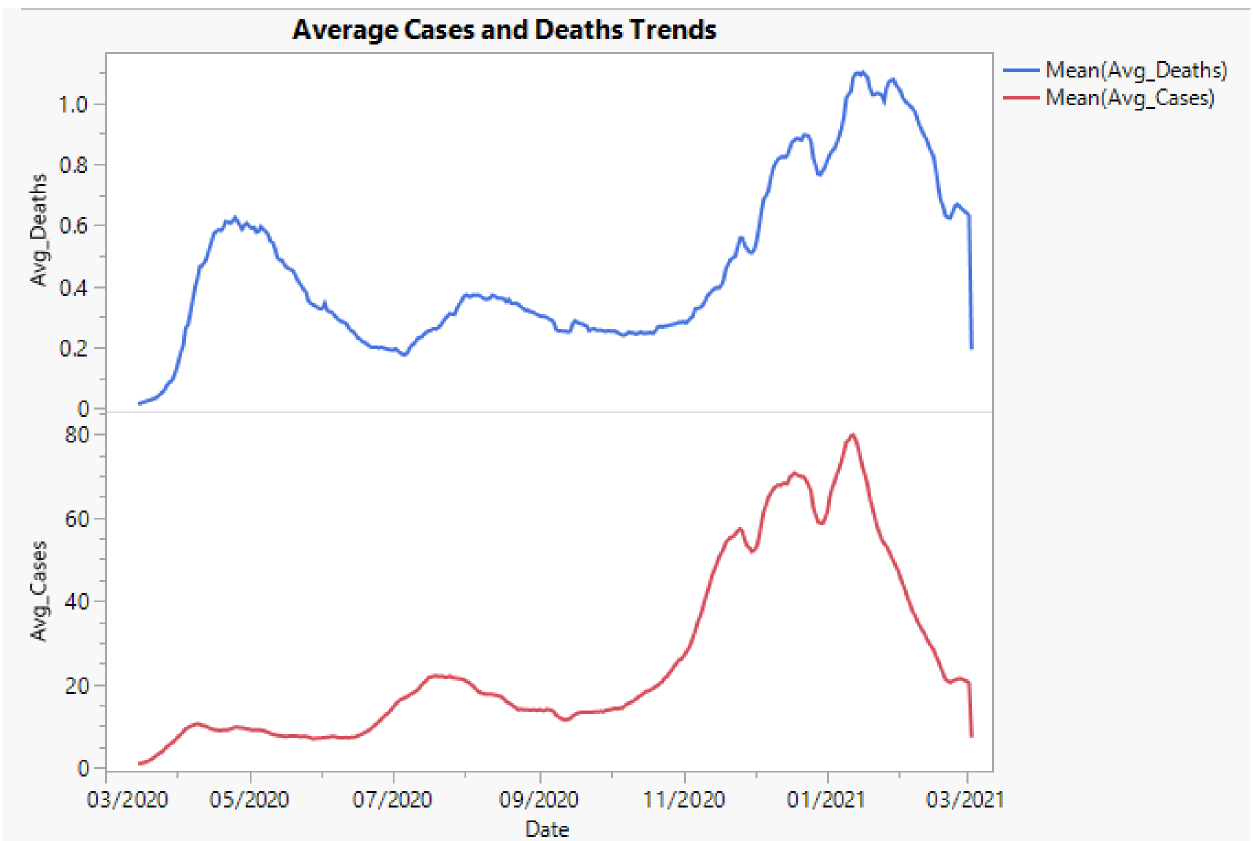


Figure 3: Trend lines of average cases and deaths over thirteen months showing cases and deaths mirror one another in the acquired dataset.

There were many ways to view the data, particularly as it related to partisanship. An important detail of the data when charting COVID-19 over time is the population density issue. Population being not evenly distributed from county to county could prove challenging if attempting to associate citizens' behaviors driven by their political leanings and linking those beliefs to subsequent case and death rates. While the seven-day rolling averages of cases and deaths proved the clear choice for response variables in this analysis, it is noticeable that a large gap exists between Democrat counties and Republican counties in both cases and deaths.

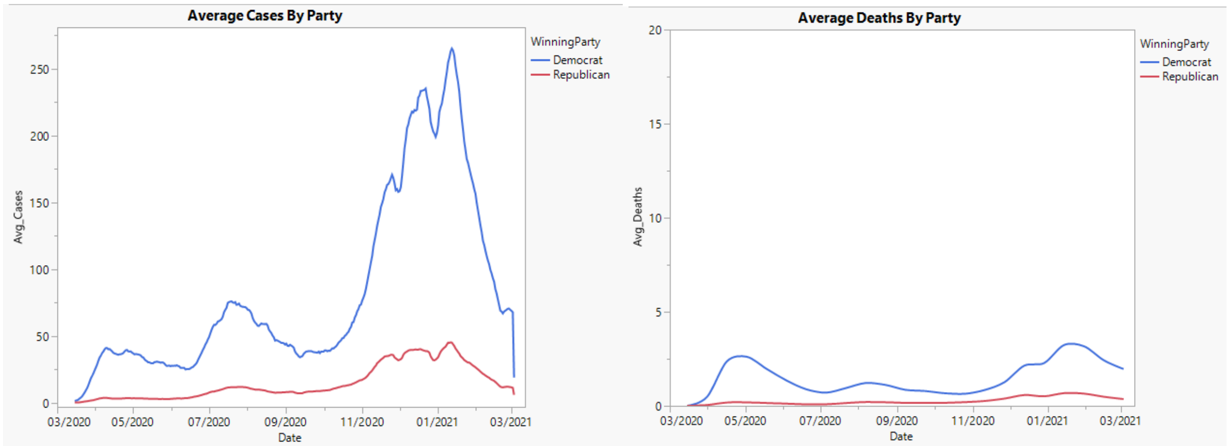


Figure 4: Trend lines of average cases and deaths over thirteen months illustrating the gap between Democratic and Republican cases. Far more Democrats were infected on average.

However, shown another way it can be seen that when controlling for population density via counting cases and deaths per one hundred thousand people, the party lines are flipped and show that on average Republican counties began to see more infections than Democratic ones around September 2020. While Democratic counties saw more cases and deaths at the start of the pandemic, Republican counties saw climbed as 2020 ended.

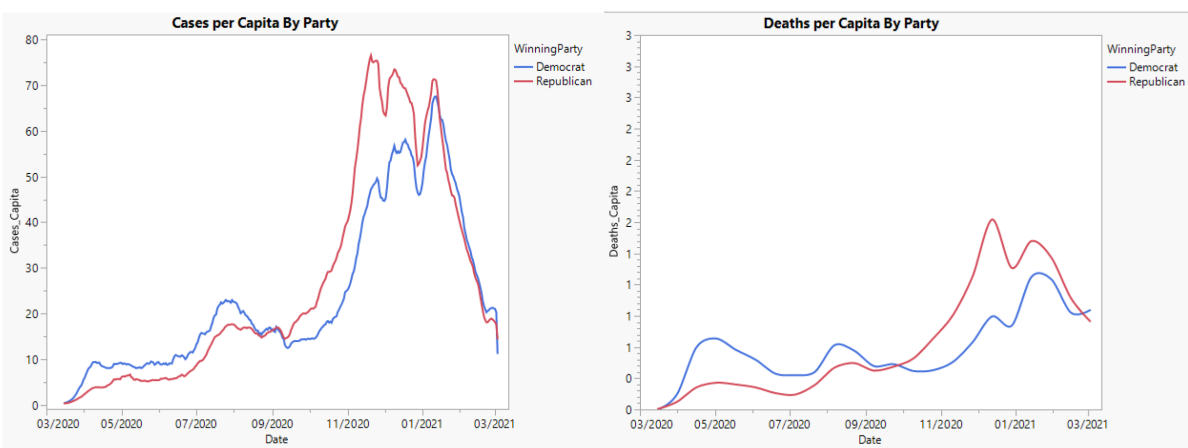


Figure 5: Cases and deaths per capita help to show how more Democrats fell ill at the start of the pandemic and then Republicans showed more cases and deaths after September 2020.

The final dates selected for analysis were March 1, 2020, to March 31, 2021. With just over a year's worth of data, it seemed a long enough timespan to capture various phases of the pandemic and brief enough to still be a manageable amount of data.

Distancing

Like the original work that inspired this analysis, distancing data was collected through cell phone GPS tracking both before and during the pandemic months. The original authors sourced their distancing data from Unacast in two forms: general reduction in movement and visitation to non-essential businesses such as restaurants and hair salons (Gollwitzer, et al., 2020). This analysis sought to find a comparison to reduction in movement only and thus the sourcing of SafeGraph's deprecated data.

The SafeGraph data measured movement in an inverse fashion to that of the original Unacast data in that it measured time spent at home instead of time spent elsewhere. Specifically, the data measured the median minutes per week spent in a dwelling at the county level. To be more granular and account for how these phones moved before a stay-at-home policy was introduced, both the original paper and this analysis took the percentage difference from the averaged four weeks of dwell time before the pandemic officially started and was subtracted from the median minutes spent at home per week of the pandemic timeframe. The percentage differences (mean=21.35, s.d.=16.92) showed a minimum of -100 indicating no difference of dwell time before or after the lockdown. In contrast, the maximum percentage of time spent at home was a 323% increase with the median percentage of 18.99% reported in the dataset.

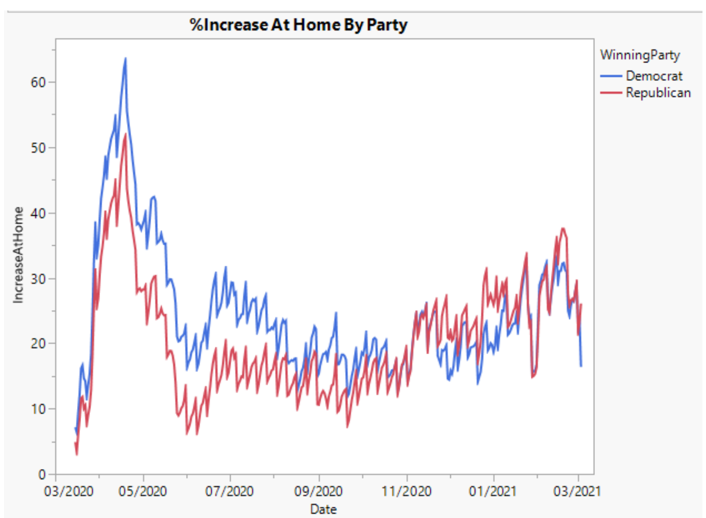


Figure 6: Percent difference in time spent at home per week with counties binned by party.

The above graph shows the same two lines representing counties by their voting choices in the 2016 election. Again, one can see that in September of 2020 that Republicans and Democrats switched on the y-axis showing that at the start of the pandemic Democrats spent more time at home and then fell below Republican minutes later on. The gap between the two also closes and overlaps at numerous points. Taken over the entire dataset, Democrat voting counties spent on average 24.6% more time at home while Republican counties spent 20.7% more time at home falling just below the total mean of 21.3%. This swapping on the y-axis just at the September 2020 mark of the time series lines up interestingly with the previously noted COVID time series. While initially Democratic counties experienced more cases and deaths, those counties spent on average more time at home. Republican counties, on average, began spending more time at home than Democratic counties just as their case numbers begin to outstrip Democratic ones.

Masking

The University of Chicago posted a dataset that provided details on masking policy throughout the United. States. Notably, the dataset provided the earliest dates for mask mandate implementation per county.

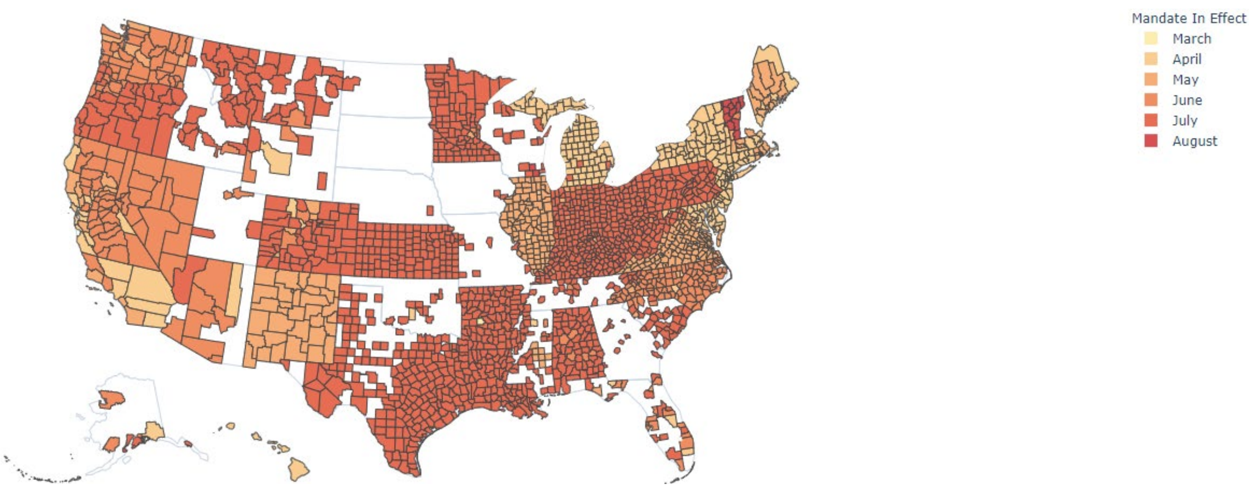


Figure 7: This choropleth map accurately recreates the choropleth map the University of Chicago posted of their data. This helped to confirm that data was preprocessed correctly. Each color represents the month of 2020 a mask mandate was introduced to a county. Note white spaces where mandates were never implemented.

The choropleth above captures a geographical representation of the adoption of mask mandates across the country. The earliest counties to adopt a mask mandate policy started in March 2020 and are primarily in the northeast region. Parts of New England states, New York, New Jersey, and Michigan are all shaded in yellow. Out west, counties in California, Wyoming, and Arizona also started mandates in March. The dominant color or month appears to be red for July 2020.

Indeed, when charted another way, one can see the pattern was relatively similar for both types of counties regarding mandate adoption. Fewer counties adopted early in the pandemic and then increased rapidly in the summer months. The scale of the adoption is drastically different owing to the sheer number of Republican counties to Democratic ones. The overall trend lines are similar with the exception that more Democratic counties adopted a mask mandate earlier on and then, in another y-axis swap, Republican counties shot up higher than Democratic ones.

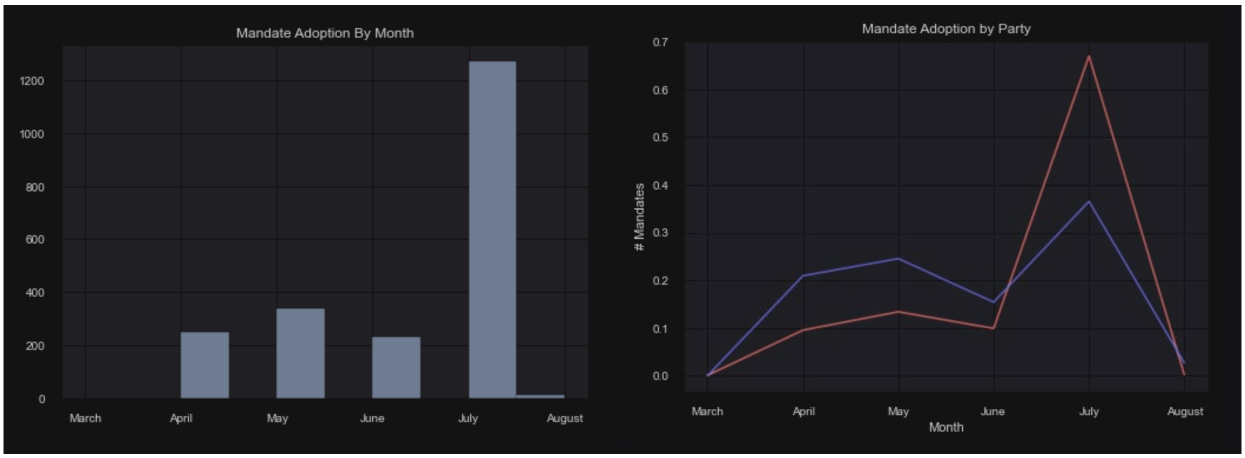


Figure 8: Left – A frequency distribution of counties binned by month each adopted a mask mandate policy. Right - A line graph depicting county adoption by month and political party.

Another dataset was collected from the *New York Times* repository that held the results of a survey conducted in July 2020 around the time most mask mandates were being instated. Members of the general public at the county level were asked what percent of the time they wore a mask in public. The results are illustrated in another choropleth map below. The Midwest and northern sections of the western region reported the lowest mask use at 20-60% of the time. Areas surrounding the Midwest and the South reported about 60-80% usage. The Northeast and West Coast reported the highest amount of mask use at around 80-100% of the time. Taking into consideration that survey data is not always reliable, this mapping, however, does seem to align with population density where the least populated areas wear masks far less than coastal regions where population density is higher. Areas of northern Maine, Vermont, New Hampshire, and California show less mask use, but are also rural areas.

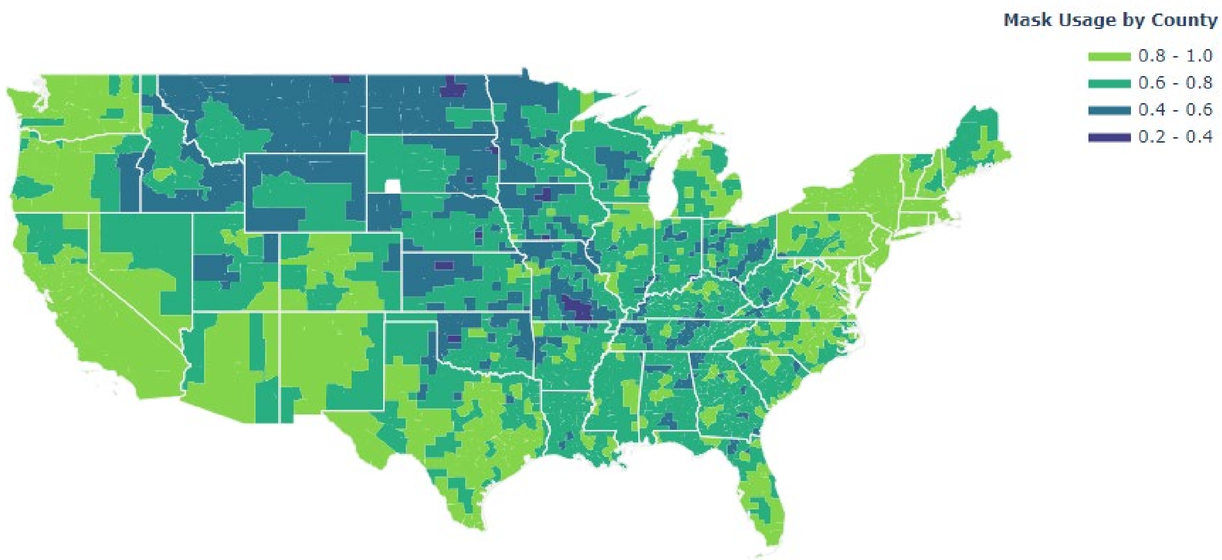


Figure 9: Results of the 2020 Mask Use Survey by the New York Times.

This dataset also could be broken down into counties by political party. The box plot below shows the spread of the reporting by Democrat and Republican party. The mean for Democratic counties sat around 85% usage with a minimum of about 45% and a maximum of 100% reported. People from Republican counties reported a mean of 70% mask use with the minimum at about 25% and a maximum of about 90%. Again, while survey data may not accurately report the true reality as peoples' memories and opinions tend to affect their responses, the surveyed individuals did paint a consistent image with regards to differences between counties of different political leanings. However, other variables should be controlled for before reaching a conclusion.

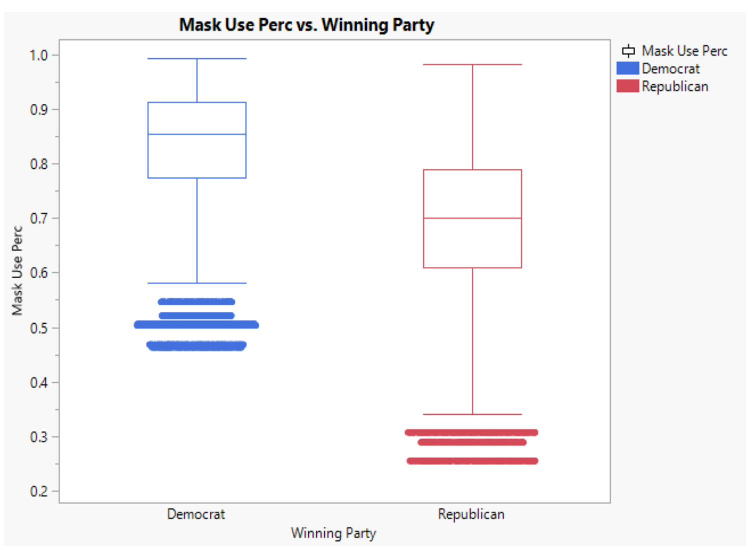


Figure 10: A box and whisker plot of the reported mask use by county and binned by political affiliation.

Despite the insights gained from visualizing both the mask mandate data and the *Times*' survey data, it was determined that neither dataset held the granularity needed for the main analysis. Unlike the distancing dataset, neither possessed the day-to-day information that would be necessary for use in a time series analysis. Not enough information can be obtained from the month-to-month information nor the one-time survey. The mask mandate dataset also included a column for defiance of local mandate orders noted in the public sphere. A number of counties openly stated that despite a mandate being instated, it would not be enforced. This raises an important point regarding the dataset, which is that it will not be able to completely account for actual mask adherence in the same way that the distancing data could track actual movement. The dataset works best at a government level and cannot be applied to the population of a county well. Therefore, masking data would not be used in the final analysis.

Sentiment

The central theory surrounding the collection of online sentiment for this analysis was to examine whether peoples' sentiments on a topic such as COVID could be used to mediate the relationship between political identity and COVID outcomes. Twitter, the micro-blogging social media platform, was chosen for its popularity. However, it was understood that not all demographics within the U.S. use or post to Twitter and this may not be representative of the entire population. The attempt was to gather a large enough sample per county despite this caveat. Twitter granted access to their new Academic API, which allowed for more than two million tweets to be queried per month. A query was then constructed to locate tweets from the dates being studied (March 2020 to April 2021) at a consistent number per date and that originated from users located in the United States mentioning COVID-19 in either text or hashtag. Various keywords were utilized in this query from 'coronavirus,' 'lockdown,' 'quarantine,' and 'COVID,' A total of 2.7 million tweets were able to be extracted with Tweepy.

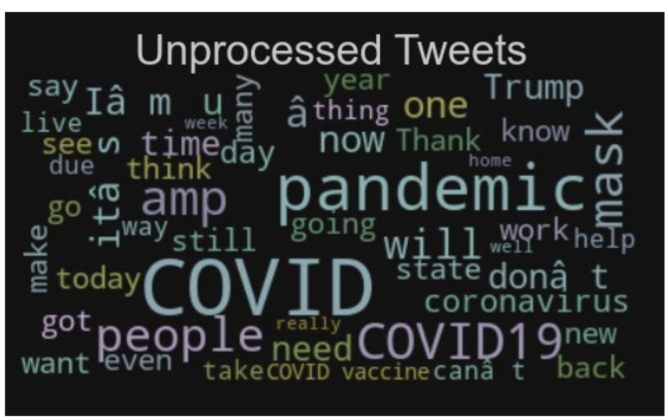


Figure 11: Word cloud showing the most frequent words used in the raw 2.7 million tweets pulled from the Twitter API.

Topic modelling and sentiment analysis models were applied to the Twitter data after extraction, cleaning, and natural language processing. The best topic-producing model was the Gibbs Sampling Dirichlet Multinomial Mixture, which fared better at identifying topics in the tweets over the standard Latent Dirichlet Allocation model. This is thought to be due to the fact that LDA assumes multiple topics per document (tweet), while Gibbs assumes only one. Using GSDMM, five topics were identified, and all were centered around the main topic of COVID-19 with a specific aspect on which to focus. The topics were COVID and politics, how schools or communities were being affected, COVID over time, safety, and adherence to safety measures, and how sports were being affected. The political and safety tweets were singled out for focus in the sentiment analysis. This reduced the data down to approximately 61,00 tweets in all.

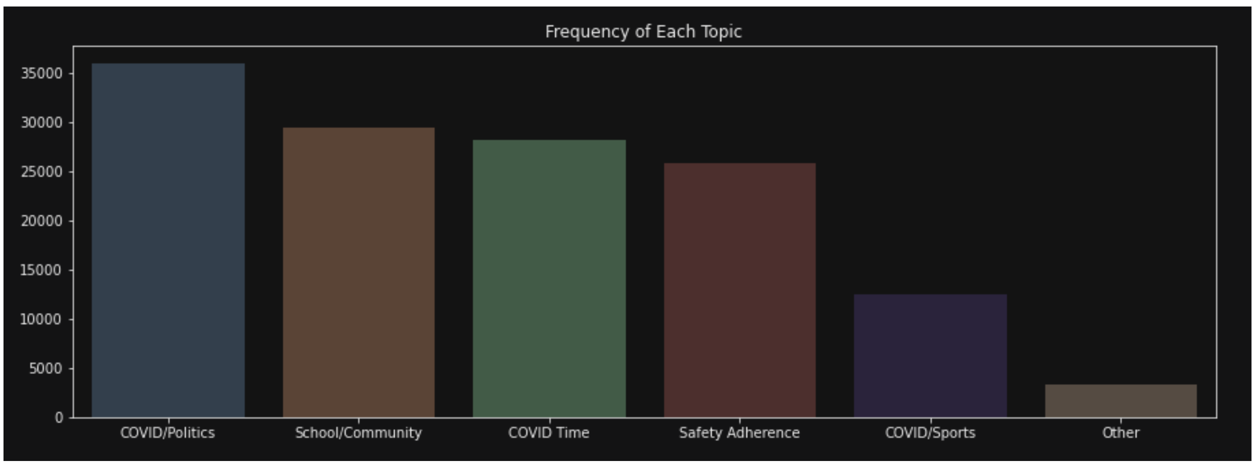


Figure 12: A frequency distribution of tweets by topic identified in the Gibbs Sampling model.

The Vader algorithm, short for Valence Aware Dictionary for Sentiment Reasoning, was chosen for sentiment analysis. While the Vader model does not classify specific emotions, it has another valuable ability for this analysis. Vader is able to both detect whether sentiment in the text is positive, negative, or neutral and also assign degree of positivity, negativity, or neutrality. This is done by scoring each individual word in the text after preprocessing has removed stopwords and then combining those scores into a compound score for the entire text.

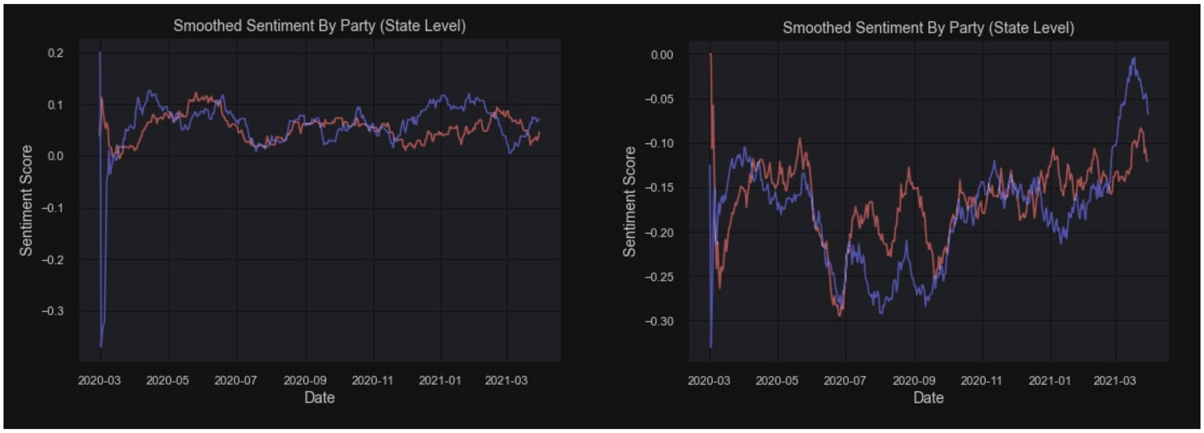


Figure 13: Left – A time series of safety sentiment on Twitter over thirteen months and binned by counties' political party. Right – A time series of COVID as a political topic over thirteen months and binned by counties' political party.

The graphs in Figure 13 show how counties by party fluctuated in sentiment over the dates of interest by safety and political topics respectively. The data is quite noisy even after smoothing with a thirty-day moving average applied. When discussing safety protocols in place for the pandemic, the y-axis asserts that most sentiments stay within the range of neutrality (between -0.1 and 0.1) and this perhaps because many posted matter-of-fact tweets that state facts about masking and amplifying news stories from more mainstream media. Political parties overlapped without much distinguishing to one from the other with the exception that Democratic sentiment started much lower than Republican sentiment around March 2020.

The political tweets, however, showed a lot more turbulence. Both trend lines seem to move in a similar pattern over time, which may indicate that specific events during the evolution of the pandemic affected all counties in similar ways. Republican sentiment appears to be slightly higher than Democratic sentiment much of the time. Republican sentiment for this topic is highest at the start of the pandemic and Democrats, meanwhile, experience their lowest sentiment at that time. By March 2021, Democratic sentiment is at its peak and substantially higher than Republican sentiment.

The text analysis of Twitter data totaled 39,383 tweets after cleaning, preprocessing, and sub-setting by topic. For this reason, sentiment data was removed as a potential mediating variable from the final analysis. There simply were not enough tweets distributed over all U.S. counties to provide a decent sample size with which to draw conclusions. This leaves the SafeGraph distancing data as the remaining variable with which to proceed on to the main statistical analysis. It was worthwhile to explore other potential variables to serve as mediators between partisanship and COVID rates and it certainly provided many insights into various aspects of the pandemic. At this point in the analysis, the current work would truly mirror the original with respect to both methodology and variables studied.

Methods & Results

Two statistical methods were used to determine whether distancing could once again prove to be a strong mediator between county level partisanship and its COVID rates, the two-level mixed model, and a mediation analysis. To account for the likely lack of independence within the sample, as individuals within a geographic region tend to be correlated with one another, counties were nested within states to create two levels in the mixed model analysis with both fitted random slopes and intercepts. The original analysis was able to do a three-level mixed model with their distancing data that nested individuals within counties as well, but the SafeGraph dataset was limited to the county level. In addition, a large number of covariate variables were gathered and accounted for to be sure no other social factor confounded the results. Most covariates were also z-scored or standardized and/or centered on their mean to create a scalable result. These transformations were performed as specified by the original paper. Another transformation that was replicated from the original was to log-scale population density. The final equation for the two-level mixed model is noted in the figure below.

$$\mathbf{outcome}_{ij} = \gamma_{00} + u_{0j} + (\gamma_{1j} + u_{1j})\ \mathbf{predictor} + \beta_{covariates} + e_{ij}$$

where: $\gamma_{00=}$grand intercept, u0j=fitted intercepts, γ1j=grand slope, u1j=fitted slopes, e=residuals, i=county, j=state

Figure 14: Represents the two-level mixed model notation.

Another issue, that came into play before the final analysis could begin, was that of heteroscedasticity in the final dataset. While the original work tracked distancing and COVID rates over an eighty-two-day span with relatively stable variance, the twelve months of data collected for this research proved to have several ‘personalities’ of variance that shifted as the pandemic continued. A Breusch-Pagan test was performed, and all divided sections of the data were considered heteroscedastic well below the p-value threshold of 0.05, even the original work’s timeline. To mitigate this to some extent and protect the reliability of the fitted model, the final dataset was subset into three smaller datasets. This allowed the research to test the original paper’s hypothesis over several different phases of the pandemic.

Phase 1 approximately replicates the original paper’s work spanning from March 15, 2020 to May 31, 2020. The original ran from March 9, 2020 to May 28, 2020. Running this new version of data from the same dates would show whether the necessary variables had been collected and appropriately preprocessed to the same standards as the original. There was a total of 187,731 rows in the Phase 1 dataset.

Phase 2 runs from June 6, 2020 to December 1, 2020 with 551,573 rows.

Finally, Phase 3 ranges from December 2, 2020 to March 3, 2021 with 274,330 rows. After joining all datasets and slicing by variance, a grand total of 353 days could be examined in the final analysis.

Validation of Distancing

The first step towards completing the final analysis was to validate the distancing data. This was accomplished by running two-level mixed models for each of the variables that were likely to have contributed to the difference in distancing and then added to the final distancing validation model. The factors the original authors decided were most likely to affect how much time people spent at home were time as both a linear and quadratic term, whether or not it was a weekend, the median income of the county (as higher earners could work from home), and whether a state policy was in place. All variables were gathered for this analysis. However, the policies referred to in this study were at the county level instead of the state level. Again, distancing was defined as the percentage difference between the mean number of minutes spent at home four weeks prior to the lockdown in February 2020 and the median number of minutes spent at home after the pandemic began and was the outcome variable in this case.

The models were run in JMP for each of the phases from the initial master dataset. Table 1 shows the r-square and adjusted r-square outputs for each model along with the outputs for the models run in the original paper. All three phases scored very well in accounting for variance within their models. Phase 1 scored the highest followed by Phase 3 and then Phase 2 with the lowest scores, but all scored much higher than the original models. Because the original models were processed in R and the newer models were processed in JMP, there is a chance that the models were not run identically. However, the log worth of each variable and their significance do suggest that the variables and the final model were significant enough to proceed to the next phase of the analysis.

Table 1: R-Square & Adjusted R-Square Outputs for Validating Distancing Data

Dataset	Time	Weekend	Median Income	Policy	Distancing
Gollwitzer	.250/.606	.269/.673	.334/.654	.295/.673	.354/.657
Phase 1	.764/.764	.785/.785	.773/.773	.780/.780	.780/.780
Phase 2	.661/.661	.625/.625	.670/.670	.670/.670	.670/.670
Phase 3	.736/.736	.733/.733	.742/.742	.742/.742	.742/.742

The Phase 1 data most closely resembles the original dataset from Gollwitzer et. al. The predictions from the fitted distancing model were applied to the Phase 1 data and plotted over time and by party. The figure below shows that the output of these predictions strongly resembles the output of the original data. This was a compelling indicator that the new dataset showed promise in replicating similar results later on and could be used as a guide to whether the other phases were setup correctly for testing.

ORIGINAL ANALYSIS OUTPUT CURRENT ANALYSIS OUTPUT

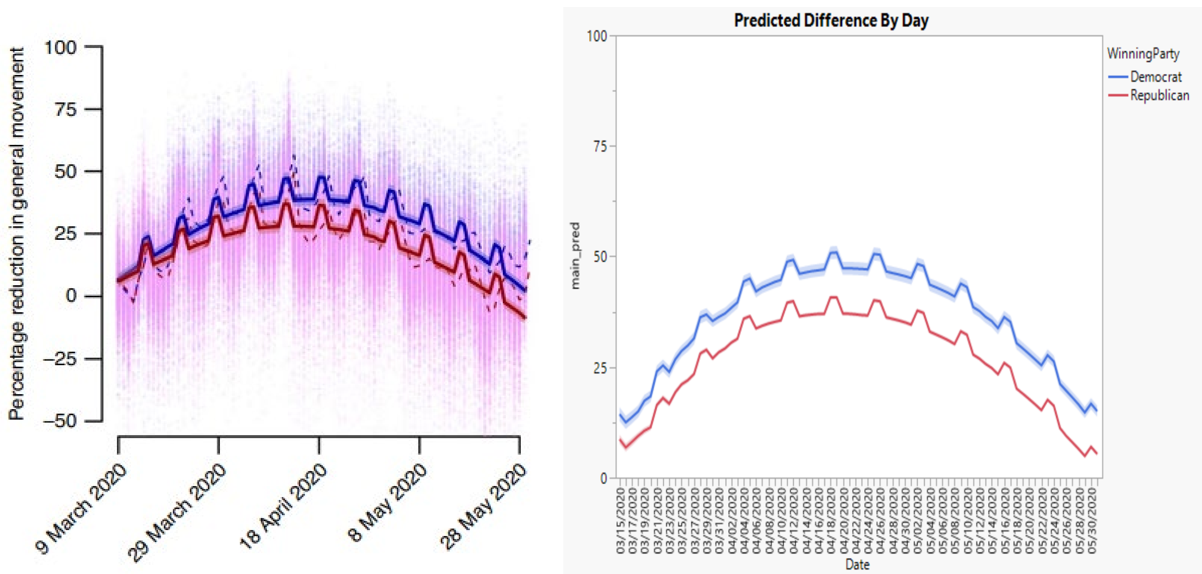


Figure 15: Left – Shows the original paper's smoothed distancing by voting gap from March to May 2020. Right – Shows this analysis' smoothed distancing by voting gap from March to May 2020. These similar graphs connote a fair amount of similarity between the original data and the current dataset.

Linking Partisanship to Physical Distancing

To test whether the distancing data was a valid proxy for partisanship, several models were developed by the original authors. The most basic model included no predictors or transformations of the variables. There was also a medium model where some variables were centered to help with normality scaling in the data. Finally, there were two types of saturated model that either included interactions among the random effect variables or did not. Another extension of this model included a breakdown of proportion of each county that worked in various industries. This data was not gathered for this analysis. The most basic model was run as well as the saturated model without the employment breakdown and included interaction. The saturated model also centered and standardized most of the covariates.

The basic model included both time terms as fixed effects. The voting gap was the predictor variable in this case and also a fixed effect with the difference in distancing as the outcome variable. Outputs show the r-square was 0.533 both adjusted and unadjusted for Phase 1, 0.638 for Phase 2, and 0.71 for Phase 3. All compared favorably with the original model, which had an r-square of 0.343/0.619.

The saturated model performed even better with r-squares of 0.772, 0.660, and 0.733. The original model also saw an increase in variance accounted for between the basic and saturated model. The original results jumped from 0.343/0.619 to 0.45/0.63. These results indicate that the included predictor variables are able to account for a reasonable amount of the variance in the data.

Aside from the fit of the model and the variance covered, the more vital outcome of the saturated model was whether voting gap performed as a significant predictor for the time spent at home. Table 2 shows the parameter estimates, confidence intervals, and p values for the voting gap in each dataset. Of the current datasets, only Phase 1 showed a significant result. This indicates that the physical distancing data was not a reasonable mediator between partisanship and COVID rates for either Phase 2 or Phase 3 of the pandemic timeline identified and, therefore, neither dataset would be run through the final mediation analysis. However, vote gap was significant to some extent with each phase when interacted with by certain variables. Specifically, vote gap and time were significant in Phase 1 as well as vote gap alone. Phase 2 showed significance for vote gap when interacted with by time and policy in place. Finally, Phase 3 had significance for vote gap when interacted with by policy and cases per one-thousand people. Conclusions on these finding will be addressed in the discussion section.

Table 2: Mixed Model Results for Linking Voting Gap to Distancing

Dataset, Variable	*Estimate*	*CI*	*p*
Gollwitzer, Vote Gap	-0.114	-0.140 - -0.087	<0.001
Phase 1, Vote Gap	-4.173	-6.580 - -1.767	<0.0012
Phase 2, Vote Gap	-0.027	-2.500 – 2.445	0.9816
Phase 3, Vote Gap	0.681	-3.378 – 4.740	0.7334

See Supplemental Materials for full outputs with covariate estimates.

Linking Physical Distancing to COVID Rates

The original work researched the link between their distancing data and COVID growth rates for cases and fatalities. Their series of mixed models showed that the data could indicate a change in COVID growth rates when distancing was lagged 17-23 days prior for cases and 25-31 days prior for deaths. This current research did not have access to the original model code and there are many published findings that confirm physical distancing is significantly linked to reducing COVID infection growth rates. Therefore, no such models were run for this analysis. Gollwitzer et. al. referenced a number of studies in their publication that thoroughly researched this question. One of those studies, Gao et. al. (2020) utilized the same SafeGraph dwelling time data from this analysis and found a significant correlation of 0.526 between dwell time and growth rates. This analysis took the median of Gollwitzer's lag span for case growth change (20 days) as an assumed appropriate metric for proceeding to the mediation analysis.

Linking Partisanship Indirectly to COVID Growth Rates

The final analysis in this research project combined a two-level mixed model with a mediation analysis in STATA. The mixed model served to decipher each variable's influence on predicting the outcome variable and then those outputs were fed into the mediation analysis script (do file) provided by the authors of the original paper. Growth rate was calculated as the difference between cases reported on a particular day and the day prior. As previously mentioned, the lag was set at 20 days on the distancing data to account for the amount of time it would supposedly take for a change in distancing to influence a change in the infection growth rate. Case growth rate become the main focus and death growth rate was shelved for the time being. Since infections must occur in order for there to be fatalities from the coronavirus, it became more important to see whether the new data could compare statistically with the original paper's findings on cases. Once the mediation analysis for partisanship, distancing, and case rates was run it was then processed through bootstrap sampling at one-hundred samples to insure consistent results.

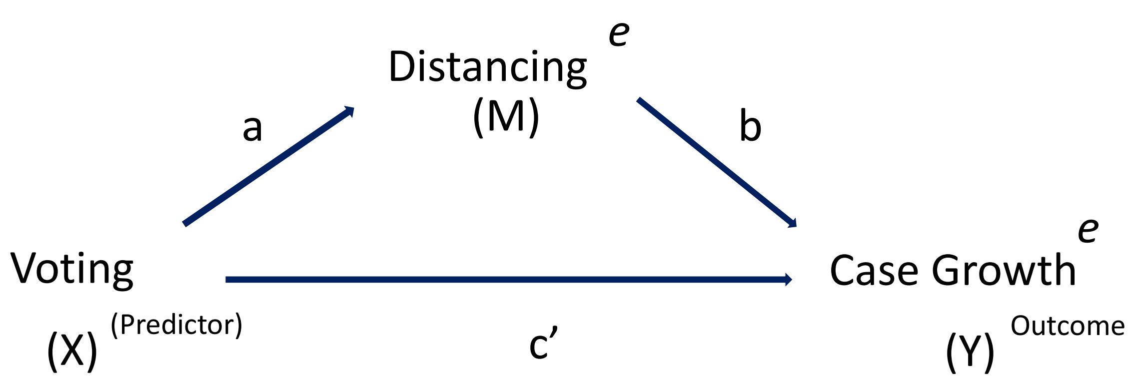


Figure 16: A path diagram showing the relationship between variables in the mediation analysis.

To reiterate, the Phase 1 dataset contained 187,731 observations. There were 16 total predictor variables including the partisanship variable and distancing lagged 20 days as the mediator and the growth rate for cases as the outcome. First, the variables were run through three separate equations that calculated the mixed model outputs for the mediated path (c /indirect path), the path between predictor and mediator (a path), and non-mediator path (c prime/direct path). Each equation produced a Walk chi-squared of high significance (<0.000) with scores of 1201, 13,978, and 1,981, respectively, which shows there was a significant difference between the observations.

Equation 1, which represents the validity of the indirect effect of partisanship on case growth rates via distancing behavior, was a significant model and showed the vote gap variable was significant to the model at 0.003.

Equation 2, which represents the validity of partisanship on distancing, was a significant model and showed the partisanship variable was significant to the model at 0.000.

Equation 3, which represents the validity of partisanship directly on case growth rates without mediation, was a significant model, but vote gap was not significant with a p-value of 0.352. Lagged distancing, however, was significantly impacting the case rate with a p-value of 0.000.

Table 3: Mediation Analysis Results					
Gollwitzer	Predictor	Mediator			Case Growth Rate
Total Effect	B = 0.272	s.e. = 0.149	z = 1.83	p = 0.067	CI[-0.020, 0.564]
Direct Effect	B = -0.583	s.e. = 0.170	z = -3.44	p = 0.001	CI[-0.915, -0.251]
Indirect Effect	B = 0.855	s.e. = 0.119	z = 7.19	p = 0.001	CI[0.622, 1.088]
Current Analysis					
Total Effect	B = .500	s.e. = .250	z = 2.01	p = 0.045	CI[.0115, .9904]
Direct Effect	B = .178	s.e. = .291	z = 0.61	p = 0.540	CI[-.3919, .7488]
Indirect Effect	B = .322	s.e. = .089	z = 3.62	p = 0.000	CI[.1480 , .4970]

The models were then used to calculate standardized effect coefficients for each of the paths (a, b, c, and c prime) through bootstrapping at one hundred replications. The original analysis produced a significant indirect coefficient of 0.855, which indicated a mediated relationship between how counties voted and the case growth rate in that county. Their total effect coefficient of 0.272 signified higher growth rates for counties that voted Republican. Finally, the original researchers claimed their direct effect of -0.583 indicated that had Trump-voting counties distanced to the same degree as Clinton counties, they would have experienced even lower rates than Democratic counties. The outputs of this current analysis do not support these findings, or at least not to the same degree. The indirect effect coefficient of 0.322 is not quite as large an effect as the original paper. However, it does seem to indicate that a significant amount of mediation is taking place in the model. The total effect is a larger coefficient than the original, but since the total effect is simply the sum of the direct and indirect effect coefficients it appears that is due to the fact that Gollwitzer's direct effect is a negative number. The direct effect for this analysis was 0.178 and did not seem to indicate the same finding that had Trump counties distanced as much as Clinton counties, it would have experienced much lower infection rates. The coefficient is a positive one and seems to show that the infection rate would still have been higher. This is a very different conclusion than the one originally drawn. The direct effect was not shown to be significant (0.540) and had a confidence interval that crossed zero. Meanwhile, the original analysis could not boast a significant total effect (0.067). Such details may muddy the conclusions that can be drawn from the original work and question whether the current dataset shares equal robustness as Gollwitzer's.

Discussion

Several interesting findings have been derived from this analysis. The most important is that only the dataset that most closely resembled that of the original paper showed a significant relationship between partisanship and physical distancing to a degree where distancing could be considered a mediator for partisanship. Neither Phase 2 nor Phase 3 were processed in the mediation analysis as a result and may suggest that the amount of variance in both datasets could not be accounted for by partisanship alone. Indeed, the voting gap variable was only significant when it interacted with another (time, policy in place). Therefore, one might conclude that Gollwitzer et. al.'s findings would not hold water in later segments of the pandemic as the variance on social distancing began to fluctuate more and more dramatically. The proxy-worthiness of distancing would not permanently work for mediating partisanship to growth rates of COVID-19. The previously noted trend of Republican counties overtaking Democratic ones in both cases and deaths around October 2020 was not able to be investigated without a significant proxy relationship between the two noted variables and should be analyzed in future works.

The Phase 1 data, which matched the data and timeline from the original paper, was significant at 0.0012, with respect to the relationship between vote gap and distancing and was run through the mediation analysis. The model output produced by the Phase 1 data was similar and equally significant to the original model, but with several differences that would not lead to the same inferences proposed by the published paper. While the model had equal significance, the model had markedly different coefficients to interpret with distancing not having as strong of a mediating effect and the direct effect changed vastly. One may conclude that the difference between the two types of distancing data used reported differently in the model.

Limitations

There were a number of limitations that presented when conducting this analysis. In the exploratory phase, computing power became an issue with the sentiment analysis data. With three million tweets, a laptop computer will not hold enough memory to process such complex data. Another issue with the Twitter data was that of users giving myriad and inaccurate entries as to their location. Some users gave more than one location. Spelling was also an issue and also just the lack of entries for location as it is an optional field that the user must decide to answer. Another method needs to be developed in order to harvest enough tweets to examine data at the county level.

For the actual analysis performed, results could be influenced by several unknown factors. The COVID data or the distancing data may contain undiscovered issues that alter the results of the models. Not all counties were represented on all dates. The lag time chosen for the mediation analysis was the median of the results from the original study a model was not fitted to this data to obtain that lag metric. While this analysis contained a much wider range of dates than the original, it was not all of the dates that could be included as the pandemic stretched into 2022 and it is possible that significant results could be obtained from dates not studied here. Also, this data was not completely transparent about individual behavior. Though individual observations were gathered by SafeGraph from the cell phone tracking, it was all aggregated into county level data points. They do, however, include their sample number for each date. In addition, because newer covariate data was used than the original study and some of those data were from 2020 numbers, which may have been influenced by the pandemic itself and do not represent the usual numbers, it is possible that the covariate data influenced the outcomes differently. But the decision was made to use the most recently updated census data. And finally, this analysis can only show correlation and not causation.

Further Research

This analysis came to some interesting conclusions, but it also suggests a wealth of future research opportunities. The Twitter analysis alone, though not achievable in this regard, invites all sorts of questions a researcher could ask about political sentiment online regarding COVID-19 in the United States. The Vader algorithm did well with the provided texts and more could be accomplished if one has the memory available.

The masking data was not adequate for this particular analysis as it did not have enough data points. However, this data and others like it could be used to conduct similar analyses. Mask use is a highly controversial topic for the pandemic and exploration of that data or even vaccine data could be utilized to explore similar hypotheses to this one.

This project was a truncated version of the original and not all the models from the original paper were run in this analysis. A full investigative project could build on top of this one with more of the same data. Or possibly, one could substitute in a new predictor variable other than the voting gap to stand for partisanship or another mediator such as masking or vaccine data. The skeleton of the project could be used to bolster further work in this area.

Data Availability

Source Links

NYT COVID DATA

https://github.com/nytimes/covid-19-data

MIT ELECTION DATA

https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/42MVDX

SAFEGRAPH DISTANCE DATA

https://cmu-delphi.github.io/delphi-epidata/api/covidcast-signals/fb-survey.html

UNIVERSITY OF CHICAGO MASK DATA

https://bfi.uchicago.edu/wp-content/uploads/BFI_WP_2020104.pdf

SENTIMENT DATA

https://developer.twitter.com/en/docs/twitter-api

COVARIATE DATA

Employment/Income

https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/

County Policies

https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Stay-At-Home-Orders-Marc/y2iy-8irm/data

Religiosity

https://data.world/garyhoov/us-religion-by-county

Demographics

https://data.census.gov/cedsci/table?q=demographic&tid=ACSDP5Y2020.DP05

Code Availability

GitHub - https://github.com/brittmorin/UNH_Practicum

Gollwitzer Code - https://osf.io/u5pmw/?view_only=33f0691a7e694276bef606cb3e22d141

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Competing Interests

Author declares no competing interests in this analysis.

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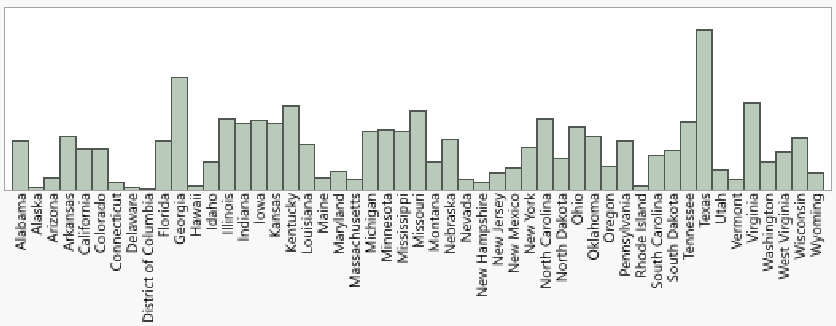
Supplemental Materials & Figures

Distributions of Variables

Distributions

State

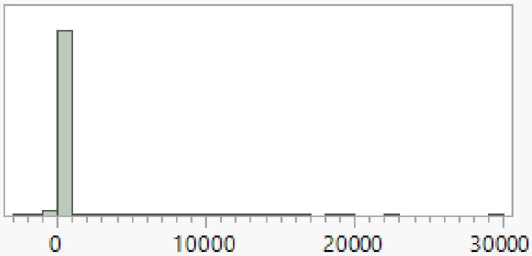


Frequencies

Level	Count	Prob
Alabama	23022	0.02270
Alaska	892	0.00088
Arizona	5215	0.00514
Arkansas	25465	0.02511
California	19533	0.01926
Colorado	19485	0.01922
Connecticut	2808	0.00277
Delaware	1054	0.00104
District of Columbia	353	0.00035
Florida	23179	0.02286
Georgia	54233	0.05348
Hawaii	1410	0.00139
Idaho	13416	0.01323
Illinois	34191	0.03372
Indiana	31631	0.03119
Iowa	33045	0.03259
Kansas	31869	0.03143
Kentucky	40062	0.03951
Louisiana	22124	0.02182
Maine	5501	0.00543
Maryland	8364	0.00825
Massachusetts	4919	0.00485
Michigan	28119	0.02773
Minnesota	29048	0.02865
Mississippi	27984	0.02760

N Missing 0
51 Levels

Raw_Cases



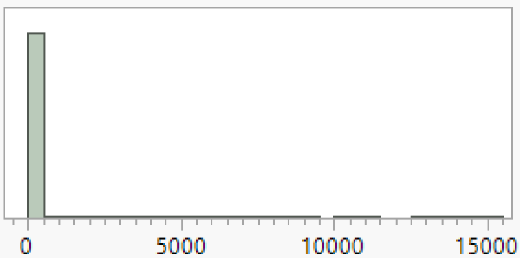
Quantiles

100.0%	maximum	29174
99.5%		638
97.5%		198
90.0%		50
75.0%	quartile	15
50.0%	median	3
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		-2
0.0%	minimum	-2321

Summary Statistics

Mean	27.21993
Std Dev	159.84562
Std Err Mean	0.1587393
Upper 95% Mean	27.531054
Lower 95% Mean	26.908806
N	1013987

Avg_Cases



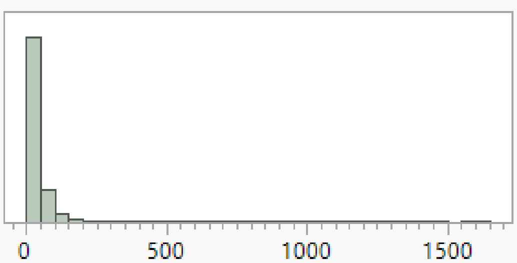
Quantiles

100.0%	maximum	15197.3
99.5%		591.5784
97.5%		189.86
90.0%		50.57
75.0%	quartile	15.71
50.0%	median	4.33
25.0%	quartile	1
10.0%		0.22
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	27.035318
Std Dev	145.83772
Std Err Mean	0.1448284
Upper 95% Mean	27.319177
Lower 95% Mean	26.75146
N	1013987

Cases_Capita



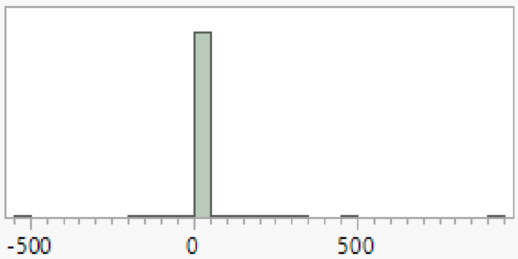
Quantiles

100.0%	maximum	1648.35
99.5%		182.3
97.5%		115.23
90.0%		70.25
75.0%	quartile	38.22
50.0%	median	14.86
25.0%	quartile	4.13
10.0%		0.91
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	27.275362
Std Dev	35.946418
Std Err Mean	0.0356976
Upper 95% Mean	27.345328
Lower 95% Mean	27.205396
N	1013987

Raw_Deaths



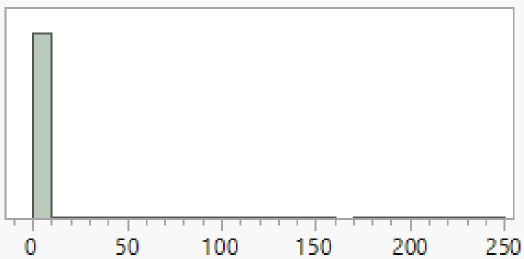
Quantiles

100.0%	maximum	930
99.5%		13
97.5%		4
90.0%		1
75.0%	quartile	0
50.0%	median	0
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	-512

Summary Statistics

Mean	0.4731777
Std Dev	3.2804255
Std Err Mean	0.0032577
Upper 95% Mean	0.4795627
Lower 95% Mean	0.4667926
N	1013987

Avg_Deaths



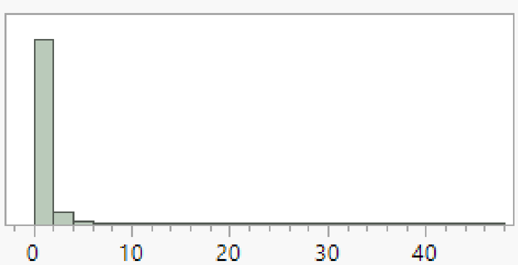
Quantiles

100.0%	maximum	241.29
99.5%		10.14
97.5%		3.29
90.0%		1
75.0%	quartile	0.31
50.0%	median	0
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	0.4786092
Std Dev	2.4330385
Std Err Mean	0.0024162
Upper 95% Mean	0.4833449
Lower 95% Mean	0.4738735
N	1013987

Deaths_Capita



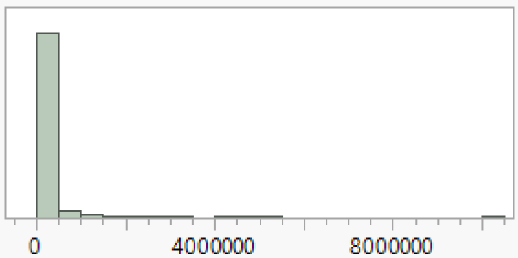
Quantiles

100.0%	maximum	46.72
99.5%		7.06
97.5%		3.68
90.0%		1.65
75.0%	quartile	0.65
50.0%	median	0
25.0%	quartile	0
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	0.5530438
Std Dev	1.2402196
Std Err Mean	0.0012316
Upper 95% Mean	0.5554578
Lower 95% Mean	0.5506299
N	1013987

TotalPopulation



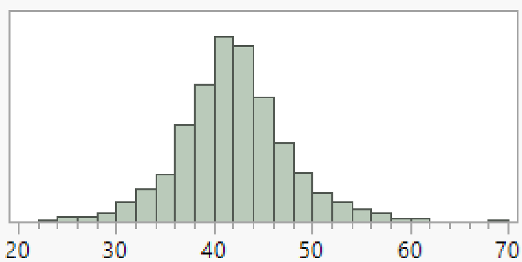
Quantiles

100.0%	maximum	10040682
99.5%		1942273
97.5%		809869
90.0%		229074
75.0%	quartile	75416
50.0%	median	28572
25.0%	quartile	12849
10.0%		6477
2.5%		3064
0.5%		2182
0.0%	minimum	2001

Summary Statistics

Mean	108963.75
Std Dev	337888.58
Std Err Mean	335.55006
Upper 95% Mean	109621.42
Lower 95% Mean	108306.09
N	1013987

MedianAge



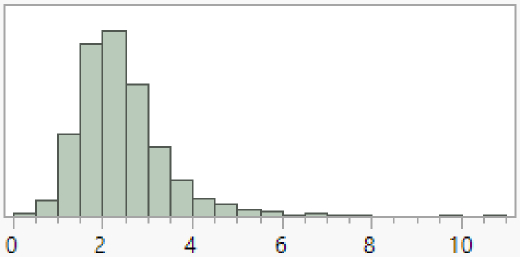
Quantiles

100.0%	maximum	68
99.5%		57
97.5%		53
90.0%		48
75.0%	quartile	44
50.0%	median	41
25.0%	quartile	38
10.0%		35
2.5%		31
0.5%		27
0.0%	minimum	22

Summary Statistics

Mean	41.446615
Std Dev	5.307664
Std Err Mean	0.0052709
Upper 95% Mean	41.456946
Lower 95% Mean	41.436284
N	1013987

Perc_Over_85



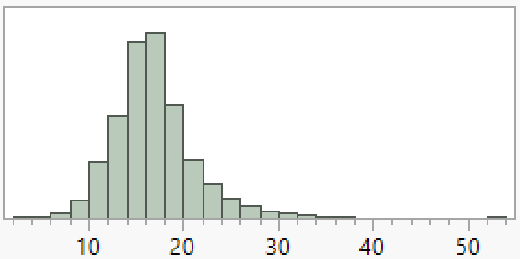
Quantiles

100.0%	maximum	10.5
99.5%		5.9
97.5%		4.7
90.0%		3.5
75.0%	quartile	2.8
50.0%	median	2.2
25.0%	quartile	1.7
10.0%		1.4
2.5%		1
0.5%		0.6
0.0%	minimum	0.2

Summary Statistics

Mean	2.333785
Std Dev	0.931028
Std Err Mean	0.0009246
Upper 95% Mean	2.3355972
Lower 95% Mean	2.3319729
N	1013987

Perc_65_84



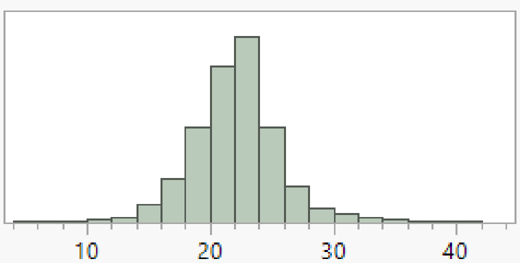
Quantiles

100.0%	maximum	52.7
99.5%		31.2
97.5%		26.4
90.0%		21.8
75.0%	quartile	18.7
50.0%	median	16.3
25.0%	quartile	14.3
10.0%		12
2.5%		9.8
0.5%		8.1
0.0%	minimum	2.8

Summary Statistics

Mean	16.721471
Std Dev	4.0646508
Std Err Mean	0.0040365
Upper 95% Mean	16.729382
Lower 95% Mean	16.713559
N	1013987

Perc_Under_18



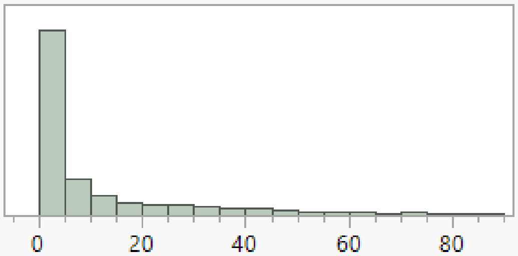
Quantiles

100.0%	maximum	41.9
99.5%		33.7
97.5%		29.5
90.0%		25.9
75.0%	quartile	23.9
50.0%	median	22.1
25.0%	quartile	20
10.0%		18
2.5%		15.5
0.5%		12.9
0.0%	minimum	5.2

Summary Statistics

Mean	22.081441
Std Dev	3.4097023
Std Err Mean	0.0033861
Upper 95% Mean	22.088078
Lower 95% Mean	22.074804
N	1013987

Perc_Black



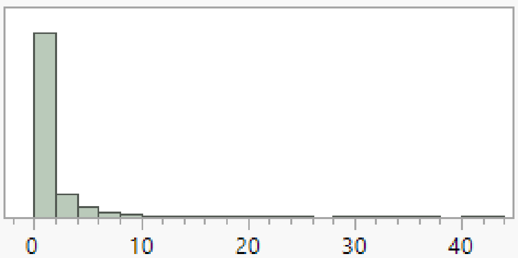
Quantiles

100.0%	maximum	87.8
99.5%		73
97.5%		53.8
90.0%		30.6
75.0%	quartile	11
50.0%	median	2.6
25.0%	quartile	0.7
10.0%		0.3
2.5%		0.1
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	9.4224927
Std Dev	14.629732
Std Err Mean	0.0145285
Upper 95% Mean	9.450968
Lower 95% Mean	9.3940174
N	1013987

Perc_Asian



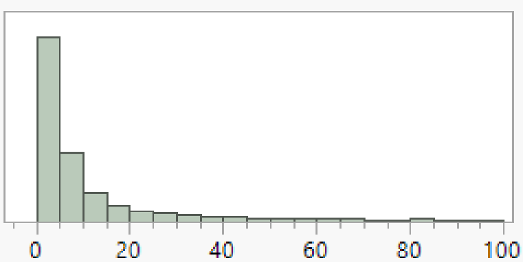
Quantiles

100.0%	maximum	42.6
99.5%		18.4
97.5%		7.3
90.0%		3.3
75.0%	quartile	1.4
50.0%	median	0.7
25.0%	quartile	0.3
10.0%		0.1
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	1.4235865
Std Dev	2.7940918
Std Err Mean	0.0027748
Upper 95% Mean	1.4290249
Lower 95% Mean	1.4181481
N	1013987

Perc_Hispanic



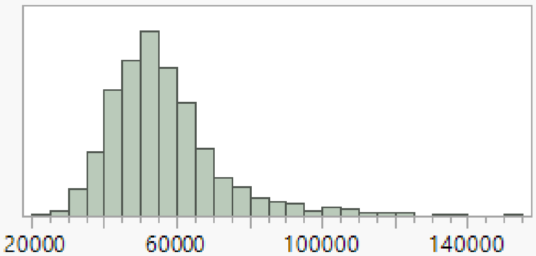
Quantiles

100.0%	maximum	98.9
99.5%		83.2
97.5%		54.9
90.0%		24.2
75.0%	quartile	10
50.0%	median	4.4
25.0%	quartile	2.3
10.0%		1.5
2.5%		0.6
0.5%		0
0.0%	minimum	0

Summary Statistics

Mean	9.5393114
Std Dev	13.757671
Std Err Mean	0.0136625
Upper 95% Mean	9.5660893
Lower 95% Mean	9.5125334
N	1013987

MedianIncome



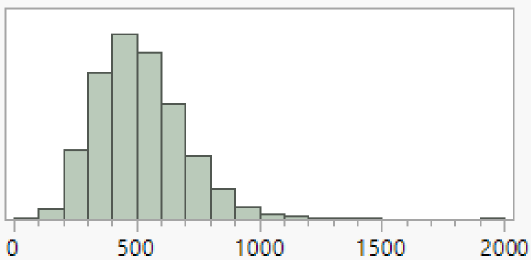
Quantiles

100.0%	maximum	151806
99.5%		112722
97.5%		92773
90.0%		73253
75.0%	quartile	62195
50.0%	median	53505
25.0%	quartile	46295
10.0%		40482
2.5%		34566
0.5%		30242
0.0%	minimum	24732

Summary Statistics

Mean	55860.974
Std Dev	14581.548
Std Err Mean	14.480629
Upper 95% Mean	55889.355
Lower 95% Mean	55832.592
N	1013987

ProportionReligious



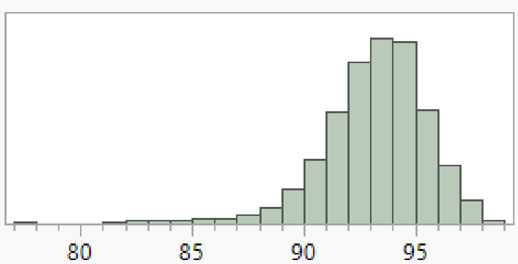
Quantiles

100.0%	maximum	1924.61
99.5%		1055.61
97.5%		891.79
90.0%		740.97
75.0%	quartile	617.78
50.0%	median	494.74
25.0%	quartile	386.04
10.0%		301.53
2.5%		223.07
0.5%		155.26
0.0%	minimum	51.32

Summary Statistics

Mean	511.06699
Std Dev	174.35227
Std Err Mean	0.1731456
Upper 95% Mean	511.40635
Lower 95% Mean	510.72763
N	1013987

ProportionEmployed



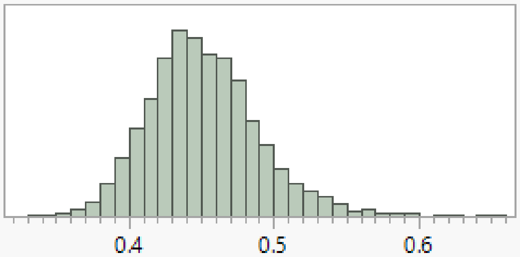
Quantiles

100.0%	maximum	98.3
99.5%		97.6
97.5%		96.9
90.0%		95.7
75.0%	quartile	94.7
50.0%	median	93.4
25.0%	quartile	91.9
10.0%		90.5
2.5%		88.4
0.5%		85.1
0.0%	minimum	77.5

Summary Statistics

Mean	93.186476
Std Dev	2.1835463
Std Err Mean	0.0021684
Upper 95% Mean	93.190727
Lower 95% Mean	93.182226
N	1013987

GiniCoefficient



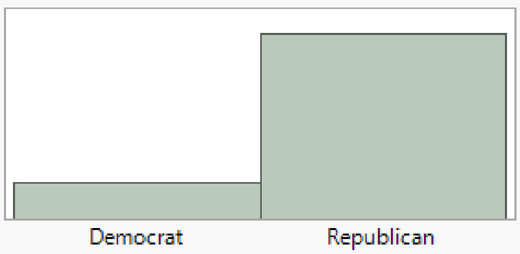
Quantiles

100.0%	maximum	0.65
99.5%		0.56
97.5%		0.53
90.0%		0.49
75.0%	quartile	0.47
50.0%	median	0.44
25.0%	quartile	0.42
10.0%		0.4
2.5%		0.38
0.5%		0.37
0.0%	minimum	0.33

Summary Statistics

Mean	0.445917
Std Dev	0.0369506
Std Err Mean	0.0000367
Upper 95% Mean	0.4459889
Lower 95% Mean	0.4458451
N	1013987

WinningParty



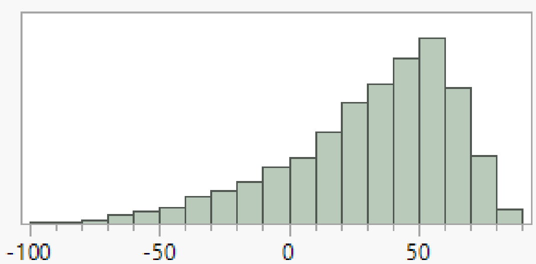
Frequencies

Level	Count	Prob
Democrat	164775	0.16250
Republican	849212	0.83750
Total	1013987	1.00000

N Missing 0

2 Levels

VoteGap



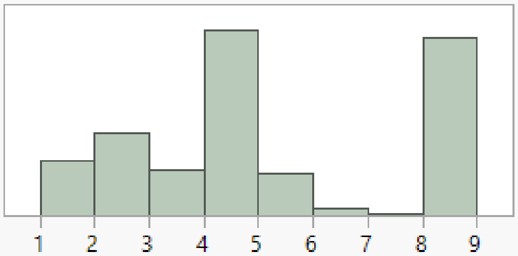
Quantiles

100.0%	maximum	86.27
99.5%		82.01
97.5%		76.69
90.0%		66.34
75.0%	quartile	55.87
50.0%	median	38.94
25.0%	quartile	14.3
10.0%		-13.63
2.5%		-45.06
0.5%		-66.69
0.0%	minimum	-91.39

Summary Statistics

Mean	31.952182
Std Dev	31.698029
Std Err Mean	0.0314786
Upper 95% Mean	32.013879
Lower 95% Mean	31.890485
N	1013987

MonthInEffect



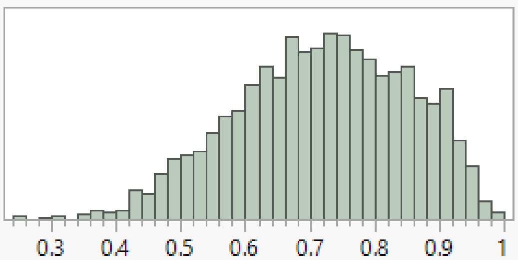
Quantiles

100.0%	maximum	8
99.5%		8
97.5%		8
90.0%		8
75.0%	quartile	8
50.0%	median	4
25.0%	quartile	3
10.0%		2
2.5%		1
0.5%		1
0.0%	minimum	1

Summary Statistics

Mean	4.6701003
Std Dev	2.4379449
Std Err Mean	0.0024211
Upper 95% Mean	4.6748455
Lower 95% Mean	4.6653551
N	1013987

PercMaskUse



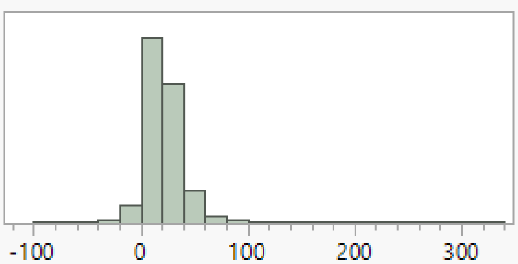
Quantiles

100.0%	maximum	0.992
99.5%		0.966
97.5%		0.938
90.0%		0.891
75.0%	quartile	0.822
50.0%	median	0.724
25.0%	quartile	0.628
10.0%		0.542
2.5%		0.46
0.5%		0.39
0.0%	minimum	0.255

Summary Statistics

Mean	0.7193945
Std Dev	0.130088
Std Err Mean	0.0001292
Upper 95% Mean	0.7196477
Lower 95% Mean	0.7191413
N	1013987

IncreaseAtHome



Quantiles

100.0%	maximum	323.00172
99.5%		91.126624
97.5%		59.11492
90.0%		40.686223
75.0%	quartile	28.680324
50.0%	median	18.990908
25.0%	quartile	11.591918
10.0%		5.2231923
2.5%		-5.545486
0.5%		-21.60392
0.0%	minimum	-100

Summary Statistics

Mean	21.34533
Std Dev	16.9231
Std Err Mean	0.016806
Upper 95% Mean	21.378269
Lower 95% Mean	21.312391
N	1013987

Validation of Distancing as Mediator for Voting Gap

Phase 1

Effect Summary

Source	LogWorth	PValue
TimeQuadNormal	20859.23	0.00000
TimeLinearNormal	14815.59	0.00000
Weekend	1473.375	0.00000
PolicyCentered	930.896	0.00000
Std VoteGap*TimeLinearNormal	729.510	0.00000
Std VoteGap*TimeQuadNormal	596.203	0.00000
Std Centered MedianAge	82.236	0.00000
Std IncomeCentered	56.067	0.00000
Std ProportionEmployed	52.465	0.00000
Std Centered Perc_65_84	39.475	0.00000
Std VoteGap*Std Centered Capita/1000	31.055	0.00000
Std Centered Capita/1000	29.232	0.00000 ^
Std Centered Perc_Black	26.136	0.00000
Std Centered Perc_Under_18	14.918	0.00000
Std Centered Perc_Over_85	9.303	0.00000
Std Centered Perc_Hispanic	6.576	0.00000
Std VoteGap*PolicyCentered	5.022	0.00001
Std Centered GiniCoefficient	4.986	0.00001
Std VoteGap	2.920	0.00120 ^
Std VoteGap*Std Centered MedianAge	2.878	0.00133
Std VoteGap*Std Centered Perc_Over_85	2.484	0.00328
Std VoteGap*Std Centered Perc_65_84	1.788	0.01631
Std VoteGap*Std Centered Perc_Hispanic	1.175	0.06682
Std VoteGap*Std Centered GiniCoefficient	0.882	0.13117
Std Centered Perc_Asian	0.796	0.15985
Std Centered ProportionReligious	0.570	0.26916
Std VoteGap*Std Centered Perc_Under_18	0.506	0.31158
Std VoteGap*Weekend	0.413	0.38671
Std VoteGap*Std Centered Perc_Asian	0.310	0.48955
Std VoteGap*Std ProportionEmployed	0.295	0.50651
Std VoteGap*Std Centered ProportionReligious	0.148	0.71105
Std VoteGap*Std LogPopDensity	0.111	0.77438
Std LogPopDensity	0.057	0.87760 ^
Std VoteGap*Std Centered Perc_Black	0.046	0.89962
Std VoteGap*Std IncomeCentered	0.005	0.98927

Summary of Fit

RSquare	0.77221
RSquare Adj	0.772168
Root Mean Square Error	8.660218
Mean of Response	29.69088

Observations (or Sum Wgts) 187731

AICc 1360591
BIC 1360987

Parameter Estimates

Term	Estimate	Std Error	DFDen	t Ratio	Prob>|t|	Lower 95%	U
Intercept	8.9284262	0.166613	8393	53.59	<.0001*	8.601824	
Std VoteGap	-4.173671	1.186425	35.8	-3.52	0.0012*	-6.580321	
(Std VoteGap-0.00157)*Std Centered Perc_Black	0.1291164	1.022974	435	0.13	0.8996	-1.881471	
(Std VoteGap-0.00157)*Std Centered Perc_Asian	0.7093863	1.026271	1232	0.69	0.4896	-1.304045	
(Std VoteGap-0.00157)*Std Centered Perc_Hispanic	1.8216997	0.991159	393.3	1.84	0.0668	-0.126934	
(Std VoteGap-0.00157)*Std Centered GiniCoefficient	-1.285881	0.851347	1396	-1.51	0.1312	-2.955939	
(Std VoteGap-0.00157)*Std Centered Perc_Over_85	2.846761	0.965909	983	2.95	0.0033*	0.9512804	
(Std VoteGap-0.00157)*Std Centered Perc_65_84	5.1603664	2.145769	1356	2.40	0.0163*	0.9509798	
(Std VoteGap-0.00157)*Std Centered Perc_Under_18	-1.063701	1.050784	1323	-1.01	0.3116	-3.125086	
(Std VoteGap-0.00157)*(Std ProportionEmployed-0.00021)	-0.631945	0.950743	603.2	-0.66	0.5065	-2.499113	
(Std VoteGap-0.00157)*Std Centered ProportionReligious	0.3138023	0.846867	1142	0.37	0.7110	-1.347788	
(Std VoteGap-0.00157)*Std Centered MedianAge	-6.90169	2.14526	1339	-3.22	0.0013*	-11.11013	
(Std VoteGap-0.00157)*Std Centered Capita/1000	-0.426929	0.036385	2e+5	-11.73	<.0001*	-0.498243	
(Std VoteGap-0.00157)*(PolicyCentered-0.33259)	0.3806655	0.085963	2e+5	4.43	<.0001*	0.2121798	
(Std VoteGap-0.00157)*(Std LogPopDensity+0.00138)	-0.309203	1.078228	666.5	-0.29	0.7744	-2.426336	
(Std VoteGap-0.00157)*(Std IncomeCentered+0.00093)	-0.015781	1.173364	918.7	-0.01	0.9893	-2.318566	
(Std VoteGap-0.00157)*(Weekend-0.29694)	0.038071	0.043982	2e+5	0.87	0.3867	-0.048134	
(Std VoteGap-0.00157)*(TimeQuadNormal-0.39248)	18.539426	0.353025	2e+5	52.52	<.0001*	17.847506	
(Std VoteGap-0.00157)*(TimeLinearNormal-0.56818)	-23.75366	0.408457	2e+5	-58.15	<.0001*	-24.55422	
TimeLinearNormal	119.02166	0.414248	2e+5	287.32	<.0001*	118.20974	
TimeQuadNormal	-126.2405	0.355505	2e+5	-355.1	<.0001*	-126.9373	
Weekend	3.6437166	0.043854	2e+5	83.09	<.0001*	3.5577641	
Std IncomeCentered	3.7855328	0.234794	4212	16.12	<.0001*	3.3252121	
Std LogPopDensity	0.030005	0.19482	5318	0.15	0.8776	-0.351922	
PolicyCentered	5.5416942	0.084243	2e+5	65.78	<.0001*	5.3765804	
Std Centered Capita/1000	0.277572	0.024407	2e+5	11.37	<.0001*	0.2297347	
Std Centered MedianAge	8.1206847	0.412011	4429	19.71	<.0001*	7.3129371	
Std Centered ProportionReligious	0.1698123	0.153656	4505	1.11	0.2692	-0.131429	
Std ProportionEmployed	-2.601078	0.167222	4537	-15.55	<.0001*	-2.928915	
Std Centered GiniCoefficient	0.7312846	0.165642	4842	4.41	<.0001*	0.4065511	
Std Centered Perc_65_84	-4.988865	0.372177	4481	-13.40	<.0001*	-5.718516	
Std Centered Perc_Asian	-0.5769	0.410342	3282	-1.41	0.1598	-1.381451	
Std Centered Perc_Black	-2.223677	0.206298	6466	-10.78	<.0001*	-2.62809	
Std Centered Perc_Hispanic	-0.946166	0.183621	5718	-5.15	<.0001*	-1.306132	
Std Centered Perc_Over_85	-1.127689	0.180924	4655	-6.23	<.0001*	-1.482386	
Std Centered Perc_Under_18	2.0175953	0.250996	3756	8.04	<.0001*	1.5254933	

REML Variance Component Estimates

Random Effect	Var Ratio	Var Component	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
FIPS*VoteGap[StateNum]	0.0177931	1.3344697	0.0514415	1.2336462	1.4352931	<.0001*	1.747
VoteGap*StateNum	0.0004345	0.0325865	0.0134497	0.0062256	0.0589474	0.0154*	0.043
Residual		74.999372	0.2486102	74.514481	75.489035		98.210
Total		76.366429	0.2495857	75.879601	76.857978		100.000

-2 LogLikelihood = 1360513.3889
Note: Total is the sum of the positive variance components.
Total including negative estimates = 76.366429

Fixed Effect Tests

Source	Nparm	DF	DFDen	F Ratio	Prob > F
Std VoteGap	1	1	35.8	12.3753	0.0012*
Std VoteGap*Std Centered Perc_Black	1	1	435	0.0159	0.8996
Std VoteGap*Std Centered Perc_Asian	1	1	1232	0.4778	0.4896
Std VoteGap*Std Centered Perc_Hispanic	1	1	393.3	3.3781	0.0668
Std VoteGap*Std Centered GiniCoefficient	1	1	1396	2.2813	0.1312
Std VoteGap*Std Centered Perc_Over_85	1	1	983	8.6862	0.0033*
Std VoteGap*Std Centered Perc_65_84	1	1	1356	5.7836	0.0163*
Std VoteGap*Std Centered Perc_Under_18	1	1	1323	1.0247	0.3116
Std VoteGap*Std ProportionEmployed	1	1	603.2	0.4418	0.5065
Std VoteGap*Std Centered ProportionReligious	1	1	1142	0.1373	0.7110
Std VoteGap*Std Centered MedianAge	1	1	1339	10.3503	0.0013*
Std VoteGap*Std Centered Capita/1000	1	1	2e+5	137.6768	<.0001*
Std VoteGap*PolicyCentered	1	1	2e+5	19.6093	<.0001*
Std VoteGap*Std LogPopDensity	1	1	666.5	0.0822	0.7744
Std VoteGap*Std IncomeCentered	1	1	918.7	0.0002	0.9893
Std VoteGap*Weekend	1	1	2e+5	0.7493	0.3867
Std VoteGap*TimeQuadNormal	1	1	2e+5	2757.926	<.0001*
Std VoteGap*TimeLinearNormal	1	1	2e+5	3381.967	<.0001*
TimeLinearNormal	1	1	2e+5	82552.56	<.0001*
TimeQuadNormal	1	1	2e+5	126097.3	<.0001*
Weekend	1	1	2e+5	6903.586	<.0001*
Std IncomeCentered	1	1	4212	259.9434	<.0001*
Std LogPopDensity	1	1	5318	0.0237	0.8776
PolicyCentered	1	1	2e+5	4327.332	<.0001*
Std Centered Capita/1000	1	1	2e+5	129.3362	<.0001*
Std Centered MedianAge	1	1	4429	388.4790	<.0001*
Std Centered ProportionReligious	1	1	4505	1.2213	0.2692
Std ProportionEmployed	1	1	4537	241.9461	<.0001*
Std Centered GiniCoefficient	1	1	4842	19.4909	<.0001*
Std Centered Perc_65_84	1	1	4481	179.6819	<.0001*
Std Centered Perc_Asian	1	1	3282	1.9766	0.1598
Std Centered Perc_Black	1	1	6466	116.1858	<.0001*
Std Centered Perc_Hispanic	1	1	5718	26.5517	<.0001*
Std Centered Perc_Over_85	1	1	4655	38.8493	<.0001*
Std Centered Perc_Under_18	1	1	3756	64.6151	<.0001*

Phase 2

Effect Summary

Source	LogWorth	PValue	
Std Centered Capita/1000	5591.584	0.00000	
Weekend	3348.798	0.00000	
TimeQuadNormal	798.313	0.00000	
TimeLinearNormal	530.793	0.00000	
Std VoteGap*TimeLinearNormal	265.280	0.00000	
PolicyCentered	87.080	0.00000	
Std VoteGap*PolicyCentered	34.024	0.00000	
Std VoteGap*Std Centered Capita/1000	27.954	0.00000	
Std Centered Perc_Asian	11.928	0.00000	
Std Centered Perc_Hispanic	11.417	0.00000	
Std VoteGap*Weekend	10.074	0.00000	
Std ProportionEmployed	7.033	0.00000	
Std LogPopDensity	5.763	0.00000	
Std Centered GiniCoefficient	5.056	0.00001	
Std Centered Perc_Under_18	4.710	0.00002	
Std Centered ProportionReligious	3.169	0.00068	
Std VoteGap*TimeQuadNormal	2.143	0.00720	
Std VoteGap*Std LogPopDensity	2.050	0.00892	
Std Centered MedianAge	1.124	0.07508	
Std Centered Perc_Black	1.071	0.08492	
Std VoteGap*Std ProportionEmployed	0.823	0.15019	
Std VoteGap*Std Centered Perc_Black	0.720	0.19057	
Std VoteGap*Std Centered Perc_Under_18	0.693	0.20300	
Std VoteGap*Std Centered Perc_Over_85	0.544	0.28588	
Std IncomeCentered	0.515	0.30540	
Std VoteGap*Std Centered Perc_65_84	0.450	0.35501	
Std Centered Perc_65_84	0.412	0.38684	^
Std VoteGap*Std Centered ProportionReligious	0.377	0.41929	
Std Centered Perc_Over_85	0.368	0.42887	^
Std VoteGap*Std IncomeCentered	0.336	0.46131	
Std VoteGap*Std Centered GiniCoefficient	0.266	0.54171	
Std VoteGap*Std Centered MedianAge	0.196	0.63725	
Std VoteGap*Std Centered Perc_Asian	0.154	0.70111	
Std VoteGap*Std Centered Perc_Hispanic	0.061	0.86847	
Std VoteGap	0.008	0.98161	^

Summary of Fit

RSquare	0.660456
RSquare Adj	0.660434
Root Mean Square Error	8.56943
Mean of Response	16.31449
Observations (or Sum Wgts)	551573

AICc	3958502
BIC	3958939

Parameter Estimates

Term	Estimate	Std Error	DFDen	t Ratio	Prob>|t|	Lower 95%	Upper 95%
Intercept	13.608707	0.138037	5678	98.59	<.0001*	13.338101	13.879312
Std VoteGap	-0.027143	1.157603	14.62	-0.02	0.9816	-2.500087	2.4458007
Std VoteGap*Std Centered Perc_Black	-1.713155	1.299683	96.72	-1.32	0.1906	-4.29276	0.8664493
Std VoteGap*Std Centered Perc_Asian	-0.489534	1.27515	1289	-0.38	0.7011	-2.991131	2.0120633
Std VoteGap*Std Centered Perc_Hispanic	-0.223042	1.338961	43.48	-0.17	0.8685	-2.922449	2.476365
Std VoteGap*Std Centered GiniCoefficient	0.7361429	1.206068	1568	0.61	0.5417	-1.629533	3.1018189
Std VoteGap*Std Centered Perc_Over_85	1.4641839	1.369926	357.4	1.07	0.2859	-1.229945	4.1583124
Std VoteGap*Std Centered Perc_65_84	-2.757664	2.980579	1458	-0.93	0.3550	-8.604343	3.0890158
Std VoteGap*Std Centered Perc_Under_18	-1.915305	1.503791	1423	-1.27	0.2030	-4.865191	1.0345801
Std VoteGap*Std ProportionEmployed	-1.873722	1.295664	152.5	-1.45	0.1502	-4.433486	0.6860427
Std VoteGap*Std Centered ProportionReligious	-0.984887	1.218763	728.5	-0.81	0.4193	-3.377594	1.4078204
Std VoteGap*Std Centered MedianAge	1.4250483	3.021459	1455	0.47	0.6373	-4.501832	7.3519282
Std VoteGap*Std Centered Capita/1000	-0.169944	0.015295	5e+5	-11.11	<.0001*	-0.199921	-0.139967
Std VoteGap*PolicyCentered[-0.49]	-0.370909	0.030162	5e+5	-12.30	<.0001*	-0.430025	-0.311793
Std VoteGap*Std LogPopDensity	-3.801806	1.443625	282	-2.63	0.0089*	-6.643455	-0.960156
Std VoteGap*Std IncomeCentered	1.1323835	1.535782	446.6	0.74	0.4613	-1.885874	4.1506409
Std VoteGap*(Weekend-0.28273)	0.1664032	0.025629	5e+5	6.49	<.0001*	0.1161703	0.216636
Std VoteGap*(TimeQuadNormal-0.33586)	0.4216057	0.156884	5e+5	2.69	0.0072*	0.1141185	0.729093
Std VoteGap*(TimeLinearNormal-0.50201)	5.5841932	0.160174	5e+5	34.86	<.0001*	5.2702574	5.898129
TimeLinearNormal	-7.949898	0.160889	5e+5	-49.41	<.0001*	-8.265235	-7.63456
TimeQuadNormal	9.6737262	0.159466	5e+5	60.66	<.0001*	9.3611775	9.9862749
Weekend	3.2042748	0.02563	5e+5	125.02	<.0001*	3.1540417	3.254508
Std IncomeCentered	0.2251265	0.219623	4174	1.03	0.3054	-0.205452	0.6557051
Std LogPopDensity	1.058459	0.221036	5153	4.79	<.0001*	0.6251338	1.4917842
PolicyCentered[-0.49]	-0.59991	0.030194	5e+5	-19.87	<.0001*	-0.659089	-0.54073
Std Centered Capita/1000	2.5148279	0.015492	5e+5	162.33	<.0001*	2.4844644	2.5451914
Std Centered MedianAge	0.6713418	0.377123	8440	1.78	0.0751	-0.067913	1.4105962
Std Centered ProportionReligious	0.574642	0.169011	5920	3.40	0.0007*	0.2433178	0.9059661
Std ProportionEmployed	-0.845742	0.158149	5410	-5.35	<.0001*	-1.155777	-0.535707
Std Centered GiniCoefficient	-0.77165	0.173405	4538	-4.45	<.0001*	-1.111608	-0.431693
Std Centered Perc_65_84	-0.321191	0.371134	6098	-0.87	0.3868	-1.048745	0.406363
Std Centered Perc_Asian	-2.729181	0.382836	4332	-7.13	<.0001*	-3.479736	-1.978626
Std Centered Perc_Black	0.3824348	0.221941	5747	1.72	0.0849	-0.052653	0.8175225
Std Centered Perc_Hispanic	1.3375618	0.192099	4398	6.96	<.0001*	0.9609509	1.7141728
Std Centered Perc_Over_85	-0.166338	0.210237	4318	-0.79	0.4289	-0.578511	0.2458342
Std Centered Perc_Under_18	0.9528892	0.222967	6565	4.27	<.0001*	0.5158023	1.3899762

REML Variance Component Estimates

Random Effect	Var Ratio	Var Component	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
FIPS*VoteGap[StateNum]	0.0408637	3.0008342	0.0915412	2.8214168	3.1802517	<.0001*	3.926
VoteGap*StateNum	0.0001012	0.0074292	0.0166739	-0.025251	0.0401095	0.6559	0.010
Residual		73.435134	0.1403464	73.160835	.		96.065
Total		76.443397	0.1654414	76.120172	.		100.000

-2 LogLikelihood = 3958423.8691
Note: Total is the sum of the positive variance components.
Total including negative estimates = 76.443397

Fixed Effect Tests

Source	Nparm	DF	DFDen	F Ratio	Prob > F
Std VoteGap	1	1	14.62	0.0005	0.9816
Std VoteGap*Std Centered Perc_Black	1	1	96.72	1.7375	0.1906
Std VoteGap*Std Centered Perc_Asian	1	1	1289	0.1474	0.7011
Std VoteGap*Std Centered Perc_Hispanic	1	1	43.48	0.0277	0.8685
Std VoteGap*Std Centered GiniCoefficient	1	1	1568	0.3725	0.5417
Std VoteGap*Std Centered Perc_Over_85	1	1	357.4	1.1423	0.2859
Std VoteGap*Std Centered Perc_65_84	1	1	1458	0.8560	0.3550
Std VoteGap*Std Centered Perc_Under_18	1	1	1423	1.6222	0.2030
Std VoteGap*Std ProportionEmployed	1	1	152.5	2.0913	0.1502
Std VoteGap*Std Centered ProportionReligious	1	1	728.5	0.6530	0.4193
Std VoteGap*Std Centered MedianAge	1	1	1455	0.2224	0.6373
Std VoteGap*Std Centered Capita/1000	1	1	5e+5	123.4628	<.0001*
Std VoteGap*PolicyCentered	1	1	5e+5	151.2235	<.0001*
Std VoteGap*Std LogPopDensity	1	1	282	6.9354	0.0089*
Std VoteGap*Std IncomeCentered	1	1	446.6	0.5437	0.4613
Std VoteGap*Weekend	1	1	5e+5	42.1547	<.0001*
Std VoteGap*TimeQuadNormal	1	1	5e+5	7.2220	0.0072*
Std VoteGap*TimeLinearNormal	1	1	5e+5	1215.451	<.0001*
TimeLinearNormal	1	1	5e+5	2441.567	<.0001*
TimeQuadNormal	1	1	5e+5	3680.021	<.0001*
Weekend	1	1	5e+5	15630.64	<.0001*
Std IncomeCentered	1	1	4174	1.0507	0.3054
Std LogPopDensity	1	1	5153	22.9309	<.0001*
PolicyCentered	1	1	5e+5	394.7540	<.0001*
Std Centered Capita/1000	1	1	5e+5	26351.86	<.0001*
Std Centered MedianAge	1	1	8440	3.1690	0.0751
Std Centered ProportionReligious	1	1	5920	11.5601	0.0007*
Std ProportionEmployed	1	1	5410	28.5986	<.0001*
Std Centered GiniCoefficient	1	1	4538	19.8025	<.0001*
Std Centered Perc_65_84	1	1	6098	0.7490	0.3868
Std Centered Perc_Asian	1	1	4332	50.8204	<.0001*
Std Centered Perc_Black	1	1	5747	2.9692	0.0849
Std Centered Perc_Hispanic	1	1	4398	48.4816	<.0001*
Std Centered Perc_Over_85	1	1	4318	0.6260	0.4289
Std Centered Perc_Under_18	1	1	6565	18.2644	<.0001*

Phase 3

Effect Summary

Source	LogWorth	PValue	
Weekend	1216.804	0.00000	
TimeLinearNormal	656.605	0.00000	
Std Centered Capita/1000	116.778	0.00000	
Std VoteGap*PolicyCentered	85.208	0.00000	
TimeQuadNormal	40.435	0.00000	
Std VoteGap*Std Centered Capita/1000	37.845	0.00000	
Std Centered Perc_Asian	26.355	0.00000	
Std Centered Perc_65_84	21.370	0.00000	
Std Centered MedianAge	19.738	0.00000	
Std VoteGap*TimeLinearNormal	12.944	0.00000	
PolicyCentered	11.121	0.00000	^
Std VoteGap*Weekend	10.896	0.00000	
Std LogPopDensity	8.893	0.00000	
Std Centered GiniCoefficient	6.323	0.00000	
Std Centered Perc_Black	4.601	0.00003	
Std Centered Perc_Over_85	2.963	0.00109	
Std VoteGap*TimeQuadNormal	2.694	0.00202	
Std ProportionEmployed	1.780	0.01660	
Std VoteGap*Std ProportionEmployed	1.435	0.03674	
Std Centered Perc_Under_18	1.292	0.05107	
Std IncomeCentered	1.172	0.06730	
Std Centered Perc_Hispanic	0.957	0.11043	
Std VoteGap*Std Centered Perc_Black	0.788	0.16276	
Std Centered ProportionReligious	0.728	0.18688	
Std VoteGap*Std Centered ProportionReligious	0.715	0.19286	
Std VoteGap*Std LogPopDensity	0.677	0.21052	
Std VoteGap*Std Centered Perc_Asian	0.661	0.21819	
Std VoteGap*Std Centered Perc_Over_85	0.550	0.28176	
Std VoteGap*Std Centered Perc_Hispanic	0.335	0.46218	
Std VoteGap*Std IncomeCentered	0.229	0.59051	
Std VoteGap*Std Centered GiniCoefficient	0.222	0.60046	
Std VoteGap*Std Centered Perc_65_84	0.178	0.66419	
Std VoteGap	0.135	0.73336	^
Std VoteGap*Std Centered MedianAge	0.072	0.84654	
Std VoteGap*Std Centered Perc_Under_18	0.050	0.89051	

Summary of Fit

RSquare	0.733526
RSquare Adj	0.733492
Root Mean Square Error	8.776272
Mean of Response	25.74828
Observations (or Sum Wgts)	274330

AICc 1992409
BIC 1992820

Parameter Estimates

Term	Estimate	Std Error	DFDen	t Ratio	Prob>|t|	Lower 95%	Upper 95%
Intercept	18.425004	0.175044	6221	105.26	<.0001*	18.081858	18.76815
Std VoteGap	0.6811825	1.979149	27.17	0.34	0.7334	-3.378523	4.7408883
Std VoteGap*Std Centered Perc_Black	-2.376331	1.69908	373.8	-1.40	0.1628	-5.717283	0.9646213
Std VoteGap*Std Centered Perc_Asian	-1.899979	1.542342	1470	-1.23	0.2182	-4.925406	1.1254486
Std VoteGap*Std Centered Perc_Hispanic	-1.273382	1.729818	321.3	-0.74	0.4622	-4.676583	2.1298182
Std VoteGap*Std Centered GiniCoefficient	0.7584714	1.44793	1880	0.52	0.6005	-2.081248	3.5981903
Std VoteGap*Std Centered Perc_Over_85	1.8375115	1.706256	1064	1.08	0.2818	-1.510497	5.1855197
Std VoteGap*Std Centered Perc_65_84	-1.564079	3.602074	1741	-0.43	0.6642	-8.628925	5.5007667
Std VoteGap*Std Centered Perc_Under_18	-0.249811	1.814518	1742	-0.14	0.8905	-3.808673	3.3090503
Std VoteGap*Std ProportionEmployed	-3.475404	1.659946	558.7	-2.09	0.0367*	-6.735902	-0.214906
Std VoteGap*Std Centered ProportionReligious	-1.945897	1.493612	1353	-1.30	0.1929	-4.875944	0.9841507
Std VoteGap*Std Centered MedianAge	0.7061777	3.64822	1723	0.19	0.8465	-6.449228	7.8615838
Std VoteGap*Std Centered Capita/1000	-0.308495	0.023748	3e+5	-12.99	<.0001*	-0.355041	-0.261949
Std VoteGap*PolicyCentered[-0.49]	1.0969316	0.055813	3e+5	19.65	<.0001*	0.9875391	1.2063241
Std VoteGap*Std LogPopDensity	-2.314377	1.846326	591.1	-1.25	0.2105	-5.940535	1.3117805
Std VoteGap*Std IncomeCentered	1.0269898	1.907901	946.9	0.54	0.5905	-2.717214	4.7711934
Std VoteGap*(Weekend-0.28556)	0.2512428	0.037099	3e+5	6.77	<.0001*	0.1785294	0.3239561
Std VoteGap*(TimeQuadNormal-0.32822)	-0.719701	0.233162	3e+5	-3.09	0.0020*	-1.176692	-0.26271
Std VoteGap*(TimeLinearNormal-0.49478)	-1.724824	0.232326	3e+5	-7.42	<.0001*	-2.180177	-1.269471
TimeLinearNormal	12.699116	0.230618	3e+5	55.07	<.0001*	12.247112	13.15112
TimeQuadNormal	-3.088715	0.22983	3e+5	-13.44	<.0001*	-3.539176	-2.638255
Weekend	2.7894194	0.0371	3e+5	75.19	<.0001*	2.7167039	2.862135
Std IncomeCentered	-0.488798	0.267088	4706	-1.83	0.0673	-1.012416	0.03482
Std LogPopDensity	-1.664546	0.273747	5376	-6.08	<.0001*	-2.201202	-1.12789
PolicyCentered[-0.49]	0.404956	0.059144	2e+5	6.85	<.0001*	0.2890346	0.5208774
Std Centered Capita/1000	0.546505	0.023704	3e+5	23.06	<.0001*	0.5000465	0.5929634
Std Centered MedianAge	4.6065305	0.495421	7719	9.30	<.0001*	3.63537	5.5776911
Std Centered ProportionReligious	-0.283166	0.214513	5325	-1.32	0.1869	-0.703699	0.1373677
Std ProportionEmployed	-0.477807	0.199391	5072	-2.40	0.0166*	-0.868699	-0.086915
Std Centered GiniCoefficient	-1.087915	0.215718	4527	-5.04	<.0001*	-1.510828	-0.665001
Std Centered Perc_65_84	-4.591446	0.473324	6364	-9.70	<.0001*	-5.519319	-3.663572
Std Centered Perc_Asian	-5.292379	0.487523	4046	-10.86	<.0001*	-6.248193	-4.336565
Std Centered Perc_Black	-1.182479	0.280375	5722	-4.22	<.0001*	-1.73212	-0.632838
Std Centered Perc_Hispanic	0.3840782	0.240562	4142	1.60	0.1104	-0.087553	0.8557097
Std Centered Perc_Over_85	-0.837704	0.256271	4704	-3.27	0.0011*	-1.340116	-0.335292
Std Centered Perc_Under_18	0.5569046	0.285399	5051	1.95	0.0511	-0.002601	1.1164105

REML Variance Component Estimates

Random Effect	Var Ratio	Var Component	Std Error	95% Lower	95% Upper	Wald p-Value	Pct of Total
FIPS*VoteGap[StateNum]	0.0540129	4.1602342	0.1349464	3.8957442	4.4247242	<.0001*	5.119
VoteGap*StateNum	0.0012098	0.0931805	0.0441807	0.0065879	0.1797732	0.0349*	0.115
Residual		77.022946	0.2097034	76.613582	.		94.767
Total		81.276361	0.2466883	80.79502	81.762036		100.000

-2 LogLikelihood = 1992331.2041
Note: Total is the sum of the positive variance components.
Total including negative estimates = 81.276361

Fixed Effect Tests

Source	Nparm	DF	DFDen	F Ratio	Prob > F
Std VoteGap	1	1	27.17	0.1185	0.7334
Std VoteGap*Std Centered Perc_Black	1	1	373.8	1.9561	0.1628
Std VoteGap*Std Centered Perc_Asian	1	1	1470	1.5175	0.2182
Std VoteGap*Std Centered Perc_Hispanic	1	1	321.3	0.5419	0.4622
Std VoteGap*Std Centered GiniCoefficient	1	1	1880	0.2744	0.6005
Std VoteGap*Std Centered Perc_Over_85	1	1	1064	1.1598	0.2818
Std VoteGap*Std Centered Perc_65_84	1	1	1741	0.1885	0.6642
Std VoteGap*Std Centered Perc_Under_18	1	1	1742	0.0190	0.8905
Std VoteGap*Std ProportionEmployed	1	1	558.7	4.3835	0.0367*
Std VoteGap*Std Centered ProportionReligious	1	1	1353	1.6973	0.1929
Std VoteGap*Std Centered MedianAge	1	1	1723	0.0375	0.8465
Std VoteGap*Std Centered Capita/1000	1	1	3e+5	168.7439	<.0001*
Std VoteGap*PolicyCentered	1	1	3e+5	386.2638	<.0001*
Std VoteGap*Std LogPopDensity	1	1	591.1	1.5713	0.2105
Std VoteGap*Std IncomeCentered	1	1	946.9	0.2897	0.5905
Std VoteGap*Weekend	1	1	3e+5	45.8626	<.0001*
Std VoteGap*TimeQuadNormal	1	1	3e+5	9.5277	0.0020*
Std VoteGap*TimeLinearNormal	1	1	3e+5	55.1179	<.0001*
TimeLinearNormal	1	1	3e+5	3032.231	<.0001*
TimeQuadNormal	1	1	3e+5	180.6101	<.0001*
Weekend	1	1	3e+5	5652.922	<.0001*
Std IncomeCentered	1	1	4706	3.3493	0.0673
Std LogPopDensity	1	1	5376	36.9736	<.0001*
PolicyCentered	1	1	2e+5	46.8804	<.0001*
Std Centered Capita/1000	1	1	3e+5	531.5678	<.0001*
Std Centered MedianAge	1	1	7719	86.4566	<.0001*
Std Centered ProportionReligious	1	1	5325	1.7425	0.1869
Std ProportionEmployed	1	1	5072	5.7424	0.0166*
Std Centered GiniCoefficient	1	1	4527	25.4340	<.0001*
Std Centered Perc_65_84	1	1	6364	94.0985	<.0001*
Std Centered Perc_Asian	1	1	4046	117.8451	<.0001*
Std Centered Perc_Black	1	1	5722	17.7873	<.0001*
Std Centered Perc_Hispanic	1	1	4142	2.5491	0.1104
Std Centered Perc_Over_85	1	1	4704	10.6852	0.0011*
Std Centered Perc_Under_18	1	1	5051	3.8076	0.0511

Mediation Output from STATA

Equation 1 (c_path): caserate = z_trump state_policy2 weekend2 z_median_household_income_2018 z_medianage_county_2018 z_pct_age0to17 z_pct_age65to84 z_pct_age85plus z_pop_density z_religion z_percentemployed z_gini z_perc_black z_perc_asian z_perc_hisplatin

```
Performing EM optimization:

Performing gradient-based optimization:

Iteration 0:   log likelihood = -962439.31

Iteration 1:   log likelihood = -962377.61

Iteration 2:   log likelihood = -962377.47

Iteration 3:   log likelihood = -962377.47  (backed up)


Computing standard errors:

Mixed-effects ML regression                 Number of obs     =    187,731

-------------------------------------------------------------

                |     No. of      Observations per Group

 Group Variable |     Groups    Minimum    Average    Maximum

----------------+--------------------------------------------

     state_fips |         50         78    3,754.6     13,221

    county_fips |      2,905          1       64.6        156

-------------------------------------------------------------


                                      Wald chi2(15)     =    1201.33

Log likelihood = -962377.47                 Prob > chi2       =     0.0000


------------------------------------------------------------------------------------

         caserate |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------------+----------------------------------------------------------------
```

```
z_trump |   .5727842   .1957359    2.93   0.003    .1891489    .9564195
state_policy2 |  -9.700722   .3174333   -30.56   0.000   -10.32288   -9.078564
weekend2 |  -.8774856   .2058065    -4.26   0.000   -1.280859   -.4741122
z_median_househ~2018 |  -.4110965   .1710004   -2.40   0.016   -.7462511   -.0759419
z_medianage_cou~2018 |  -.2209524   .3033391   -0.73   0.466   -.8154861    .3735813
z_pct_age0to17 |  -.2055343   .1554227   -1.32   0.186   -.5101572    .0990887
z_pct_age65to84 |  -.3768463    .302042   -1.25   0.212   -.9688378    .2151451
z_pct_age85plus |  -.3643495   .1422436   -2.56   0.010   -.6431418   -.0855573
z_pop_density |   1.137398   .1652849    6.88   0.000    .8134459    1.461351
z_religion |  -.2278012   .1233894   -1.85   0.065     -.46964    .0140376
z_percentemployed |   .3259839   .1475147    2.21   0.027    .0368603    .6151074
z_gini |  -.0934035   .1209596   -0.77   0.440     -.33048    .1436731
z_perc_black |   .8738068   .1969857    4.44   0.000    .4877219    1.259892
z_perc_asian |  -.3126837    .144349   -2.17   0.030   -.5956025   -.0297649
z_perc_hisplatin |   .8057681   .1693474    4.76   0.000    .4738533    1.137683
_cons |   9.715367   .4135998   23.49   0.000    8.904726    10.52601
------------------------------------------------------------------------------------------
------------------------------------------------------------------------------
Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
state_fips: Identity         |
sd(_cons) |   2.606013   .3189675     2.050182    3.312539
-----------------------------+------------------------------------------------
county_fips: Identity        |
sd(_cons) |   .0000301   .0000144     .0000117    .0000771
-----------------------------+------------------------------------------------
sd(Residual) |   40.73516   .0664895     40.60505    40.86568
------------------------------------------------------------------------------
```

LR test vs. linear model: chi2(2) = 248.47 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

Equation 2 (a_path): z_dist1_lag_wk23 = z_trump state_policy2 weekend2 z_median_household_income_2018 z_medianage_county_2018 z_pct_age0to17 z_pct_age65to84 z_pct_age85plusz_pop_density z_religion z_percentemployed z_gini z_perc_black z_perc_asian z_perc_hisplatin

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log likelihood = -823071.8

Iteration 1: log likelihood = -823071.8

Computing standard errors:

Mixed-effects ML regression Number of obs = 187,731

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
state_fips	50	78	3,754.6	13,221
county_fips	2,905	1	64.6	156

Wald chi2(15) = 13978.29

Log likelihood = -823071.8 Prob > chi2 = 0.0000

----

z_dist1_lag_wk23 | Coef. Std. Err. z P>|z| [95% Conf. Interval]

```
---------------------+----------------------------------------------------------------
           z_trump |   -2.44597   .2698372    -9.06   0.000    -2.974841   -1.917098
      state_policy2 |   17.69359   .1553053   113.93   0.000     17.3892    17.99798
          weekend2 |   .3258158   .0964295     3.38   0.001     .1368174    .5148142
z_median_househ~2018 |   2.910725   .2366427    12.30   0.000     2.446914    3.374536
z_medianage_cou~2018 |   4.305255    .410812    10.48   0.000     3.500079    5.110432
     z_pct_age0to17 |   1.451149   .2072042     7.00   0.000     1.045037    1.857262
    z_pct_age65to84 |  -1.904388   .4063282    -4.69   0.000    -2.700777   -1.107999
   z_pct_age85plus |  -.3475431   .1886217    -1.84   0.065    -.7172348    .0221487
      z_pop_density |   1.092045   .2302174     4.74   0.000     .6408274    1.543263
         z_religion |  -.2957013   .1648071    -1.79   0.073    -.6187174    .0273148
  z_percentemployed |  -1.582788   .2007372    -7.88   0.000    -1.976225    -1.18935
             z_gini |  -.1510895   .1617153    -0.93   0.350    -.4680458    .1658667
        z_perc_black |  -.2331266   .2742726    -0.85   0.395     -.770691    .3044378
        z_perc_asian |  -.4033457   .2129179    -1.89   0.058    -.8206572    .0139658
   z_perc_hisplatin |   .1796545   .2312782     0.78   0.437    -.2736425    .6329516
             _cons |   19.24425   .8530939    22.56   0.000     17.57222    20.91628
--------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
state_fips: Identity         |
                  sd(_cons) |   5.799601   .6228398      4.698774     7.15833
-----------------------------+------------------------------------------------
county_fips: Identity        |
                  sd(_cons) |   6.391316   .1008888      6.196605    6.592145
-----------------------------+------------------------------------------------
               sd(Residual) |   19.08343    .031405      19.02197    19.14508
```

LR test vs. linear model: chi2(2) = 18099.51 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

Equation 3 (b_path & c_prime): caserate = z_dist1_lag_wk23 z_trump state_policy2 weekend2 z_median_household_income_2018 z_medianage_county_2018 z_pct_age0to17 z_pct_age65to84 z_pct_age85plus z_pop_density z_religion z_percentemployed z_gini z_perc_black z_perc_asian z_perc_hisplatin

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0: log likelihood = -962043.84

Iteration 1: log likelihood = -961983.67

Iteration 2: log likelihood = -961983.58

Iteration 3: log likelihood = -961983.58 (backed up)

Computing standard errors:

Mixed-effects ML regression Number of obs = 187,731

Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
state_fips	50	78	3,754.6	13,221
county_fips	2,905	1	64.6	156

Wald chi2(16) = 1981.53

Log likelihood = -961983.58 Prob > chi2 = 0.0000

----

caserate | Coef. Std. Err. z P>|z| [95% Conf. Interval]

```
---------------------+----------------------------------------------------------------
   z_dist1_lag_wk23 |  -.1318444   .0046798   -28.17   0.000    -.1410166   -.1226723
            z_trump |   .1784694   .1916394     0.93   0.352     -.197137    .5540757
      state_policy2 |  -7.337807   .3212423   -22.84   0.000    -7.967431   -6.708184
           weekend2 |  -.8380519   .2053897    -4.08   0.000    -1.240608   -.4354955
z_median_househ~2018 |  -.0454803   .1696796    -0.27   0.789    -.3780462    .2870856
z_medianage_cou~2018 |   .4256838   .3019535     1.41   0.159    -.1661342    1.017502
     z_pct_age0to17 |  -.0215242   .1544633    -0.14   0.889    -.3242668    .2812184
    z_pct_age65to84 |  -.6792259   .3001108    -2.26   0.024    -1.267432   -.0910195
    z_pct_age85plus |  -.4071343   .1409754    -2.89   0.004    -.6834411   -.1308276
      z_pop_density |   1.221653   .1619352     7.54   0.000     .9042663    1.539041
         z_religion |  -.2665872   .1222501    -2.18   0.029     -.506193   -.0269814
  z_percentemployed |   .0809308   .1453387     0.56   0.578    -.2039278    .3657894
             z_gini |  -.1206225   .1203108    -1.00   0.316    -.3564274    .1151824
       z_perc_black |   .7671036   .1914339     4.01   0.000        .3919    1.142307
       z_perc_asian |  -.3476335   .1406076    -2.47   0.013    -.6232194   -.0720476
   z_perc_hisplatin |   .8092192    .165718     4.88   0.000     .4844179    1.134021
              _cons |   12.24884   .3515669    34.84   0.000     11.55978    12.93789
--------------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects Parameters  |   Estimate   Std. Err.     [95% Conf. Interval]
-----------------------------+------------------------------------------------
state_fips: Identity         |
                   sd(_cons) |   2.031054   .2687705      1.567045    2.632458
-----------------------------+------------------------------------------------
county_fips: Identity        |
                   sd(_cons) |    .000031   .0000111      .0000153    .0000627
-----------------------------+------------------------------------------------
```

sd(Residual) | 40.65206 .0663543 40.52222 40.78232

LR test vs. linear model: chi2(2) = 157.09 Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

The mediator, z_dist1_lag_wk23, is a level 1 variable

c_path = .57278419

a_path = -2.4459697

b_path = -.13184442

c_prime = .17846937 same as dir_eff

ind_eff = .32248747

dir_eff = .17846937

tot_eff = .50095684

proportion of total effect mediated = .64374302

ratio of indirect to direct effect = 1.8069625

ratio of total to direct effect = 2.8069625

. bootstrap indeff = r(ind_eff) direff = r(dir_eff) toteff = r(tot_eff), reps(100) cluster(state_fips) idcluster(nstate_fips) group(county_fips): ml_mediation, dv(caserate) iv(z_trump) mv(z_dist1_lag_wk23) cv(state_policy2 weekend2 z_median_household_income_2018 z_medianage_county_2018 z_pct_age0to17 z_pct_age65to84 z_pct_age85plus z_pop_density z_religion z_percentemployed z_gini z_perc_black z_perc_asian z_perc_hisplatin) l3id(state_fips) l2id(county_fips) mle

(running ml_mediation on estimation sample)

Bootstrap replications (100)

----+--- 1 ---+--- 2 ---+--- 3 ---+--- 4 ---+--- 5

.... 50

```
..................................................  100

Bootstrap results                    Number of obs    =    187,731
                                       Replications     =       100

      command:  ml_mediation, dv(caserate) iv(z_trump) mv(z_dist1_lag_wk23)
                    cv(state_policy2 weekend2 z_median_household_income_2018
                    z_medianage_county_2018 z_pct_age0to17 z_pct_age65to84
                    z_pct_age85plus z_pop_density z_religion z_percentemployed z_gini
                    z_perc_black z_perc_asian z_perc_hisplatin) l3id(state_fips)
                    l2id(county_fips) mle
       indeff:  r(ind_eff)
       direff:  r(dir_eff)
       toteff:  r(tot_eff)

                    (Replications based on 50 clusters in state_fips)
------------------------------------------------------------------------------
             |   Observed   Bootstrap                         Normal-based
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      indeff |   .3224875   .0890438     3.62   0.000     .1479647    .4970102
      direff |   .1784694   .2910112     0.61   0.540    -.3919022    .7488409
      toteff |   .5009568   .2497123     2.01   0.045     .0115297     .990384
------------------------------------------------------------------------------
```