Report.md

Final Project Report

Data-Driven Analysis of Popular Beliefs about COVID-19

Authors: Joseph Koshakow, Vivian Lee, James Mahler, Bradley Warren

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Abstract: Given the rising concerns about the long-standing socioeconomic inequalities in our country that have been exposed since Covid-19 came about, we sought to explore these strong claims and take a data-driven approach to examine the correlation between a region's socioeconomic makeup and how it has been affected by the virus throughout 2020. We contribute a Streamlit web application with interactive maps and visualizations that enables users to (1) explore the relationships between different socioeconomic indicators and Covid-19 statistics and (2) analyze the most common words used in tweets written by Twitter users from different states throughout the summer of 2020. We supplement our app with a narrative article that both acts as an instructional tutorial and highlights several insights we were able to gain from using our app.

Introduction

In this work, we present a Streamlit web application with interactive visualizations that enable the exploration of the relationships between different socioeconomic indicators, posts on Twitter (tweets) and Covid-19 statistics across United States counties. We demonstrate the utility of our app with a mini case study where we explore the Bureau of Labor Statistics' claim about the role the ability to telework has on covid susceptibility. We present our insights in the form of an interactive narrative embedded in our app which doubles as a guided tutorial that teaches users how to use the app to explore their own questions and encourages them to develop evidence-based opinions.

Related Work

Our work was motivated by increasing calls for awareness of social inequalities in our country that have been exposed by Covid-19. These include news articles and paper publications about African-Americans experiencing a disproportionate number of Covid-related deaths, reduced childcare services and subsequent increase in female unemployment, and Covid's negative impact on poor and vulnerable groups [5, 3, 4]. Such articles have sparked both discussions and debates between our own friends and families. As a result, we decided to create an app that would use publicly available data to help support or dispel users' beliefs and opinions. We show examples of how the app helped answer a few of our own initial questions and the additional insights we were able to gain from it in our results below.

Methods

Initial Hypotheses: We started by writing down a set of questions about the virus' impact; these came from commonly held beliefs and hearsay among our personal social networks and newsfeeds (Table 1).

Questions (Correlations Explored)	Hypothesis	Nationwide Result
Population vs number of covid cases	Positive	Negative (-0.07)
Poverty vs number of covid cases	Positive	Positive (0.13)
Median household income vs number of covid cases	None	Negative (-0.15)
Education level vs number of covid cases	Negative	Negative (-0.16)

Table 1: Our set of questions explored, initial hypotheses prior to looking at the data, and the actual results along with their correlations when considering all US counties

Datasets: We acquired the data for our app from established public sources like the Delphi Research Group at Carnegie Mellon University (Delphi), the United States Department of Agriculture (USDA), and Twitter [1, 7]. Once our data was organized and visualizations implemented, we used our app to see what answers the data could provide to our questions.

Tweets Analysis

Data Retrieval: Twitter has a public API that allows you to programmatically fetch tweets and tweet related data. Our COVID tweet dataset provides 239,861,658 tweet IDs, but did not provide the actual tweet content or any geo location [2]. We used the Tweepy library to connect with the Twitter API and used the tweet IDs to retrieve tweet contents and geo data. We organized the tweets into two categories: (1) Global tweets where we take a random sample of roughly 24,000 tweet IDs from all over the world and get the tweet contents. (2) US State tweets where for all the tweet IDs with associated geo data, we fetch the tweet contents and store each US state's tweets separately.

Visualization Design Decisions: We provide two ways to visualize the tweets, with an option for the user to toggle between the two options. The first option is through a word cloud, which is a visually appealing way to display aggregated contents of tweets that also gives a relative comparison of word use. Additionally for the state tweets we shape the word cloud in the shape of the state borders, which allows to encode the state into the visualization as well help the user connect the state to the words. The second option is through a bar chart that displays word counts. Bar charts give more accurate numbers for each word and allow you to more easily compare words and give a sense of scale. We believe that users with different analytical preferences will prefer different different representations for the tweets which is why we included both.

Socioeconomic Indicators Analysis

Data Retrieval: With the understanding that the socioeconomic makeup of a state can vary significantly between its counties, we chose to fetch all of the county-level covid data from Delphi's covidcast endpoint. The span of time varied for each feature and we found that some counties had more recorded data than others (Appendix A).

On our initial fetch, we retrieved raw numbers for the numeric covid features. However, we later switched to retrieving features that were scaled appropriately to account for the different population sizes between counties (e.g. the number of cases per 100,000 people and percent-based features). We removed data rows with values < 0, deemed impossible, and removed rows that represented state totals instead of individual counties. We also merged the covidcast datasets with the US Census Bureau's 2019 FIPS Codes dataset to obtain the county names. For our socioeconomic indicator data, we used the most recent data published by the USDA. In our analysis, we look at the following 4 indicator categories: Poverty (2018), Unemployment and Median Household Income (2018), Population (2018), and Education (2014-2018). Each indicator has a number of different features measured. For brevity, we do not list them here but encourage readers to check out our app online.

Visualization Design Decisions: We used the Altair visualization library to create two side-by-side maps for each US state. The counties on the left map are colored based on the user-selected socioeconomic feature and those on the right map based on the user-selected covid statistic. We also add interactive features like tooltips, linked highlighting for counties between the two maps, and the ability to select which counties are displayed or not displayed on the correlation and time series plots below the maps by clicking on the counties on the covid state map. Users can change the default behavior of the multi-select feature (all vs none) by clicking a checkbox above the map. We organize our covid features into two distinct groups: cumulative and daily. Each cumulative feature is accompanied by a correlation plot between itself and the selected socioeconomic feature. Users can specify the date range and aggregate function used for the daily features. These are accompanied by a time series plot to show the change in the daily feature over the specified date range for the selected counties. We use layering and add a gray background behind the maps to handle cases where a county has no data for the selected feature.l

Though the side-by-side state maps allowed for easy intra-state comparisons, we received feedback that our app design did not facilitate inter-state comparisons. At that iteration of our app, the user could manually change the state displayed by selecting a new state from a dropdown list in the sidebar but could not view multiple states simultaneously unless they had multiple browser windows open. In response to this feedback, we decided to add similar interactive maps to compare socioeconomic and covid features across the entire United States. With these new maps, the user can see how all of the counties in the US compare. These maps enable a fuller birds-eye view of the socioeconomic and covid differences across the country and allow the user to identify clusters or belts of counties that have similar metrics.

Results

The results of our analysis are summarized in Table 1. We used additional news articles and research publications that covered topics similar to the questions we explored to get a better understanding of our results and find hidden variables in some of the correlations.

We were surprised to see a weak negative relationship (-0.07) between county population size and cumulative number of covid cases per 100K people, given some of the early news articles that suggested a positive correlation between population density and covid cases (Appendix B and C). When we look at the correlations within individual states, we find that they are not consistent. Florida shows a negative correlation (-0.11), California and New York show positive correlations (0.13 and 0.59), and Washington seems to show virtually no correlation (-0.01) for these variables. So ultimately we conclude that population size is not an indicative feature for predicting covid susceptibility.

The Bureau of Labor and Statistics (Bureau) has suggested that the ability to work from home (telework) is a hidden variable in estimating covid's impact [6]. We use our app to explore additional correlations that can support the validity of their claim. We find that there is indeed a positive correlation (0.12) between low education (percentage of adults who did not complete high school) and the cumulative number of cases in a US county. Conversely, there is a negative correlation (-0.16) between the percentage of adults who completed high school and cumulative number of cases in a county. Since high-paying white collar jobs result in higher median household income (MHHI), we analyze that socioeconomic feature next and find a negative correlation (-0.15) between MHHI and cumulative cases (Appendix B, D, E). Our results support the Bureau's claim; we find that the ability to telework is largely influenced by socioeconomic factors and it in turn has a large influence on the size of the negative impact covid has on a county.

Discussion

In this project, we were able to put together an application that lets users explore COVID data across the United States. Users are able to explore the association between various demographic data, such as income and education, and various COVID metrics, such as cumulative and incident cases, related deaths, mask wearing, and more on a county-by-county basis across the United States. This lets users see whether or not their inferences about such associations is backed up by data or not. We also allow users to see how COVID is being talked about in different states, with the use of word clouds and word frequency charts from Twitter data.

Limitations: One primary limitation of our work is the lack of more data to explore. There are many more questions to be asked on this topic (see the next section), but there is only so much time and data available for this project. More socioeconomic features could have led to the uncovering of additional hidden variables and correlations. Some counties had little to no data for certain features so we were unable to develop a conclusive insight about their individual socioeconomic and covid correlations.

Future Work

There are several ways in which our work could be built upon. One interesting thing to look at would be the association between major events and the COVID data in the following weeks following such events. For example, one could look at whether or not COVID cases spiked after large gatherings such as political events (i.e. Trump rallies). Another such study could be the trend in COVID cases in college towns when students returned to campus. Many in the media have suggested that these events have led to significant increases in COVID cases, so it would be interesting to analyze the data to see whether or not these claims have data to support them.

Lastly, our work could be built upon by studying the economics of the pandemic. We know that the pandemic has led to a large increase in unemployment, and that many small businesses have been forced to close. This leads to many potential questions: who is suffering the most economically? How have strict lockdowns played a role in this? And many more.

References

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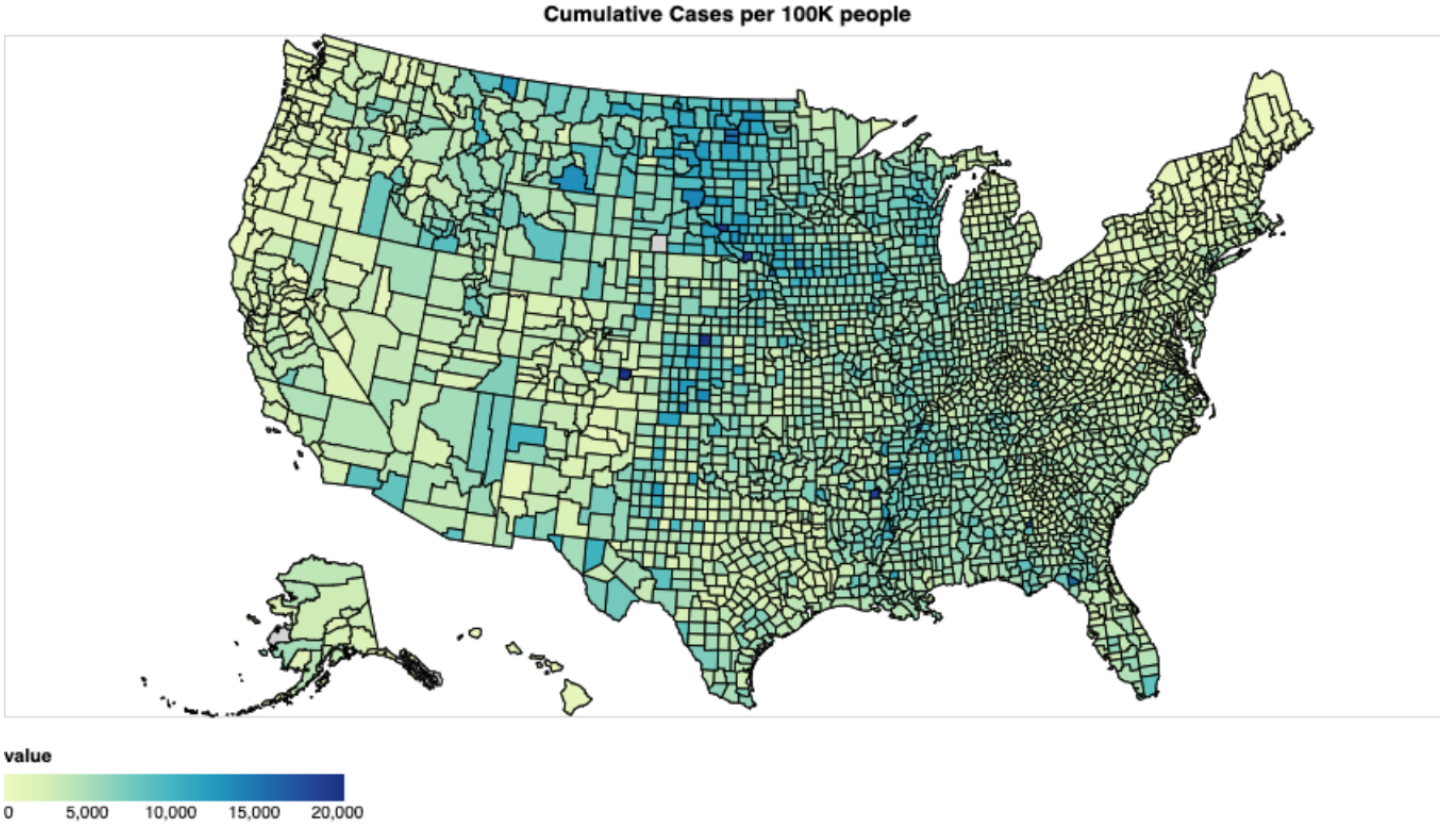
Appendix

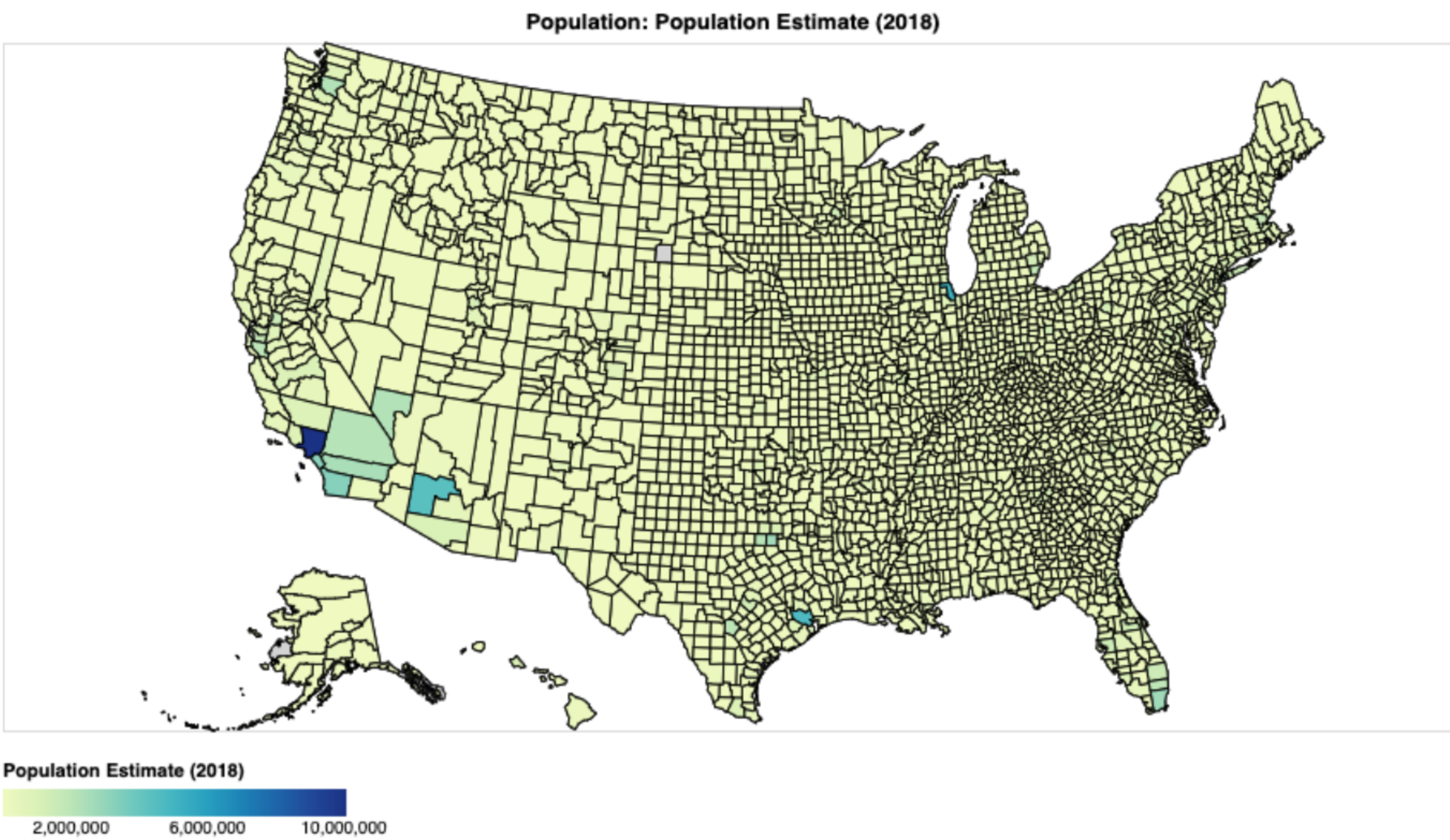
Appendix A: Covid-19 Feature and the available date range for each dataset. Note that the available date range for counties within the same dataset varied as some counties did not have as much recorded data as others. This data was fetched on Dec 2, 2020.

Covid-19 Feature	Earliest Date Available	Latest Date Available
Cumulative Cases per 100K people	N/A	Nov 29, 2020
Daily New Cases per 100K people	Jan 25, 2020	Nov 29, 2020
Cumulative Deaths per 100K people	N/A	Nov 29, 2020
Daily Deaths per 100K people	Jan 25, 2020	Nov 29, 2020
Daily % Covid-Related Doctor Visits	Feb 1, 2020	Nov 27, 2020
% People Wearing Masks in Public in Past 5 Days	Sep 8, 2020	Nov 30, 2020
% People Tested for Covid-19 in Past 14 Days	Sep 8, 2020	Nov 30, 2020
% Positive Covid Tests in Past 14 Days	Sep 9, 2020	Nov 30, 2020
% People Not Tested who Wanted Tests	Sep 8, 2020	Nov 30, 2020

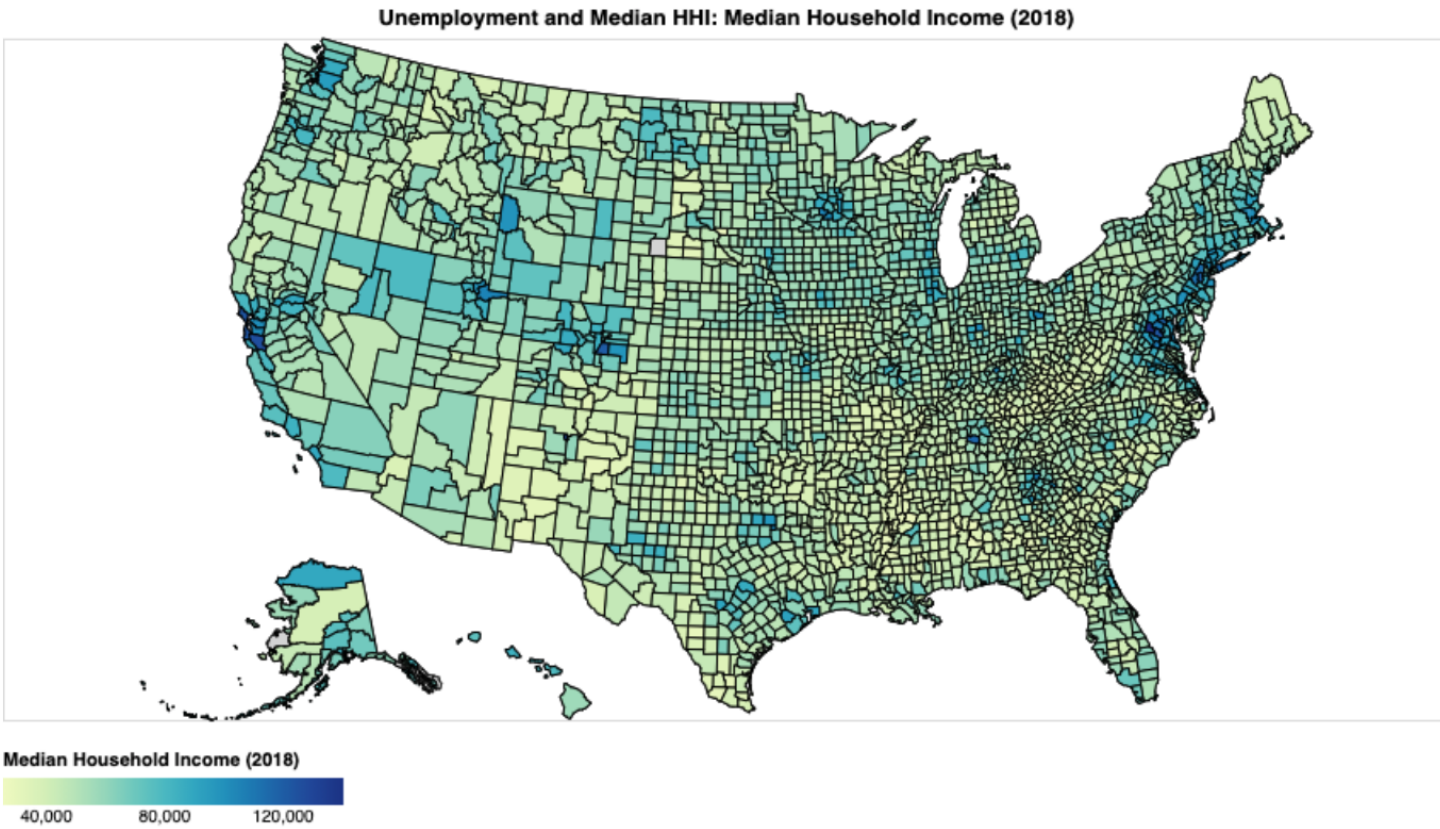
Appendix B: Map of US counties colored based on their cumulative number of Covid-19 cases per 100K people as of Nov 29, 2020. Values increase as color changes from light green to dark blue.



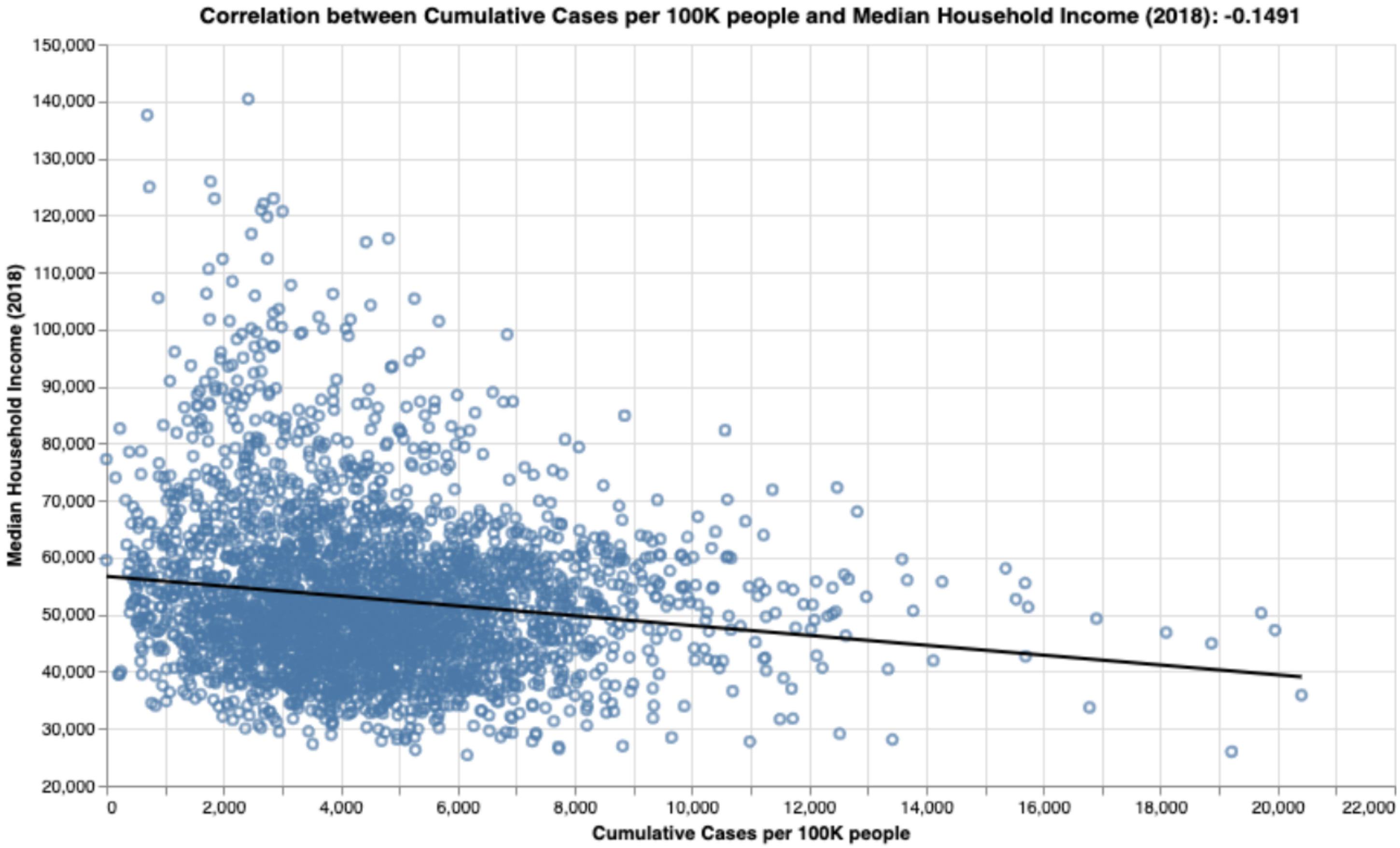
Appendix C: Map of US counties colored based on their estimated populations in 2018 recorded by the USDA. Values increase as color changes from light green to dark blue.



Appendix D: Map of US counties colored based on their reported median household incomes in 2018 recorded by the USDA. Values increase as color changes from light green to dark blue.



Appendix E: Correlation plot of median household income (2018) vs cumulative number of Covid-19 cases per 100K people as of Nov 29, 2020. The plot shows a negative correlation (-0.1491) between the two features.


Correlation between Cumulative Cases per 100K people and Median Household Income (2018): -0.1491
Median Household Income (2018)
150,000
140,000
130,000
120,000
110,000
100,000
90,000
80,000
70,000
60,000
50,000
40,000
30,000
20,000
0
2,000
4,000
6,000
8,000
10,000
12,000
14,000
16,000
18,000
20,000
22,000
Cumulative Cases per 100K people