Article

People in Pandemic: Factors Impacting Compliance with Interventions

Morteza Maleki [1,*], Mohsen Bahrami [2], Monica Menendez [3], Jose Balsa-Barreiro [3]

[1] Department of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, Georgia 30332, United States
[2] Massachusetts Institute of Technology, Institute for Data, Systems and Society, 77 Massachusetts Avenue, Cambridge, MA 02139, United States
[3] Division of Engineering, New York University Abu Dhabi, Abu Dhabi 129188, United Arab Emirates
* Correspondence: mmaleki3@gatech.edu

Abstract: Extensive research has been conducted on people's response to governmental orders and behavioral analysis of such responses since the COVID-19 pandemic in 2020. While most of the scholarly work has addressed the relationship between various socioeconomic variables with following governmental orders correctly, little attention has been paid to what constitutes a response and if people behave differently when faced with different mandates no matter how similar they may seem at the first glance. This work attempts to shed light on the fact that a response may be different depending on various socioeconomic status of the individuals and suggests people's behaviors to be analyzed after careful consideration of these variables specifically. In this work, the relationship between these socioeconomic variables and three main governmental mandates and/or policies for the U.S. population has been analyzed in order to isolate the most influential variables impacting behavior in response to these policies.

Keywords: COVID-19; non-pharmaceutical interventions, mask usage; movement change; social distancing; vaccination; behavioral analysis; policy recommendations; governmental intervention

Citation: Maleki, M.; Bahrami, M.; Menendez. M. and Balsa-Barreiro, J. People in Pandemic: Factors Impacting Compliance with Interventions. *Sustainability* **2021**, *1*, 0. ...

Received: December 5, 2021
Accepted: NA
Published: NA

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

1. Introduction

The emergence of the novel SARS-CoV-2 virus (aka COVID-19) has dramatically impacted the world since the last year and half. Since the first cases were reported in the Chinese province of Wuhan in late 2019, the virus has been rapidly spreading across the globe. In March 2020, the situation was declared a pandemic by the World Health Organisation (WHO) when the world counted 4,291 deaths and more than 118,000 cases distributed in 114 countries. Until July 2021, 182M cases and 3.95M deaths were officially reported. Only the United States accounts for 33.6M of cases and 605K deaths [1].

The COVID-19 pandemic caught most states, especially western ones, devoid of answers. The still remaining large number of unanswered questions and the need to contain the impact of the pandemic forced most of the countries to adopt policies aiming to keep social distancing and to limit human mobility. Since the disease caused by coronavirus is a type of respiratory disease, policies were based on two main non-pharmaceutical interventions (NPIs), which were shelter-in-place, and face covering or mask wearing [2–4]. The shelter-in-place policies aimed to minimize the number and frequency of interactions among people by suggesting them to stay at home unless for essential reasons like commuting for work, attendance to medical appointments, or shopping for their daily-life. Such policies are followed by closing non-essential businesses and limiting the reception capacity of essential businesses in order to leave enough space for customers to keep social distancing.

Many studies have analyzed the effectiveness of such interventions and their impact on socio-economic status of urban areas. Those studies mostly use statistical modeling techniques to show the effectiveness of lockdown policies in mitigating the disease spread by reducing the level of human mobility and interactions [3–10]. Although these studies indicate that the adherence to social distancing order is crucial in controlling the disease spread, Holtz et al. [11] show ignoring the effects of social and geographical spillovers could negatively impact the effectiveness of such policies. Another line of research pertains to modeling and predicting the disease spread under various opening and closing scenarios [7,12]. These studies trace important insights for the implementation of more optimal policies.

Although all the mentioned studies discuss on the benefits of social distancing during the pandemic, they also indicate that the compliance to such policies show significant differences among socio-demographic groups, confirming the disproportionate impact of COVID-19 on these groups [7,13–15]. They show that the lower income neighborhoods are hit harder by the pandemic because they could not reduce their mobility levels. Lower income neighborhoods have been suffering from both higher infection as well as higher unemployment rates. Of course, there also are other factors such as education level and political beliefs that explain differences on adherence to social distancing measures [16–18], but less important in comparison to poverty level of neighborhoods. For example, Painter and Qiu [17] showed it in political terms, where American residents in Republican counties were less likely to completely stay at home after a state order. But also, they find that Democrats were less likely to respond to a state-level order when it was issued by a Republican governor relative to one issued by a Democratic governor. Other research analyzed the effectiveness of face covering in slowing the spread of coronavirus, showing significant differences among neighborhoods in adherence to mask wearing mandates [19–21].

The adoption of these interventions was temporary until the arrival of a pharmaceutical solution in form of massive vaccination campaign once it was approved. The provisional adoption of NPIs facilitated an escalated medical care into society. The crucial objective was to massively reduce the number of deaths caused directly by the virus, but also to avoid the collapse of the health system by keeping an optimal attention to all the people affected by the virus and/or any other ailments [1]. The successive approval of vaccines since the end of 2020 allowed to find a solution, which will be carried out along a transition period. This period is conducted for several months until a sufficiently large percentage of immunized population is reached. In this way, this could reduce exponentially the impact of the virus.

Most of the western countries had shown severe difficulties in efficiently containing the virus. From the very first moment, the different national strategies ranged from a coexistence with the virus to its total suppression (i.e., Zero COVID), being referent in both extremes the policies initially adopted by Sweden and China [22]. The unequal impact of the virus is very noticeable over the space. The virus has demonstrated a relevant variability in its spatial behavior, showing very different levels of incidence across multiple scales. Substantial differences were evident across continents, nations, regions, cities, and even neighborhoods. Thus, it is revealed the great territorial complexity associated to the virus and the emergence of vast territorial inequalities across multiple scales.

The real impact of the virus goes far beyond the uniquely health issues, producing a great uncertainty about its effects in other sectors. In fact, the pandemic foreshadows difficult economic scenarios [23]. Thus, some scholars anticipate an impoverishment of large sections of communities and emphasizing social inequalities. Beyond the great differences in terms of wealth (social coverage policies) and resources (i.e. health response capacity) with which the countries faced this pandemic, total number of cases reveals the real spread of the virus within each scale/community. The social behavior component of this community largely help to understand much better the actual impact of the virus.

Regardless of the particular interventions adopted in each region, a critical factor relates to the level of compliance with rules and recommendations by people. Thus, adherence of citizens to rules and their social behavior must be evaluated in order to better understand the real impact of the pandemic within each region. Collective responses should be investigated considering multiple factors and variables, which allows us to address the socio-spatial complexity behind the virus. Among these factors, aspects related to individual ideological and political preferences, the income and educational level and/or the the place where live (rural vs. urban) must be considered such differentiating factors on the virus spreading.

The impact of the virus was initially concentrated in large cities in most of the countries during the first wave. According to United Nations [24], urban areas became ground zero of the COVID-19 pandemic by concentrating around 90 percent of reported cases during the first wave. In the United States, the impact of the virus in the central states, less populated, was delayed and more contained in the first months. There, the compliance with the official rules was more lax due to the perception of a more distant danger.

In this paper we analyze the correlation between a group of socioeconomic variables with the people's response to the three main governmental policies adopted by American authorities for containing the pandemic: (a) mask adoption, (b) movement change, and (c) vaccination participation. The aim is to isolate what were most influential variables impacting people responses to these policies. The results allow us to know more about our collective behavior within human communities, in addition to design and implement more efficient and optimal policies in cases of emergencies in near future.

"In this study, we analyze which ones were the most influential factors/variables that explain the different compliance with the governmental policies for struggling against the COVID-19 pandemic. For each one of these governmental policies, we establish three main regressions. The dependent variables refer to these 3 governmental policies, whereas a set of 12 explanatory variables is considered. A detailed explanation of these variables is presented in the following subsections: (2.2.1) dependent and (2.2.2) explanatory variables."

For this purpose, this paper is structured as follows: Section 2 details materials and methods, Section 3 presents the results, Section 4 discusses about the findings presented, and finally Section 5 summarizes the most relevant findings presented along this paper.

2. Materials and Methods

We collect a bunch of data from different sources. These data are two-folded by concerning both the society (income, education, political preference) but also with the healthcare system (xxx). These variables are considered in relationship with the three main governmental policies adopted by American authorities for containing the COVID-19 pandemic: (a) mask adoption, (b) movement change, and (c) vaccination participation. In this way we individually individually quantify and identify the most influential factors for explaining the virus spreading across the United States.

Our analysis approach is conducted by applying a multiple regression to isolate the association between individual variables and people responses to three main governmental policies before introduced. For each one of these policies, we run a multiple regression model in order to evaluate the correlation between particular explanatory variables and people responses. Regression model for each individual people response is shown and explained in Section x.

The basic spatial unit here considered for conducting our analysis approach are counties. Briefly, the United States counts with 3,143 counties (and county equivalents) with great differences in both size and population. The largest ones are placed in the western sector, while the most densely populated are in both coastal shorelines. For running models across multiple scales, we implement a method based on Geographical Weighted Regression (GWR).

With regard to the software, we conduct our research by using some libraries for statistical analysis in Python (xxx and xxx), Tableau and ArcGIS for data mapping. Following, this section is organized into two sub-sections: (2.1) Datasets and variables, and (2.2) computational analysis.

2.1. Datasets and variables

We collect data from different official and unofficial/private sources such as the U.S. Census Bureau [1], the U.S. COVID-19 Atlas [2], the Facebook Dataset for Good Initiative [3], and a comprehensive survey published at New York Times [4].

The access to these datasets is guaranteed through a repository that we created for this research project in Github: https://github.com/mprtrmrtz/maskmandate

2.1.1. Epidemiological data

Epidemiological data are collected from different sources. The U.S. COVID-19 ATLAS gathers COVID-19 data related to number of test counts, new cases, and deaths. These data are available at level of counties and are updated on a weekly basis.

In addition to these, we collect some other indicators related to the health system that help better understand the impact of the pandemic. The data includes the percentage of essential workers and number of testing clinics by counties. All these data are collected from thecovidatlas.org portal.

In short, we collected 48,837 rows of data for the period between July 2 and July 14, 2020.

- ***Vaccination rate (VR)*** This variable presents the percentage of population who are completely vaccinated according to the dataset presented in the sub-section 2.1.1. The data is averaged from the beginning of 2021 until mid June 2021.
- ***COVID Average Testing (AT)*** We use the COVID-19 average testing counts from July 2nd to July 14th, 2020.
- ***COVID New Confirmed Cases (CC)*** This variable is the rate of new confirmed COVID-19 cases in 7 days period from July 2nd to July 14th, 2020.
- ***COVID New Confirmed Deaths (CD)*** The rate of new confirmed COVID-19 deaths in 7 days period from July 2nd to July 14th, 2020.

2.1.2. Healthcare Capacity

The variables we used are X, Y, and Z, and after initial evaluation we used percent essential workers.

- ***Percent Essential Workers (PW)*** from uscovidatlas.org, which is a dummy variable equal to 1 if there is a testing clinic in one county and equal to 0 if not. Data is last updated in June 1st, 2021.

2.1.3. Human mobility

We extract this data from Facebook Data for Good Initiative. This dataset provides information about human mobility in comparison to a baseline period that predates most social distancing policies. It also contains the percentage of devices completely stayed at home for the chosen time frame. Thus, this dataset allowed to determine how people

[1] https://data.census.gov/cedsci/
[2] https://theuscovidatlas.org/
[3] https://dataforgood.facebook.com/dfg/
[4] https://www.nytimes.com/interactive/2020/07/17/upshot/coronavirus-face-mask-map.html

reply to mandatory recommendations related to social distancing and shelter-in-place during the pandemic. This dataset is available at: https://data.humdata.org/dataset/movement-range-maps

- ***Movement change (MC)*** This variable represents the variation in human mobility at one time in comparison to a baseline of prior to the pandemic emergence in February 2020, when no shelter-in-place orders were issued. This parameter is estimated according to the dataset presented in the sub-section 2.1.2. These values have been averaged for dates between July 2nd and July 14th 2020, both days included.

2.1.4. Mask adoption

This data were extracted from a survey conducted by The New York Times between July 2nd and July 14th, 2020. In short, 250,000 responses from people resident across the country explicitly replied to the next question: "How often do you wear a mask in public when you expect to be within six feet of another person?" They could take five different options in an increasing level of accomplishment: (a) never, (b) rarely, (c) sometimes, (d) frequently, and (e) always. The sample allowed us to project how was the real mask adoption by counties. This dataset is available at: https://github.com/nytimes/covid-19-data/tree/master/mask-use

- ***Mask usage (MU)*** This variable shows the percentage of people declared they always comply with the mask mandate within six feet (about 1.8 meters) of other individuals in the survey presented in the sub-section 2.1.3.

2.1.5. Political preference

Based on the results of the last presidential elections (2020), we estimated the political preference by counties. For this, we collect the percentage of votes of the two major political parties in each county for implementing a rate between 0 and 1 for the most important parties: Democrats and Republicans.

- ***Political Index*** We use this variable to show the political preference in each county from the perspective of the winner of the last U.S. presidential elections and actual American President. This variable is a binary, equal to 1 if President Biden won that county and equal to 0 if he lost that county in the 2020 U.S. Presidential Election. We use this binary variable as an indicator of political preference for each county.

2.1.6. Socio-economic indicators

We also collect data providing information about various socio-economic indicators by county. Between them, we include population density, rate of unemployment, and some multiple indicators related to the level of poverty, security, average household income, and education. These datasets are sourced from the U.S. Census Bureau and the U.S. Department of Agriculture, Economic Research Service [5] and these corresponds to the most recent years published (2019 and 2020).

- ***Rurality Index (RI)*** We estimate a rurality index, which is based on the percentage of the rural areas across counties [25]. This index ranges from 0 to 1, where 1 corresponds to completely rural and 0 to completely urban areas.
- ***Unemployment (UN)*** We use the unemployment rate per county according to the U.S. Census Bureau in 2019, previous to the emergence of the pandemic.
- ***Poverty estimate (PE)*** Poverty estimate measures from the dataset provided by ers.usda.gov is the poverty estimate value measured last updated in 2019.

[5] https://ers.usda.gov/

- ***Education Level (HC)*** This data is collected from the USDA website [6], which provides the percentage of people with a bachelor's degree or higher qualification in each county. Data is last updated in 2019.
- ***Percent Rurality (PR)*** The rurality index corresponding to each county.
- ***Population density (PD)*** This rate refers to the average population by area unit. Data was last updated on June 8$^{\text{th}}$, 2020.
- ***Percent of Essential Workers (PE)*** This variable refers to the percentage of people working on essential services in each county. Data is last updated in June 1st, 2021.

3. Analysis & Results

In this section, we initially conduct a regression analysis to understand the significant variable associated with people's response to the three different interventions, namely: social distancing, wearing mask, and vaccination. Then we attempt to get more meaningful results using instrumental regression method.

3.1. Regression Analysis

3.1.1. OLS Multiple Regression

Multiple linear regression (MLR), also known simply as multiple regression, is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. The goal of multiple linear regression is to model the linear relationship between the explanatory (independent) variables and response (dependent) variables. In essence, multiple regression is the extension of ordinary least-squares (OLS) regression because it involves more than one explanatory variable.

The regression models implemented are based on the following equations:

$$\textbf{Change in Movement}_i = \alpha_c^{OLS} + \beta_c^{OLS} \times BW_i + \gamma_c^{OLS} \times HC_i + \delta_c^{OLS} \times CONTROLS_i + \epsilon_{i,c}^{OLS} \tag{1}$$

$$\textbf{Mask Usage}_i = \alpha_m^{OLS} + \beta_m^{OLS} \times BW_i + \gamma_m^{OLS} \times HC_i + \delta_m^{OLS} \times CONTROLS_i + \epsilon_{i,m}^{OLS} \tag{2}$$

$$\textbf{Vaccination Rate}_i = \alpha_v^{OLS} + \beta_v^{OLS} \times BW_i + \gamma_v^{OLS} \times HC_i + \delta_v^{OLS} \times CONTROLS_i + \epsilon_{i,v}^{OLS} \tag{3}$$

These equations depict the relationship between independent variables and each dependent variable. Result of all three multiple regressions are displayed in Tables 2-4

- Change in mobility (MO):
  Table xx shows the OLS regression results for Change in Movement regression by implementing three models. As the models 1-3 were implemented, R2 and adjusted R2 factors was improved by about 80 percent resulting in more confidence in the model 3. Political preference (BW) has negative impact on mobility in the model 1 and is statistically significant. The same is happening in models 2 and 3, according to Table 1. However, the coefficient betaC1 which is derived from model 3 has a

[6] https://ers.usda.gov/

more significant value.in absolute terms compared to Models 1 and 2. Therefore, if a county voted for Biden in the 2020 elections it would have been expected to observe 0.045 units less movement during the data frame studied from July 2 to July 14.
Education level (HC) is introduced in Model 2 and it is not statistically significant. However, when more controls are included in Model 3, betaC2 becomes significant and its value is estimated to be 0.458 meaning 1 unit increase in percentage of people with College degree or higher was correlated with 0.478 unit increase in mobility.
This can be a good example to show that using the right control variables is important to isolate the estimated coefficients and also the estimation may not always conform with our perception of reality which may require further explanation to comprehend. For example, at the first glance, one might think that more educated people would follow shelter in place guidelines because they are more aware of the benefits of such acts, however, this is not happening in fact for a variety of reasons which will be more discussed later. All in all, it seems like voting for president Biden did have an impact, although not significant, on the dependent variable MO but the more the education level, the higher change in mobility.

- Mask Usage OLS Regression Results:
Table 3 shows regression results for impact of independent variables on mask usage (FR).
Biden Win has a positive impact on Mask Usage score in model 1 and is statistically significant. The same is true of models 2 and 3 in Table 2, however, the coefficient betaM1 which is derived from model 3 has a less significant value compared to Models 1 and 2 and that can be explained by introduction of other control variables in Model 2 and Model 3 and presence of Education variable. Therefore, if a county voted for Biden in the 2020 elections it would have been expected to observe 0.274 units more mask usage on average in the time of pandemic.
Percent Higher College) is introduced in Model 2 and Model 3 and it is statistically significant and betaM2 becomes more significant and its value is estimated to be 1.143 meaning 1 unit increase in percentage of people with College degree or higher is correlated with 1.143 unit increase in Mask Usage score.
All in all, it seems like voting for president Biden and more educated people (Percent College Education population) did have meaningful significant impact on Mask Usage score dependent variable but Education seems like to have greater impact which will be further discussed in the discussion section.

- Vaccination Rate OLS Regression Results:
Table 3 shows regression results for impact of independent variables on Vaccination Rates.
Biden Win has a positive impact on Mask Usage score in model 1 and is statistically significant. However, the same is not true of models 2 and 3 in Table 3. The coefficient betaV1 which is derived from model 3 and model 2 is not statistically significant value compared to Model 1 and that can be explained by introduction of other control variables in Model 2 and Model 3 and presence of Education variable. Therefore, if a county voted for Biden in the 2020 elections it would have been expected to not observe any increase or decrease in vaccination rates on average during the pandemic. Percent Higher College is introduced in Model 2 and Model 3 and it is statistically significant and betaV2 becomes more significant and its value is estimated to be 75.689 meaning 1 unit increase in percentage of people with College degree or higher is correlated with 75.689 percent increase in Vaccination Rates. All in all, it seems like voting for president Biden did not have any positive or negative impact on vaccination rates and Percent College Education population in each county did have a meaningful and statistically significant impact on Vaccination

Rates dependent variable. This result is fascinating as it is expected that the political preference to play an important role in whether to get vaccinated but we prove that Education level is the key driver on that decision making instead of who people in that county voted for. More analysis on this subject will be performed in the discussion section.

3.1.2. IV Regression

Instrumental variable (IV) is a method for. . . .. We use the three following regression models1. Result of all three multiple IV Regressions are displayed in Tables 4-6.

Result of all three multiple IV Regressions are displayed in Tables 4-6. We use the three following regression models[1] :

$$\textbf{Change in Movement}_i = \alpha_c^{IV} + \beta_c^{IV} \times BW_i + \gamma_c^{IV} \times HC_i + \delta_c^{IV} \times CONTROLS_i + \epsilon_{i,c}^{IV} \tag{4}$$

$$\textbf{Mask Usage}_i = \alpha_m^{IV} + \beta_m^{IV} \times BW_i + \gamma_m^{IV} \times HC_i + \delta_m^{IV} \times CONTROLS_i + \epsilon_{i,m}^{IV} \tag{5}$$

$$\textbf{Vaccination Rate}_i = \alpha_v^{IV} + \beta_v^{IV} \times BW_i + \gamma_v^{IV} \times HC_i + \delta_v^{IV} \times CONTROLS_i + \epsilon_{i,v}^{IV} \tag{6}$$

1. Zi is an instrument for HCi.

Figure 5 depicts the relationship between independent variables and each dependant variable of interest used in IV Regression models using Investment on Education as an instrument for Education variable. Control variables were also used for controlling the instrument as well as Education variable. Tables 4-6 also depict the resulting IV regression output of each corresponding Equations 4-6.

Now are going to present the results applying IV regression method. We analyze four models . Model (1) being the most simplest and capturing merely Percent Higher Education without any control variables. Model(2) utilizes the same Education variable but takes into account Population Density as control variable as well. Model (3) includes all non-explicit control variables in addition to Education variable of interest. In model (4) Percent Essential Workers in each county is also included in addition to Biden Win dummy variable.

Figure 5 depicts the relationship between independent variables and each dependant variable of interest used in IV Regression models using Investment on Education. Control variables were also used for controlling the instrument as well as Education variable. Tables 4-6 also depict the resulting IV regression output of each corresponding Equations 4-6.

- Change in Movement IV Regression Results:
  Table 4 shows the IV regression results for Change in Movement regression. As the models 1-4 were developed, the R2 and adjusted R2 was improved significantly resulting in more confidence in the model 4. Biden Win has a negative impact on Change in Movement in model 4 and is statistically significant. Since Model (4) is the only time Biden Win is introduced in IV regression, the results can be accepted since control variables are all included in this model. Therefore, if a county voted for Biden in the 2020 elections it would have been expected to observe 0.057 units less movement in the time of pandemic from July 2 to July 14. This result is slightly different from what was observed in OLS regression and since the Wu-Hausman test is rejected, it means that what OLS regression estimation can be accepted, therefore approving significance of Biden Win. Percent Higher College is introduced in

Table 1: Change in Movement Multiple OLS Regressions

	Dependent variable:		
	Change in Movement		
	(1)	(2)	(3)
Pop_density	-0.00001***	-0.00001***	-0.00001***
	(0.00000)	(0.00000)	(0.00000)
Percent_Higher_College		0.026	0.478***
		(0.022)	(0.045)
Biden_Win	-0.032***	-0.035***	-0.045***
	(0.005)	(0.006)	(0.006)
COVID_Confirmed			-0.0001***
			(0.00003)
Percent_Ess_Workers			0.601***
			(0.059)
Poverty	-0.00000***	-0.00000***	-0.00000**
	(0.00000)	(0.00000)	(0.00000)
Hospital_Occ_rate			-0.059***
			(0.012)
Unemployment			0.004**
			(0.002)
Constant	0.009***	0.004	-0.413***
	(0.002)	(0.005)	(0.041)
Observations	2,513	2,513	2,164
R^2	0.101	0.102	0.179
Adjusted R^2	0.100	0.101	0.176
Residual Std. Error	0.093 (df = 2509)	0.093 (df = 2508)	0.090 (df = 2155)
F Statistic	94.453*** (df = 3; 2509)	71.225*** (df = 4; 2508)	58.770*** (df = 8; 2155)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2: Mask Usage Score Multiple OLS Regressions

	Dependent variable:		
	Mask Adoption Score		
	(1)	(2)	(3)
Pop_density	0.00002*	0.00001	-0.00000
	(0.00001)	(0.00001)	(0.00001)
Percent_Higher_College		0.952***	1.143***
		(0.088)	(0.165)
Biden_Win	0.446***	0.350***	0.274***
	(0.021)	(0.023)	(0.024)
COVID_Confirmed			-0.00004
			(0.0001)
Percent_Ess_Workers			-0.358*
			(0.210)
Poverty	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
Hospital_Occ_rate			0.383***
			(0.047)
Unemployment			0.084***
			(0.006)
Constant	3.805***	3.616***	3.339***
	(0.008)	(0.019)	(0.142)
Observations	3,111	3,111	2,495
R^2	0.180	0.210	0.310
Adjusted R^2	0.179	0.209	0.307
Residual Std. Error	0.421 (df = 3107)	0.413 (df = 3106)	0.388 (df = 2486)
F Statistic	227.770*** (df = 3; 3107)	206.525*** (df = 4; 3106)	139.332*** (df = 8; 2486)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Vaccine Participation Multiple OLS Regressions

	Dependent variable:		
	Vaccine Participation Percent		
	(1)	(2)	(3)
Pop_density	0.001	-0.0004	-0.001
	(0.0004)	(0.0004)	(0.0004)
Percent_Higher_College		67.587***	75.689***
		(3.143)	(5.499)
Biden_Win	8.056***	0.732	0.892
	(0.726)	(0.758)	(0.807)
COVID_Confirmed			-0.014***
			(0.005)
Percent_Ess_Workers			14.335**
			(6.987)
Unemployment		1.930***	1.494***
		(0.191)	(0.211)
Poverty	0.00001*	0.00000	0.00002**
	(0.00001)	(0.00001)	(0.00001)
Hospital_Occ_rate			1.846
			(1.569)
Constant	27.883***	6.880***	-0.306
	(0.284)	(1.194)	(4.724)
Observations	3,111	3,111	2,495
R^2	0.053	0.176	0.198
Adjusted R^2	0.052	0.175	0.195
Residual Std. Error	14.286 (df = 3107)	13.331 (df = 3105)	12.917 (df = 2486)
F Statistic	58.370*** (df = 3; 3107)	132.875*** (df = 5; 3105)	76.642*** (df = 8; 2486)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 4: Updated Vaccine Participation Multiple OLS Regressions

	Dependent variable:		
	Updated Vaccine Participation Percent		
	(1)	(2)	(3)
Pop_density	0.001	-0.0004	-0.0005
	(0.0005)	(0.0004)	(0.0004)
Percent_Higher_College		75.123***	83.381***
		(3.609)	(6.281)
Biden_Win	10.335***	2.110**	2.004**
	(0.830)	(0.871)	(0.921)
COVID_Confirmed			-0.012**
			(0.005)
Percent_Ess_Workers			17.003**
			(7.981)
Unemployment		2.456***	1.998***
		(0.219)	(0.241)
Poverty	0.00002**	0.00001	0.00002*
	(0.00001)	(0.00001)	(0.00001)
Hospital_Occ_rate			4.039**
			(1.792)
Constant	33.951***	9.386***	0.497
	(0.325)	(1.372)	(5.397)
Observations	3,111	3,111	2,495
R^2	0.067	0.182	0.202
Adjusted R^2	0.066	0.181	0.199
Residual Std. Error	16.350 (df = 3107)	15.308 (df = 3105)	14.756 (df = 2486)
F Statistic	74.150*** (df = 3; 3107)	138.624*** (df = 5; 3105)	78.489*** (df = 8; 2486)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Updated Change in Movement Multiple OLS Regressions

	Dependent variable:		
	Updated Change in Movement		
	(1)	(2)	(3)
Pop_density	-0.00000***	-0.00000**	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
Biden_Win	-0.028***	-0.016***	-0.018***
	(0.003)	(0.003)	(0.003)
Poverty	-0.00000***	-0.00000***	0.000
	(0.00000)	(0.00000)	(0.00000)
Percent_Higher_College		-0.104***	0.046*
		(0.012)	(0.026)
COVID_Confirmed			-0.0001***
			(0.00002)
Percent_Ess_Workers			0.261***
			(0.034)
Hospital_Occ_rate			0.018***
			(0.006)
Unemployment			-0.002**
			(0.001)
Constant	-0.044***	-0.023***	-0.191***
	(0.001)	(0.003)	(0.024)
Observations	2,115	2,115	1,907
R^2	0.102	0.132	0.178
Adjusted R^2	0.101	0.130	0.174
Residual Std. Error	0.049 (df = 2111)	0.048 (df = 2110)	0.046 (df = 1898)
F Statistic	79.782*** (df = 3; 2111)	80.072*** (df = 4; 2110)	51.326*** (df = 8; 1898)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Updated Change in Movement vs Change in Movement Comparison

	Dependent variable:	
	Movement Change	Updated Movement Change
	(1)	(2)
Pop_density	-0.00001***	
	(0.00000)	
Percent_Higher_College	0.478***	
	(0.045)	
Biden_Win	-0.045***	
	(0.006)	
COVID_Confirmed	-0.0001***	
	(0.00003)	
Percent_Ess_Workers	0.601***	
	(0.059)	
Poverty	-0.00000**	
	(0.00000)	
Hospital_Occ_rate	-0.059***	
	(0.012)	
Unemployment	0.004**	
	(0.002)	
Pop_density		-0.00000***
		(0.00000)
Percent_Higher_College		0.046*
		(0.026)
Biden_Win		-0.018***
		(0.003)
COVID_Confirmed		-0.0001***
		(0.00002)
Percent_Ess_Workers		0.261***
		(0.034)
Poverty		0.000
		(0.00000)
Hospital_Occ_rate		0.018***
		(0.006)
Unemployment		-0.002**
		(0.001)
Constant	-0.413***	-0.191***
	(0.041)	(0.024)
Observations	2,164	1,907
R^2	0.179	0.178
Adjusted R^2	0.176	0.174
Residual Std. Error	0.090 (df = 2155)	0.046 (df = 1898)
F Statistic	58.770*** (df = 8; 2155)	51.326*** (df = 8; 1898)

Note: *p<0.1; **p<0.05; ***p<0.01

all models from 1-4 and although initially statistically significant in models 1-3, after introduction of Biden Win variable, the estimated value lost its significance therefore not approving the fact that Percent population with College Education or Higher had a casual impact on less movement of individuals. Comparing the results of IV regression for Education with OLS regression, it can be discussed that Education had neither a positive or negative causal impact on change in movement All in all, it seems like voting for president Biden did have an impact, although not very large, on Change in Movement dependent variable but education did not have a causal impact on the Change in Movement.

- Mask Usage IV Regression Results:
  Table 5 shows the IV regression results for Mask Mandate dependent variable. As the models 1-4 were developed, the R2 and adjusted R2 was improved significantly resulting in more confidence in the model 4. Biden Win has a positive impact on Mask Usage in model 4 and is statistically significant. Since Model (4) is the only time Biden Win is introduced in IV regression, the results can be accepted since control variables are all included in this model. Therefore, if a county voted for Biden in the 2020 elections it would have been expected to observe 0.355 units more Mask Usage on average in the time of pandemic from July 2 to July 14. This result is slightly different from what was observed in OLS regression and since the Wu-Hausman test is rejected, it means that what OLS regression estimation can be accepted, therefore approving significance of Biden Win on Mask Usage.
  Percent Higher College is introduced in all models from 1-4 and although initially statistically significant in models 1-2, after introduction of Biden Win and other control variables, the estimated value lost its significance therefore not approving the fact that Percent population with College Education or Higher had a casual impact on Mask Usage of individuals. Comparing the results of IV regression for Education with OLS regression, it can be discussed that Education had neither a positive or negative causal impact on change in movement.
  All in all, it seems like voting for president Biden did have an impact, although not very large, on Mask Usage dependent variable but education did not have a causal impact on the Mask Usage between July 2 to July 14.

- Vaccination Rate:
  Table 6 shows the IV regression results for Vaccination Rate dependent variable Biden Win has no impact on Vaccination Rate as it can be seen in Model (4). Since Model (4) is the only time Biden Win is introduced in IV regression, the results can be accepted since control variables are all included in this model. Therefore, if a county voted for Biden in the 2020 elections it would note have been expected to observe any changes in vaccination rates. This result is consistent with what was observed in OLS regression and since the Wu-Hausman test is rejected, it means that what OLS regression estimation can be accepted, therefore approving the insignificance of Biden Win. Percent Higher College is introduced in all models from 1-4 and statistically significant in all models, after introduction of Biden Win variable, the estimated value kept its significance therefore approving the fact that Percent population with College Education or Higher had a casual impact on Vaccination Rates of individuals. Comparing the results of IV regression for Education with OLS regression, it can be discussed that Education definitely a causal impact on Vaccination Rates on average. This fact will be discussed in more detail in the discussion section.
  All in all, it seems like voting for president Biden did not have an impact Vaccination Rates dependent variable but education did indeed have a significant causal impact on the Vaccination Rates. Since the Wu-Hausman test is rejected, OLS regression estimated value for beta2V can be accepted.

3.1.3. OLS vs IV Regression Comparison

Now we are carrying out a comparison between the results obtained with both multiple regression methods shown before: OLS and IV regression. This comparison is shown for the three independent variables

- Mask Usage

  BetaMIV and BetaMOLS are both statistically significant in the final model. However, since the Wu-Hausman test is rejecetd, OLS result will be accepted. Therefore BetaMOLS will be assumed to be the more accurate estimation of impact of Biden Win on Mask Usage in this work. GammaMIV is not statistically significant but GammaMOLS is on the other hand in the final models. Since Wu-Hausman test in IV regression is rejected, OLS result will be accepted which means although Education does not have a causal impact on Mask Usage, there is a strong correlation in that relationship and GammaMOLS is the significance of that relationship.

- Change in Movement

  BetaCOLS and BetaCIV are both statistically significant and possess similar negative values. This confirms a negative association between Biden Win and Change in Movement. Since Wu-Hausman test is rejected for the IV regression, OLS result will be accepted. GammaMOLS is statistically significant, on the other hand GammaMIV is not. This shows there is no causal impact of Education on Change in Movement. However since Wu-Hausman test is rejected, it can be inferred that OLS result can be accepted and although there is no proved causal relationship between Education and Change in Movement, there is a strong correlation between these two variables.

- Vaccination Rate

  BetaVOLS and BetaVIV are both not statistically significant proving the fact that there is neither a causal nor a correlation relationship between Biden Win and Vaccination Rates. This significant finding will be further discussed in the discussion section. GammaVOLS and GammaVIV on the other hand are both statistically significant and very large in value. This result is significant as it proves the causal relationship between Education and Vaccination Rates in addition to the obvious strong positive correlation between these two variables. This finding is fascinating as one might think political preference is the main driver in making decisions when it comes to participating in the vaccination, but we show that not only there is no causal relationship between Biden Win (or Trump Win) and Vaccination, there is no correlation. On the other hand, we show that this relationship strongly holds between Education and Vaccination Rates.

3.2. Spatial visualizations

What we see in these maps? We need at least 2-4 paragraphs explaining these maps in general or in particular.

What we do here and how it is relevant this process

Figure 6 displays the visualization of all three dependent variables along with Education and Political Preference in the US. It has been tried to cluster the data in each map into 5 clusters so the differences and similarities would be easier to observe.

As can be seen, not every variable has the same outcome in a particular county or even a state and when analyzing these variables, various socioeconomic logic should be considered.

Table 7: Causal Impact of Percent with College Education or Higher on Change in Movement

	Dependent variable:			
	Change in Movement			
	(1)	(2)	(3)	(4)
Percent_Higher_College	-0.708***	-0.647***	0.181	0.802
	(0.087)	(0.113)	(0.124)	(0.535)
Biden_Win				-0.057***
				(0.016)
COVID_Confirmed				-0.0001***
				(0.00002)
Percent_Ess_Workers				1.175*
				(0.653)
Pop_density		-0.00000	-0.00001***	-0.00001***
		(0.00000)	(0.00000)	(0.00000)
Poverty			-0.00000***	
			(0.00000)	
Constant	0.169***	0.154***	-0.050	-0.794*
	(0.024)	(0.030)	(0.032)	(0.464)
Weak instruments	0	0	0	
Wu-Hausman	0	0	0	
Observations	1,140	1,140	1,136	1,129
R^2	-0.219	-0.145	0.057	0.174
Adjusted R^2	-0.220	-0.147	0.055	0.170
Residual Std. Error	0.100 (df = 1138)	0.097 (df = 1137)	0.087 (df = 1132)	0.082 (df = 1123)

Note: *p<0.1; **p<0.05; ***p<0.01

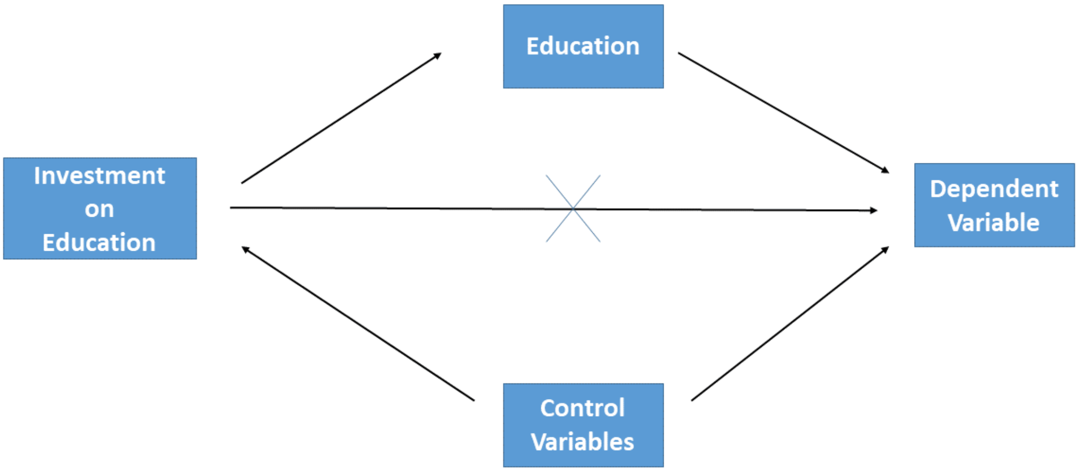

Figure 1. Correlation Matrix

Table 8: Causal Impact of Percent with College Education or Higher on Updated Change in Movement

	Dependent variable:			
	Updated Change in Movement IV Regression			
	(1)	(2)	(3)	(4)
Percent_Higher_College	-0.317***	-0.270***	0.039	-0.257***
	(0.039)	(0.050)	(0.063)	(0.097)
Pop_density		-0.00000**	-0.00001***	-0.00000**
		(0.00000)	(0.00000)	(0.00000)
Poverty			-0.00000***	
			(0.00000)	
Biden_Win				-0.002
				(0.011)
Constant	0.027**	0.015	-0.062***	0.012
	(0.011)	(0.013)	(0.016)	(0.023)
Weak instruments	0	0	0	
Wu-Hausman	0	0.03	0	
Observations	1,088	1,088	1,084	1,078
R^2	0.077	0.140	0.055	0.150
Adjusted R^2	0.076	0.138	0.053	0.147
Residual Std. Error	0.043 (df = 1086)	0.042 (df = 1085)	0.044 (df = 1080)	0.041 (df = 1074)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Causal Impact of Percent with College degree or Higher on Mask Mandate Adoption

	Dependent variable:			
	Mask Mandate Adoption			
	(1)	(2)	(3)	(4)
Percent_Higher_College	3.123***	3.151***	0.663	1.999**
	(0.366)	(0.487)	(0.571)	(0.835)
Biden_Win				0.256***
				(0.090)
Pop_density		-0.00000	0.00002	0.00000
		(0.00002)	(0.00002)	(0.00001)
Poverty			0.00000***	
			(0.00000)	
Constant	3.223***	3.216***	3.829***	3.441***
	(0.098)	(0.127)	(0.146)	(0.193)
Weak instruments	0	0	0	
Wu-Hausman	0	0	0.06	
Observations	1,167	1,167	1,167	1,160
R^2	0.108	0.104	0.177	0.262
Adjusted R^2	0.107	0.102	0.175	0.260
Residual Std. Error	0.420 (df = 1165)	0.421 (df = 1164)	0.403 (df = 1163)	0.383 (df = 1156)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10: Causal Impact of Percent with College degree or Higher on Vaccination Participation

	Dependent variable:			
	Vaccination Completeness Percent IV Regression			
	(1)	(2)	(3)	(4)
Percent_Higher_College	75.962***	74.004***	70.760***	58.045*
	(13.462)	(17.886)	(21.734)	(33.259)
Biden_Win				4.026
				(3.594)
Pop_density		0.0001	0.0001	0.0001
		(0.001)	(0.001)	(0.001)
Poverty			0.00000	
			(0.00001)	
Constant	21.042***	21.530***	22.241***	24.448***
	(3.610)	(4.686)	(5.569)	(7.673)
Weak instruments	0	0	0	
Wu-Hausman	0.23	0.4	0.57	
Observations	1,171	1,171	1,167	1,160
R^2	0.133	0.136	0.138	0.154
Adjusted R^2	0.133	0.134	0.136	0.151
Residual Std. Error	15.420 (df = 1169)	15.407 (df = 1168)	15.355 (df = 1163)	15.240 (df = 1156)
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 11: OLS vs IV Regressions Comparisons among Various Dependant Variables

	Dependent variable:					
	Mask Mandate Adoption		Movement Change		Vaccination	
	OLS	*instrumental variable*	*OLS*	*instrumental variable*	*OLS*	*instrumental variable*
	(1)	(2)	(3)	(4)	(5)	(6)
Pop_density	-0.00000	0.00001	-0.00001***	-0.00001***	-0.001	-0.0001
	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.0004)	(0.0004)
Percent_Higher_College	1.143***	-0.367	0.478***	0.802	75.689***	182.942**
	(0.165)	(2.353)	(0.045)	(0.535)	(5.499)	(91.502)
Biden_Win	0.274***	0.355***	-0.045***	-0.057***	0.892	0.144
	(0.024)	(0.071)	(0.006)	(0.016)	(0.807)	(2.770)
COVID_Confirmed	-0.00004	0.0002	-0.0001***	-0.0001***	-0.014***	-0.002
	(0.0001)	(0.0001)	(0.00003)	(0.00002)	(0.005)	(0.004)
Percent_Ess_Workers	-0.358*	-2.082	0.601***	1.175*	14.335**	162.163
	(0.210)	(2.856)	(0.059)	(0.653)	(6.987)	(111.061)
Poverty	0.00000***		-0.00000**		0.00002**	
	(0.00000)		(0.00000)		(0.00001)	
Hospital_Occ_rate	0.383***		-0.059***		1.846	
	(0.047)		(0.012)		(1.569)	
Unemployment	0.084***		0.004**		1.494***	
	(0.006)		(0.002)		(0.211)	
Constant	3.339***	5.070**	-0.413***	-0.794*	-0.306	-95.741
	(0.142)	(2.032)	(0.041)	(0.464)	(4.724)	(79.031)
Observations	2,495	1,160	2,164	1,129	2,495	1,160
R^2	0.310	0.313	0.179	0.174	0.198	0.022
Adjusted R^2	0.307	0.310	0.176	0.170	0.195	0.018
Residual Std. Error	0.388 (df = 2486)	0.369 (df = 1154)	0.090 (df = 2155)	0.082 (df = 1123)	12.917 (df = 2486)	14.363 (df = 1154)
F Statistic	139.332*** (df = 8; 2486)		58.770*** (df = 8; 2155)		76.642*** (df = 8; 2486)	

Note: *p<0.1; **p<0.05; ***p<0.01

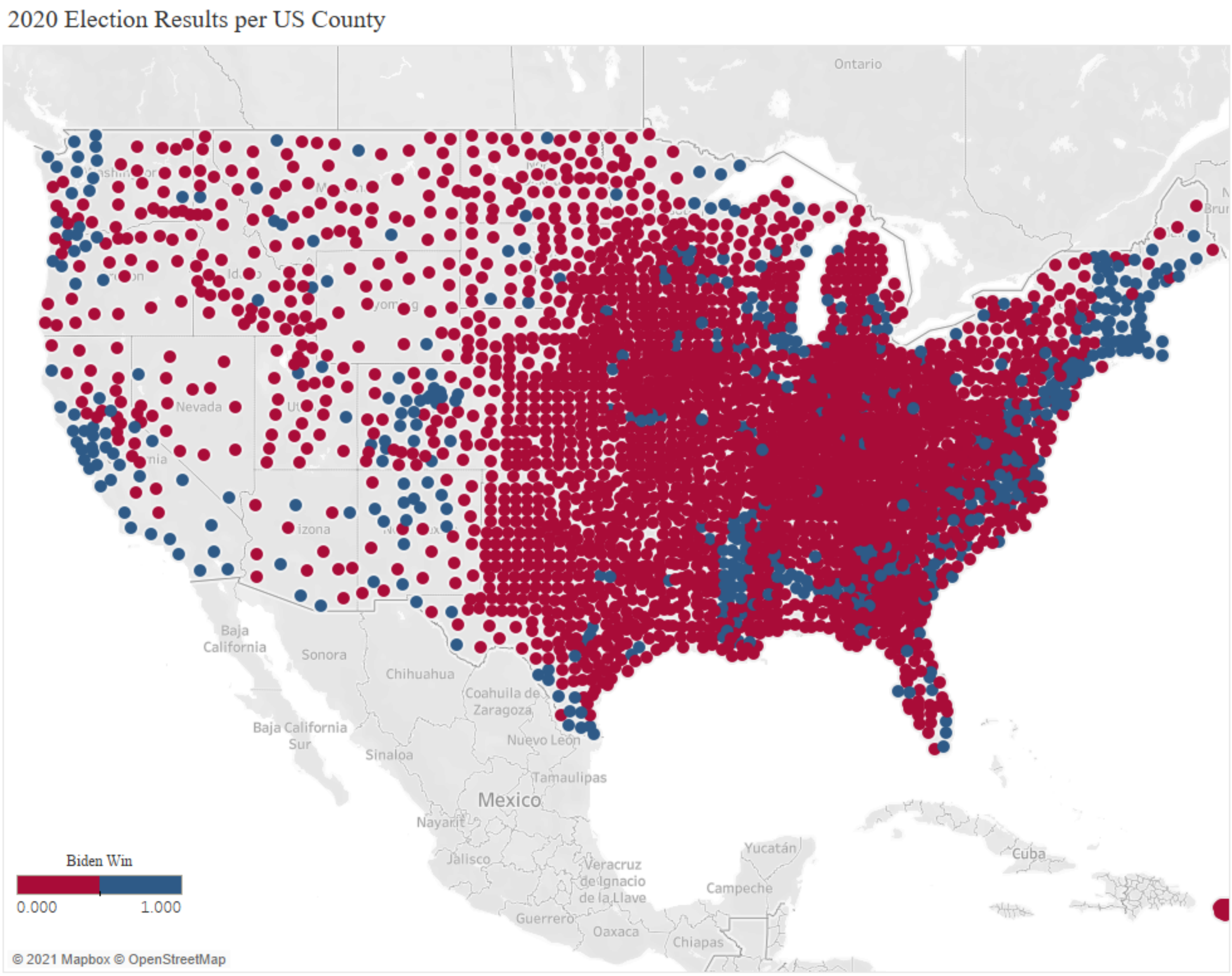

Figure 2. US 2020 Election results per county

[showframe]geometry lipsum graphicx [1-2] [3-10]

[showframe]geometry lipsum graphicx [1-2] [3-10]

[showframe]geometry lipsum graphicx [1-2] [3-10]

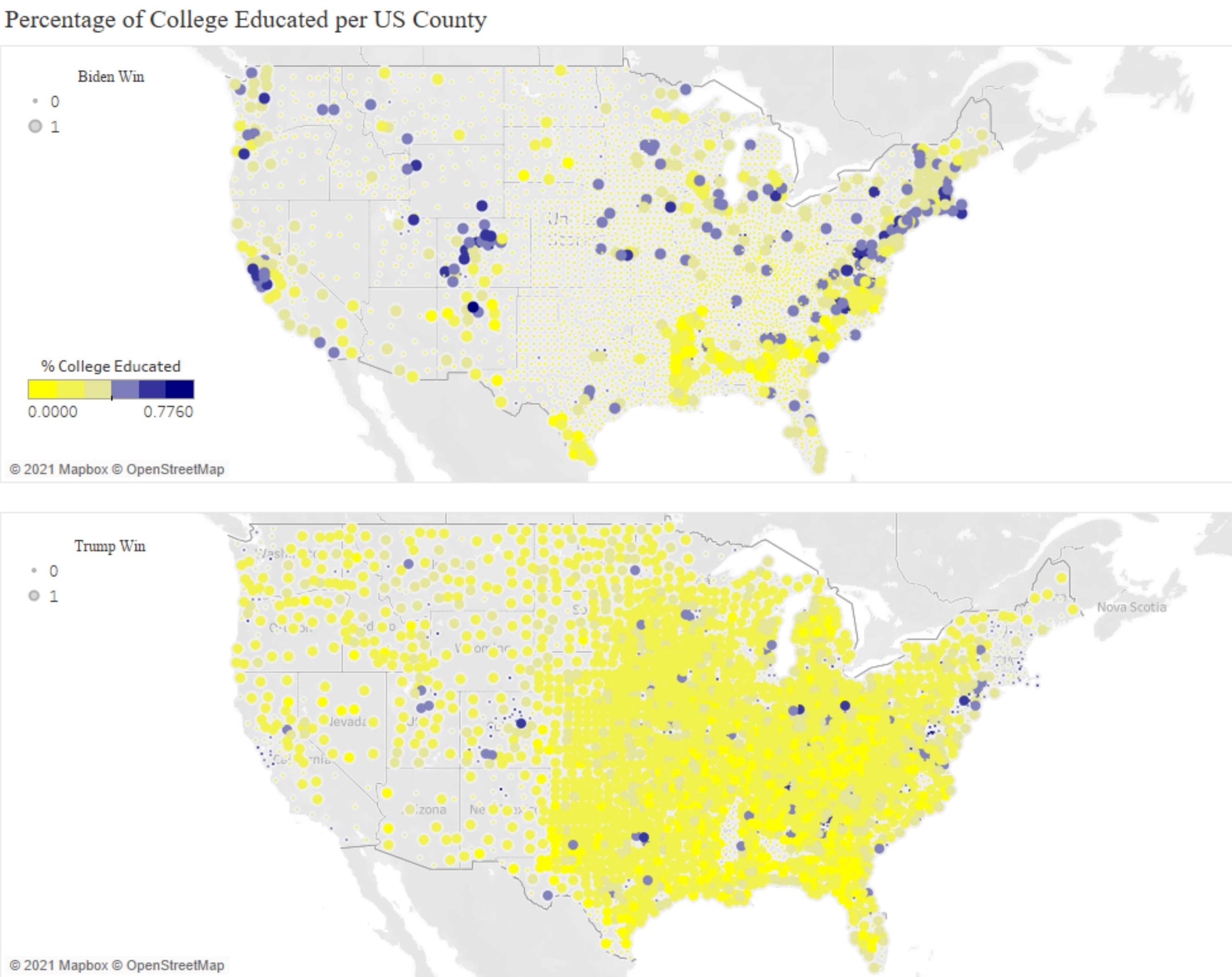

Figure 3. US 2020 Election results per county

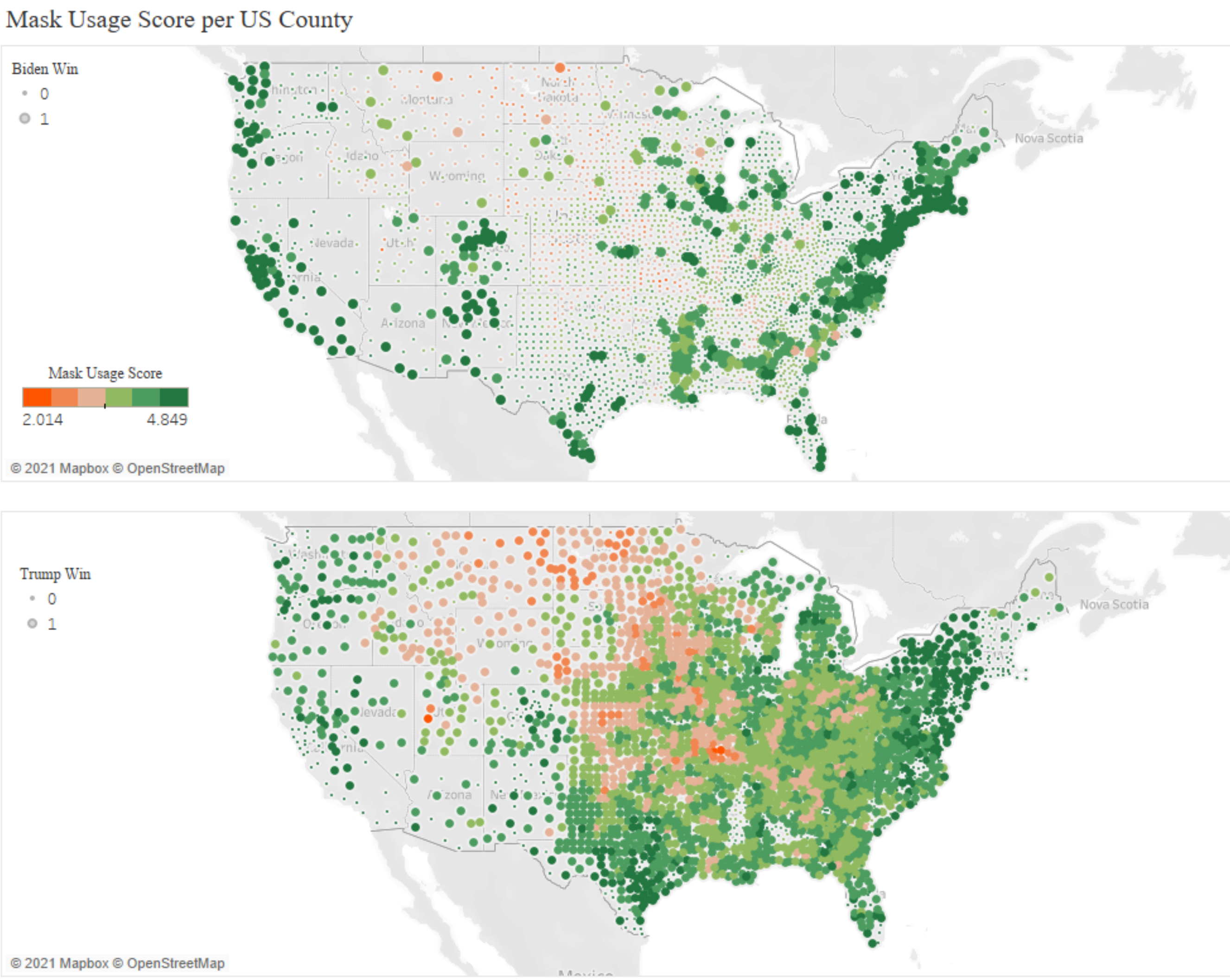

Figure 4. US 2020 Election results per county

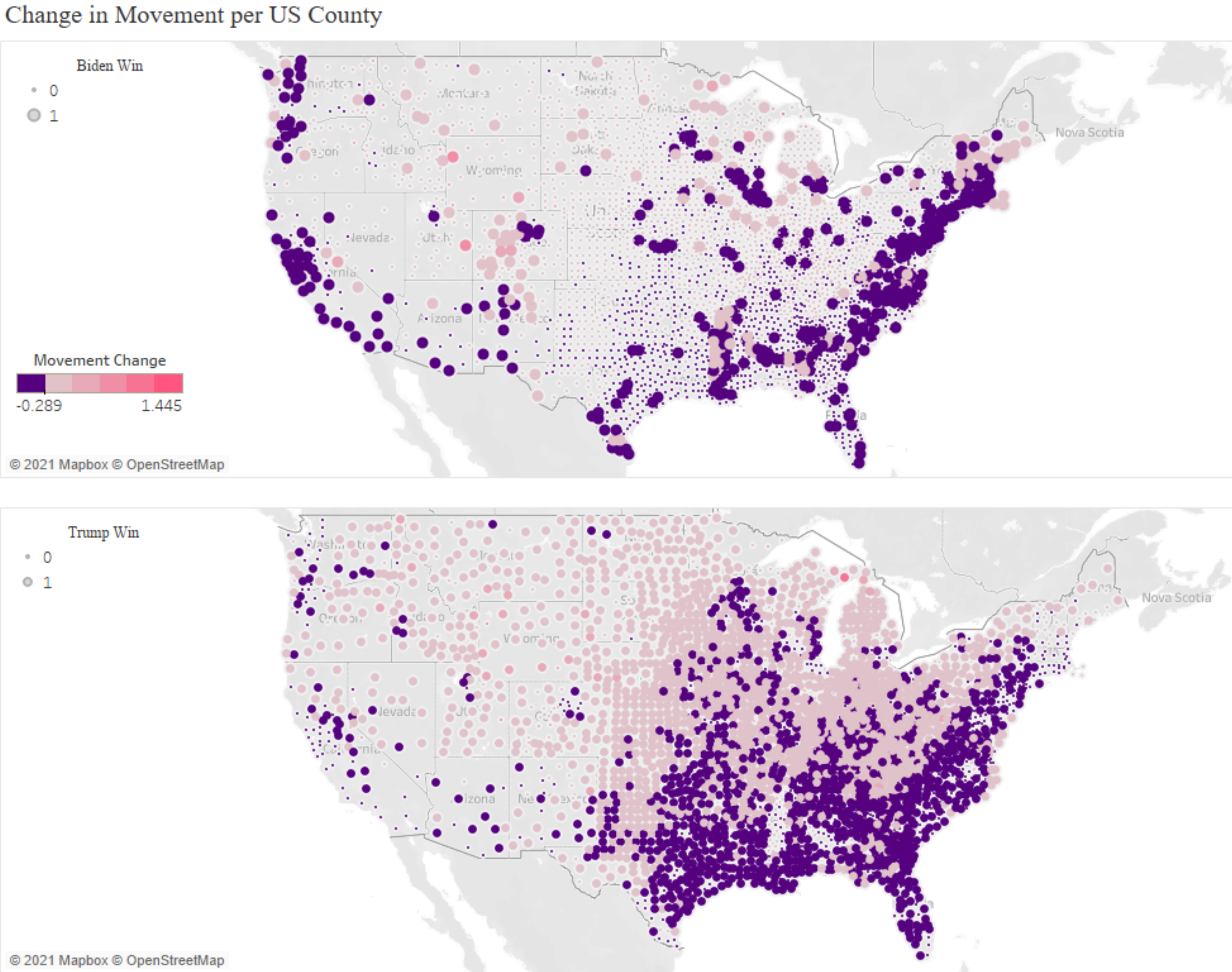

Figure 5. US 2020 Election results per county

[showframe]geometry lipsum graphicx [1-2] [3-10]

[showframe]geometry lipsum graphicx [1-2] [3-10]

[showframe]geometry lipsum graphicx [1-2] [3-10]

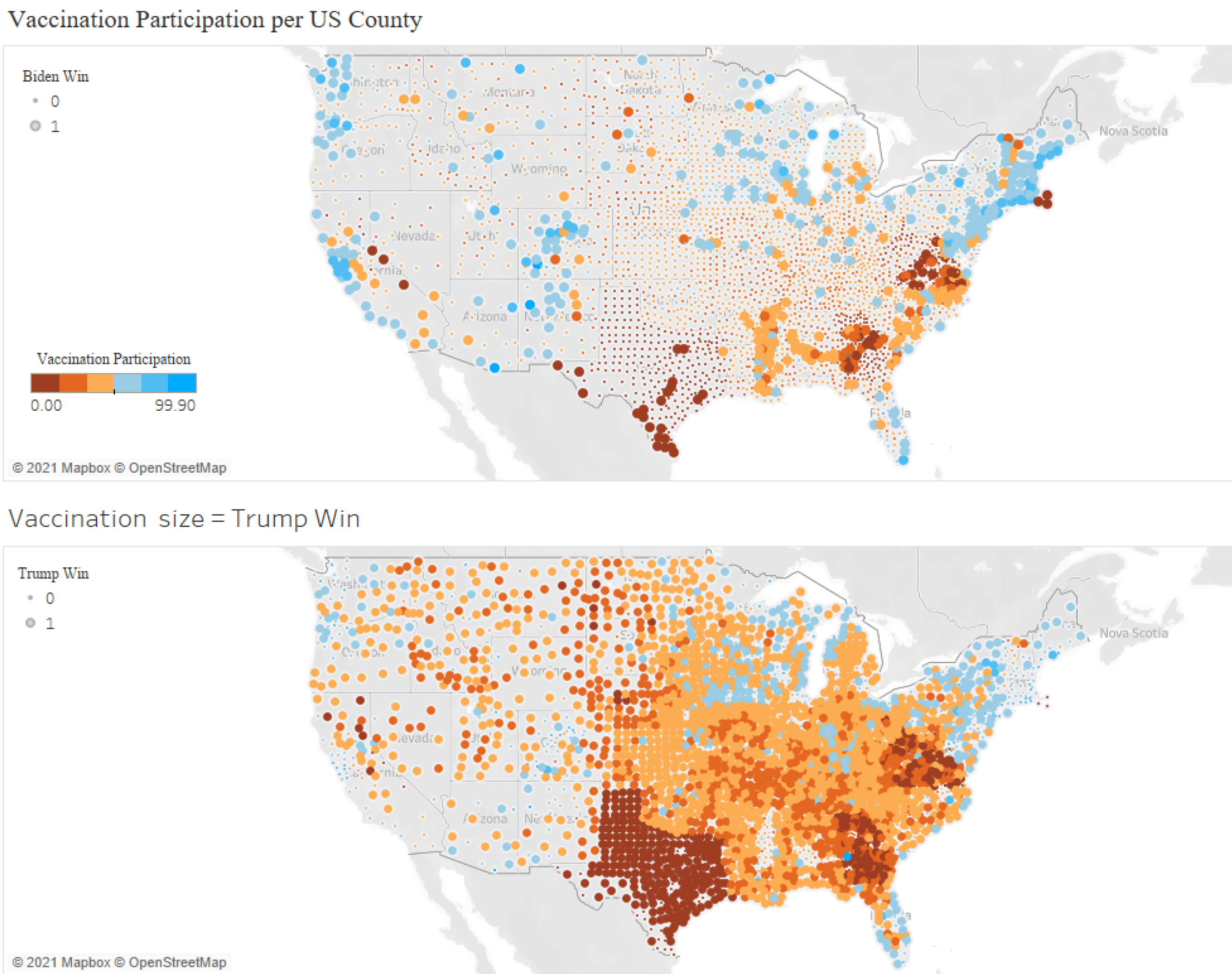

Figure 6. US 2020 Election results per county

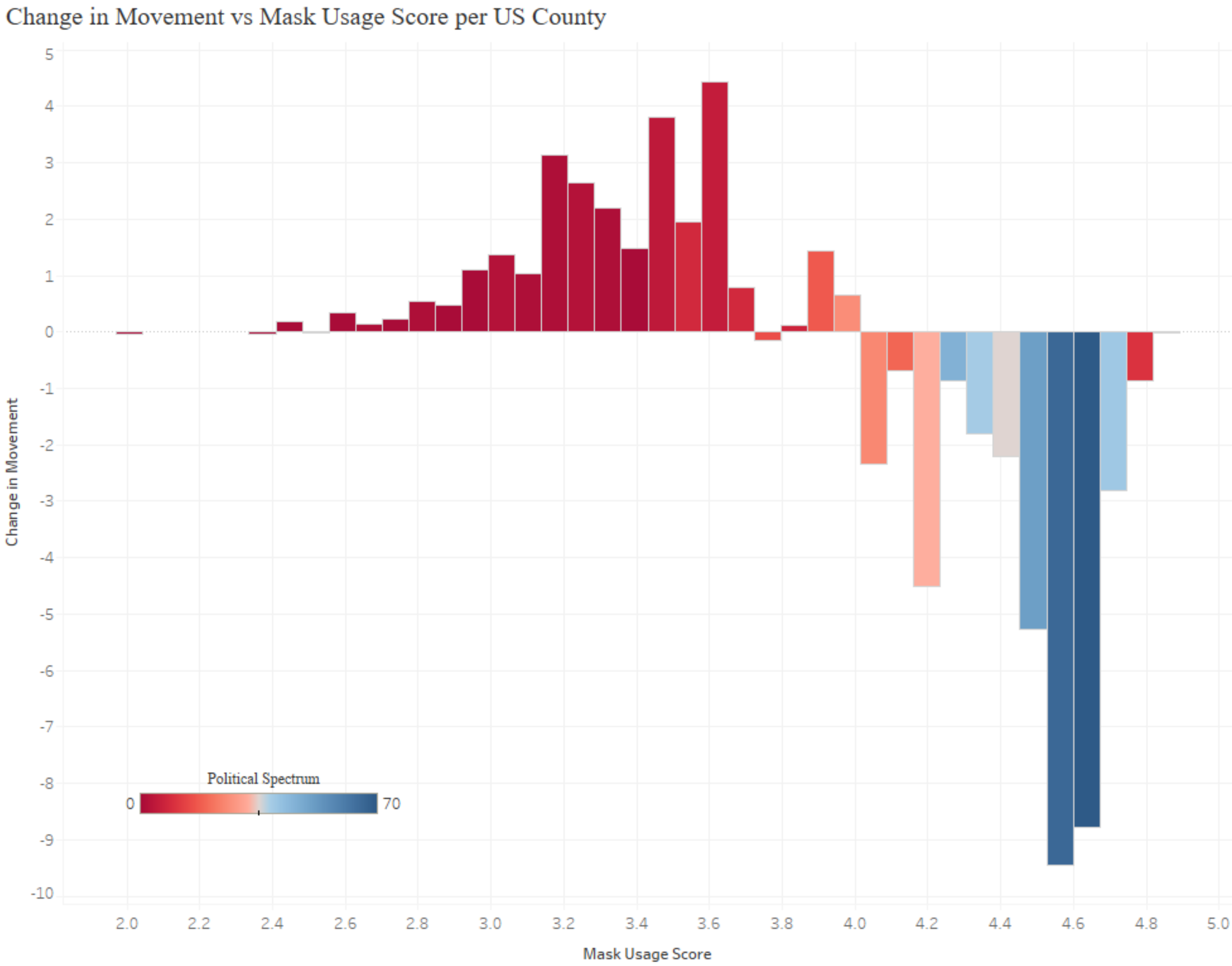

Figure 7. US 2020 Election results per county

4. Discussion and conclusions

In this article, we attempt to draw a big framework for analyzing which ones were the most influential factors that explained the actual influence of the COVID-19 pandemic across the United States. For this, it is studied the correlation between a group of socioeconomic and demographic variables with regard to three main governmental policies adopted by American authorities for containing the pandemic: (a) mask adoption, (b) movement change, and (d) vaccination participation. The primary aim was to isolate what were most influential variables impacting behavior in response to these policies.

There are a large number of factors related to where one lives that predispose the social behavior of certain communities to the pandemic. Factors related with xxxx and xxx have shown more influence on the impact of the pandemic.

hen looking at various socioeconomic variables and attempting to isolate theirimpact on Mask Adoption, Movement Change, and Vaccination Participation, severalkey facts need to be considered: A more detailed study requires to consider some relevant aspects related to the three main governmental policies adopted. With regard to (a) mask adoption, this factor 1. Mask Mandate Adoption is not necessarily highly correlated with the other governmental orders such as Shelter in Place orders which is captured under Movement Change in this workpolicies. We show that using Percent Essential Workers Population in each county. These are people who may want to comply with any and all governmental mandates but because they have to be mobile, will not be able to stay at home, but that does not necessarily mean they do not follow other governmental orders. It is shown in the Essential Workers in comparison with the rest of population, which scarcely used the mask (PERCENTAGE), but they moved more (PERCENTAGE) and accepted more the vaccine (PERCENTAGE)in each country did not comply with the Mask Mandate and also moved significantly more compared to other people but took up the vaccination at a good rate. A similar trend is observed according to political preference. 3. Another example of this can be counties where Trump had the highest share in the 2020 presidential elections, barely four months after the collection of movement and mask adoption data used in this research. As it can be seen, inIn thoserepublican counties where Trump won, there isit is observed a lower Always mask adoption and more change in movement,. Hhowever, unlike what would be expected, there isit was not observed any no correlation between supporting voting for Trump and rate of Vaccination vaccination at a county levelParticipation. It demonstrates how the impact of politician This can be explained by the behavior of politicians and how impactful their behaviors can be on theon population is not always massively accepted. Since the Trump administration was the government in charge when the vaccine was developed and released, the vaccination participation, or in other words following governmental orders, has been shown to be far more compliant than mask use adoption and stay at home orders. The spatial pattern of population distribution 4. Another important factor to consider when comparing population's response to governmental orders in time of pandemic is considering how dense the populationis and how rural that county might be based on the most recent census to come toan accurate conclusionshows some influence on the results.. As can be seen in the US map comparisons between Percent Rurality and Mask Use Adoption, t It was observed here is a positive correlation between a county being ruralthe level of rurality and 625 complying less with the mask mandate. This factor is related to the transmission pattern of the disease and a distant perception of danger. In fact, the vast majority of COVID-19 cases were located in urban areas during the first wave (xx)..One possible explanation might be that since the population of people is less dense in the rural areas, people might not see the need to 'Always' follow the mask mandate but if they would be in a city, they will always wear on a mask. With regard to (b) movement change XXXXXXXX With regard to (c) vaccination participation, we observe how level of education is a relevant factor to be considered629 5. There also seems like a strong correlation between percent population with at least 630 a college degree or higher and vaccination participation. This can be a good policy 631 Thus, according to the population with at least a college degree was a XX higher to get the vaccine. In this way, future policies and recommendation whichrecommendations must be addressed to can suggest to governments to invest more on educating 632 the population so in times of pandemics they would be more compliant with 633 beneficial remedies such as vaccinationeducation. Finally, it is important to point out that performingwe have noticed that the sufficient number of testing demonstrates a strong correlation with more mask wearing and vaccination participation, but less evident in movement change in movement, and more vaccination participation. Same These same relationship can be seen in the announcement 637 of confirmed COVID cases or COVID death cases which suggests that being trans- parent and educating the public and at the same time providing enough testing to them significantly improves governmental order adoption by the population.

Some of the datasets were limited in time or space We tried to simplify a huge complexity related to a amount of factors that can be behind the actual spread of the virus and their incidence Results are based on an aggregation of data in counties. However, great differences could be shown at a individual scale. Some factors were not considered because lack of data, but they could have a relevant influence. Our methodology of data aggregation could show some relevant inconsistences for some datasets Some of the correlations could not be relevant or they were obvious

The results obtained allow us to know more about our social behavior within human communities, in addition to adopt more optimal and efficient policies in cases of emergencies in the next future. In following studies, we will xxxxx

Funding: This research received no external funding

Institutional Review Board Statement: Not applicable

Informed Consent Statement: Not applicable

Data Availability Statement: All data and code used in this research project are available at: https://github.com/mprtrmrtz/maskmandate

Acknowledgments: We are indebted to the organizations for providing the datasets we have used in this research.

Conflicts of Interest: The authors declare no conflict of interest.

5. References

1. Johns Hopkins Coronavirus Resource Center, 2021.
2. Li, Q.; Guan, X.; Wu, P.; Wang, X.; Zhou, L.; Tong, Y.; Ren, R.; Leung, K.S.; Lau, E.H.; Wong, J.Y.; others. Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. *New England journal of medicine* **2020**.
3. Jia, J.S.; Lu, X.; Yuan, Y.; Xu, G.; Jia, J.; Christakis, N.A. Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature* **2020**, *582*, 389–394.
4. Zhang, S.; Wang, Z.; Chang, R.; Wang, H.; Xu, C.; Yu, X.; Tsamlag, L.; Dong, Y.; Wang, H.; Cai, Y. COVID-19 containment: China provides important lessons for global response. *Frontiers of Medicine* **2020**, p. 1.
5. Kraemer, M.U.; Yang, C.H.; Gutierrez, B.; Wu, C.H.; Klein, B.; Pigott, D.M.; Du Plessis, L.; Faria, N.R.; Li, R.; Hanage, W.P.; others. The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science* **2020**, *368*, 493–497.
6. Schlosser, F.; Maier, B.F.; Jack, O.; Hinrichs, D.; Zachariae, A.; Brockmann, D. COVID-19 lockdown induces disease-mitigating structural changes in mobility networks. *Proceedings of the National Academy of Sciences* **2020**, *117*, 32883–32890.
7. Chang, S.; Pierson, E.; Koh, P.W.; Gerardin, J.; Redbird, B.; Grusky, D.; Leskovec, J. Mobility network models of COVID-19 explain inequities and inform reopening. *Nature* **2021**, *589*, 82–87.
8. Lemaitre, J.C.; Perez-Saez, J.; Azman, A.; Rinaldo, A.; Fellay, J. Assessing the impact of non-pharmaceutical interventions on SARS-CoV-2 transmission in Switzerland. *medRxiv* **2020**.

9. Flaxman, S.; Mishra, S.; Gandy, A.; Unwin, H.J.T.; Mellan, T.A.; Coupland, H.; Whittaker, C.; Zhu, H.; Berah, T.; Eaton, J.W.; others. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature* **2020**, *584*, 257–261.
10. Aleta, A.; Martin-Corral, D.; y Piontti, A.P.; Ajelli, M.; Litvinova, M.; Chinazzi, M.; Dean, N.E.; Halloran, M.E.; Longini Jr, I.M.; Merler, S.; others. Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19. *Nature Human Behaviour* **2020**, *4*, 964–971.
11. Holtz, D.; Zhao, M.; Benzell, S.G.; Cao, C.Y.; Rahimian, M.A.; Yang, J.; Allen, J.; Collis, A.; Moehring, A.; Sowrirajan, T.; others. Interdependence and the cost of uncoordinated responses to COVID-19. *Proceedings of the National Academy of Sciences* **2020**, *117*, 19837–19843.
12. Benzell, S.G.; Collis, A.; Nicolaides, C. Rationing social contact during the COVID-19 pandemic: Transmission risk and social benefits of US locations. *Proceedings of the National Academy of Sciences* **2020**, *117*, 14642–14644.
13. Hunter, R.F.; Garcia, L.; de Sa, T.H.; Zapata-Diomedi, B.; Millett, C.; Woodcock, J.; Moro, E.; others. Effect of COVID-19 response policies on walking behavior in US cities. *Nature communications* **2021**, *12*, 1–9.
14. Chiou, L.; Tucker, C. Social distancing, internet access and inequality. Technical report, National Bureau of Economic Research, 2020.
15. Chetty, R.; Friedman, J.N.; Hendren, N.; Stepner, M.; others. The economic impacts of COVID-19: Evidence from a new public database built using private sector data. Technical report, National Bureau of Economic Research, 2020.
16. Olsen, A.L.; Hjorth, F. Willingness to distance in the COVID-19 pandemic. *OSF* **2020**, *633*.
17. Painter, M.; Qiu, T. Political beliefs affect compliance with covid-19 social distancing orders. *Covid Economics* **2020**, *4*, 103–123.
18. Allcott, H.; Boxell, L.; Conway, J.; Gentzkow, M.; Thaler, M.; Yang, D. Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic. *Journal of Public Economics* **2020**, *191*, 104254.
19. Adjodah, D.; Dinakar, K.; Chinazzi, M.; Fraiberger, S.P.; Pentland, A.; Bates, S.; Staller, K.; Vespignani, A.; Bhatt, D.L. Association between COVID-19 outcomes and mask mandates, adherence, and attitudes. *PLOS ONE* **2021**, *16*, e0252315.
20. Li, T.; Liu, Y.; Li, M.; Qian, X.; Dai, S.Y. Mask or no mask for COVID-19: A public health and market study. *PloS one* **2020**, *15*, e0237691.
21. Haischer, M.H.; Beilfuss, R.; Hart, M.R.; Opielinski, L.; Wrucke, D.; Zirgaitis, G.; Uhrich, T.D.; Hunter, S.K. Who is wearing a mask? Gender-, age-, and location-related differences during the COVID-19 pandemic. *Plos one* **2020**, *15*, e0240785.
22. Yan, B.; Zhang, X.; Wu, L.; Zhu, H.; Chen, B. Why do countries respond differently to COVID-19? A comparative study of Sweden, China, France, and Japan. *The American review of public administration* **2020**, *50*, 762–769.
23. Ortega, A. Coronavirus: trends and landscapes for the aftermath, 2020.
24. Policy Brief: COVID-19 in an Urban World. Technical report, United Nations, 2020.
25. Waldorf, B.; Kim, A. The Index of Relative Rurality (IRR): US county data for 2000 and 2010. *Purdue Univ. Res. Repos* **2018**.

Appendix

Correlations

At first correlation between a selected subset of variables from each dataset with other variables were analyzed in order to avoid a potential multicollinearity effect. Correlation matrix for this selected subset of variables is displayed in Figure 8.

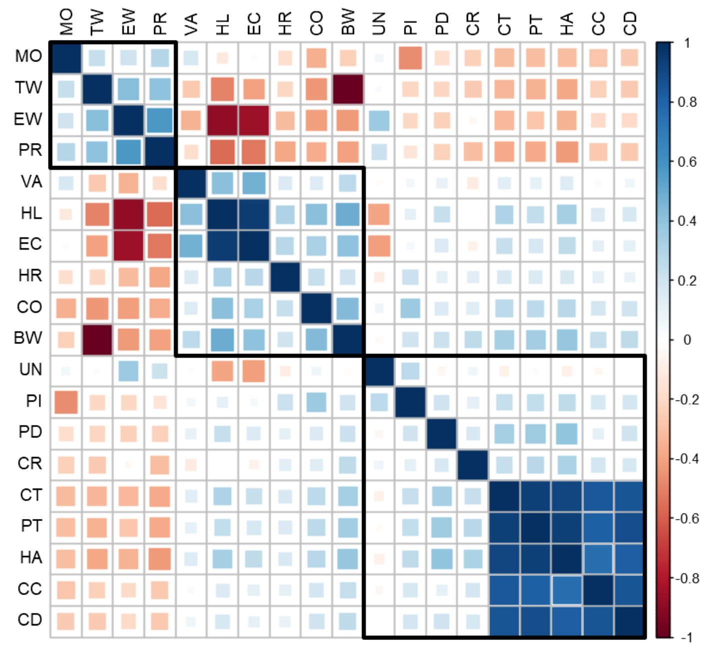

Figure 8. Independent Variables Correlation Matrix

Based on the results shown in in Figure 8 we can check some particularly strong positive/negative correlations between variables. Blue tones show positive, whereas brown tones show negative correlations between variables. Higher level of correlation are shown in darkest tones. This last effect is also emphasized according to the box size. For running the model, These variables are later removed from the modeling successive iterations in order to avoid multicolinearity effect among variables.

We have found the correlations between variables related mostly to . . . .PT, HA with all the COVID-19 related parameters. This means that. . . ., which was partially expected. The most relevant negative correlations is between HL, EC with EW, and TW with BW.

Some of the correlations are expected and some are very surprising. For instance, it is expected for COVID-19 casualty, testing, and patient related variables to be correlated to one another, however, one might not guess that counties where Trump had the highest vote in 2020 election had proportionately lower percentage of people with college degree or higher.

After analyzing the relationship among independent variables and their correlation, the variables having strong correlation with others were removed from the list of independent variables and finally Population Density, Percent Educated, Poverty Estimates, Unemployment, COVID-19 Confirmed Cases, Percentage of Essential Workers, Biden Win, Crime Rate, and Hospital Occupancy Rate were selected as independent variables capturing the socio-economic status of each county.

In summary, the most significant correlations are shown in Table 12. Parameters related to socio-economical factors such the education level (College Degree or Higher), political preference (BW), income level (poverty estimate) and/or the level of attendance of the public health systems (Hospital Beds) show a significant correlation with the perception and social behavior against pandemic (Vaccination, Mask Usage, etc). As it is highly expected, COVID-19 related variables are strongly correlated each other. Therefore, in order to avoid bias and multicollinearity in the model, only COVID-19 confirmed cases (CC) is used in the regression models as a dependant variable that is representative of all the COVID-19 related variables. Additionally, Percentage of Rurality of each county was removed from all regression models as it is strongly positively related to percentage of essential workers and strongly negatively correlated with education level (percentage of people who hold a college degree or higher) to avoid bias. The correlations are further examined in section 3.1.1.

Table 12: Positive and Negative Correlations Among Selected Subset of Variables

Correlations	Variable A	Variable B
Positive	COVID-19 Confirmed Cases	COVID-19 Death Cases
	COVID-19 Confirmed Cases	COVID-19 Testing Count
	COVID-19 Confirmed Cases	Poverty Estimate
	COVID-19 Confirmed Cases	Hospital Beds
	Percent Essential Workers	Percent Rurality
	Percent Higher College Degree	Biden Win
Negative	College Degree or Higher	Percent Essential Workers
	Percent Higher College Degree	Percent Rurality
	Trump Win	Mask Usage Score
	Vaccination	High School Degree or Less

According to Table 12, it is observed a strong positive correlation between higher level of education (higher HL) and vaccination participation (higher VA?). From a political standpoint, it seems like that at the first glance in counties where Biden won there is also a high percentage of people with higher education level, whereas those counties where Trump won they used less mask (lower NR//RA?). A more exhaustive analysis about whether any of the above correlations are meaningful or even causal requires to implement a mathematical analysis based on the multiple OLS regression and Instrumental regression method. This allowed replying the following questions: 1. Do people behave the same towards governmental orders and interventions during the pandemic? 2. Is there a difference in response between Mask Mandate, Stay at Home orders, and Vaccination encouragement? 3. What factors are the most important in encouraging people to comply with interventions during the pandemic? 4. Does having a particular political opinion influence the individual's respond to orders? 5. What is the relationship between level of education and complying with certain instructions during the pandemic? 6. Can we isolate a causal relationship between a policy and a socioeconomic status? 7. What actions can governments take to increase the likelihood of policy adoption among the population?

5.0.1. Relationships

In Figure 9 a generally weak correlation exists between dependant variables. However, the correlations are all in the same direction,i.e. where mask mandate is adopted more, there is less movement and more vaccination participation and vice versa. It seems like people who decided to follow the governmental orders generally speaking did so regardless of the intervention.

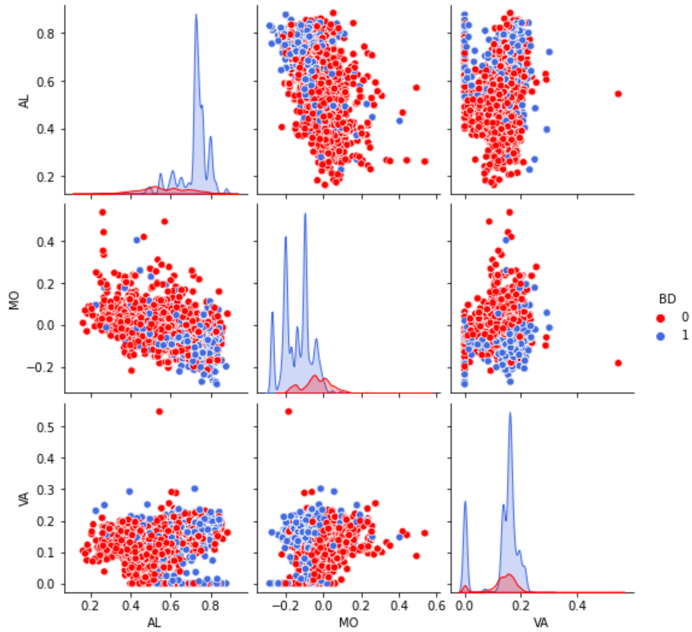

Figure 9. Correlation Matrix

665 Figure 10 displays the relationships between Education Level, Unemployment, Population Density, and Poverty. It can be seen that these variables are not strongly correlated with one another and little correlated.

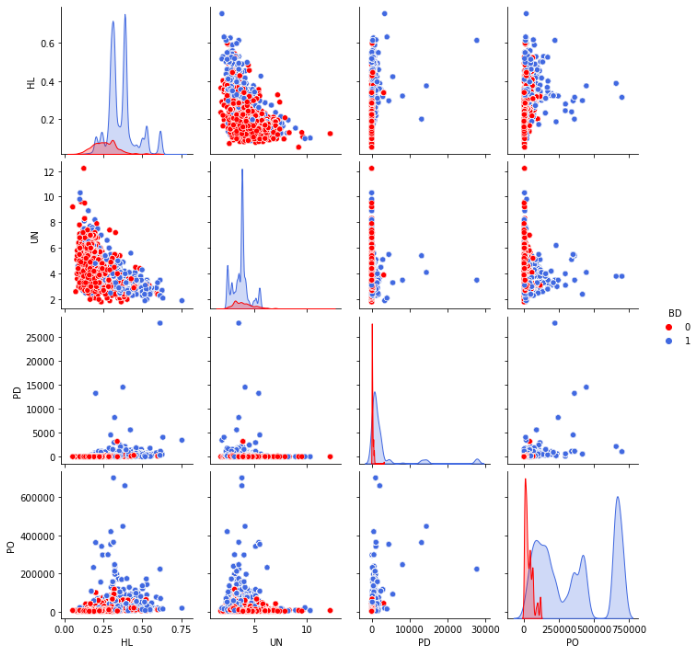

Figure 10. Correlation Matrix

Figure 11 illustrates the relationship between COVID-19 Confirmed, Percent Essential workers, Hospital Occupancy Rate, and Crime rate per 100k.

As can be observed in Table 12, COVID-19 related variables are strongly correlated with one another which is highly expected. Therefore, in order to avoid bias and multicollinearity in the model, only the variable CC (COVID-19 Confirmed Cases) is used in the regression models as a dependent variable which acts as a representative of all the

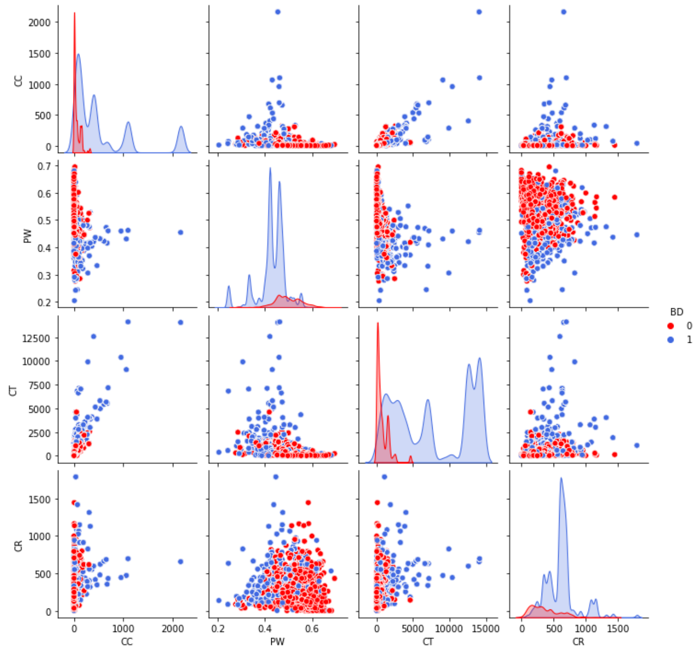

Figure 11. Correlation Matrix

COVID-19 related variables.

Additionally, it is observed a strong correlation between the number of COVID-19 confirmed cases and the aggregate number of bedrooms in the hospitals and the poverty estimate by counties. Since the final regression models have been developed using step-wise selection method, Poverty Estimate variable has been added or removed when seen fit.

Moreover, Percent Rurality was removed from all regression models showing a strongly positive correlation with the percentage of essential workers and a strongly negative correlation with the percentage of people who hold a college degree or higher to avoid bias.

From a political standpoint, it is initially observed how those counties ruled by Democratic Party have a higher percentage of people with more education level, whereas those counties ruled by Republican party presented a lower Mask Usage Score.

And finally, it is observed a strong positive correlation between percentage of people with high educational level and vaccination participation.

Whether any of the above correlations are meaningful or even causal requires deeper mathematical analysis. For that purpose, Multiple OLS regression and Instrumental Variable regression was implemented to answer the following questions:

1. Do people behave the same towards governmental orders and interventions at the time of pandemic?
2. Is there a difference in response between Mask Mandate, Stay at Home orders, and Vaccination encouragement?
3. What factors are the most important in encouraging people to comply with interventions at the time of pandemic?
4. Does having a particular political opinion impact how an individuals respond to orders?

5. What is the relationship between the level of education and complying with certain instructions in times of pandemic?
6. Can we isolate a causal relationship between a policy and a socioeconomic status?
7. What actions can governments take to increase the likelihood of policy adoption among the population?

As mentioned earlier, three policies or interventions which have been the most crucial in preventing the COVID-19 infection are evaluated:

- Change in Movement (shelter in place orders)
- Mask Score (Mask Mandate Adoption)
- Vaccination (Vaccination Participation)

Figure ????? show a generally weak correlation between each dependant variable. However, the correlations are all in the same direction,i.e. where mask mandate is more adopted, the movement is lower whereas the vaccination participation is higher. It seems like people who decided to follow the governmental orders generally speaking did so regardless of the intervention.

The goal of this work is to analyze this hypothesis and isolate any meaningful and even causal relationships impacting policy adoption. This factor is graphically presented in Figures 3 and 4.

Additionally, influence of political preferences seems to be relevant. Thus it is observed an isolated cluster of counties voting for President Biden with the same behavior in regards to one or two of the dependent variables; for example, relationship between Vaccination Participation and Change in Movement behaviours.

Figure ?????? displays the relationships between Education Level, Unemployment, Population Density, and Poverty. Each node corresponds to a individual county. It can be seen that these variables are not strongly correlated with one another. The scatter plots are labeled with political preference and as it can be seen in some instances a similar behaviour from counties with the same political belief.

In addition, Figure ?????? illustrates the relationship between COVID-19 Confirmed, Percent, Essential workers, Hospital Occupancy Rate, and crime rate. The same behaviour can be seen from counties with the same political preference here as well.

After analyzing the relationship among independent variables and their correlation, the variables having strong correlation with others were removed from the list of independent variables. Finally a list of variables such as Population Density, Percent Educated, Poverty Estimates, Unemployment, COVID-19 Confirmed, Percent Essential Workers, Biden Win, Crime Rate, Hospital Occupancy Rate were selected as independent variables that draw the socio-economic status of each county.