Article

People in Pandemic: Factors Impacting Compliance with Interventions

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1 **Abstract:**

1. Introduction

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

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

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

34 Although all the mentioned studies discuss on the benefits of social distancing
35 during the pandemic, they also indicate that the compliance to such policies show

significant differences among socio-demographic groups, confirming the disproportion-ate 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 slow-ing 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 pharma-ceutical 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 com-plexity 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, ad-herence 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 ad-dress 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.

136 *2.1. Datasets and variables*

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

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

142 2.1.1. Epidemological data

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

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

150 In short, we collected 48,837 rows of data for the period between July 2 and July 14,
151 2020.

152 • *Vaccination rate (VR)* This variable presents the percentage of population who are
153 completely vaccinated according to the dataset presented in the sub-section 2.1.1.
154 The data is averaged from the beginning of 2021 until mid June 2021.

155 • *COVID Average Testing (AT)* We use the COVID-19 average testing counts from
156 July 2nd to July 14th, 2020.

157 • *COVID new confirmed cases (CC)* This variable is the rate of new confirmed
158 COVID-19 cases in 7 days period from July 2nd to July 14th, 2020.

159 • *COVID New Deaths (CD)* The rate of new confirmed COVID-19 deaths in 7 days
160 period from July 2nd to July 14th, 2020.

161 – *Testing Clinic* from uscovidatlas.org, which is a dummy variable equal to 1 if
162 there is a testing clinic in one county and equal to 0 if not. Data is last updated
163 in June 1st, 2021.

164 2.1.2. Human mobility

165 We extract this data from Facebook Data for Good Initiative. This dataset provides
166 information about human mobility in comparison to a baseline period that predates most
167 social distancing policies. It also contains the percentage of devices completely stayed at
168 home for the chosen time frame. Thus, this dataset allowed to determine how people
169 reply to mandatory recommendations related to social distancing and shelter-in-place
170 during the pandemic. This dataset is available at: https://data.humdata.org/dataset/
171 movement-range-maps

172 • *Movement change (MC)* This variable represents the variation in human mobility at
173 one time in comparison to a baseline of prior to the pandemic emergence in February
174 2020, when no shelter-in-place orders were issued. This parameter is estimated
175 according to the dataset presented in the sub-section 2.1.2. These values have been
176 averaged for dates between July 2nd and July 14th 2020, both days included.

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[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

2.1.3. 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.

2.1.4. 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.

2.1.5. 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.

- *Education Level (EC??)* 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 8th, 2020.

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

219 • *Percent of Essential Workers (PE)* This variable refers to the percentage of people
220 working on essential services in each county. Data is last updated in June 1st, 2021.

221 *2.2. Experimental setting*
222 2.2.1. Explanatory variables

223 **3. Analysis & Results**

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

228 *3.1. Regression analysis*

229 3.1.1. OLS multiple regression

230 Multiple linear regression (MLR), also known simply as multiple regression, is
231 a statistical technique that uses several explanatory variables to predict the outcome
232 of a response variable. The goal of multiple linear regression is to model the linear
233 relationship between the explanatory (independent) variables and response (dependent)
234 variables. In essence, multiple regression is the extension of ordinary least-squares (OLS)
235 regression because it involves more than one explanatory variable.
236 The regression models implemented are based on the following equations:

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

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

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

237

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

240 • Change in mobility (MO):

241

242 Table xx shows the OLS regression results for Change in Movement regression by
243 implementing three models. As the models 1-3 were implemented, R2 and adjusted
244 R2 factors was improved by about 80 percent resulting in more confidence in the
245 model 3. Political preference (BW) has negative impact on mobility in the model 1
246 and is statistically significant. The same is happening in models 2 and 3, according
247 to Table 1. However, the coefficient betaC1 which is derived from model 3 has a
248 more significant value.in absolute terms compared to Models 1 and 2. Therefore,
249 if a county voted for Biden in the 2020 elections it would have been expected to
250 observe 0.045 units less movement during the data frame studied from July 2 to
251 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. Instrumental variable multiple regression results

***************** Explanation of what IV Reg is and talk about Causality **************

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] :

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

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

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

***************** Jose Questions *****************

What are the following sub-subsections? Please, explain briefly them

***************** End of Jose Questions *****************

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.

***************** Jose Questions *****************

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.

***************** End of Jose Questions *****************

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

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

339   variable. Tables 4-6 also depict the resulting IV regression output of each corresponding
340   Equations 4-6.
341   •   Change in Movement IV Regression Results:
342

343   Table 4 shows the IV regression results for Change in Movement regression. As the
344   models 1-4 were developed, the R2 and adjusted R2 was improved significantly
345   resulting in more confidence in the model 4. Biden Win has a negative impact on
346   Change in Movement in model 4 and is statistically significant. Since Model (4) is
347   the only time Biden Win is introduced in IV regression, the results can be accepted
348   since control variables are all included in this model. Therefore, if a county voted
349   for Biden in the 2020 elections it would have been expected to observe 0.057 units
350   less movement in the time of pandemic from July 2 to July 14. This result is slightly
351   different from what was observed in OLS regression and since the Wu-Hausman test
352   is rejected, it means that what OLS regression estimation can be accepted, therefore
353   approving significance of Biden Win. Percent Higher College is introduced in
354   all models from 1-4 and although initially statistically significant in models 1-3,
355   after introduction of Biden Win variable, the estimated value lost its significance
356   therefore not approving the fact that Percent population with College Education
357   or Higher had a casual impact on less movement of individuals. Comparing the
358   results of IV regression for Education with OLS regression, it can be discussed that
359   Education had neither a positive or negative causal impact on change in movement
360   All in all, it seems like voting for president Biden did have an impact, although not
361   very large, on Change in Movement dependent variable but education did not have
362   a causal impact on the Change in Movement.

363   •   Mask Usage IV Regression Results:
364

365   Table 5 shows the IV regression results for Mask Mandate dependent variable. As
366   the models 1-4 were developed, the R2 and adjusted R2 was improved significantly
367   resulting in more confidence in the model 4. Biden Win has a positive impact on
368   Mask Usage in model 4 and is statistically significant. Since Model (4) is the only
369   time Biden Win is introduced in IV regression, the results can be accepted since
370   control variables are all included in this model. Therefore, if a county voted for
371   Biden in the 2020 elections it would have been expected to observe 0.355 units
372   more Mask Usage on average in the time of pandemic from July 2 to July 14. This
373   result is slightly different from what was observed in OLS regression and since the
374   Wu-Hausman test is rejected, it means that what OLS regression estimation can be
375   accepted, therefore approving significance of Biden Win on Mask Usage.
376   Percent Higher College is introduced in all models from 1-4 and although initially
377   statistically significant in models 1-2, after introduction of Biden Win and other
378   control variables, the estimated value lost its significance therefore not approving
379   the fact that Percent population with College Education or Higher had a casual
380   impact on Mask Usage of individuals. Comparing the results of IV regression for
381   Education with OLS regression, it can be discussed that Education had neither a
382   positive or negative causal impact on change in movement.
383   All in all, it seems like voting for president Biden did have an impact, although not
384   very large, on Mask Usage dependent variable but education did not have a causal
385   impact on the Mask Usage between July 2 to July 14.
386   •   Vaccination rate:
387   Table 6 shows the IV regression results for Vaccination Rate dependent variable
388   Biden Win has no impact on Vaccination Rate as it can be seen in Model (4). Since
389   Model (4) is the only time Biden Win is introduced in IV regression, the results
390   can be accepted since control variables are all included in this model. Therefore, if
391   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

***************** **Jose Questions** *****************

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

***************** **End of Jose Questions** *****************

- 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

***************** **Jose Questions** *****************

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

***************** **End of Jose Questions** *****************

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

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: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
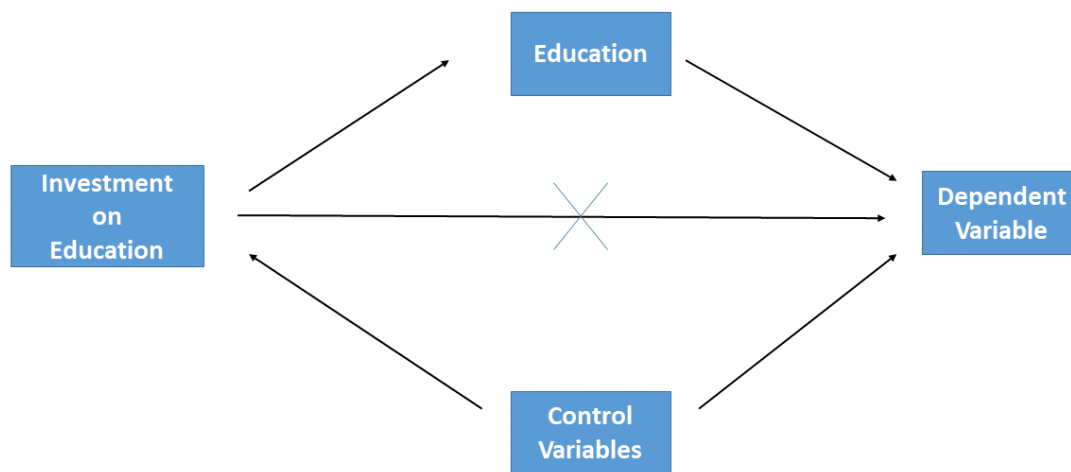
Figure 1. Correlation Matrix

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

2020 Election Results per US County
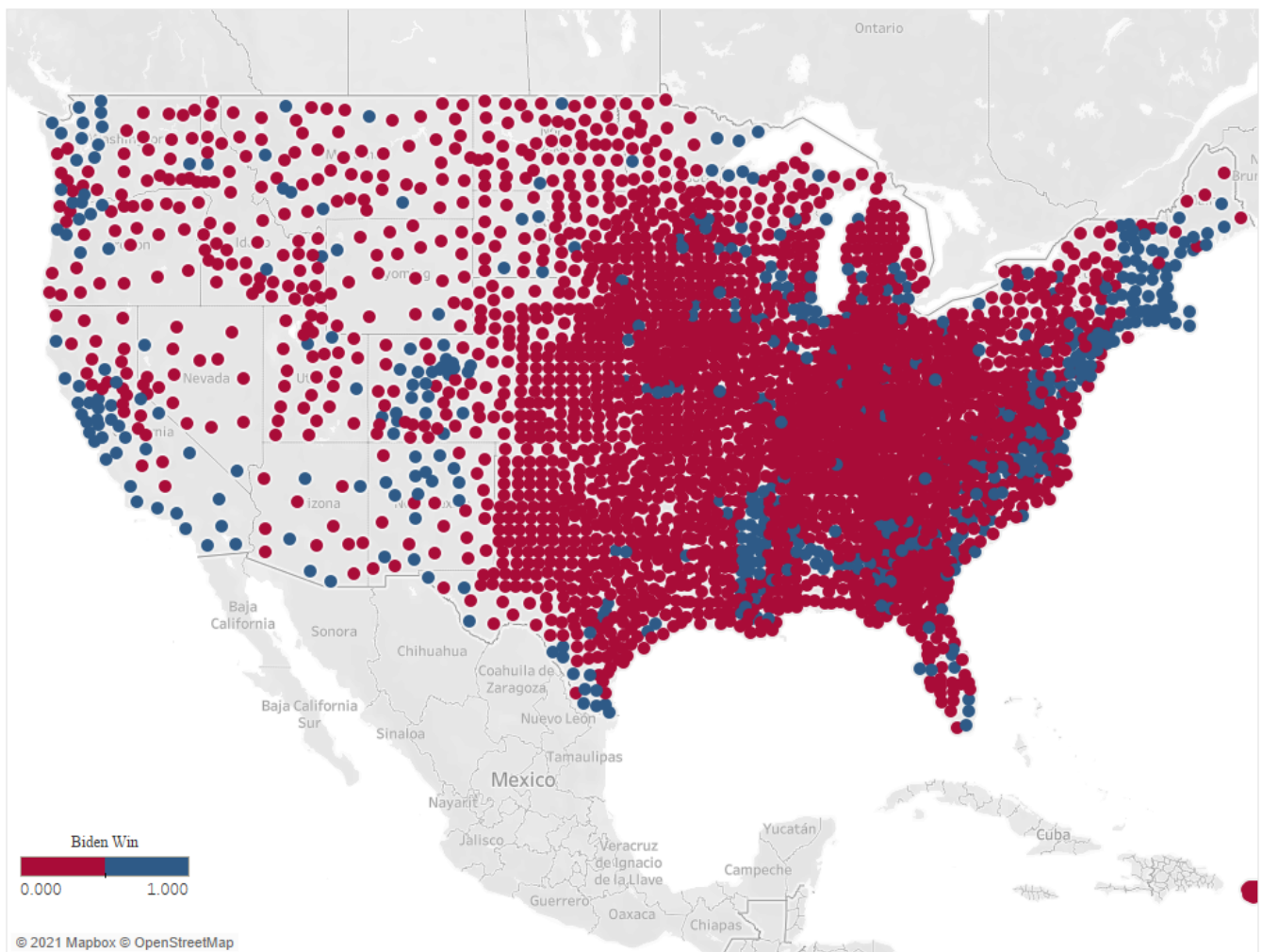
Figure 2. US 2020 Election results per county

455 map into 5 clusters so the differences and similarities would be easier to observe.

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

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

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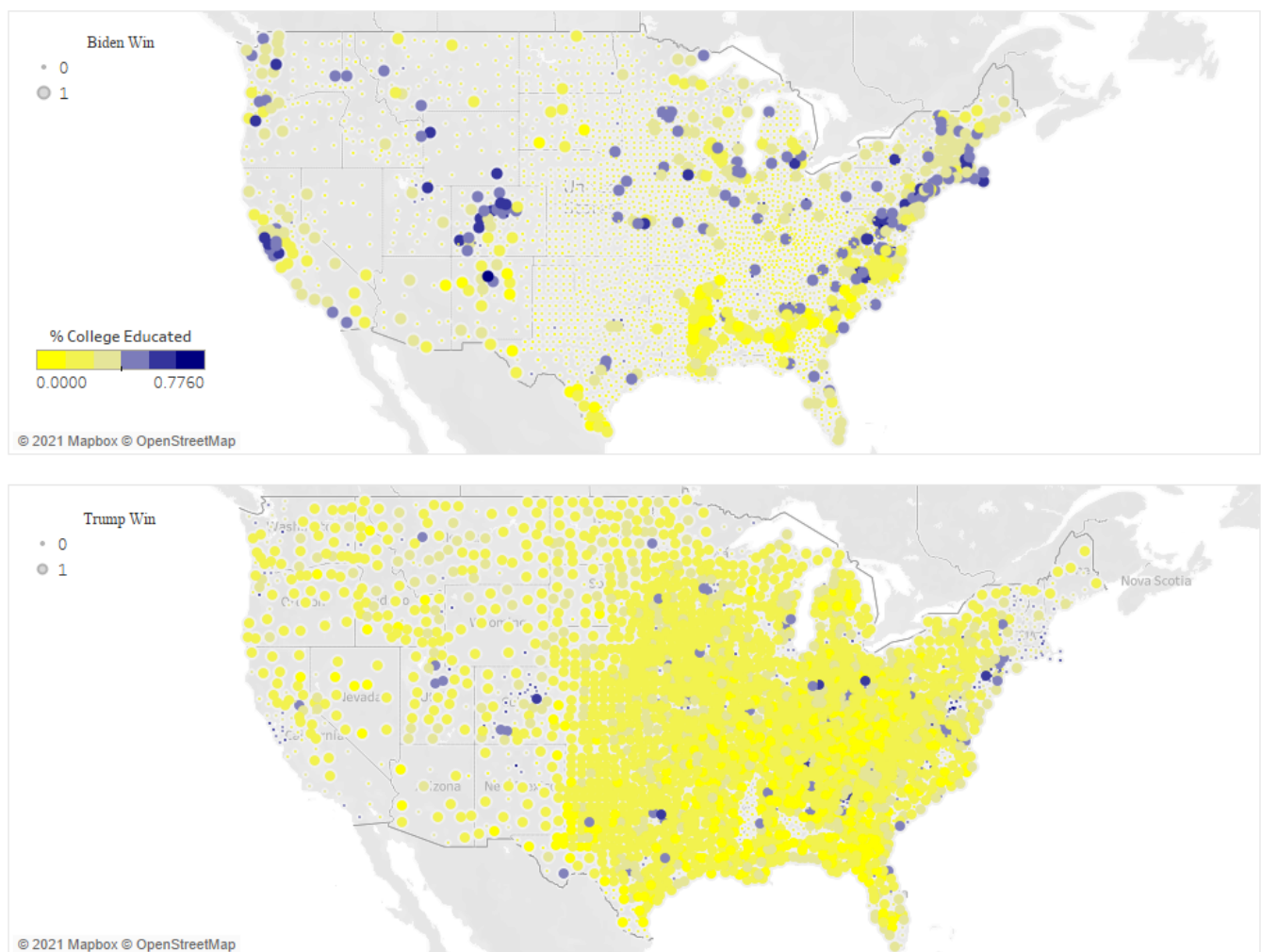
Figure 3. US 2020 Election results per county

Mask Usage Score per US County
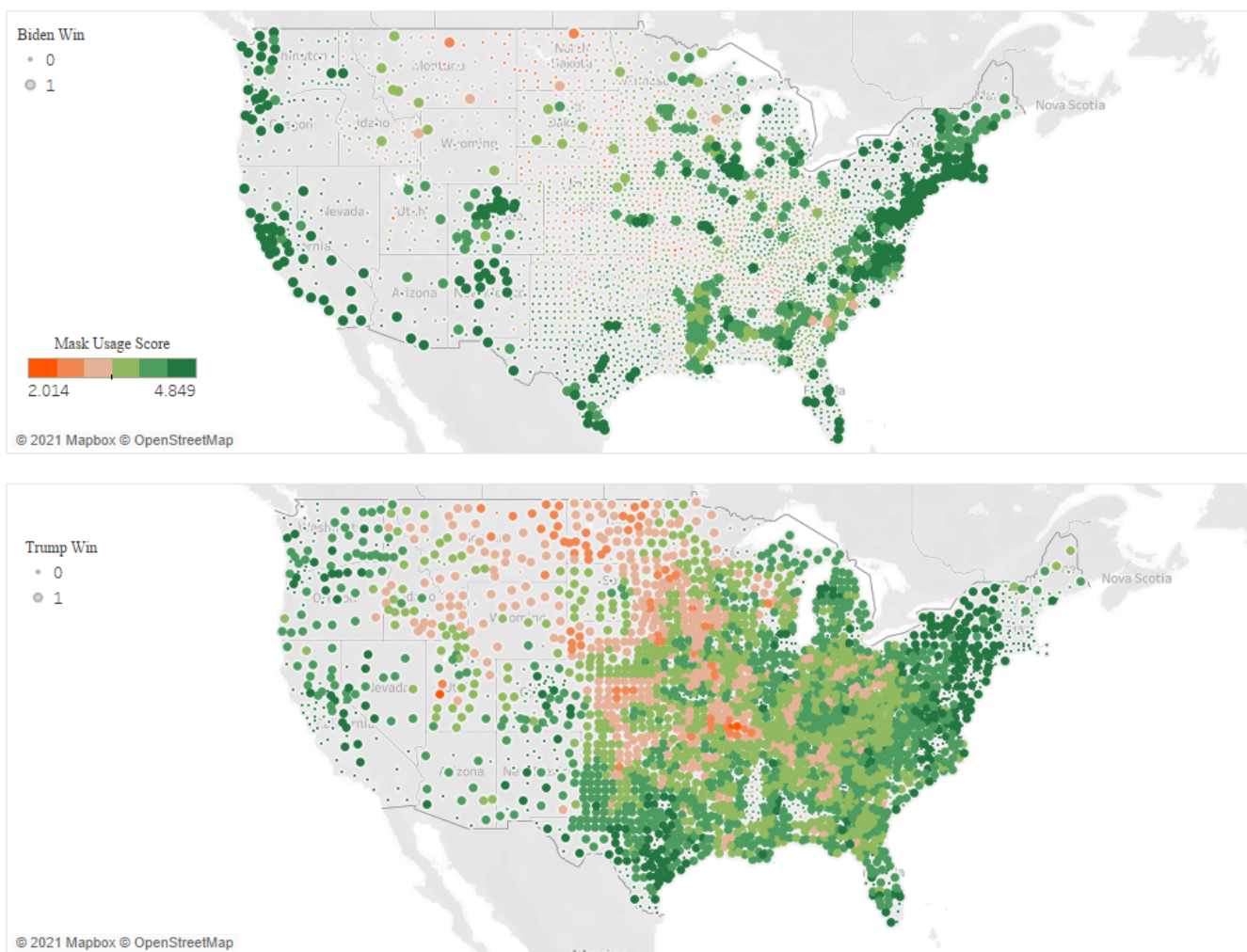
Figure 4. US 2020 Election results per county
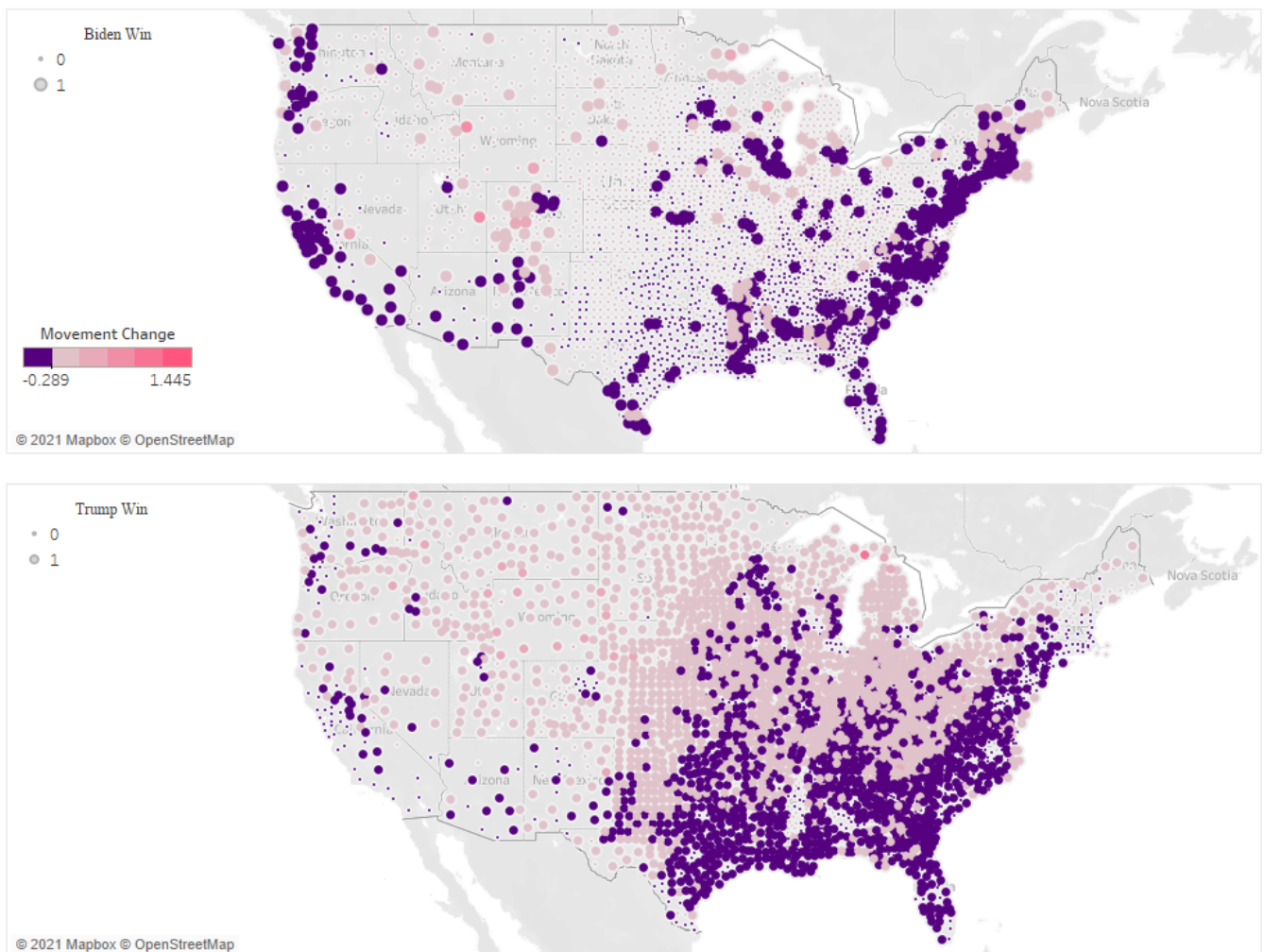
Figure 5. US 2020 Election results per county

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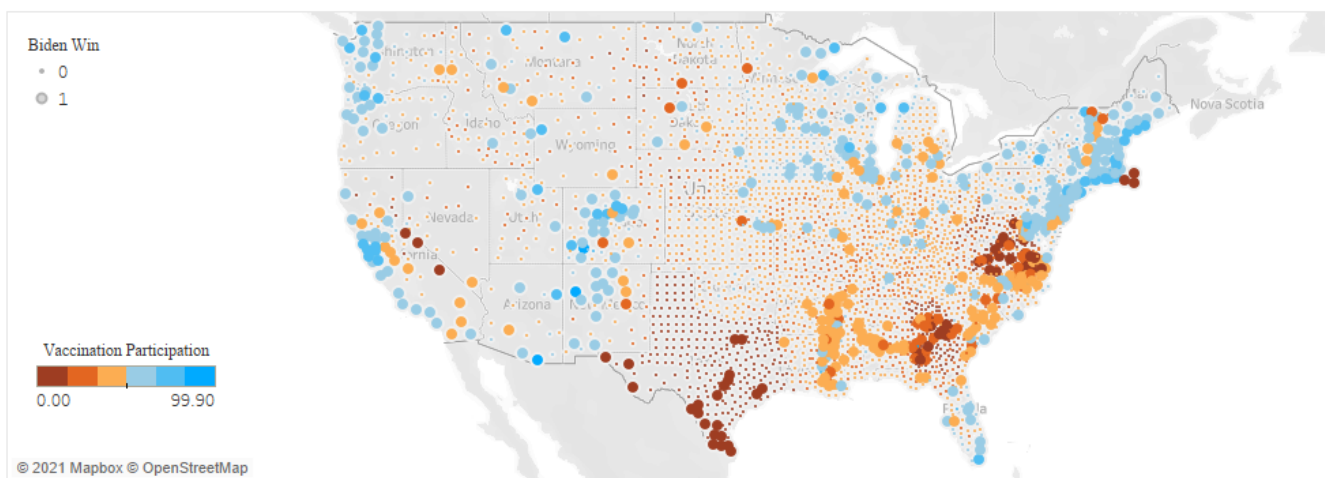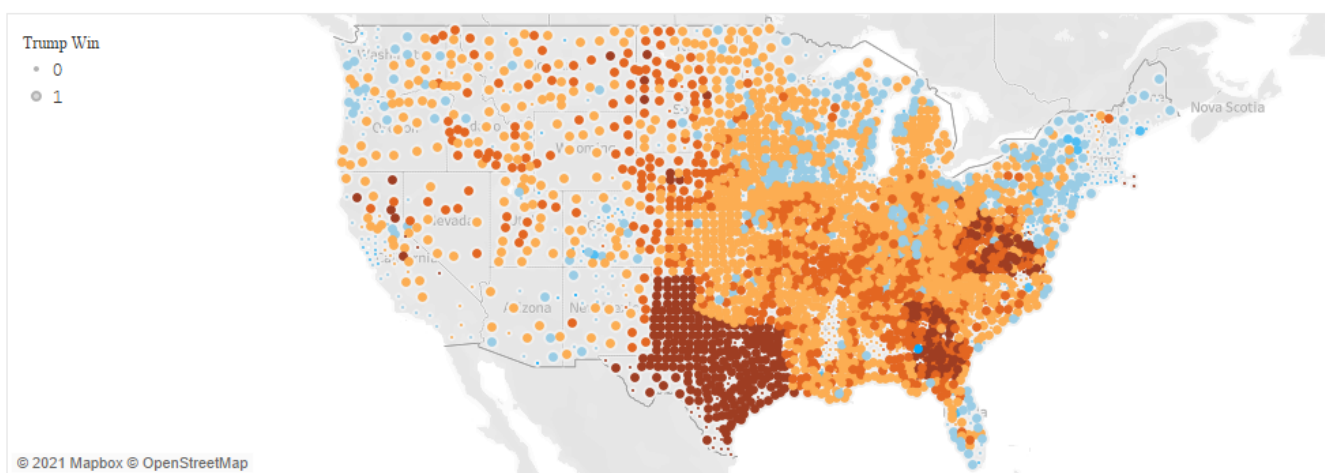
Figure 6. US 2020 Election results per county
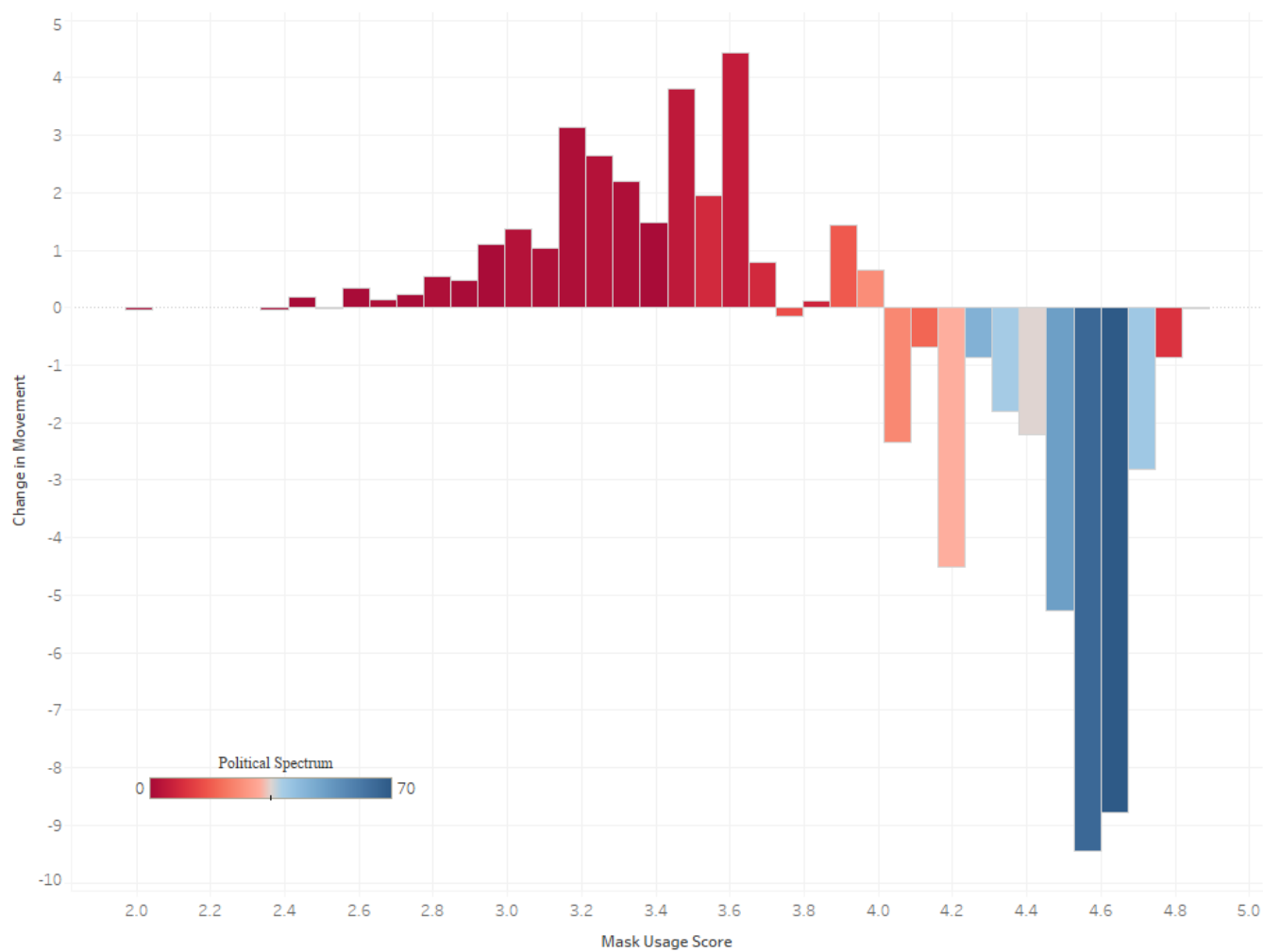
Figure 7. US 2020 Election results per county

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

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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.
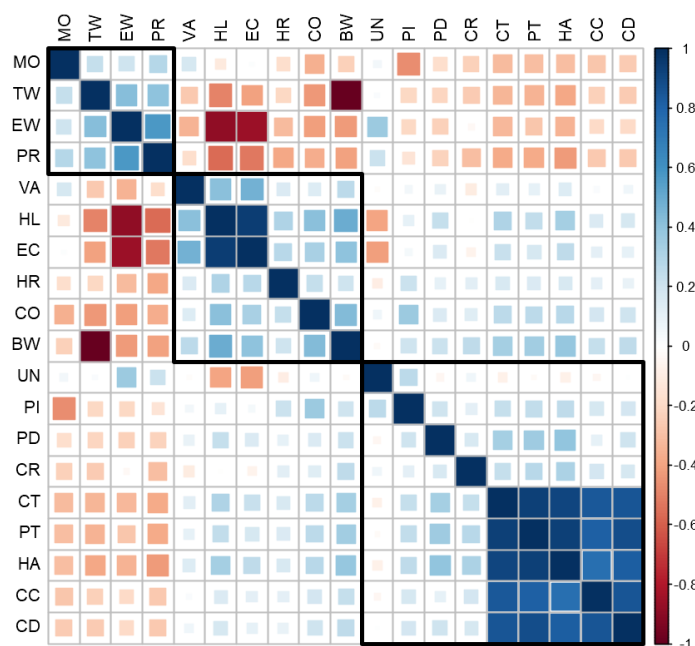

Figure 8. Independent Variables Correlation Matrix

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.

***************** **Jose Questions** *****************

What is the most important things to highlight here according to the previous charts?

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?

677 A more exhaustive analysis of the correlations ??? between some particular variables
678 is shown in section 3.1.1.

679 ******************* End of Jose Questions *******************

680

681 5.0.1. Relationships

682 ******************* Jose Questions *******************

683

684 What we do here? You choose a selected group of variables and check the relation-
685 ship between these selected group of variables, right? The point is to explain why we
686 do this (a zoom view of the chart before?), and why you select some of the variables
687 and not other ones. Let me make some insights -> We analyze the correlation of a set of
688 parameters/variables related with COVID-19 and socioeconomical indicators, in relation
689 with the influence of political preference.
690 In the successive charts, each county is shown like a node in the scatterplots, where
691 colours represent political preference. Red colours represent . . . (value 0) and blue colour
692 . . . (value 1). In the diagonal, we see some linear charts where. . . .

693 ******************* End of Jose Questions *******************

694

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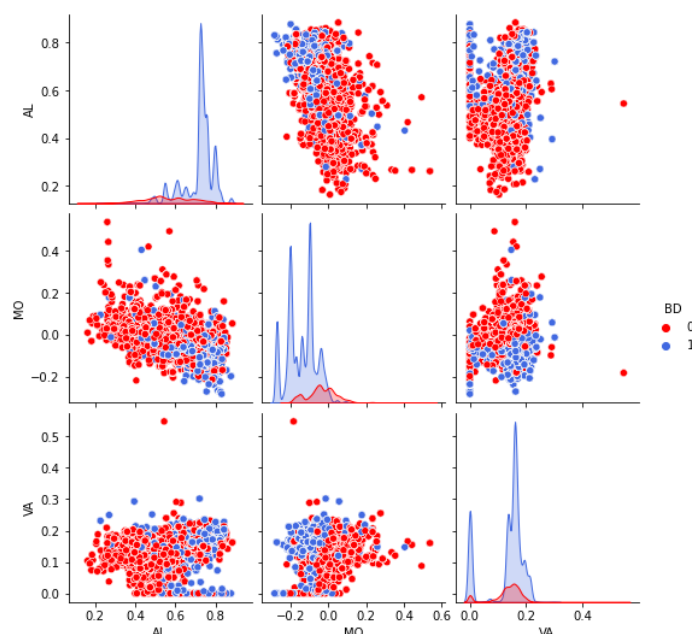regardless of the intervention.

Figure 9. Correlation Matrix

699
700 Figure 10 displays the relationships between Education Level, Unemployment,
701 Population Density, and Poverty. It can be seen that these variables are not strongly
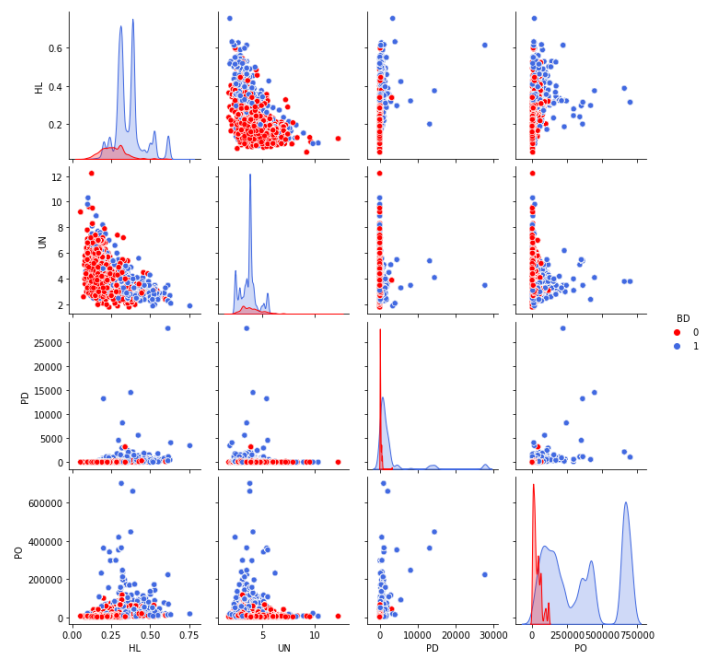702 correlated with one another and little correlated.

703 ******************* Jose Questions *******************

704

Figure 10. Correlation Matrix

Extend what we see here and why is relevant for this research

****************** **End of Jose Questions** ******************

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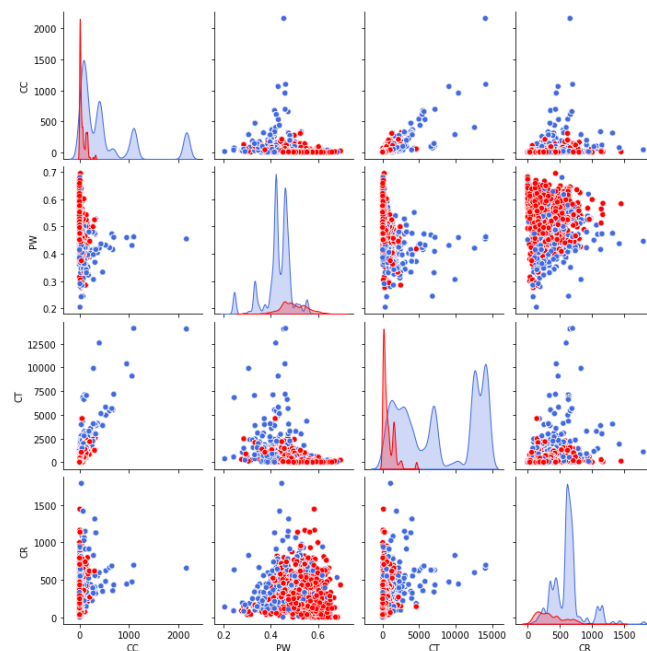

Figure 11. Correlation Matrix

****************** **Jose Questions** ******************

Extend what we see here and why is relevant for this research

713   ***************** **End of Jose Questions** *****************

714

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

720

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

726

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

731

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

735

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

738

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

742   1.   Do people behave the same towards governmental orders and interventions at the
743   time of pandemic?
744   2.   Is there a difference in response between Mask Mandate, Stay at Home orders, and
745   Vaccination encouragement?
746   3.   What factors are the most important in encouraging people to comply with inter-
747   ventions at the time of pandemic?
748   4.   Does having a particular political opinion impact how an individuals respond to
749   orders?
750   5.   What is the relationship between the level of education and complying with certain
751   instructions in times of pandemic?
752   6.   Can we isolate a causal relationship between a policy and a socioeconomic status?
753   7.   What actions can governments take to increase the likelihood of policy adoption
754   among the population?

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

757   •   Change in Movement (shelter in place orders)
758   •   Mask Score (Mask Mandate Adoption)
759   •   Vaccination (Vaccination Participation)

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

764 regardless of the intervention.

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

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

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

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

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