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Abstract

This study provides empirical evidence supporting that the coronavirus may spread in a natural manner, or the spread accelerates with community population, if both local and national leaders downplay the danger of the epidemic. People may compensate inadequate information and take self-protective actions to slow the spread, although it is not enough to stop the natural spread. The larger the number of core voters for the national leader, the larger community cases. These results are derived by comparing the coronavirus outbreaks in Florida, in which the governor follows President Trump's approach, and in Ohio, in which the governor has taken a much more cautious approach.

Keyword: Covid-19, Outbreak, Political Factors, Information

JEL Classification Number: 118

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1 Introduction

It is generally perceived that the more transparent information is, the better the decision. It is well known that through the middle of March 2020, President Trump downplayed the danger of, and overstated the government's capability of handling, the outbreak.[1] Many local governors sent messages similar to the President. If people would believe the overly-optimistic messages from the government, they would underprepare against the outbreak, thereby catching the virus and spreading it to others. The present study investigates this scenario.

For this purpose, the present study focuses on the U.S. states of Florida and Ohio. We choose these states for several reasons.

1. The governors of the states took very different approaches against the outbreak.

Governor DeSantis of Florida is widely regarded as a disciple of President Trump. He has followed closely the policy taken by Mr. Trump.[2] In contrast, Governor DeWine of Ohio has kept a distance from the president since the time of election.[3] Ohio was the first to close schools in the middle of March.[4] It is considered to be one of the more successful states in controlling the virus.[5]

2. Other than the governors' policies, Florida and Ohio are fairly similar politically and economically.

Both are well-known swing states, in which Republican and Democratic candidates have divided the total votes almost evenly between them in most of the past elections. Both governors were elected for the first time in 2018 elections and succeeded successful Republican governors. Both states are highly industrial with large industrial cities: Miami (population, 5,502,400), Tampa (2,441,900), and Orland (1,510,600) in Florida and Columbus (860,090),

[1]For example, see an Washington Post article by Blake (2020), which time-lines Mr. Trump's early remarks on the outbreak.

[2]In his Guardian article, Luscombe (2020) introduces the governor as a self-confesssed Donald Trump diciple (and often referred to as a "mini-Trump)." Also see Nazaryan (2020).

[3]See Gomez (2018).

[4]Camera (2020).

[5]It has a much smaller number of cases in comparison with some of the neighboring industrial state; for example, as of May 2, 2020, the number of cases is 19,335 in Ohio whereas it is 50,983 in Pennsylvania, 42,348 in Michigan, 56,055 in Illinois, and 18,941 in Indiana.

Cleveland (388,072) and Cincinnati (298,800) in Ohio. There is, however, one important difference, which is geographical.

3. Most of Florida is on the Florida peninsula whereas Ohio is bordered with other industrial states, Pennsylvania, Michigan and Indiana, which makes it difficult to control the outbreak.

2 Results

It is natural that at the national level, policy makers are inclined to downplay the danger of a new disease that is potentially highly dangerous; ample reports show that in many countries, economic considerations slowed the necessary first step against the coronavirus outbreak.[6] If, however, the national government is hesitant to deal with a potential pandemic, carefully designed policy at the local level may be effective in controlling the coronavirus outbreak. If, instead, local and national governments equivocally downplay the danger, the outbreak would get worsened.

In order to investigate these possibilities, this study estamates the county-wise coronavirus cases per capita on county-wise population, population density, per capita income, area, median age, and the ratio between the number of votes for the governor in the 2018 election and that for the president in the 2016 election (GP ratio) which represents the political factor in the determination of the coronavirus spread. In particular in the case of Florida, the GP ratio may be thought of as representing the number of "core Trump voters."

In an election, people tend to vote for the candidate with whom they share philosophy and value. As a result, the number of coronavirus cases and the GP ratio can be endogenously determined by such a missing factor. In order to deal with this endogeneity problem, we adopt 2 stage OLS and obtain the following findings:

Observation 1 In Florida, in which the local leader followed the national leader by downplaying the danger of the virus at an early stage of the outbreak,

(1) the spread of the coronavirus accelerates with population,

(2) population density is a factor mitigating the spread, and

[6] See Blake (2020), Lowry (2020), and Ward (2020), for example.

(3) the larger the number of "core Trump voters," the worse the spread of the virus.

Observation 2 None of these phenomena are observed in Ohio, in which the local leader has adopted a highly cautious policy against the outbreak.

These observations may be interpreted as follows. If the public is not well informed of the danger of the virus, the spread of the coronavirus follows the natural course, in which it accelerates with population. It is logical that the larger the community, the more likely someone in the community catches the virus. This implies that the number of cases accelerates with population since the virus spreads exponentially over time.

A theoretical prediction driven from this acceleration effect is that people living in more populated areas would behave more carefully against the outbreak. This prediction is consistent with the fact that the higher the population density, the lower the case (Observation 1.2).

Ohio's experience show that if the local leader informs the public of the danger of the virus, neither demographic nor political factor influences the outbreak even if the national leader downplays it. This suggests the possibility that, as in Ohio, the spread of a pandemic can be significantly controlled by the local government's providing right information, even if the national leader downplays the danger of the virus. Conversely, if the local and national leaders equivocally downplay the danger of a pandemic, as is shown by Florida experiences, the pandemic may be spread by people who support and believe in those leaders.

3 Literature

The volume of studies on coronavirus pandemic has rapidly been increasing. This study contributes to the literature that is concerned with political factors as a determinant of the outbreak. In directly dealing with the spread of virus infection cases, it is closely related to Bursztyn, Rao, Roth and Yanagizawa-Drott (2020), which investigate the effect of misinformation on the spread of a pandemic. That study focuses on two Fox news shows, Hanity and Tucker Carlson Tonight, the former of which is more pro-Trump than the latter. It shows that greater viewership of Hannity is strongly associated with more COVID-19 cases and deaths in the early stages of the pandemic. Both this and their studies are based on Johns Hopkins data.

The rest of the literature that is concerned with the political influence on the spread of coronavirus focuses on the effectiveness of social distancing. In focusing on the effect of political leadership, Njzenman, Cavalcanti, and Da Mata (2020) investigate the effect on social distancing of the Brazilian president's dismissal on coronavirus risk. The study reports that the president's dismissal reduced social distancing more in pro-government localities, which is measured by geo-localized mobile phone data. Adolph, Amano, Bang-Jensen, Fullman and Wilkerson (2020) show that Republican governors and governors from states with more Trump supporters were slower to adopt social distancing policies. Allcott, Boxell, Conway, Gentzkow, Thaler and Yang (2020) report significant gaps between Republicans and Democrats in beliefs about personal risk, which may influence the future path of the pandemic. Barrios and Hockberg (2020) show that as Trump vote share rises, individuals search less for information on the virus and unemployment benefits, and they exhibit lower reductions in both their daily distance traveled and their visits to non-essential businesses. Anderson (2020) provides some evidence that mandatory measures on social distancing have been effective at reducing the frequency of visits to locations outside of one's home. At the same time, voluntary social distancing is moderated by partisanship and media consumptions. Brzezinski, Kecht, Van Dijcke, and Wright (2020) show that individual skeptical about the human causes of climate change are less likely to comply with social distancing and that this effect is observed both in Democratic and Republican leaning counties.

More broadly speaking the present study is related to several studies that treat the epidemiology of coronavirus pandemic from the social scientific viewpoint. By using internet data, Fetzer, Hensel, Hermle and Roth (2020) document a rapid surge in economic anxieties after the arrival of the coronavirus in the US and substantial heterogeneity in participants' beliefs about the mortality from and contagiousness of the virus. More over, it document that participants' subjective mental models understate the non-linear nature of disease spread and shape the extent of economic worries. Using county-day measures on population movement derived from cell phone location data, Wright, Sonin, Driscoll, and Wilson (2020) investigate whether compliance with local shelter-in-place ordinances varies across US counties with different economic endowments. Their theoretical model implies poverty and negative economic shocks from the US trade war will reduce compliance with social distancing.

There is a large volume of empirical studies that capture the effect of misinformation by medias. For studies in that literature, see Bursztyn et al. (2020).

4 Method

We first estimate the coronavirus cases on demographic and economic factors, which can be assumed to be exogenous with respect to the cononavirus outbreak. Those are county-wise population P_j, population density D_j, per capita income I_j, area A_j, and median age M_j and The estimation equation is:

$$[N/P] = c + \beta_P P + \beta_D D + \beta_I I + \beta_A A + \beta_M M \tag{1}$$

where $[N/P]_j$ is the number of coronavirus cases per capita in county j.

Second, we include political factors into the estimation. As an explanatory variable, we include the relative number of votes for the governor (Mr. DeSantis or Mr. DeWine), who won the 2018 election, for the president, who won in 2016 election. Call this relative number the GP ratio, which is denoted as $[GP]$. The estimation equation is:

$$[N/P] = c + \beta_G [GP] + \beta_C [\text{control variables}], \tag{2}$$

where control variables consists of P, D, I,, A and M.

The reason why we use the GP ratio, $[GP]$, as an explanatory variable is to avoid multicollinearity. It would be nice if we could use the votes for all candidates as explanatory variables. However, since all candidates are Republicans and since candidates other than Republican and Democratic candidates, if there were, received very small numbers of votes, the numbers of votes for candidates are closely correlated to one another, thereby creating multicollinearity in explanatory variables.

Estimation equation (2) may suffer from the endogeneity problem if the relative coronavirus case, $[N/P]$ is regressed on the actual GP ratio. This is because the life style of people, including how they deal with the virus, and their voting decisions are likely to be influenced from the same basic personal philosophy towards life; in such a case, both the number of per capita cases, $[N/P]$, and the GP ratio, $[GP]$, are endogenous variables, which prevents unbiased estimation.

In contrast, we may treat as exogenous variables the number of per capita cases, $[N/P]$, and the control variables, county-wise population P_j, population density D_j, median age A_j and per capita income I_j, because it can be expected that the endogeneity problem between those variables and the relative virus case is much less severe. Of course, at an individual level, where to live, what occupation to choose, and how much income to make are all related to the person's philosophy toward life. At the same time, as is noted above, a person's philosophy matters in deciding how he cope with of the virus, which determines the likelihood of his contracting the virus. Thus, within an individual, income and the likelihood of infection are simultaneously determined by such exogenous factors as age, education, and upbringing. If, however, ten people gathers, they may have ten different personal philosophies, which give rises to a variety of life style. Thus, we may assume that people choose where to live sufficiently randomly, the individual relationship between personal philosophy and age will be averaged out, and population, median age and per capita income can be treated as exogenous in the determination of average attitude towards the coronavirus.

4.1 Data

We use only publically available data. The data source for coronavirus cases is the same as Bursztyn et al (2020). Because, unlike Bursztyn et al. (2020), we do not have access to the original data, we complied data from the coronavirus site by the Johns Hopkins University Coronavirus Resource Center at

https://coronavirus.jhu.edu/us-map/

Every day, this site refreshes, and updates, the numbers of cases and deaths in each U.S. county. Our estimation is based on April 15th data for Florida and April 20th data for Ohio. In place of descriptive statistics, we present the plots of vectors of main variables; the left-hand side panels are on Florida whereas the right-hand side panels are on Ohio.

Florida population estimates for 2019 are obtained from Population and Demographic Data - Florida Products, Office of Economic and Demographic Research of the Florida Legislature.[7] Ohio population estimates are taken from Ohio Demographics at the Cubit site.[8] For both Florida and Ohio, per capita income data are obtained from the US Department of Commerce, Bureau of Economic Analysis: Local Area Personal Income, 2018.[9] Data on Florida county-wise area is taken from the site of Florida Association of Counties: County Population and General Information.[10] Data on Ohio county-wise area is taken from USA.com.[11] Florida median age data is from Economic Research Federal Reserve Board of St. Louis, the 2020 estimates by the Bureau of Economic and Business Research, University of Florida.[12]

[7] http://edr.state.fl.us/Content/population-demographics/data/index-floridaproducts.cfm

[8] https://www.ohio-demographics.com/counties_by_population

[9] https://www.bea.gov/data/income-saving/personal-income-county-metro-and-other-areas

[10] https://www.fl-counties.com/county-population-and-general-information

[11] http://www.usa.com/rank/ohio-state–land-area–county-rank.htm

[12] See https://www.bebr.ufl.edu/population/website-article/aging-florida

Ohio median age data is from the Cleveland.com.[13] Election data are taken from *New York Times* site.

4.2 Effects of Demographic and Economic Factors

Tables 1 and 2, respectively, present estimation results on equation 1 for Florida and Ohio. The most striking finding is that totally different factors have contributed to the coronavirus outbreak between Florida and Ohio. Our estimations show that the regression coefficient, R^2, is so much higher with Florida data than with Ohio data. None of the explanatory variables are significant for every estimation with Ohio data. For Florida, in contrast, the effects of some exogenous variables are highly significant.

Finding 1 The effects on per capita coronavirus case, of population, population density and per capita income are all significant at least at the 10 percent level in Florida. In contrast, they are uniformly insignificant in Ohio.

The second striking finding is that population is strongly significant (at a less than 1% level) and positive for Florida data. In the estimation with only population (column I), the constant term is significant as well. Since the dependent variable is the per capita case, N/P, this suggests that the number of cases can be expressed as the following second order equation of population.

$$N_j = 41.5(P_j/10^5) + 5.8(P_j/10^5)^2. \tag{3}$$

This equation implies that as population increases, the coronavirus cases increase with an acceleration rate of 11.6 people per 10,000 people. With respect to this acceleration rate, Tables 1 and 5 shows the following:

Finding 2 In Florida, as community population increases, the coronavirus cases increase with an acceleration rate between 11 and 15 per 10,000 people, with/without control variables included.

This result is consistent with the natural characteristic of epidemic that the larger population, the more likely someone in a community will contract the virus from some outside source. Once someone contracts the virus, the

[13] https://www.cleveland.com/datacentral/2017/12/ranking_every_ohio_city_county_6.html

disease is expected to spread exponentially; at an early stage of spread, many incidences have been reported that shows that one person can pass the disease to a large number of people very quickly. Finding 2 is consistent with this fact.

Table 1 shows that in Florida, the effect of population density on per capital coronavirus is significant are negative except when no other variables are controlled. Surprisingly, per capita income has a positive effect on coronavirus cases, although the effect is often very weak.

4.3 Effects of Political Factors

Tables 3 summarizes the estimation results with voter behavior included in explanatory variables for both Florida and Ohio. These results confirm Findings 1 by covering the exogenous variables studied above. That is, in Ohio, the per capita number of coronavirus cases is very little to do with the factors that we focus on.

In Florida, the effect of relative DeSantis votes is highly significant and positive on per capita number of coronavirus cases. In Ohio, no such effect is observed with respect to relative DeWine votes.

Finding 3 In Florida, the GP ratio is positively correlated to the coronavirus cases. Such a correlation is not observed in Ohio.

The total Florida votes for Mr. Trump (4,617,886) is much larger than that for Mr. DeSantis (4,070,186). That the relative votes between them matters imply that Mr. DeSantis lost Mr. Trump's votes disproportionately over different counties. Given that Mr. DeSantis is a well-known Trump follower, and that the Republican lost a large number of seats in the House of Representatives in the 2018 mid term election, those who voted for Mr. DeSantis may be thought of as the core of Trump supporters. Then, an interesting question is: In which type of county, did Mr. DeSantis lose the votes more?

In order to investigate this question, we regress the GP ratio on population, population density, per capita income, area and median age. Table 4 summarizes the estimation results. In all estimations, the effects of per capita income and median age are positive and significant (at the 1% level with 8 specifications and at the 5% level with 5 specifications). This implies that the poorer the county is and the younger it is, the relatively more Trump voters opted not to vote for DeSantis.

The last question is whether or not the GP ratio may be thought of as a determinant of the coronavirus spread. In order to address this question, as is noted in Section 4, we adopt two stage OLS to estimate the effect of the GP ratio on coronavirus cases. Table 4 suggests that per capita income and median age may be good first-stage explanatory variables.

Table 5, which summarizes the main result of this study, presents the second stage estimation results with these first-stage explanatory variables. Our estimation results can be summarized as follows:

Finding 4 Under the assumption that population, population density, per capita income, area, and median age are exogenous in the determination of the number of coronavirus cases, an increase in GP ratio, an increase in population, and a decrease in population density contributes to the number of per capita coronavirus cases.

5 Conclusion

Our results provide some evidence supporting that the coronavirus may spread in a natural manner if the public is not properly informed of the nature of the disease; in Florida, the outbreak accelerates with an increase in population. People may compensate the lack of adequate information by taking self-protective actions; this may explain why higher population density mitigate the spread. This, however, is not enough to stop the natural spread. If, as in Ohio, the local leader informs the danger of the epidemic, none of these effect emerges.

Developing a cheap-talk game, Horyo and Yano (2020) shows that a government can easily manipulate information if the government desires to convey decision relevant information for the publich but also that which intersects the decision relevant information. This theoretical prediction is empirically supporetd by the recent work of Ajzenman, Cavalcanti, and Da Mata (2020), Bursztyn, Rao, Roth, and Yanagizawa-Drott (2020), and Brzezinski, Adam, Valentin Kecht, Van Dijckel, and Wright (2020) as well as the present study. The recent work of Blickle (2020) indicates shows that the future course of a society can be badly affected by a pandemic. Our results suggest the importance of transparency in the information provided by the government.

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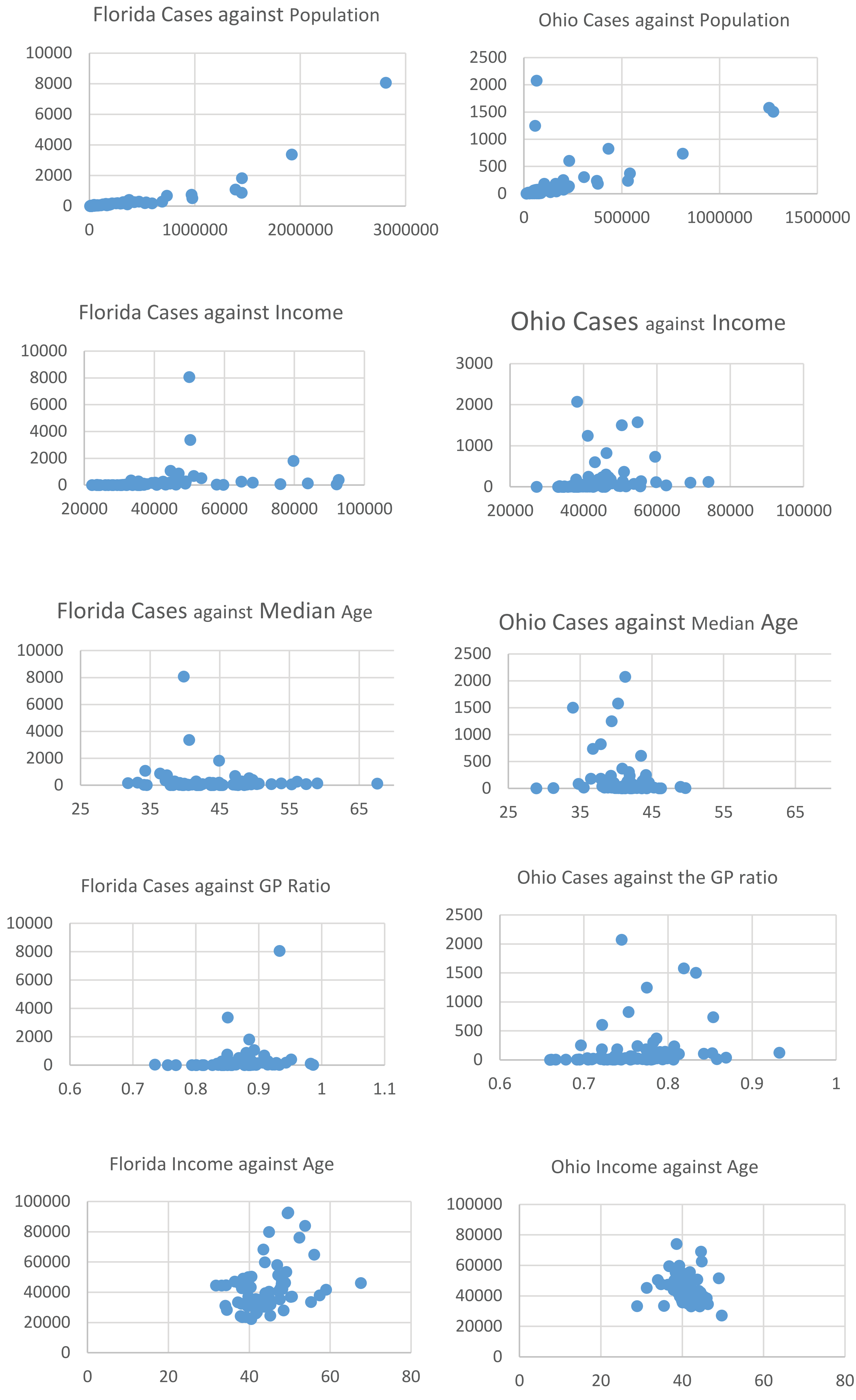

Figure 1: Descriptive Statistics

Dependent Variable	Per Capita Coronavirus Cases in Florida Counties								
	I	II	III	IV	V	VI	VII	VIII	IX
Constant	0.0004 ***	0.0005 ***	0.0002	0.0002 *	6E-04	0.0004 ***	2E-04	0.0003 **	0.0002
	7.8302	7.62426	1.0281	1.9705	1.452	8.2827	1.781	2.2659	0.6762
Population	6E-10 ***					8E-10 ***	7E-10 ***	9E-10 ***	9E-10 ***
	6.5423					6.0856	5.853	5.2486	5.2184
Population Density		2.64E-07 ***				-2E-07 **	-0 **	-4E-07 ***	-4E-07 ***
		2.78592				-2.053	-2.28	-2.678	-2.671
Per Capita Income			1E-08 ***				6E-09 *	7E-09 **	6E-09 *
			2.9779				1.954	2.2703	1.9059
Area				4E-07 ***				-2E-07	-2E-07
				3.1207				-1.389	-1.366
Median Age					3E-07				0.0000
					0.034				0.4331
R2	0.4	0.12341	0.1217	0.1234	2E-05	0.4383	0.471	0.4025	0.4887
Observations	66	66	66	66	66	66	66	66	66

The second rows report t values.

***, 1% significant, **, 5% significant, and *, 10% significant

Table 1: Economic Determinants of the Florida Coronavirus Outbreak

Dependent Variable	Per Capita Coronavirus Cases in Ohio Counties								
	I	II	III	IV	V	VI	VII	VIII	IX
Constant	0.001154 **	0.001148 **	0.002343	0.001798	0.0016	0.001149 **	0.002635	0.001684	0.003803
	2.256498	2.235825	0.939623	0.773049	0.2687	2.223766	0.969152	0.274256	0.873478
Population	-8.8E-11					-1.2E-09	-2.4E-09	5.75E-10	4.54E-10
	-0.04393					-0.11738	-0.21778	0.041461	0.03252
Population Density		-2E-08				5.41E-07	1.29E-06	-4.5E-08	-4.1E-08
		-0.02196				0.11112	0.255219	-0.00707	-0.00632
Per Capita Income			-2.7E-08				-3.6E-08	-3.8E-08	-4E-08
			-0.48899				-0.55675	-0.59216	-0.60872
Area				583.87				-2.3E-06	-2.5E-06
				-0.28707				-0.34466	-0.37839
Median Age					-1E-05				-3.4E-05
					-0.07096				-0.21748
R2	2.27E-05	5.67E-06	0.002805	0.000969	5.92E-05	0.00017	0.00389	0.005331	0.005911
Observations	88	88	88	88	88	88	88	88	88

The second rows report t values.

***, 1% significant, **, 5% significant, and *, 10% significant

Table 2: Economic Determinants of the Ohio Coronavirus Outbreak

Dependent Variable	Per Capita Corona Virus Cases in Florida Counties						Per Capita Corona Virus Cases in Ohio Counties					
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	-0.003 ***	-0.0022 ***	-0.0022 ***	-0.002 **	-0.002 **	-0.00182 **	0.000694	0.0005	0.0006	-0.00359	-0.00246	-0.0019
	-3.14797	-2.8308	-2.8914	-2.57635	-2.335	-2.29271	0.099779	0.0646	0.0754	-0.40482	-0.26168	-0.14354
Population		5.2E-10 ***	7.2E-10 **	7.06E-10 ***	8E-10 ***	8.37E-10 ***		-2E-10	-1E-09	-3.6E-09	-3.4E-10	-3.6E-10
		6.20307	6.04631	5.915416	5.193	4.992225		-0.076	-0.114	-0.32571	-0.02465	-0.02578
Population Density			-2E-07 ***	-2.4E-07 **	-3E-07 **	-3.2E-07 **			5E-07	1.75E-06	2.69E-07	2.65E-07
			-2.2395	-2.29617	-2.62	-2.57912			0.1004	0.341689	0.041804	0.040905
Per Capita Income				3.28E-09	3E-09	3.61E-09				-8.9E-08	-9.3E-08	-9.3E-08
				1.064675	1.065	1.115818				-0.92026	-0.9551	-0.94028
Area					-2E-07	-1.9E-07					-2.5E-06	-2.6E-06
					-1.269	-1.26314					-0.38273	-0.38473
Median Age						-2.6E-06						-9.4E-06
						-0.36228						-0.05925
GP Ratio	0.004144 ***	0.003 ***	0.00301 ***	0.002731 ***	0.003 ***	0.002752 ***	0.00059	0.0009	0.0008	0.011291	0.0116	0.011401
	3.782883	3.37745	3.49082	2.894225	2.814	2.780058	0.948697	0.089	0.0756	0.737769	0.752966	0.718666
R^2	0.182737	0.49262	0.53059	0.534786	0.547	0.547945	4.9E-05	0.0001	0.0002	0.010458	0.012245	0.012288
Observations	66	66	66	66	66	66	88	88	88	88	88	88

The second rows report t values.
***, 1% significant, **, 5% significant, and *, 10% significant

Table 3: Political Factors and Coronavirus Outbreaks in Florida and Ohio

Dependent Variable	GP Ratio												
	I	II	III	IV	V	VI	VII	Viii	IX	X	XI	XII	XIII
Constant	0.863252 ***	0.864664 ***	0.813248 ***	0.8556 ***	0.777847 ***	0.744446 ***	0.813428 ***	0.814052 ***	0.732349 ***	0.743478 ***	0.731071 ***	0.733612 ***	0.738566 ***
	124.8747	122.2174	52.21011	62.23087	26.1831	20.2826	51.78831	51.89021	17.85657	19.1011	18.9115	19.60995	18.61385
Population	1.97E-08 *							7.64E-09			2.49E-08 **	1.49E-08	2.69E-08
	1.691196							0.676179			2.301067	1.315543	1.245159
Population Density		1.27E-05					2.54E-06			1.4E-05			-1E-05
		1.238713					0.257924			1.457212			-0.63705
Per Capita Income			1.33E-06 ***			1.08E-06 ***	1.3E-06 ***	1.25E-06 ***				8.86E-07 **	9.49E-07 **
			3.847942			3.0251	3.583151	3.434487				2.308517	2.351089
Area				1.74E-05					1.99E-05				-9.8E-06
				1.119222					1.369127				-0.4887
Median Age					0.002104 ***	0.001794 **			0.002743 ***	0.002732 ***	0.002954 ***	0.002117 **	0.002125 **
					3.140283	2.059346			3.165088	3.159566	3.466905	2.351733	2.326443
R2	0.042778	0.108155	0.187886	0.019197	0.133512	0.239106	0.188743	0.193737	0.15376	0.156995	0.196142	0.259769	0.265037
Obserbations	66	66	66	66	66	66	66	66	66	66	66	66	66

The second rows report t values.
***, 1% significant, **, 5% significant, and *, 10% significant

Table 4: Determinants of the GP ratio

Dependent Variable	Per Capita Coronavirus Cases in Florida Counties							
	I		II		III		IV	
Constant	-0.00378	*	-0.00234		-0.00273	*	-0.00306	*
	-1.81692		-1.41092		-1.68754		-1.88121	
Population			5.6E-10	***	7.67E-10	***	9.22E-10	***
			6.295174		6.167414		5.337078	
Population Density					-2.5E-07	**	-3.5E-07	**
					-2.30313		-2.63953	
Area							-2.1E-07	
							-1.28866	
GP Ratio	0.005042	**	0.00318		0.003655	*	0.004215	**
	2.105903		1.661803		1.961881		2.214428	
R2	0.064804		0.425783		0.471165		0.48518	
Observations	66		66		66		66	

2 Stage OLS, First stage independent variables: DT Ratio on Median Age and Per Capital Income

The second rows report t values.
***, 1% significant, **, 5% significant, and *, 10% significant

Table 5: Political Determinants of the Florida Coronavirus Outbreak