COVID-19 and American Attitudes

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Introduction

Within this research we are studying the impacts of COVID-19 and the attitudes of Americans. It is safe to say that the Coronavirus impacted everyone in the world, but some people experienced much greater trauma than others. During the pandemic the United States government created many initiatives to support businesses, citizens, and other groups impacted by the economic fallout caused by COVID-19. One of the main government initiatives was the Coronavirus Aid, Relief, and Economic Security Act, or better known as the CARES Act. The CARES act was met with many different levels of support from US citizens. Our research question is “How likely is someone from each state to support the CARES act based on how they were impacted by COVID-19?”. This question is important because it would highlight how Americans value government programs based on how they were impacted by the original cause the program was addressing. Personal impact from COVID-19 would be measured on a state by state basis, where there would be measures put in place to discern how the average person from each state was affected. To determine how each state's average person was impacted we used data from how the entire state was impacted by COVID-19 and also personal adversities that state residents experienced. Some of the measures of adversities would include whether or not a person or someone close to them had COVID-19, how their work status has changed since the pandemic began, how their state was impacted by COVID-19, and many more.

In this research we also will attempt to compare our findings with support for other Government sponsored public support programs that had a mixture of public support. The main program that we will be comparing the CARES act to is the Affordable Care Act (ACA), which was a healthcare reform program that began in 2010. We chose the ACA for comparison because like the CARES act, it was focused around public health and financial support. Like the CARES act, the ACA was also met with a mixture of public support and dissent. By comparing different government assistance programs that were put in place due to similar circumstances, such as millions of people losing their jobs or ability to go to their job, policy can be developed around the parts of these previous programs that citizens and corporations benefited from the most. Not only can policy be developed based on these programs, but government agencies can see what types of policies that citizens benefit from and support the most, and many will run campaigns on support for these programs.

Following this brief introduction to our research paper, we will have a section discussing the literature review portion of our project. The literature review section will cover existing literature that already exists surrounding our research topic and how that prior literature will mesh with our research. The next section will go into detail about the theoretical framework of our research, this section will conceptualize the key dependent and independent variables used in our research. The data and methods section of our paper will go into detail into the sources of the data we used for our analysis and conceptualize any foreign concepts. The section will also explain the statistical methods we used to reach our findings. The final sections of our paper will be the results and conclusion section. In the results section, which serves to be the final summary of our findings from our research, we will explain the results of our statistical tests using graphs and how consistent our results are with our original hypothesis. Finally our conclusion will serve to summarize our findings from the entire research and how our research will serve to contribute to existing literature, we will also discuss potential ethical harms that might arise. In this paper the term COVID will be referring to the coronavirus disease 2019, which is caused by the virus SARS-CoV-2.

Literature Review

We were unable to find any specific literature about the support for the CARES Act based on personal information, this is likely due to how recent the CARES Act was passed at the time this study was conducted. To remedy this lack of previous literature we seeked to research similar government programs that had a mixed public acceptance. We searched for other programs that were tasked with alleviating financial stress for American citizens and chose the Affordable Care Act (ACA) and the American Recovery and Reinvestment Act (ARRA). Both of these programs were met with varied public support, which made them suitable for comparison with the CARES Act.

The Affordable Care Act (ACA, also known as Obamacare), was a federal statute that was signed into law in 2010. The goal of the ACA was to overhaul the American healthcare system and reduce the amount of people who lack health insurance, as well as make health insurance more affordable for all Americans. According to Franz et al. (2020), the ACA has helped millions of Americans since its inception in 2010, and between 2010 to 2016 the uninsured rate dropped by nearly half. In absolute numbers more white Americans became insured due to the ACA, but a greater percentage of non-white Americans became insured. The ACA was met with strong opposition from the Republican party and their supporters, resulting in the ACA becoming a very controversial and politicized act, sparking much debate. We chose the ACA because it has a similar goal of alleviating the financial burdens that American citizens face, while also having a mixture of support and opposition. While the ACA was a much more controversial topic compared to the CARES Act, we believe that it will still serve as an optimal comparison.

The American Recovery and Reinvestment Act (ARRA) was a stimulus bill signed into law by former president Barack Obama in 2009. The overall goal of the ARRA was to help Americans deal with the worldwide financial recession that was occurring during this time period. Specifically, the ARRA aimed at preventing further economic deterioration and to save jobs of American citizens. Steinbrook (2009) says that this program allocated $87 billion for Medicaid, $24.7 billion to subsidize private health insurance for those that lost their jobs, $19.2 billion for health information technology, and $10 billion for the National Institutes of Health. It also provided $650 million to support prevention and wellness activities targeting obesity, smoking, and other risk factors for chronic diseases. Not only did it provide great health coverage benefits, it also provided up to $800 per family in tax withholding deductions. Like many initiatives in politics, the ARRA was met with a mixture of public support and opposition. Supporters for the ARRA were mainly comprised of Democratic party members and supporters, as the bill was originally introduced and sponsored by Democrats.

Based on previous literature of the ACA and the ARRA, we can infer that these initiatives share many similarities in structure, but seem to differ in public support and opposition. The similarities between the acts include the fact they are all aimed at reducing the financial burden of individual citizens through direct government intervention. While the CARES Act was met with plenty of opposition, it dwarfs in comparison when compared to the political opposition of the ACA and ARRA. This difference in opinion could be caused by a multitude of reasons, such as the politicians that supported it or the severe nature of the COVID pandemic compared to the reasons that caused the ACA and ARRA respectively. Despite these differences, the similarities between the acts makes them favorable candidates for comparison and analysis.

Theoretical Framework

Our null hypothesis is that there will be no statistically significant correlation between our independent variables and the average person from each state's support for the CARES Act. The alternative hypothesis is that there would be a statistically significant relationship between at least one independent variable showing support for the CARES Act. According to the 2010 CCES (Ansolabehere, 2012), 48.3% of those that were surveyed supported the American Recovery and Reinvestment Act, or ARRA. While this does not represent the majority of Americans, it does show that there is a large portion of the population that does support the program. Unfortunately, there could be some that oppose, and also support, the program based simply on political party affiliation, or other beliefs about government policy. We theorize that there will be a relationship between someone's work status changing, getting COVID, or experiencing a death due to COVID and their general support for the CARES Act on a state-by-state basis. We theorize these relationships will exist due to the dramatic increase in COVID cases and deaths early on in the pandemic, and the damage that was done to the American healthcare system, jobs, and the lives of all citizens that were affected by the COVID outbreak.

Given the previous observations of the ARRA based on people's reaction during times of uncertainty or upheaval, it can be inferred that people who experienced negative live events during the beginning of the COVID outbreak will be more likely to show support for the CARES Act. For the purposes of this study the chief life events that would be considered negative would be a change in work status, becoming diagnosed with COVID, having someone close to you die from COVID, and having poor physical health. In addition, we included research on other neutral life attributes such as a person's political party, and whether or not they support the Medicare for All program. We predict that political parties and support for Medicare for All would have a strong impact on support for CARES Act, specifically, we predict that Republicans would show less support for the program and Medicare for All supporters would show more support for the program.

Within this research, stakeholders, or individuals likely to be affected, will be the American populace, political candidates, policy makers and governmental institutions tasked with implementing the CARES Act. Assessments made within the research, or inferred from it, should be viewed as a preliminary step and not definitive proof towards actions related to standing or future policies. Additional research should expound further on individual parts to mitigate misinformation as a potential harm. This ethical harm could arise if our testing was done improperly or false conclusions were drawn from our findings. To mitigate this scenario from occurring, the combination of the approaches listed in the research with supplementary code provided for external review will serve to prevent possible errors from occuring. There are also ethical harms that could be introduced where lack of sentiment in policy could be misinterpreted as unwanted, unneeded, or least valued when in reality the opposite might be the case.

Conversely, There are also ethical benefits that can be gleaned from the research. The American people would receive ethical benefits through having their personal sentiments to proposals more clearly defined for policy makers. For policy makers, this could suggest additional insights into which measures would be accepted by all parties and the population. Additionally, regulatory and other governmental institutions could derive some notion on how policy is adopted.

Data and Methods

The main data for this research came from the 2020 Cooperative Election Study (CCES) which is a 50,000+ person national stratified sample survey administered by YouGov. Another source of data that was used for COVID related information came from the Center for Disease Control (CDC). This data (Lee, 2020) provided daily information regarding cases and deaths for each state which allowed us to choose specific time frames and dates when thresholds were crossed. For example, we found the date that each state crossed 1,000 cases, then found out how many days were between that date and when the first case was reported in the United States of America. We also used another data set (Schmalfeldt et al, n.d.) that had the party affiliation of the Governor of each state during the time the CCES study was conducted, and joined this data set with the other data frame. Finally, we used data from the 2020 Population and Housing State Data from census.gov for the population levels of each state in 2020.

Our key dependent variable is the percentage of people that support the CARES Act in each state. The key independent variables in our final model are the percentage of people that support expanding Medicare, the average health of the citizens of each state, the number of days between the first case in the United States and when each state passed 1,000 total cases. To get the average health of each state, the respondent was asked what, in general, their health was. The response was a five-point 1 through 5 rating, from “Excellent” to “Poor”, and these responses were used to calculate the average health of each state.

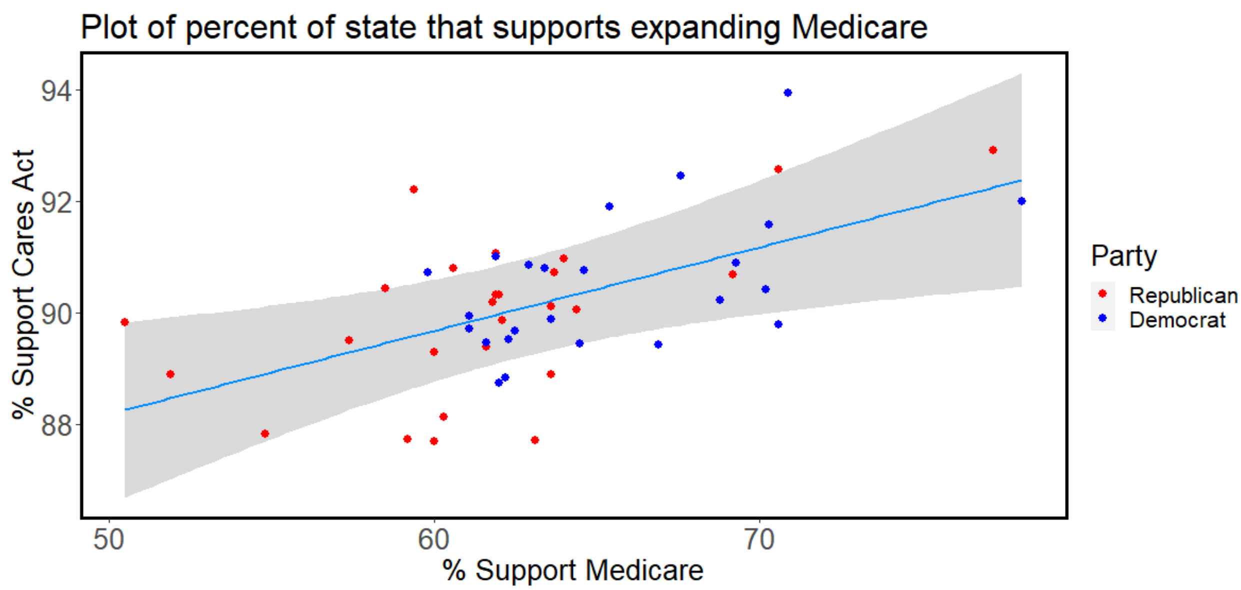
Another independent variable was used to see whether the respondent either had COVID, knew someone with COVID, or did not have COVID or knew someone with COVID. Another group of independent variables looked at whether an individual's work status has changed, which allowed ten different choices and allowed multiple responses. Lastly, we included an independent variable that looked at the percentage of each state that knew someone who died from COVID: a family member, friend, or coworker. The dependent variable is the percentage of people in a state that supports the CARES Act, and is measured as a yes or no question as to whether or not they support the program. As with the CARES Act, each respondent was asked whether they support or oppose expanding Medicare, and was calculated as a percentage of average support for the state. Work status is measured as a question of if the respondents work status has not changed, and if it has in what ways has it changed. Some options are: work more hours, work reduced hours, lost one job, lost only job, laid off, laid off but went back to work, and an individual can select all that apply. The number of days between the first case in the United States and when each state passed 1,000 cases is used to show when a state has surpassed a threshold. The 1,000 cases mark was selected as it is a large number that most Americans did not expect to see. It may be a better indicator to see how many days it took to reach a certain level per 1,000 citizens in a state to account for the different sizes of populations in each state, which could be performed in a future study.

The control variable that we will be using is the party affiliation of the Governor for each state, this variable gives an accurate depiction of the predominant political party in each state. The reason that political parties were added to the study is that we think that the majority political party in each state could influence how the citizens of each state decide whether they support or oppose the CARES Act. We are using ordinary least squares for our model, and have chosen this due to the fact that our dependent variable is continuous and a ratio. The dependent variable is a percentage of a population, which could range from any value from zero to one-hundred. Since the dependent variable is also a percentage of the population, it is also a ratio variable, making a linear model a good choice for

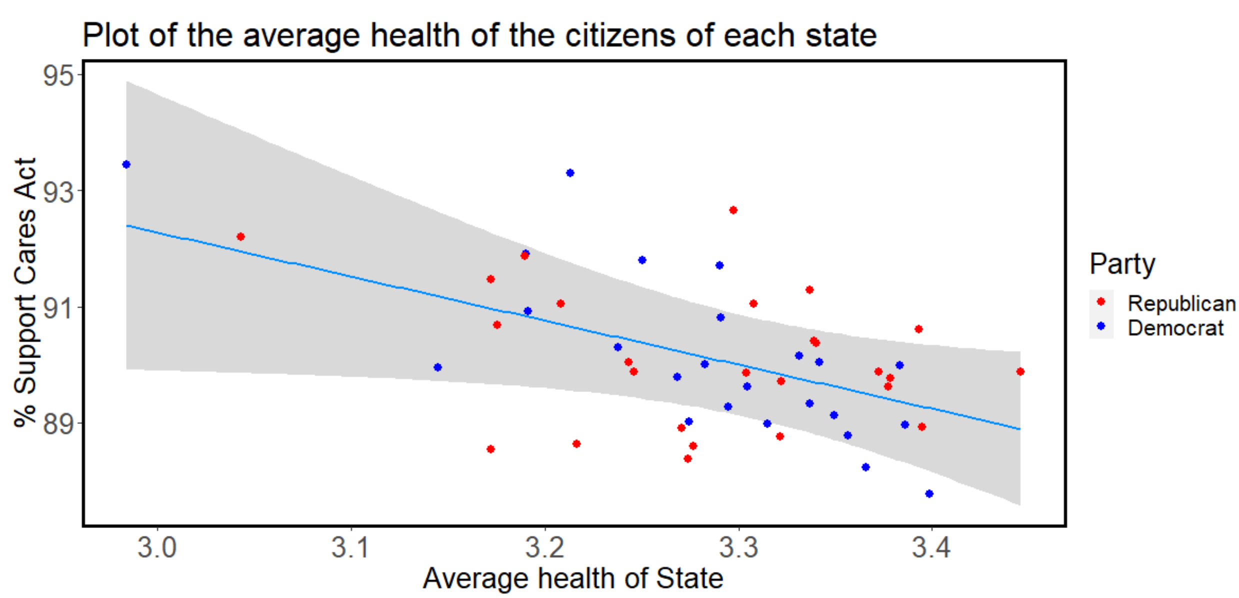
To make the data easier to understand and work with, the variables that coincided with the support for the CARES Act and the support for expanding Medicare had their "Oppose" value recoded from 2 to 0 so that "Oppose" would be 0 and support would be 1, which would be typical values. The variable for the physical health of each respondent was also reverse coded, where 1 indicated a person with excellent health and 5 indicated a person with poor health. Our team decided that it made more sense for a higher value to represent someone with a higher health, and the variable was recoded to indicate this. The remaining variables were all "dummy" variables, and were re-coded the same as the CARES Act variable, where 2s were re-coded as 0s. Since variables related to having COVID were multiple responses, our team decided to group the responses into three distinct variables. The first variable grouped everyone that responded that they had gotten COVID, but did not know anyone else that had COVID. The second variable group was made up of those that had not had COVID, but did know a family member, friend, or coworker that had gotten COVID. The third variable group was respondents that did not have COVID or know anyone that had COVID. The way our data frame was put together, and how well CCES did with ensuring that as many people responded to questions as possible, our team did not have any NA values in our data that needed to be dropped prior to aggregating it into state level data. In total, the model used had eighteen independent variables, which consisted of three separate groups of dummy variables, and four other independent variables. To calculate the percentage of each dummy variable, each response was aggregated based on the state the respondent lived in, and the value was divided by the number of respondents from that state. The summary statistics of our data frame can be found at the end of this report in Table 1, after the references section. Due to the large number of variables that were included in the model, the tables and test results for our research can be found at the end of the document to keep the report streamlined.

Results

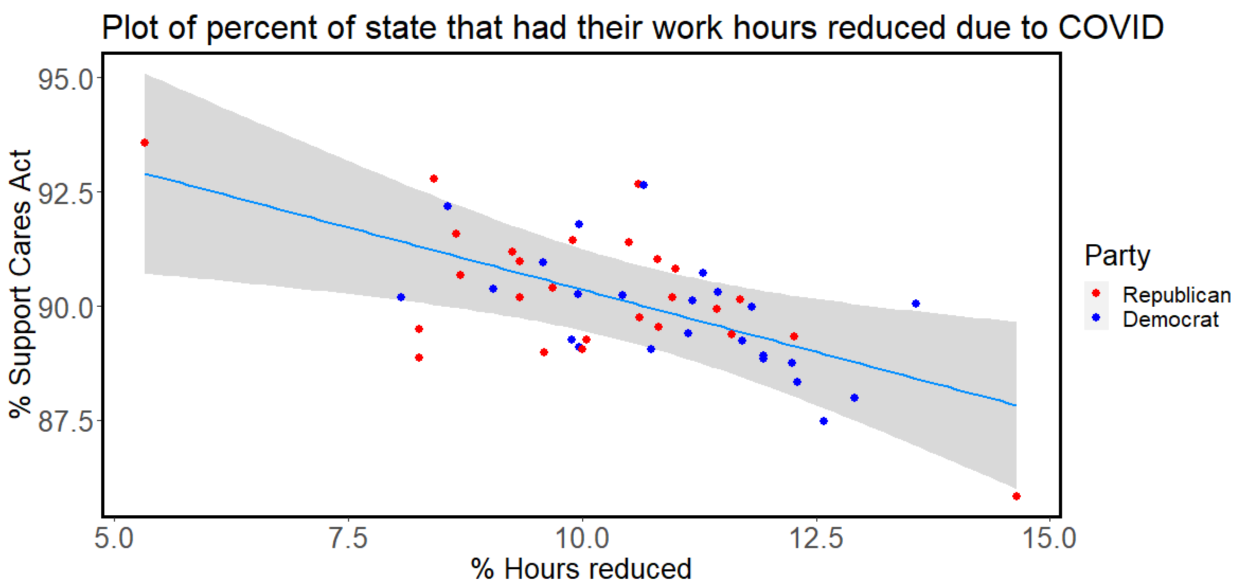
For this research we used a linear regression model due to the fact that our dependent variable was a continuous variable. If this test were to be repeated, it could be done using a logistic regression model with each respondent acting individually instead of showing the response at a state level. To validate our model we measured the correlation between observed residuals and expected residuals under normality. The value we got from the test was 0.995, which shows that our model is valid to use in linear regression, and can be seen in Table 2. Table 2 includes all variables included in the model, as well as the baseline level dummy variables that were not included in the model. Our final model had a p-value of 0.000005394, which is significantly below the alpha level of .05, thus we reject the null hypothesis that there will be no statistically significant correlation between our independent variables and the average person from each state's support for the CARES Act. The individual independent variables that were statistically significant were percent of a state that supports expanding Medicare, the average health of a states citizens, percent of a state that had their work hours reduced, percent of a state that lost their only job due to COVID, percent of a state that had a friend die from COVID and percent of a state that had a coworker die from COVID. Surprisingly, the political party variable was not statistically significant like we thought we would have expected. While this was not in the scope of our report, we believe that the cause of this was due to the CARES Act being passed during a Republican presidency and supported by the President, but it resembles policies that Democrats would support. Due to the smaller variation of support for the CARES Act between states, it means that there is not a lot of variation to explain.



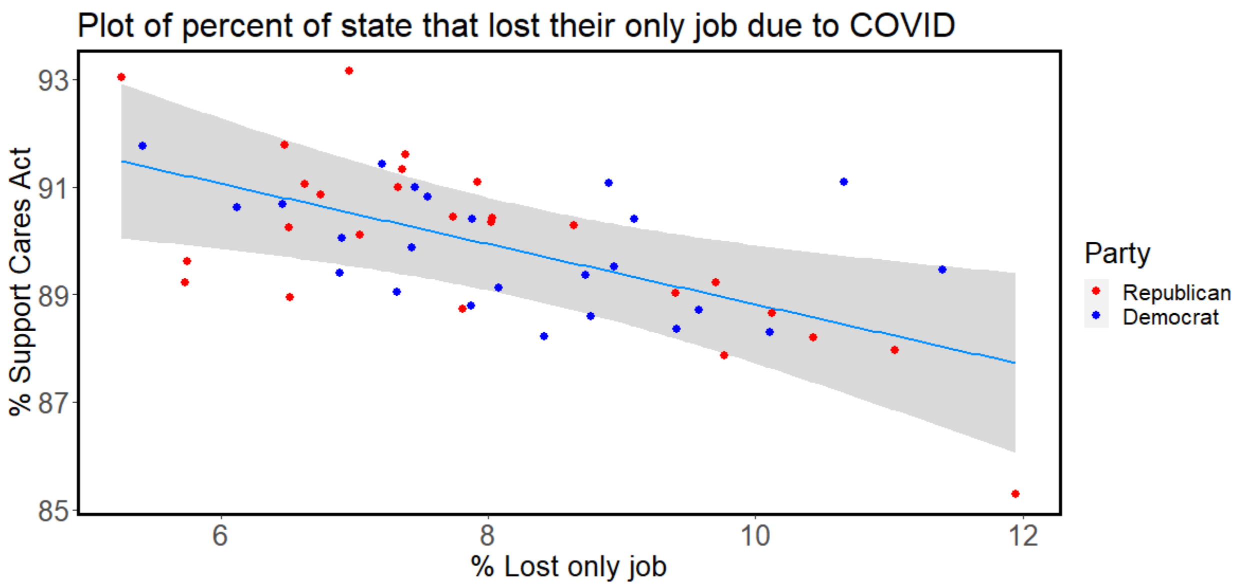
The regression plot for the percent that support expanding Medicare shows that there is a mild positive correlation with the percent that support the CARES Act. The p-value for the percent that support expanding Medicare was 0.009, well below alpha. This is a result that we expected overall, but it was also expected that the individual states, based on the political party of the Governor, that were Democrat would have a higher level of support for the CARES Act as well as expanding Medicare.



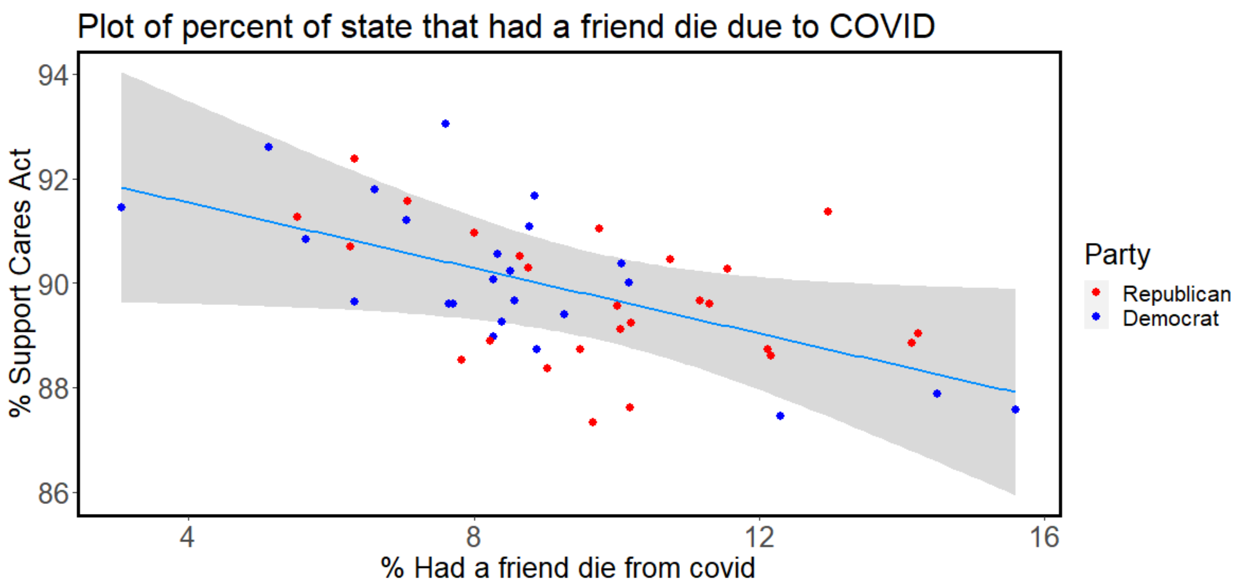
The regression plot for the average health of the citizens of each state shows that there is a mild negative correlation with the percent that support the CARES Act. The p-value for the average health of the citizens of each state was 0.04, below alpha. While a little surprising, the result does make sense. If someone were to think of themselves as being a healthy individual, they may not support a program that assists others during a crisis that typically, but not always, affects those that may not be as healthy. This would then translate to a state that is considered to be a healthier state not supporting such a program. Also, this may not be a good indicator since it is self reported, and many people do not realize how unhealthy they are or if they have some underlying medical condition.



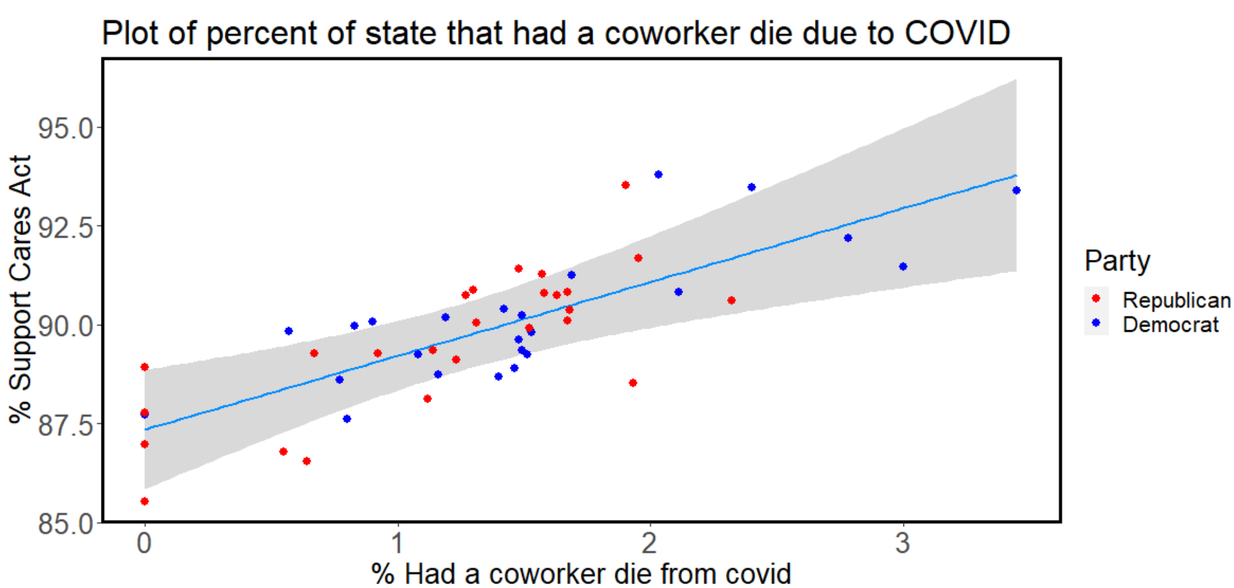
The regression plot for the percent of a state that had their hours reduced due to COVID shows that there is a mild negative correlation with the percent that support the CARES Act, with a p-value of 0.008, well below alpha. Another work related variable that was significant was the percent of a state that lost their only job due to COVID. The regression plot for this variable also shows a mild negative correlation, something we also did not expect. These two variables being negatively correlated with the support for the CARES Act is not what we expected, and there may be other variables that are causing this to occur. Looking at how someone's work status affects their support for financial programs is a good opportunity for future research and may uncover some valuable information about how someone decides to support or oppose government programs.



The last two variables that were significant were related to knowing someone that died from COVID. Specifically, these variables looked at the correlation between percent of a state that had a friend die and percent of a state that had a coworker die, with p-values of 0.046 and 0.001, respectively. The regression plot for the percent of a state that had a friend die due to COVID shows that there is a mild negative correlation with the percent that support the CARES Act. There must be other variables that are affecting this variable, because most would think that having a friend die due to a disease may increase support for a government program related to that disease.



The regression plot for the percent of a state that had a coworker die due to COVID shows that there is a mild negative correlation with the percent that support the CARES Act, and also makes sense. Someone that lost a coworker due to a disease may not want to go to work and be around others that may have the disease. The CARES Act provided workers with extended unemployment benefits, so those that had a coworker die may have taken advantage of those benefits and would support a program similar in the future.



Conclusion

Since the 2016 election, political polarization has only gotten stronger. Despite this, there was still a majority support for the CARES Act. We believe that the majority of Americans, irrespective of their political affiliation, support programs that provide targeted relief funds for economic incentives aimed to support the citizens of the country during times of crisis. In our belief in the goodwill and unity of the American people, we proposed to research the likelihood of individuals from each state to support the CARES act based on how they were impacted by COVID-19.

Making a determination proved challenging as the causes surrounding the lack of CARES Act support were not readily apparent due to little variation in support when compared to other initiatives such as ACA and ARRA. Since support was mainly positive and there was not much variation in the overall support, it made it more difficult to observe patterns and trends in the data. It is also possible that there were other variables that were impacting the results that were not being measured.

Our findings was that there was a relationship with at least one of our independent variables, and we rejected the null hypothesis. This information could be useful when shaping public policy or for political candidates when developing a campaign. Public policy could be shaped to provide more economic, financial, and healthcare support earlier during a nationwide crisis, such as a pandemic or economic downturn. Politicians can also use this information to see where the country is going in terms of support for public programs that provide these types of services, like Medicare for All or the Affordable Care Act.

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Table 1. Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
% support CARES Act	50	89.56	2.373	82	88.8	89.8	90.6	95
Political party	50	0.48	0.505	0	0	0	1	1
% Support Medicare	50	63.498	5.251	50.5	61.1	62.4	65.2	78.1
Average health	50	3.284	0.09	2.984	3.239	3.296	3.341	3.446
Days until total cases reached 1,000	50	79.76	27.515	52	65	70	79	166
% Had COVID	50	4.652	1.348	1.33	3.987	4.63	5.585	8.01
% Knew someone that had COVID	50	49.114	6.63	31.62	43.902	49.135	54.143	61.78
% Did not have COVID and knew no one that had COVID	50	46.13	7.462	31.83	40.603	45.93	51.377	65.81
% Work hours reduced	50	10.493	1.618	5.33	9.582	10.605	11.562	14.65
% Work hours reduced but restored	50	5.795	1.271	2.76	5.207	5.69	6.917	7.92
% Temporarily laid off	50	4.495	1.362	2	3.805	4.465	5.175	9.57
% Temporarily laid off but rehired	50	3.942	1.026	1.05	3.428	3.94	4.735	6.16
% Lost one job	50	2.397	0.597	1.05	2.065	2.4	2.67	3.58
% Lost only job	50	8.057	1.587	5.26	6.923	7.84	9.052	11.95
% Not working before COVID	50	20.718	2.425	14.65	18.87	20.865	22.01	27.55
% Hours increased	50	5.971	0.905	4.36	5.255	6.085	6.445	8.45
% Taken additional jobs	50	3.67	0.917	0	3.188	3.665	4.157	6.29
% No change in work status	50	44.405	2.782	39.13	42.728	44.37	45.875	51.85
% Family died of COVID	50	4.444	1.492	1.05	3.683	4.235	5.285	8.02
% Friend died of COVID	50	9.222	2.556	3.06	7.74	8.82	10.198	15.61
% Coworker died of COVID	50	1.352	0.741	0	0.905	1.44	1.67	3.45
% Knows no one that died of COVID	50	36.918	6.439	23.65	32.585	35.625	40.39	53.44

Table 2. Attitudes toward CARES Act

	Dependent variable:
	% Support CARES Act
Political party	-0.711
	p = 0.230
% Support Medicare	0.149***
	p = 0.010
Average health	-7.589**
	p = 0.040
Days until total cases reached 1,000	-0.017
	p = 0.227
% Had COVID	-0.056
	p = 0.855
% Knew someone that had COVID	-0.089
	p = 0.187
% Work hours reduced	-0.545***
	p = 0.008
% Work hours reduced but restored	-0.193
	p = 0.338
% Temporarily laid off	0.145
	p = 0.635
% Temporarily laid off but rehired	-0.317
	p = 0.296
% Lost one job	0.351
	p = 0.469
% Lost only job	-0.562***
	p = 0.006
% Not working before COVID	-0.162
	p = 0.250
% Hours increased	-0.688
	p = 0.115

Table 2. Attitudes toward CARES Act (cont.)	
	Dependent variable:
	% Support CARES Act
% Taken additional jobs	0.12
	p = 0.631
% Family died of COVID	0.195
	p = 0.492
% Friend died of COVID	-0.312**
	p = 0.046
% Coworker died of COVID	1.865***
	p = 0.001
Constant	128.892***
	p = 0.000
Observations	50
R2	0.782
Adjusted R2	0.655
Residual Std. Error	1.393 (df = 31)
F Statistic	6.179*** (df = 18; 31)
Note:	*p<0.1; **p<0.05; ***p<0.01