This is a paper written by a Master of Public Administration student. Their faculty mentor was Professor Lori Weber. Though formatted slightly differently for this journal, the style guide used for this paper was Turabian's Manual for Writers of Term Papers, Theses, and Dissertations, which is typical for papers in this discipline and used in-text citations.

THE IMPACT OF COVID-19 ON UNEMPLOYMENT IN THE FIFTY US STATES

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Introduction

In December 2019, health officials in Wuhan, China, noticed that individuals were experiencing pneumonia-like symptoms, yet traditional treatments did not work very well on patients (Katella, 2021). This would eventually become known as COVID-19 to the world. By January 31, the World Health Organization declared a global health emergency due to the virus's transmissibility and being a novel virus with limited treatment (Katella, 2021). Without any treatments for the virus, the world's initial reaction in many places, including America, was to contain the spread of the virus so hospitals did not become overwhelmed with patients (Katel- la, 2021). This led to President Trump issuing a National Emergency on March 13, 2020, which soon led to California issuing the first stay-at-home order in the United States on March 19, 2020 (Aran- go & Cowan, 2020). Soon many other states started issuing policies and recommendations regarding containing the spread of COVID-19.

States within the United States started issuing lockdown orders which led to an increase in unemployment which peaked at its highest in April 2020. Unemployment continued to be much higher throughout the year than the previous year. This research study sought to under- stand if COVID-19 policies, COVID-19 cases, or economic factors in all fifty US states significantly impact unemployment. Could it be that lockdown orders have the strongest effect on unemployment, or could it be more factors such as COVID-19 case rate, states with a higher percentage of hospitality sectors, or even if the state Governor's political part was Republican or Democrat? These indicators help explain the high unemployment states endured during the first year of the 2020 COVID-19 pandemic.

Literature Review

Unemployment in the U.S.

One of the main contributors to the dramatic rise of unemployment across the country was lockdown orders implemented by many states (Bayly, 2020). According to the U.S. Bureau of Labor and Statistics (2023), the unemployment rate rose from 4.4% in March 2020, with 7 million people unemployed, to 14.7% in April 2020 at 23 million. This spike in unemployment was the highest unemployment rate since the great depression peaked unemployment of 24.9% (Bayly, 2020). Unemployment stayed high throughout the year 2020, with December 2020 having an unemployment rate of 6.7% (U.S. Bureau of Labor and Statistics, 2023).

Unemployment is not just an economic indicator of the country's health and economy but also an actual lived experience for individual persons within a country. Unemployment could cause an array of issues for individuals beyond the loss of income. Unemployment could cause scarring, which is a prolonged negative experience on future employment, and lead to more incidents of future unemployment (Egdell & Beck, 2020).

Unemployment scarring could occur in two ways. The first is a poor entrance into the labor market (Egdell & Beck, 2020). These individuals may be graduating from high school or college and entering a labor market in an economic downturn, such as a recession (Wachter, 2020). These individuals typically are younger, between 18-24 years old, and when entering a tough labor market can experience career displacement, setting their career prospects back or on hold for many years, which can lead to loss of substantial future earnings (Wachter, 2020).

A second way in which unemployment scarring occurs is job losers, which are individuals who were in the labor market working and lost their employment involuntarily (Wachter, 2020). While evidence has shown that unemployment scarring could happen due to any duration of involuntary unemployment, the longer the period of unemployment, the higher the possibility of more substantial, longer, lasting effects of scarring can occur (Egdell & Beck, 2020). Unemployment, either due to poor labor market entrance or job loss, can negatively affect the individual's mental health, leading to anxiety, depression, and low self-esteem (Autin et al., 2020). Additionally, there can be years of lost earnings. Watcher (2020) found that during the 2007-2009 Great Recession, job losers "lost an average of 2.5 years' worth of average annual earning" (p. 565).

There is also the possibility of physical harm being caused by unemployment. Individuals could possibly see a shortened life expectancy (Egdell & Beck, 2020 and Sullivan & von Wachter, 2009). Sullivan and von Watcher (2009) researched death records between 1980-2006 and correlation to job displacement and found that if the hazards of job displacement continued indefinitely, it could lead to an individual losing around 1-1.5 years of their life expectancy (Sullivan & von Wachter, 2009). This means that job displacement can affect all aspects of an individual's life, including physiological, economic, and physical.

Unemployment encompasses not only those who are not working, there are various types of unemployment and ways the U.S. government counts them. Three types of unemployment can occur within an economy: frictional, structural, and cyclical (Rissman, 1997).

Frictional unemployment can be thought of as the natural time individual skills match the employer's needs for that skill (Hayes, 2022). Factors that cause unemployment during this time are workers searching for a job that matches their abilities, employers putting in the time to recruit qualified individuals, and workers selecting a suitable geographical location to work and moving there (Hayes, 2022 Rissman, 1997). Individuals may not know where a job that is aligned with their skills is located, and the time it takes to search for the job is the time they are unemployed (Rissman, 1997).

Structural unemployment is the loss of jobs that are no longer needed due to technological advances in society (Hayes, 2022, n.p). The economy is restricting itself to new technology, and workers in those previous occupations will need to find new employment (Rissman, 1997). An example of structural employment is the job of a lamplighter. Before the invention of electric lights, lamplighters would set and extinguish street lights throughout a city. However, the need for lamplighters became obsolete due to electric lights, so those workers had to find a new job.

The final type of unemployment is cyclical unemployment. Cyclical unemployment occurs when labor demand falls across multiple sectors of the economy (Rissman, 1997). This can be seen as a recession as many jobs are lost across a wide breadth of society during a similar time due to labor reduction by employers (Rissman, 1997). This is typically a relatively short loss of labor across industries as industries can reverse job loss due to government intervention and economic expansion (Rissman, 1997). Governments usually want to stop or alleviate cyclical unemployment with policies to stimulate the economy (Hayes, 2022, n.p.)

This type of unemployment is what mainly occurred during the COVID-19 pandemic in 2020.

The U.S. Bureau of Labor and Statistics (2015) counts those as employed as "unemployed if they do not have a job, have actively looked for work in the prior four weeks, and are currently available for work" (n.p). Actively looking for a job could be contacting employers, friends, and family for work options, submitting resumes, working with job recruiters, or answering job advertisements (How the Government Measures Unemployment, n.d.). Those who choose to be unemployed, individuals who are unable to work due to age, retired workers, and individuals who are going to school and are not working are not counted as unemployed by the U.S. Bureau of Labor Statistics (How the Government Measures Unemployment, n.d.).

Non-pharmaceutical Interventions

Some of the strategies to prevent the spread of disease also contributed to changes in the labor market, with non-pharmaceutical interventions implemented in states, California being one of them. Non-pharmaceutical interventions are strategies designed to prevent the spread of transmissible diseases. This is especially important when a disease is new, as it may be the most effective way to prevent illness and death (Ahlers et al., 2022). Because COVID-19 was a novel disease that spread quickly, many states took non-pharmacological interventions to prevent its spread to its citizens (Ahlers et al., 2022). In the United States, no national policy or law required every state to follow the same method. Therefore, every state issued their own policies and guidelines (Avery et al., 2021). One of the most common non-pharmaceutical interventions was the stay-at-home order, which required individuals to stay home and only leave for essential items such as groceries or doctor visits (Avery et al., 2021). Many states also restricted what kind of work could be done in person, and put in place restrictions on non-essential business, restrictions on dining in at restaurants and bars, and limiting the number of people who could gather inside. Additionally, some states restricted in-person activities including schools requiring moving to remote learning during the pandemic (Avery et al., 2021). All these restrictions were put in place to save people's lives and to limit the spread of the virus, yet the consequences on unemployment were severe.

States could also institute mandatory personal protective equipment (PPE) practices when around other individuals or inside (Shvetsova, et al., 2022). States could issue recommendations or mandatory guidelines to their citizens on wearing PPE in public such as mask-wearing (Shvetsova, et al., 2022). Mask-wearing was initially a precautionary tool but became an effective tool to stop the spread of air droplets that contain COVID-19 from infective individuals, reducing the spread of the virus (Shvetsova, et al., 2022).

Vulnerable Economies

A state economy may also be at a clear disadvantage to a pandemic due to the sector of its economy. States may be vulnerable to a virus that spreads quickly in groups/crowds, and level of vulnerability may depend on strictness of the COVID-19 preventative measures a state government has put in place (OCED, 2021). Restrictions on travel, such as driving or flying from one place to another, and prohibiting non-essential businesses from operating in public caused a sharp decline in jobs in the hospitality sector of the economy (Gursoy, 2020). Reductions in individual habits such as going to bars, restaurants, and hotels, taking a cruise, or attending sports events caused a decrease or halt in revenue for the leisure and hospitality sector of the economy and state economy (Chen, Garcia-Gomez & Zaremba, 2020). Casino and gambling jobs typically depend on air travel and gathering those indoors, which means the spread of COVID-19 and COVID-19 prevention policies affect those businesses immensely (Chen, Garcia-Gomez & Zaremba, 2020, p. 2). Additionally, International travel in 2020 declined by 58% compared to 2019, affecting 200 million jobs worldwide (Chen, Garcia-Gomez & Zaremba, 2020).

The COVID-19 pandemic led to an increased change in working habits due to the spread of a novel virus and the stringency of economic policies set forth by states (De Fraja, Mizen, Taneja & Thwaites, 2021). Businesses relying on people being in person, entertaining in person, and being in large crowds found it hard to operate at all during a pandemic or because of the state economic policies to prevent COVID-19. This is in contrast to other sectors of the economy. Essential industries such as medicine, necessary goods (farming and grocery stores), and critical infrastructure (for example, energy production) must continue through national shutdowns due to the massive negative impact if they were not to operate in a country (OCED, 2021). Remote work also allowed certain industries to be more resilient compared to leisure and hospitality (OCED, 2021). Industries like financial activities, IT, public administration, education, telecommunication, and so on were able to move to remote work as compared to other jobs (OCED, 2021), allowing employees to work and continue more normal business compared to an industry that requires in-person work (OCED, 2021).

Methods

There were five sources of data, which were compiled into two datasets used to answer the research questions. The data sources were the Local Area Unemployment Statistics Report, New York Times Coronavirus Tracker, Oxford COVID-19 Government Response Tracker, Quarterly Census of Employment and Wages, and National Governor Associate. These were compiled into the March to December 2020 dataset and the March to June 2020 dataset.

The dependent variable is the unemployment rate. The independent variables are the COVID-19 case rate, Stringency Index, percentage of state economies in the hospitality sector, and whether the state had a Republican Governor. The March to June 2020 dataset and the March to December 2020 dataset analyses were conducted in Posit Cloud, formerly known as R-Studio, performing multiple regression analysis, correlation matrix, variant inflation factor test, and scatter plot analysis.

The March to June 2020 dataset and the March to December 2020 dataset represent two timeframes within 2020. The March to June 2020 dataset represented when states were near the end of their strictest lockdown orders implemented in 2020. The March to December 2020 dataset represents the timeframe when stringency policies within the U.S. had loosened across various states. Comparing these two timeframes could give insight into what caused unemployment to be continuously high throughout 2020. Could it show that only one variable was causing the unemployment to be high, or could multiple factors have caused unemployment to be high?

Results

Using the U.S. Bureau of Labor Statistics local area unemployment statistics data, this paper first identified the states with the highest unemployment rates. Figure 1 shows the unemployment rate from December 2019 compared to the last four months of 2020. Figure 1 also shows the United States national average unemployment rate, which is shown in the orange line. The reason for showing December 2019 is that this month was before the pandemic response measure that occurred across the country in various ways, such as lockdowns. Late 2020 saw an increase in COVID-19 nationwide, which saw many states implement stricter stringency policies. Figure 2 shows the top five states with the highest unemployment rates for each period. Starting in 2019, the highest unemployment rates were in Mississippi (5.5%), Alaska (5.2%), Louisiana (5.1%), New Mexico (5.1%), and West Virginia (5%). The national unemployment rate at this time was 3.6%, showing these states were around 1.9% to 1.4% higher than the national average. In comparison, the lowest unemployment rates in December 2019 were Hawaii (2%), North Dakota (2%), Utah (2.5%), Colorado (2.6%), and Iowa (2.6%).

Also shown in Figure 2 is the final quarter of 2020. This data shows that the largest unemployment rates were in September 2020, and all states saw a decrease in unemployment by December 2020. Hawaii, Nevada, California, and New York had the nation's top 4 highest unemployment rates. Hawaii had the highest unemployment rate at 14.2% unemployment rate in September. Massachusetts's unemployment decreased by 7.6% in December 2020, making it 0.2% smaller than New Mexico.

The states that saw the highest impact of the COVID-19 pandemic on unemployment are shown in Figure 3, showing the states that saw the largest increase in unemployment as compared to December 2019. Hawaii, which had the lowest unemployment rate at the end of 2019, saw the highest impact on unemployment rates. During 2020, Hawaii saw a 12.2% jump from 2%-14.2% in September. Nevada also saw a considerable increase as well with a 9.8% increase in unemployment from December 2019 at 3.8% to September 2020 at 13.6%. California saw an increase in unemployment by 6.2% from December 2019 to September 2020.

The lowest unemployment in states with the lowest increase in unemployment in 2020 is shown in Figure 4.

In Figure 4, the unemployment rate is shown starting in 2019 as a baseline and showing the last quarter of the year in 2020. Figure 4 shows that Montana, Utah, Wyoming, and South Dakota had a modest rise in unemployment from December 2019 to December 2020. Figure 4 also shows Nebraska having a lower unemployment rate in December 2020 at 2.8% compared to December 2019 at 3.1 with a difference of 0.3%.

Both Figure 3 and Figure 4 show a decrease in unemployment overall throughout the final quarter of 2020, trending downward from March through April 2020, which saw the highest increase in unemployment in 2020.

Next, this research used Posit to analyze both the March to June 2020 dataset and the March to December 2020 dataset to perform a more statistical data analysis. Figure 5, drawn from the March to December 2020 dataset, shows the scatterplot of Lockdown orders and Unemployment. On the x-axis is the stringency index, and on the y-axis is the unemployment rate of December 2020 subtracted unemployment of December 2019. Each plot represents a state, colored red if that state voted for Trump and colored blue if they voted for Biden. Figure 4 shows that most states that voted for Trump had lower unemployment and fewer stringency policies. However, this data had a few outliers, such as Arizona voting for Biden but having very low unemployment and stringency policies.

Figure 6 was created to see if changing the data from president to governor would change the outliers on the March to December 2020 dataset. Still, the scatterplot colored the plots red if they had a Republican governor and blue if they had a Democratic governor. This was done because state governors had more authority with stringency policies in their state than the federal government. This change gave a better grouping of states by their governor. Figure 6 shows that most states with Republican governors had overall lower unemployment and lower stringency policies. There were also a few outliers in Figure 6. One example is Nebraska. Nebraska had a democratic governor yet had very low unemployment and one of the weakest stringency policies. One possible explanation is that Nebraska has a unicameral legislative body and had a majority Republican body with 35 Republicans in the body as compared to 15 Democrats (2020 Nebraska Legislative Session, n.d.).

Figure 7 shows a scatterplot using the March to December 2020 dataset, but the x-axis has been changed to the COVID-19 cases rate. The scatterplot is colored red if they voted for President Trump and blue if they voted for President Biden. This plot shows that states with the lowest unemployment had the highest COVID-19 incident rates. Figure 7 shows that states with 2 points or lower on the average unemployment scale were predominately states that voted for Trump, with 7 states under 2 points being blue states while 22 were red states. Additionally, over 600 COVID-19 cases per state population were predominantly red states (22 red states compared to 7 blue states). Additionally, states with less than 600 cases were mostly blue states (18 blue states and 3 red states). Figure 7 scatterplot shows a possible correlation between low unemployment and higher overall COVID-19 cases.

Figure 7 shows draws from the March to June 2020 dataset, which shows the scatterplot of the stringency index and unemployment rate. On the x-axis is the stringency index, and on the y-axis is the unemployment rate of June 2020 subtracted unemployment of December 2019. Each plot represents a state, and they are colored red if the state has a Republican governor and colored blue if the state has a Democratic governor. Figure 7 shows a clear divide between red states and blue states. States with a stringency index of 12 or higher were predominantly blue (24 blue states and 6 red states). Additionally, Figure 7 shows that red states still had the lowest unemployment rates and weakest lockdown orders early on in the pandemic compared to blue states. A scatterplot of COVID cases and unemployment is not shown using the June time frame, as early on in the pandemic, had much lower cases of COVID-19 in nearly all states compared to the end of the year.

The next analysis step was to do a correlation matrix and multiple regression analysis on each dataset. The correlation matrix shows numbers on a scale of -1 to 1. Correlation is the independent variable's effect on the dependent variable (Pollock & Edwards, 2016). A number variable with a positive number is a positive correlation between two variables meaning they move in the same direction (Pollock & Edwards, 2016). The higher the positive number, the more correlated the variables (Pollock & Edwards, 2016). If the number is 0, there is no correlation between the two variables (Pollock & Edwards, 2016). If the number is negative, a negative correlation means they move in the opposite direction (Pollock & Edwards, 2016). The statistical significance in a correlation is statistically significant at 0.01 and 0.05.

A good use of the correlation matrix is also to see if collinearity exists. Collinearity (also known as multicollinearity) is when multiple independent variables are highly correlated. Predicting if variables are genuinely independent becomes difficult with colinearity, meaning regression results are less trustworthy (Tamura, Takano, Miyashiro, Nakata & Matsui, 2019). Detecting multicollinearity requires more than just a correlation matrix (Tamura, et al, 2019). A variance inflation factor or VIF is necessary. A VIF "estimates how much the variance of a regression coefficient is inflated due to multicollinearity" (Investopedia team, 2023, n.p). A VIF score of 1 means there is no correlation. Between 1-5 is moderately correlated and above 5 is highly correlated (Investopedia team, 2023). VIF scores of 5 or more indicate multicollinearity and independent variables must be removed or changed to reduce multicollinearity. This research uses the VIF function on both time frame datasets.

First, I tested Hypothesis 1, that COVID cases will affect unemployment in this longer time period in addition to the share of the state's economic sector which is vulnerable, by conducting a correlation and multiple regression analysis.

The correlation result (Table 1) shows that the unemployment rate positively correlated to stringency and was statistically significant ($r=0.42$, $p = 0.003$). The unemployment rate and COVID-19 case rate showed a weak negative correlation between COVID-19 and unemployment ($r = -0.31$, $p = .027$). This negative correlation is similar to Figure 7, which shows that states with high COVID-19 cases were lower in unemployment. This, however, does not show if COVID-19 affected lockdown orders. Republican Governors and the unemployment rate were negatively correlated and statically significant (r= -0.38, p = .007). The percentage of state economies in the hospitality sector had a weak positive correlation to unemployment but was not statistically significant compared to the other variables (r = 019, p = .181).

The next step was to run a multiple regression on the dependent and independent variables in the March to December 2020 dataset. Multiple regression analysis could show if there is a statistically significant relationship between the multiple independent variables. A multiple regression analysis goes deeper than a correlation as it can show if the independent variable affects the dependent variable (Pollock & Edwards, 2016). A multiple regression analysis will produce a p-value that represents whether the null hypothesis of the regression was rejected or not (Pollock & Edwards, 2018). A p-value of .05 or lower means you can reject the null hypothesis and show there is a relationship between the dependent and independent variables (Pollock & Edwards, 2018). The smaller the p-value, the stronger the evidence that the independent variable affects the dependent variable. The estimated coefficient in the regression results will provide the way in which the independent variable influences the dependent variable, such as if it has a negative or positive slope (Pollock & Edwards, 2018).

Multiple regression analysis is required to see if any of the independent variables grow weaker or stronger and affect the dependent variable when running through the same model. By looking at just bivariate regression or bi-variate correlation of all the independent variables, it shows some significant relationship between each independent variable. However, unemployment numbers could be affected by multiple independent variables at once.

Table 2 shows a multiple regression analysis with unemployment as the dependent variable and stringency index, percentage of states economies in the hospitality sector, COVID-19 case rate, and Republican Governor variables as the independent variables. The regression results indicated the model was significant (F = 4.691, p =0.003). The regression only showed that the percentage of state economies in the hospitality sector had contributed significantly to the model (B = 0.30, p = 0.02). However, the stringency index (B = 0.19, p = 0.30), COVID-19 case rate (B = -0.18, p = 0.24), and Republican Governor (B = -0.26, p = 0.11) did not contribute significantly to the model. The final predictive model was: unemployment case rate=-0.68 + (0.19 stringency index) + (0.30 % of states economies in the hospitality sector) + (-0.18 COVID-19 case rate) + (-0.261 Republican Governor).

Table 2 showed that during the March to December 2020 dataset, states with a higher percentage of economies in the hospitality sector had an increase of 0.19 points of unemployment when controlling for Republican Governors, Stringency Index, and COVID-19 cases rate. Regression showed that Hypothesis 1 was partially correct as the share of the state's economic sector which is vulnerable affected unemployment, but it did not show any other variables, such as the COVID-19 case rate having an impact.

Table 3 shows the VIF on the multiple regression to check multicollinearity for the independent variables. The VIF report did not show any multicollinearity between the independent variables, as all results came well below 5.

This paper now tests Hypothesis 2, that the largest factors affecting unemployment are the stringency of COVID-19 policies and the state's economic sector. I tested this by conducting a correlation and multiple regression analysis. The correlation result (Table 4) shows that the unemployment rate was also positively correlated with stringency and was statistically significant (r = 0.27, p = 0.05). Un- employment and COVID-19 case rates were positively correlated and statically significant (r = 0.30, p = 0.04). Additionally, republican governor and unemployment were negatively correlated and significant (r = -0.39, p = .01). Percentage of states economies in the hospitality sector and the unemployment rate were also shown, like Table 1, positively correlated but not statically significant (r = 016, p = 0.27).

Table 5 shows the multiple regression results of the March to June 2020 Dataset. The regression results indicated the model was significant (F = 4.761, p = .003). The regression showed that the percentage of state economies in the hospitality sector (B = 0.36, p = .01) and the COVID-19 case rate (B = 0.32, p = 0.03) contributed to the model. However, similar to Table 1, the stringency index (B = 0.16, p =0.3) and Republican Governor (B = -0.26, p = .10) did not contribute significantly to the model. The final predictive model was: unemployment case rate=-3.16 + (0.16 stringency index) + (0.35 % of states economies in the hospitality sector) + (0.32 COVID-19 case rate) + (-0.26 Republican Governor).

Table 5 showed that during the March to June 2020 Dataset, states with a higher percentage of economies in the hospitality sector had an increase of 0.36 points of unemployment when controlling for Republican Governors, Stringency Index, and COVID-19 cases rate. This was more than double the effect of unemployment as compared to the March to December 2020 dataset. Additionally, an increase in the COVID-19 case rate also led to an increase of 0.32 points of unemployment when controlling for Republican Governors, the Stringency Index, and the percentage of state economies in the hospitality sector. Table 5 showed that hypothesis 2 was partially correct, with the percentage of state economies in the hospitality sector having an effect on unemployment. However, it was also wrong as the stringency index during the March to June dataset did not impact unemployment but, rather, showed that the COVID-19 case rate affected unemployment. Both multiple regressions in Tables 2 and 5 did not show Republican Governors having a statistically significant effect on unemployment.

Table 6 measures VIF to see if the March to June 2020 dataset was experiencing multicollinearity. As shown in Table 3, the results did not show any multicollinearity between the independent variables, as all results came well below 5.

Discussion

The data of this research first showed that there was a commonality between states with the highest unemployment in the final quarter of 2020: Hawaii, Nevada, California, New York, and Massachusetts. In December, New Mexico had the 5th highest unemployment rate, beating Massachusetts by 0.2%. These top 5 states also saw the highest impact of unemployment as compared to December 2019. The initial data seemed to suggest there was something similar between the five states that caused them all to have continued highest unemployment. This paper also showed the states with the lowest impact of COVID-19. These five lowest-impact states had relatively low unemployment in both datasets.

This paper then used two data sets, March to December 2020 and March to June 2020, to see if COVID-19 policies, COVID-19 cases, or state economic factors have a larger impact on unemployment. Each dataset is representative of a different time during the pandemic in 2020. The March to December 2020 timeframe represents the end of 2020, while the March to June 2020 timeframe represents the end of the strictest stringency policies in the United States. As represented by the March to June 2020 dataset, the first part of the pandemic shows that the COVID-19 case rate affected unemployment. However, the March to December 2020 dataset, encompassing the end of the year 2020 did not show COVID-19 having a continued effect. The data showed the COVID-19 case rate initially affected the unemployment rate, but that effect did not continue in the December timeframe.

Additionally, neither dataset showed a statistical significance of stringency policies on unemployment. This could be due to the strongest stringency policies at the initial start of the pandemic and loosening as the pandemic continued.

Additionally, this paper did show a clear relationship in both datasets: states with a large percentage hospitality sector experienced more unemployment. This result makes sense as this sector was more vulnerable to community spread (such as indoor concerts or casinos). These sectors also experience more restrictions, making working from home, as other economic sectors could, difficult. This paper named unemployment as the dependent variable. Additional research could use the hospitality sector as the dependent variable, seeing what independent variable most affects its unemployment numbers.

This research shows that governments during a pandemic must be aware of the multifaceted effects on their economy, especially unemployment. It also shows that there are factors in addition to government stringency policies affecting unemployment during COVID-19 and highlights the effect of the specific sector of the economy. More research into unemployment and pandemics could give future administrations tools for effectively dealing with a pandemic early on to try to minimize the suffering people endure during high unemployment.

Future Research

Future research could look at more variables to determine if there is a relationship between unemployment and factors such as the state GDP, how educated the state's population is, and the state's poverty percentage. Additionally, future research could explore 2021 and 2022 to see if any variables related to COVID-19 early on were having a lingering effect on unemployment. Since unemployment continued to drop rapidly in 2021 and 2022, it would be interesting to see the full picture of unemployment during the COVID-19 pandemic. Additionally, this study only covered the two periods of 2020, the end of many lockdown orders and right after they ended. Additional research could focus early on, such as a dataset covering just March 2020 to April 2020, or focus on where the highest unemployment percentages were all around the country. That dataset may be able to show the effect of stringency orders as compared to the two datasets within this paper. Lastly, future research could compare other countries along with U.S. states in 2020 to see if there were similar trends between the independent variables considered in this paper.

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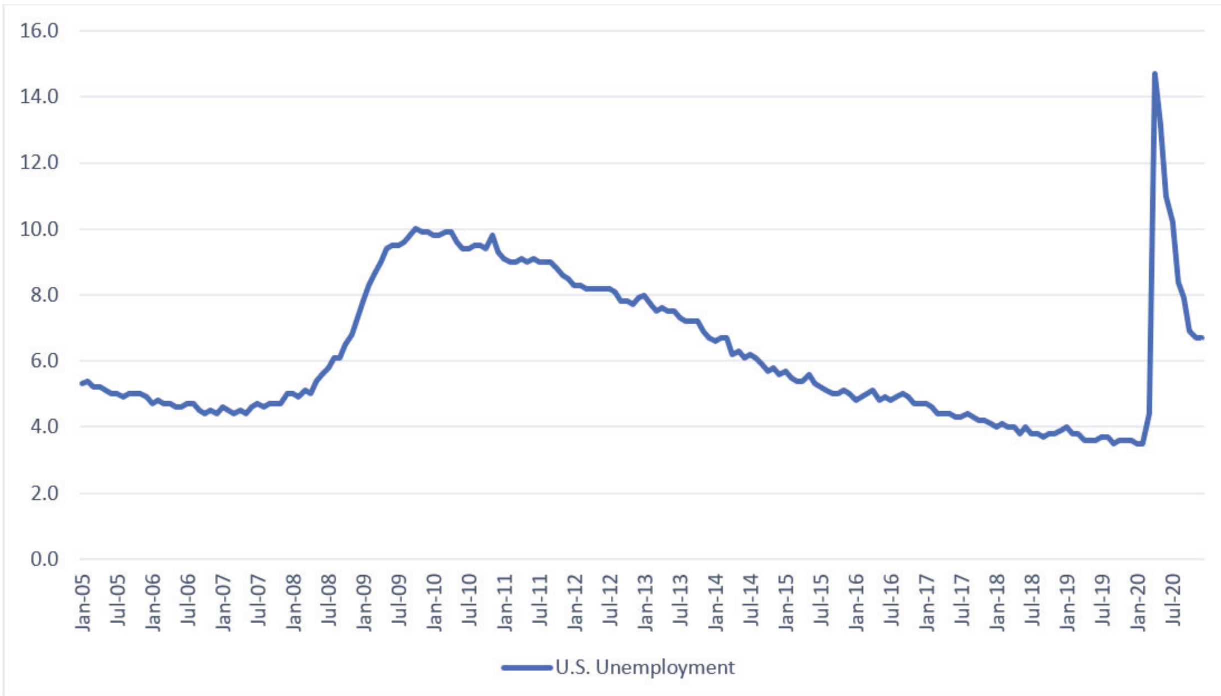
Figure 1: United States unemployment rates, January 2005 - December 2020



Local area unemployment statistics (https://www.bls.gov/lau/, 2023)

Figure 2:States with the highest unemployment rates

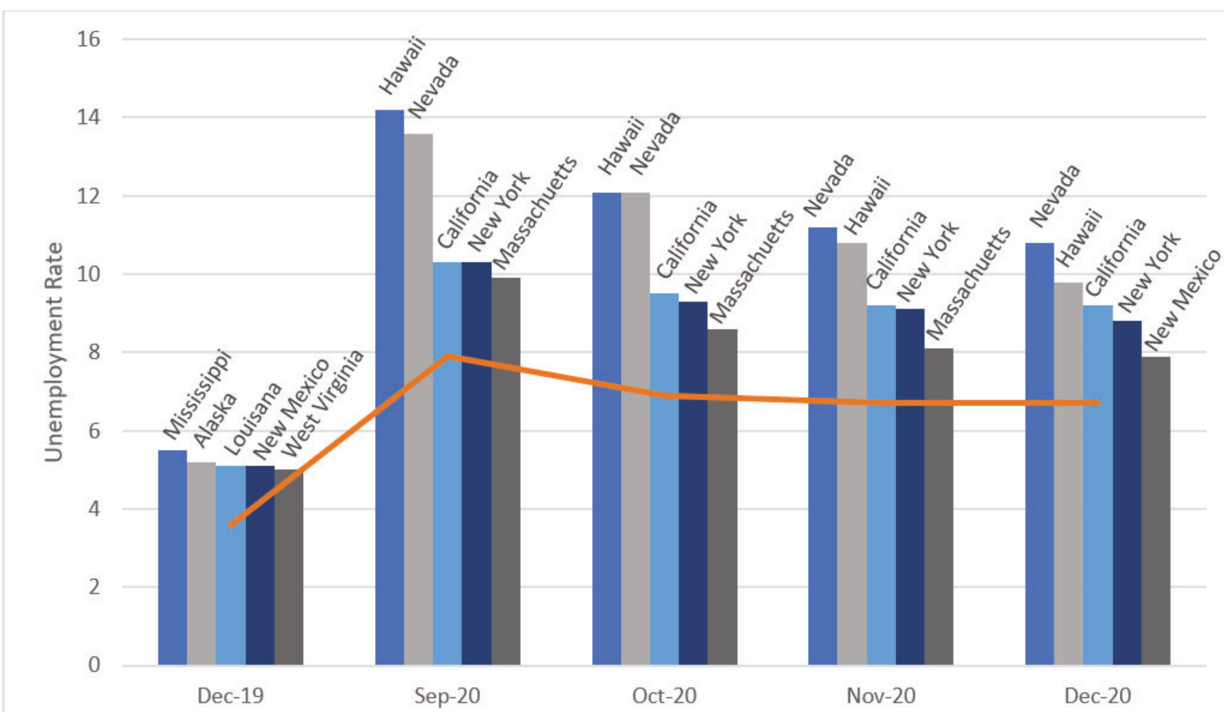


Figure 3: States with the highest impact of COVID-19 on unemployment rates

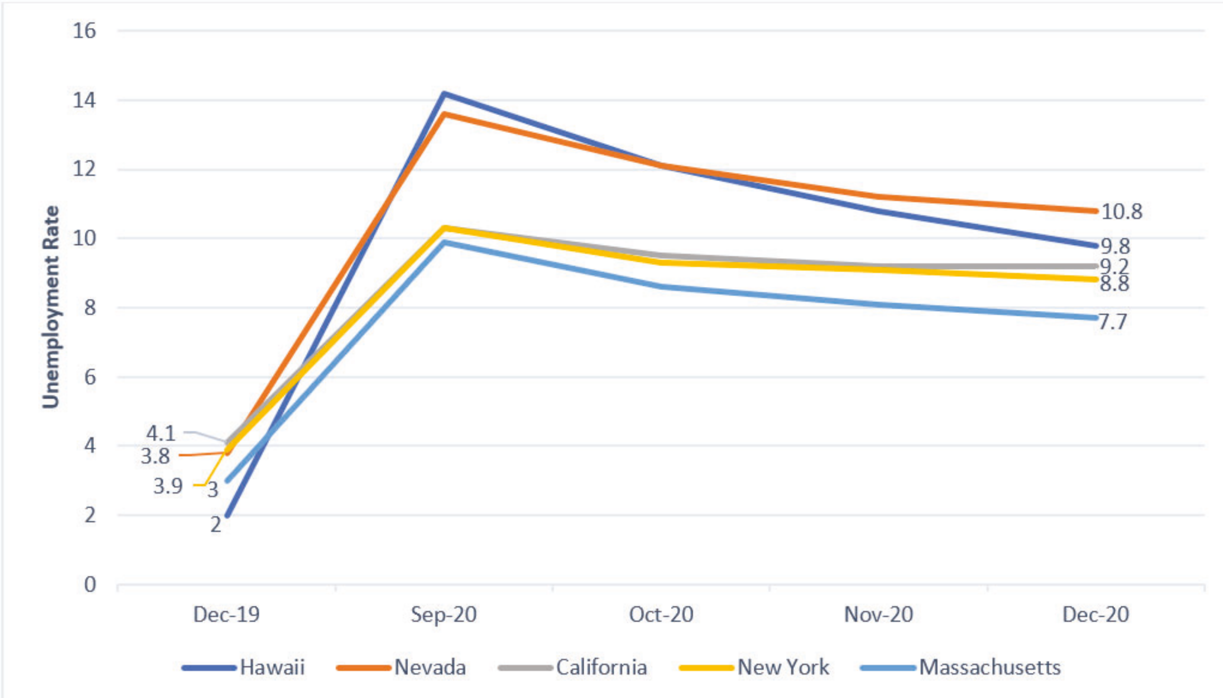


Figure 4: States with the lowest impact of COVID-19 on unemployment rates

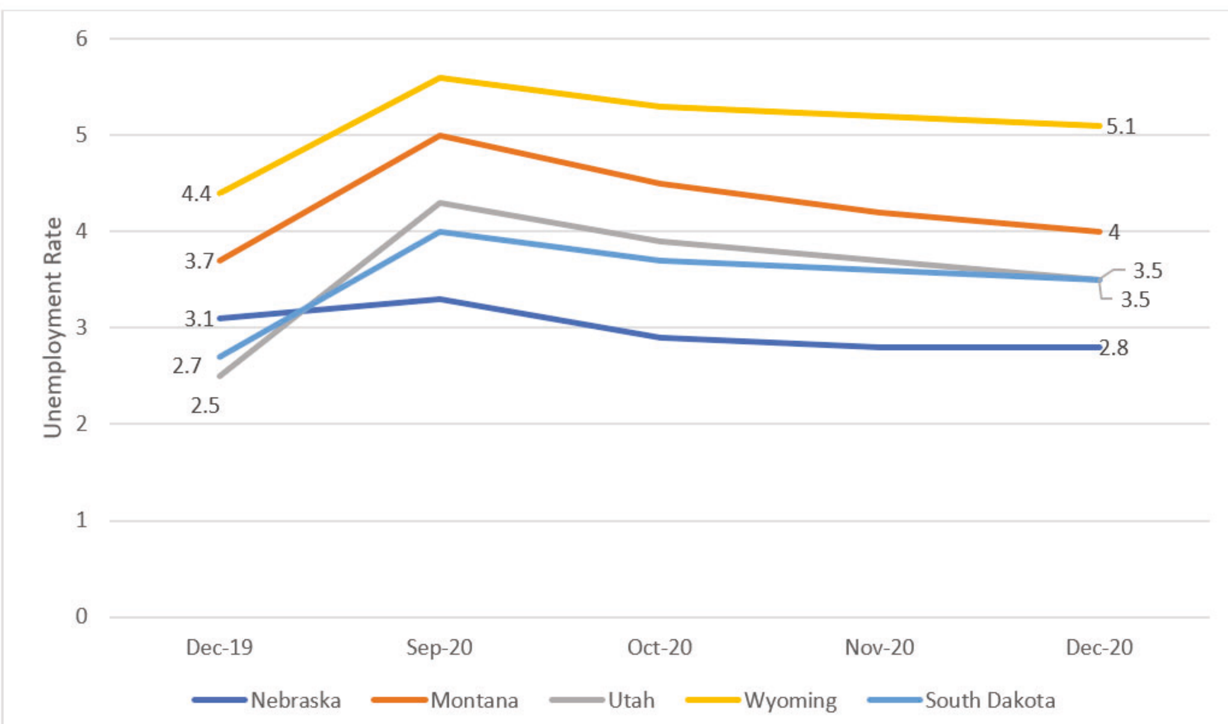


Figure 5:Stringency Index and Unemployment by State and how they voted in the 2020 Presidenial election. March to December 2020 Dataset

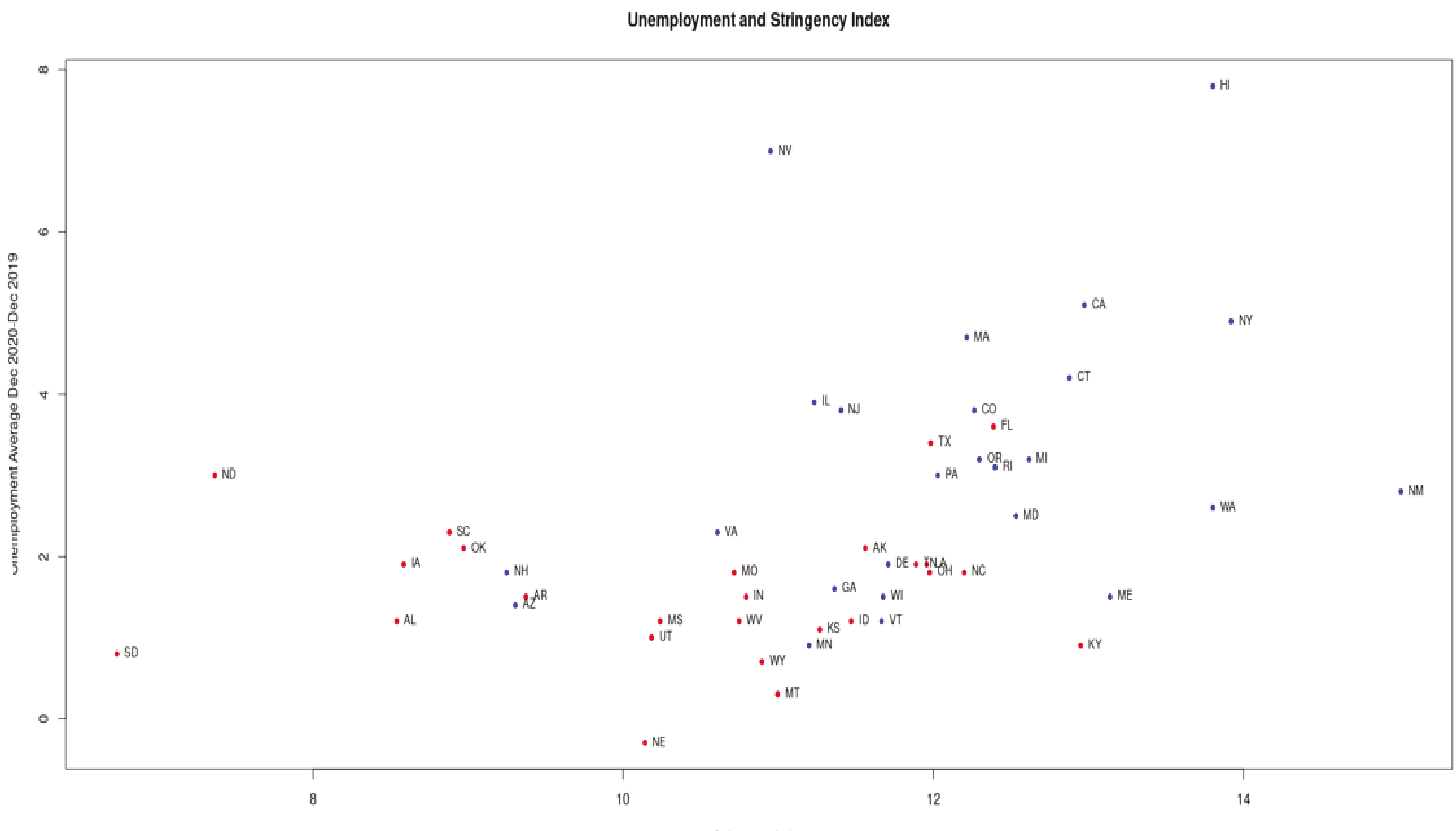


Figure 6:Stringency Index and Unemployment by State and Governor Political Party. March to December 2020 Dataset

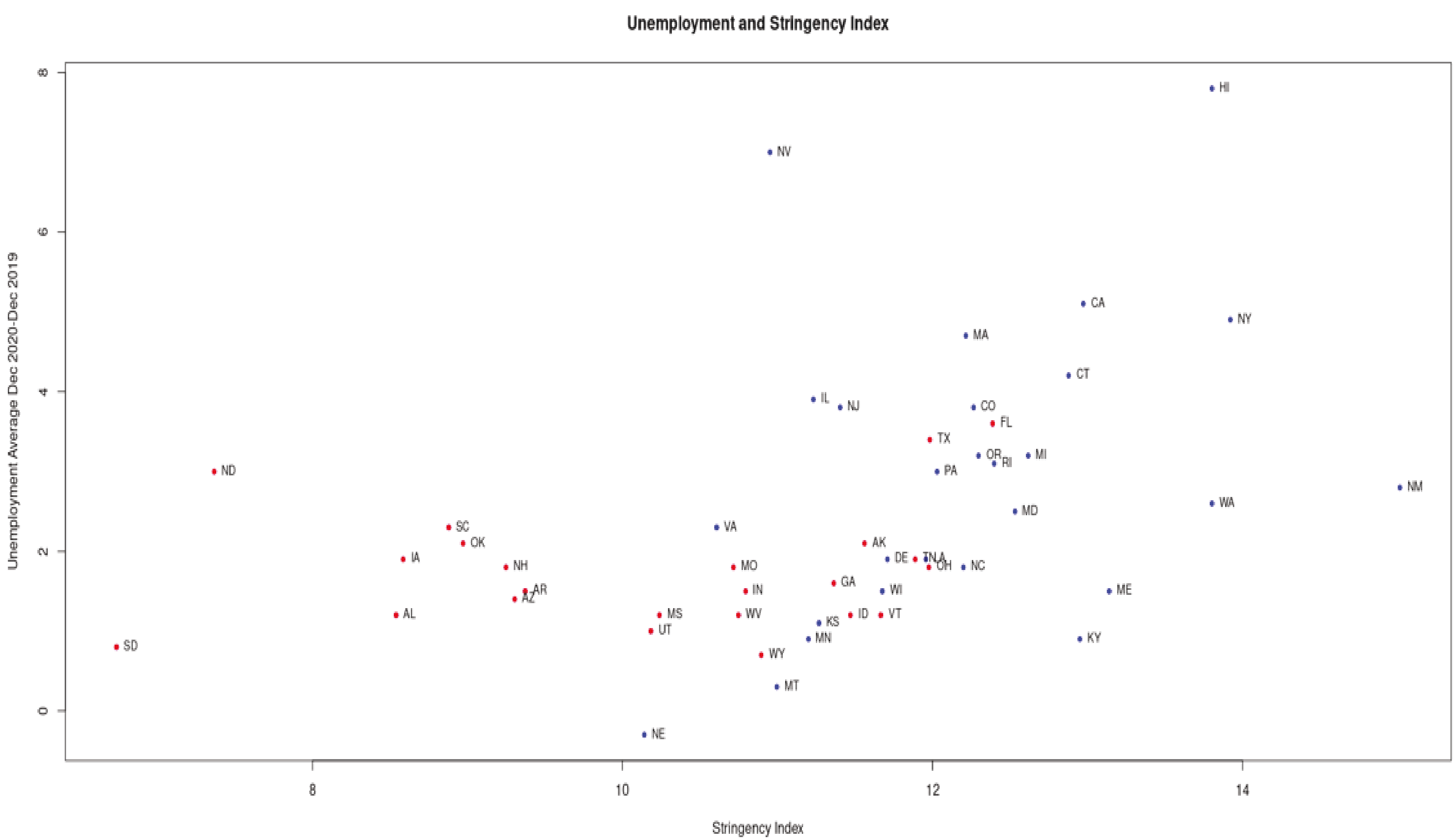


Figure 7: COVID-19 Average cases and Unemployment by State and Governor Political Party. March to December 2020 Dataset

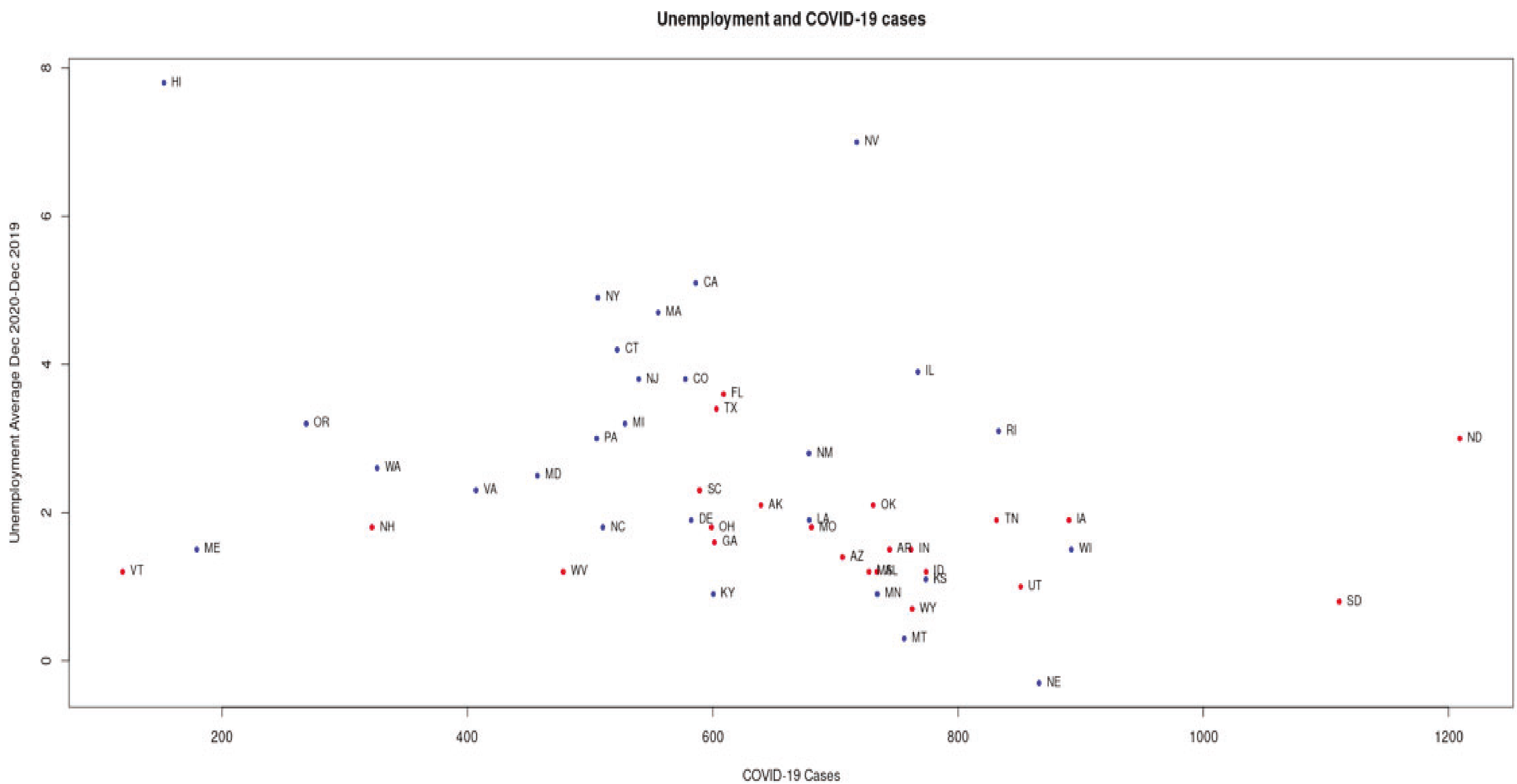


Figure 8:Stringency Index and Unemployment by State and Governor Political Party. March to June 2020 Dataset

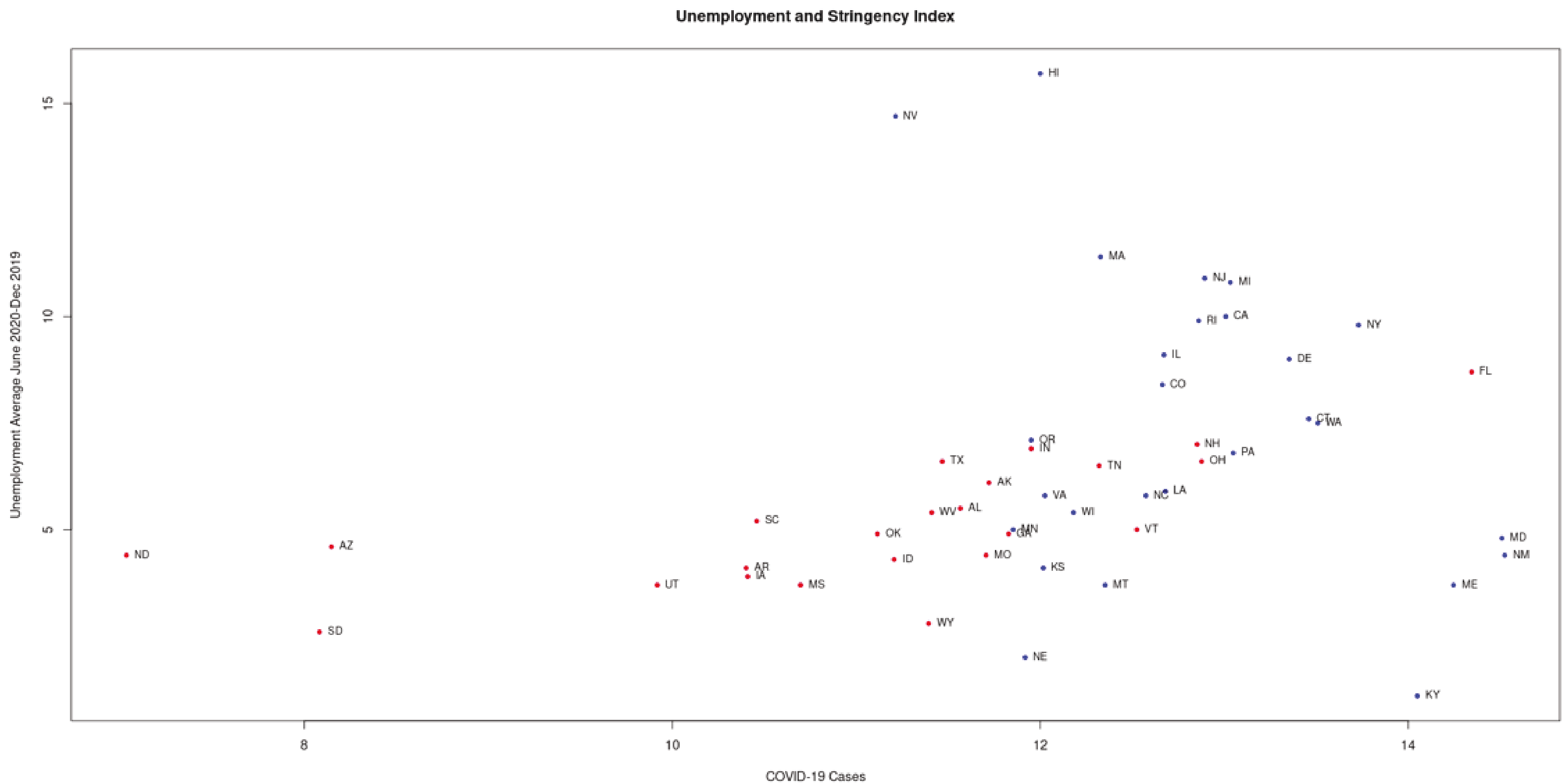


Table 1: March to December 2020 Dataset Correlation for all Variables

		Unemployment	Stringency Index	% of states economies in the hospitality sector	Covid-19 case rate	Republican Governor
		(1)	(2)	(3)	(4)	(5)
(1)Unemployment rate	Correlation Coefficient	1.00	.042**	0.19	-0.31*	-0.38**
	p-value		0.0027	0.1806	0.0271	0.0068
(2) Stringency Index	Correlation Coefficient		1.00	-0.14	-0.57**	-0.61**
	p-value			0.3456	0.0000	0.0000
(3) % of states economies in the hospitality sector	Correlation Coefficient			1.00	0.19	0.18
	p-value				0.1873	0.2125
(4) Covid-19 case rate	Correlation Coefficient				1.00	0.29
	p-value					0.0404*
(5) Republican Governor	Correlation Coefficient					1.00
	p-value					
(n=50)						
**Correlation is significant at the 0.01 level (2-tailed)						
*Correlation is significant at the 0.05 level (2-tailed)						

Table 2: Multiple Regression Analyses1 to examine March to December 2020 dataset with unemployment as DV

Variables	**b**	**B**	**p**
Stringency Index	0.184	0.194	0.298
% of states economies in the hospitality sector	0.284	0.300	0.024*
Covid-19 case rate	- 0.001	-0.184	0.239
Republican Governor	-0.822	-0.261	0.11
Intercept	-0.682		0.798
Adjusted R square	0.232		

Ordinary Least Squares recession analysis was used. All significant tails are two-tailed

Table 3: VIF (December): Results

Stringency	COVID-19	Republican Governor	Hospitality
2.158080	1.516098	1.627737	1.058126

Table 4: March to June 2020 Dataset Correlation for all Variables

		Unemployment	Stringency Index	% of states economies in the hospitality sector	Covid-19 case rate	Republican Governor
		(1)	(2)	(3)	(4)	(5)
(1)Unemployment	Correlation Coefficient	1.00	0.27*	0.16	0.30*	-0.39**
	p-value		0.0543	0.2671	0.0364	0.0056
(2) Stringency Index	Correlation Coefficient		1.00	-0.23	0.14	-0.56**
	p-value			0.1161	0.3450	0.0000
(3) % of states economies in the hospitality sector	Correlation Coefficient			1.00	-0.35**	0.18
	p-value				0.0135	0.2125
(4) Covid-19 case rate	Correlation Coefficient				1.00	-0.30*
	p-value					0.0354
(5) Republican Governor	Correlation Coefficient					1.00
	p-value					
(n=50)						
**Correlation is significant at the 0.01 level (2-tailed)						
*Correlation is significant at the 0.05 level (2-tailed)						

Table 5: Multiple Regression Analyses2 March to June 2020 Dataset with unemployment as DV

Variables	**b**	**B**	**p**
Stringency Index	0.313	0.161	0.300
% of states economies in the hospitality sector	0.632	0.355	0.012*
Covid-19 case rate	2.146	0.319	0.026*
Republican Governor	-1.569	-0.263	0.101
Intercept	-3.1558		0.5124
Adjusted R square	0.235		

Ordinary Least Squares recession analysis was used. All significant tails are two-tailed

Table 6: VIF(June): Results

Stringency	COVID-19	Republican Governor	Hospitality
1.517283	1.227709	1.586040	1.181206