The Impact of COVID-19 Policies on Employment Outcome: Evidence from the United States

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Abstract

The COVID-19 pandemic led to global health measures such as lockdowns and business closures, which, while necessary to limit virus spread, caused significant economic impacts. This study examines the effect of strict COVID-19 policies on employment outcomes in the United States using a difference-in-difference strategy. By analyzing Census Population Survey data from 2019 to 2021, it compares employment trends in states with strict versus lenient policies for individuals aged 18-65 in the labor force. The results show a 43% decrease in employment probabilities in states with strict policies after policy implementation. The paper includes checks and trend analysis to support these findings.

1 Introduction

The COVID-19 pandemic has caused a global crisis that has shaken economies worldwide. It has not only disrupted everyday life, it has fundamentally altered how economies function, including that of the United States. The economic fallout has exposed vulnerabilities in various states, with some more severely affected than others. The pandemic prompted governments to adopt and implement public health measures to slow the spread of the virus. In the United States, these measures ranged from stay-at-home orders and mask mandates to full-scale business closures and travel restrictions. By March 2020, many states mandated lockdown requiring non-essential businesses to shut down, limited social gatherings, and encouraged individuals to stay at home.

Existing studies have explored the economic implications of COVID-19 policies. (Chetty et al. 2020) analyzed real-time economic data to show that high-income earners experienced minor disruption compared to lower-income earners, who faced steep declines in unemployment. Similarly, Gupta et al. (2020) found that employment losses were concentrated in sectors requiring physical presence, such as retail and hospitality, which were disproportionately affected by strict lockdown orders. Furthermore, (Dingel and Neiman. 2020) ranked occupations based on their ability to transition to remote work, also presenting the findings that jobs that require physical presence were the most affected by COVID-19 policies.

(Cho. at.el, 2020) studies the impact of COVID-19 on employment in metropolitan areas, analyzing the relationship between the size and population of metropolitan areas and the employment outcome. They found that employment losses are directly proportional to the size of metropolitan cities. Based on these findings and existing literature, this paper will explore the impact of COVID-19 policies and their economic effects across states and regions.

This paper is structured as follows. Section 2 offers a brief background on policy and its challenges. Section 3 outlines the data and their sources, leading to Section 4, which details the model specification and hypotheses. Section 5 discusses the baseline results and their policy implications, while Section 6 offers concluding remarks. Additionally, the tables and graphs section at the end includes the necessary figures and tables.

2 Policy Background

The COVID-19 pandemic had different phases and periods in the United States. The initial phase of the pandemic spanned from early 2020 to mid-2021, during which the measures varied widely by state. These measures included lockdowns, stay-at-home orders, school and business closures, mask mandates, and travel restrictions. Starting in March 2020, states adopted different levels of stringency based on political, demographic, and public health factors. For example, states like California and New York placed strict policies, including widespread business closures and travel bans, while some of the other states like Texas and Florida were more relaxed in terms of these measures.

The Oxford COVID-19 Government Response Tracker indicators highlight this variation in policies and responses between states. While these measures are crucial to reducing the transmission, (Chernozhukov et al., 2021) also finds that due to these measures, states have suffered economic drawbacks especially in sectors where in-person values more.

2.1 Economic Impacts of Policy

For example, in April 2020, the US unemployment rate skyrocketed to 14.8 % (FRED., 2020). The US economy has not seen an unemployment rate of this caliber since the 2009 recession and the Great Depression of 1929. The nation's unemployment rate increased tremendously in just a few months after governments began adopting social distancing measures and mandating a 'stay at home' order. Since the government has made a stay-at-home order mandatory throughout all the states in the US, it was hard for certain occupations/industries to open. Most of the industries that had to close down were the industries that have a high proximity to in-person services, such as: Hospitality, retail, constructions, etc. compared to the industries which have low physical proximity. (Dingel, Neiman., 2020) analyzed different occupations within industries and uses indicators suggesting a level of physical proximity and work-from-home.

2.2 Variation of State Policies

(Hale et al. 2020) studied the variation of COVID-19 policies across states, and use the indicators to rank the states with home permanence indicators. The timeline of policy implementation also varied, and most states responded early by enacting initial lockdowns in March 2020. Although some states maintained strict measures through 2020, others began relaxing restrictions as early as mid-2020, influenced by political pressures and economic considerations. The states that issued statewide stay-at-home orders early as March 2020 were California, New York, Illinois, New Jersey, Ohio, Louisiana, Delaware, Massachusett, Michigan, Indiana, West Virginia, Oregan, Alaska, Kansas, Maryland, Virginia. The states that did not issue statewide stay-at-home orders were as follows: Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Utah, Wyoming. (Hale et al. 2020)

2.3 Challenges in Measuring Policy Effects

Assessing the causal impacts of COVID-19 policies is complex due to overlapping interventions of policies. For example, the simultaneous implementation of lockdowns, mask mandates, and travel restrictions makes it challenging to isolate the effects of individual policies. Additionally, existing economic trends and voluntary behavioral changes complicate causal inference. Over time, compliance with these measures declined due to economic strain and fatigue.

This study seeks to address these challenges using a difference-in-differences framework, using state-level variation in policy stringency to estimate the causal impact of COVID-19 policies on employment outcomes.

3 Data & Descriptive Statistics

3.1 Data Sources

Table 1: Description of Variables used in this Study

Code	Definition
employment_status	Binary Variable - 1 if individual is Employed
treatment	Binary Variable - 1 if individual belong to Stringest Policy State.
post_policy	Binary Variable - 1 if post March 2020.
age	Continuous Variable
female	Binary Variable - 1 if female
black	Binary Variable - 1 if individual is black
asian	Binary Variable - 1 if individual is Asian
pacific_islander	Binary Variable - 1 if individual is Hawaiian/Pacific Islander
two_or more_races	Binary Variable - 1 if individual belongs to Two or More Races
Region	Continous Variable - contains Regions such as: Northeast, Midwest, South, West Regions.
edu_category	Continous Variable - 1 - Less than High School, 2 - High School Graduate, 3 - Some College, 4 - Bachelor's Degree, 5 - Graduate Degree
Years	Continuous Variable - 2019 to 2021
ym_date_int	Continuous Variable - (Year, Month) format into integer

This study uses repeated cross-sectional data from the Current Population Survey (CPS), which offers detailed information on employment, wages, and demographics in the US labor market. This analysis spans June 2019 - June 2021. By focusing on these years, the study can capture the pre-pandemic and pandemic years to assess the employment impact of COVID-19 policies. The paper also restricts the sample to individuals aged 18 to 65 years in order to examine the working-age population specifically. Table 1 provides a brief overview of the description of the variables used in this analysis. The table contains mixed binary and continuous variables.

The primary dependent variable in this analysis is the employment status, which is a binary variable. The primary independent variables include states with strictest measures, states with lower strictness policy, and post pandemic, a binary variable that identifies the period of COVID-19, with values of 1 for values March 2020 and beyond. The analysis also included demographic variables such as age, sex, and education to obtain individual characteristics that could influence employment outcomes. The variable education is grouped into various categories, where individuals can fall into: Less than High School, High School Graduate, Some College, Bachelor's Degree and Graduate Degree. Similarly, the variable region is also grouped into four categories such as: Northeast, Midwest, South, and West Regions.

As discussed earlier, the paper is inspired by the study by (Hale et al. 2020) on the variation of COVID-19 policies across states. This paper studies the author's analysis about rankings on strict policy states and uses it as a treatment and control groups for further analysis. The treatment group remains the top ten states with strict policies, whereas the control groups include the ten states with the least restrictive policies during the same period. The treated states include Washington, DC, New Jersey, Maryland, Massachusetts, Hawaii, California, New York, Washington, Virginia, and Minnesota. The control states include Montana, Wyoming, Idaho, South Dakota, Mississippi, Arkansas, West Virginia, North Dakota, Oklahoma, South Carolina. March 2019 was selected as the baseline because the policy was implemented in March for most states, including initial state shutdowns. The study analyzes the period from June 2019 to March 2020 as the pre-treatment period, while April 2020 to June 2021 presents a post-treatment period.

3.2 Descriptive Statistics

Table 2: Basic Summary Statistics

	Mean	SD	Min	Max	N
Binary Variables					
Employment Status	.9412514	.2351537	0	1	488812
Strict Policy States	.6199705	.4853942	0	1	488812
Post March 2020	.5537712	.4971008	0	1	488812
Female	.4758394	.4994164	0	1	488812
Black	.0971641	.2961815	0	1	488812
Asian	.0870826	.2819563	0	1	488812
Hawaiian/Pacific Islander	.0068943	.0827451	0	1	488812
Two or more races	.021362	.144588	0	1	488812
Continuous Variables					
Age	41.6404	12.86847	18	65	488812
Region	30.88251	11.17308	11	42	488812
Education Classification	3.195063	1.16426	1	5	488812
States	28.13392	16.98365	5	56	488812

Source: Current Population Survey Data.

Table 2 provides a summary of the statistics of the sample consisting of 488,812 observations. The primary variables that are included in the model are listed in the table. The age variable shows that the data are limited to individuals who are aged between 18 to 65 inclusively, in order to ensure that the paper only catches the working class individuals. The data span from 2019 to 2021, with the adjustment of the months, for example, only considering data from June 2019 to June 2021, which indicates the balanced pretreatment group and the control group. This paper also categorizes the education classification into five divisions in order to use as the heterogeneity analysis.

4 Empirical Framework

4.1 Model Specification

The main empirical strategy employed in this paper is a Logit model with a causal Difference-In-Difference Method framework, which allows us to compare differences in employment outcomes in states with strict COVID policies and states with lenient COVID policies before and after the pandemic. The model specification can be represented as follows.

$$logit(P(Y = 1)) = \alpha_i + \lambda_t + \beta_1 \text{Treatment} + \beta_2 \text{Post} + \beta_3 (\text{Treatment} \times \text{Post}) + \gamma X_{it} + \epsilon_{it} \quad (1)$$

where β_3 captures the interaction between states with strict policy and post-pandemic variables, representing the differential change in employment outcome in stringent policy states due to the pandemic. The model also captures individual and time fixed effects, reducing bias problems. The fixed effects include α_i and λ_t, capturing state and month fixed effects respectively. Furthermore, the regression models were weighted using the CPS's *wtfinl* sample to ensure representativeness and estimated with clustered standard error at the state level, accounting for heterogeneity.

4.2 Hypothesis

:

$$H_0 : \beta_3 = 0 \quad \text{(No differential impact on states with stringest policies)} \quad (2)$$

$$H_1 : \beta_3 < 0 \quad \text{(Negative differential impact on states with stringest policies)} \quad (3)$$

Equations 2 and 3 outline the hypotheses for the model in equation 1. The null hypothesis proposes that employment outcomes for the treatment and control groups do not differ significantly, while the alternative suggests that outcomes are negative for both groups. This is essential for conducting a robustness check to determine whether the difference-in-differences assumption holds.

5 Results

5.1 Baseline Results

Figure 1 depicts the unemployment rate trend from June 2019 to June 2021 across all states, including those with strict and lenient policies. The scatter plot reveals a sharp increase around March 2020, coinciding with the implementation of COVID-19 policies. According to the Federal Reserve Economic Database, the unemployment rate reached a record high in the United States. It gradually declined throughout the year, stabilizing at a near-normal rate by mid-2021.

Furthermore, the paper uses the Difference-In-Difference model to estimate the impact of COVID-19 policies on employment. Table 5 provides a baseline for the regression results. The table is divided into three columns. Column (1) provides insights without any control variables, while columns (2) - (3) provide in-depth analysis using controls and fixed effects, respectively. The findings suggest a statistically significant decrease in employment outcomes between states with policies after March 2020. The result suggests that the one-unit increase in stringency in a certain state will decrease probability of employment outcomes by 63.62%, which is a massive drop. Some of the statistically significant states include California, the District of Columbia, and Hawaii, where the probability of employment outcome drops by about 41%, 20%, and 68%, respectively. All of the races provided were also negatively impacted by the pandemic, with blacks being the most significantly impacted. Among the education category, the highly affected one remains to be one with a Bachelor's Degree and a Graduate Degree compared to high school graduates and individuals who attended some college. This can be the case because people who have obtained a higher degree are larger than those who have obtained the high school and some college degree.

5.2 Robustness Check

Table 3: Statistical Results For Parallel Pre-Trend Check

	(1)
Pre March 2020	0.00 (0.010)
Stringent Policy States	0.06 (0.058)
DiD (Treatment Pre-March 2020)	-0.01 (0.013)
Observations	200,225

Note: Robust Standard Errors in Parenthesis
Source: Current Population Survey Data

These estimates ensure the primary assumption of the identification strategy. The primary assumption of the Difference-In-Difference model is to ensure that the parallel trend holds for the pretreatment period. In order to validate the Different-In-Different model, the paper delves into parallel trend check.

Table 3 provides the statistical results for the parallel pre-trend check. The result shows no statistical significance in impact between the treatment and control group before the policy is implemented. The p-value for the difference appears to be greater than $\alpha = 0.05$, suggesting that it fails to reject the null hypothesis. The null hypothesis is shown in equation 1, we accept the fact that there is no differential impact between states before the pre-policy period. It ensures the parallel trend assumption.

Figure 1 validates the statistical test done in Table 3. The graph illustrates before March 2020, the coefficient intervals includes 0, which is in pre-treatment period. As it

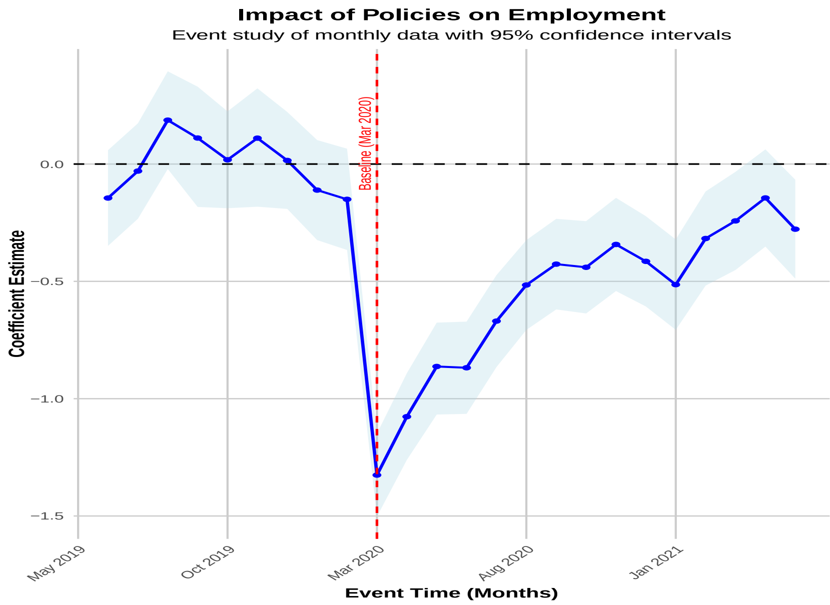

Figure 1: Impact of Policies on Employment: Event Study of Monthly Data with 95% Confidence Intervals

passes March 2020, the coefficient estimates steeply decreases, which demonstrates that in the post-treatment period, treatment and control groups are not parallel. It ensures the parallel trend assumption. During the pretreatment years, the model satisfies the parallel trend assumption and ensures that the baseline results are significant without any bias in formed. All of this evidence suggests that the model is robust and significant.

5.3 Heterogeneity Analysis

As this paper has established the robustness of the results, it analyzes the robustness of the subgroups. The study looks at the education subgroup and the regional groups to see its robustness. Before entering the DiD analysis, the paper introduces the subsample means for the selected individual characteristics grouped by the education level in Table 6. As shown in the table, individual characteristics vary depending on the level of education. The subsample looks at the individual who is between 18-65 years of age inclusively. As the level of education increases, there is not much difference in the individual's age. However, we can distinguish that the average age is highest for the individual with a Graduate Degree. As the level of education increases, the percentage of women also increases. Among all races, the percentage of Asians has the highest level of education. The percentages of individuals who identify with two or more races increase as the level of education increases to some college degree.

The DID results are shown in Table 8, which is distributed in six columns. Column (1) shows the results considering all educational levels. Columns (2) - (6) show the results for the education levels: Less than High School, High School Graduate, Some College, Bachelor's Degree, Graduate Degree, respectively. We can see that the difference-in-difference coefficient is statistically significant across the education level, except for the ones for (6). The results show to be statistically significant for the age variables.

Furthermore, among all races, Blacks were the most affected by COVID-19 policies at all levels of education.

Furthermore, this paper studies another subsample means for individual characteristics grouped by regions in Table 7. The regions include the Northeast Region, Midwest Region, South Region, and West Region. Looking into regions also provides us with information about states according to their place on the map. As shown in the table, individual characteristics vary depending on the region the individual is from. The subsample looks at the individual characteristics that is between 18-65 years of age inclusively. The percentages of female workers are highest in Northeast Region and South Region. The sample mean of age decreases across the regions. According to the table, we can also see the percentage of each race across regions. The percentages of Blacks are highest in the South Region, whereas the percentages of Asians are highest in the West region. The percentage of Hawaiian and Pacific Islander is highest in the West Region.

The relative DID results are presented in Table 9, which is distributed in 5 columns. Column (1) shows the baseline results. Columns (2) - (6) provide the region-based results according to the regions: Northeast, Midwest, South, and West regions, respectively. We can see that the difference-in-difference coefficient is statistically significant for the Midwest, South, and West Region. Among these three regions, the most affected is the western region. Some of the states that fall under the west region are Alaska, Arizona, California, Oregon, and Washington. It makes sense for it to be highly impacted among the three regions because there are states which implemented strict policies on opening the economy. The findings indicate that the differential impact was about 42%.

6 Summary & Concluding Remarks

This paper investigated the COVID-19 policies and their impact on employment outcomes in various states. The states were grouped into two: Stringest Policy States and Lenient Policy States. The stringest policy states include of states who implemented stricter state policies to prevent higher number of cases whereas the lenient policy states were more relaxed on the policies, or implemented the policies later compare to other states. Some of the interesting perspectives of this classification are geographical location, political perspective, and size of the state. The paper also focuses on the education variable. The education variable is categorized into five parts. It is used to perform the heterogeneity analysis. The findings indicate that the pandemic has affected employment outcomes in states with strict policies, influencing variations between states, regions, and individual characteristics. The baseline results suggest that the disproportionate impact was 43%, and the variation with regions and education suggests consistent percentages.

This research can be further explored into two parts. First, the research could also dive into measuring the size of metropolitan areas, where it dives in deep in and investigates the effect of population in the metropolitan cities. The analysis of metropolitan areas can give more insight into the effect of policies compared to the state-wide analysis. The statewide analysis does not look at the population. I believe that this could be one of the tracks in which research could be delved more in the future.

Finally, research can be further explored on the policy and its implications employing the staggered difference-in-difference model to analyze the larger length of data, looking at different phases of the pandemic, which come with different stages of policy. This can also be considered as one of the limitations of this paper, which future research may explore.

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7 Tables & Graphs

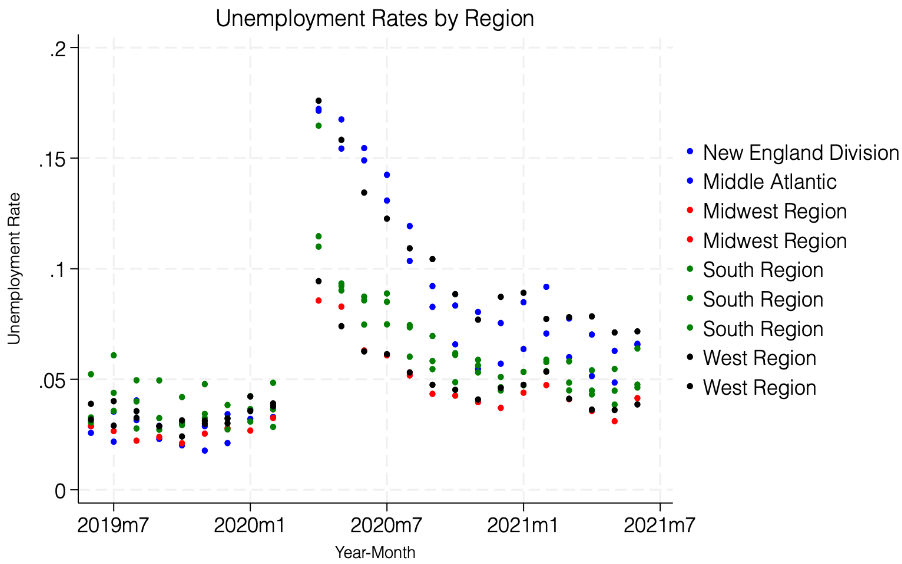

Figure 2: Unemployment Rates by Region

Table 4: Balance Test by Stringest Policy States

	Leinient Policy States	Stringest Policy States	Difference	Std. Error	N
Age	41.60	41.67	-0.07*	(0.04)	488812
Female	0.47	0.48	-0.01**	(0.00)	488812
Black	0.09	0.10	-0.02**	(0.00)	488812
Asian	0.01	0.13	-0.12**	(0.00)	488812
Hawaiian/Pacific Islander	0.00	0.01	-0.01**	(0.00)	488812
Two or more races	0.02	0.03	-0.01**	(0.00)	488812
Education Classification	3.00	3.32	-0.32**	(0.00)	488812
Employment Status	0.95	0.93	0.02**	(0.00)	488812

Note: Difference defined across States.
Source: Current Population Survey Data.

Table 5: Baseline Regressions Results

	Employment Status		
	(1)	(2)	(3)
Stringest Policy States	-0.06*	-0.13***	-0.05
	(0.028)	(0.028)	(0.054)
Post March 2020	-0.33***	-0.33***	0.06
	(0.030)	(0.029)	(0.034)
Treatment × Post	-0.41***	-0.44***	-0.43***
	(0.035)	(0.035)	(0.035)
Age		0.01***	0.01***
		(0.001)	(0.001)
Female		-0.11***	-0.11***
		(0.014)	(0.014)
Black		-0.35***	-0.38***
		(0.023)	(0.024)
Asian		-0.19***	-0.16***
		(0.027)	(0.028)
Hawaiian/Pacific Islander		-0.15	-0.12
		(0.092)	(0.096)
Two or more races		-0.35***	-0.34***
		(0.045)	(0.046)
High School Graduate		0.30***	0.29***
		(0.027)	(0.027)
Some College		0.46***	0.44***
		(0.027)	(0.028)
Bachelor's Degree		0.90***	0.89***
		(0.029)	(0.029)
Graduate Degree		1.32***	1.31***
		(0.035)	(0.035)
Observations	488,812	488,812	488,812
Controls	No	Yes	Yes
Fixed Effects	No	No	Yes

Note: Robust Standard Errors in Parenthesis. Fixed Effects include states and months
Source: Current Population Survey Data

Table 6: Summary Stats by Education Level

	All	Less than High School	High School Graduate	Some College	Bachelor's Degree	Graduate Degree
Age	41.640398	41.984098	41.330451	40.866733	41.316257	43.841087
	(12.868473)	(13.385371)	(13.720685)	(13.469424)	(12.184789)	(10.894123)
Female	0.475839	0.367574	0.407087	0.499264	0.511499	0.531136
	(0.499416)	(0.482152)	(0.491293)	(0.500001)	(0.499870)	(0.499033)
Black	0.097164	0.095705	0.115709	0.108012	0.078384	0.080129
	(0.296181)	(0.294191)	(0.319876)	(0.310397)	(0.268777)	(0.271494)
Asian	0.087083	0.060852	0.054957	0.055840	0.116563	0.154012
	(0.281956)	(0.239063)	(0.227897)	(0.229613)	(0.320900)	(0.360963)
Hawaiian/Pacific Islander	0.006894	0.007705	0.010775	0.007793	0.004501	0.002715
	(0.082745)	(0.087440)	(0.103244)	(0.087934)	(0.066938)	(0.052039)
Two or more races	0.021362	0.022033	0.023348	0.024965	0.019435	0.014934
	(0.144588)	(0.146793)	(0.151007)	(0.156019)	(0.138049)	(0.121291)

Note: Summary statistics by Education
Source: Current Population Survey Data.

Table 7: Summary Stats by Region

	All	Northeast Region	Midwest Region	South Region	West Region
Individual Characteristics					
Age	41.6403975	42.1932527	41.6508455	41.4980340	41.4859988
	(12.8684734)	(12.8903101)	(13.1947216)	(12.7622306)	(12.8453368)
Female	0.4758394	0.4865217	0.4707416	0.4845554	0.4654612
	(0.4994164)	(0.4998210)	(0.4991481)	(0.4997631)	(0.4988069)
Black	0.0971641	0.1190758	0.0310390	0.1866843	0.0356056
	(0.2961815)	(0.3238794)	(0.1734248)	(0.3896592)	(0.1853051)
Asian	0.0870826	0.1008624	0.0297351	0.0379190	0.1333405
	(0.2819563)	(0.3011481)	(0.1698574)	(0.1910010)	(0.3399432)
Hawaiian/Pacific Islander	0.0068943	0.0011390	0.0009730	0.0020094	0.0149094
	(0.0827451)	(0.0337302)	(0.0311782)	(0.0447819)	(0.1211907)
Two or more races	0.0213620	0.0146987	0.0125713	0.0159821	0.0309393
	(0.1445880)	(0.1203445)	(0.1114158)	(0.1254063)	(0.1731538)
Less than High School	0.0623962	0.0527309	0.0409442	0.0581469	0.0758518
	(0.2418740)	(0.2234970)	(0.1981629)	(0.2340218)	(0.2647615)
High School Graduate	0.2538379	0.2278353	0.2481561	0.2717150	0.2538949
	(0.4352064)	(0.4194381)	(0.4319471)	(0.4448452)	(0.4352393)
Some College	0.2682892	0.2151109	0.3468387	0.2509396	0.2860162
	(0.4430694)	(0.4109015)	(0.4759685)	(0.4335553)	(0.4518982)
Bachelor's Degree	0.2572605	0.2975213	0.2581976	0.2422476	0.2495306
	(0.4371246)	(0.4571703)	(0.4376475)	(0.4284448)	(0.4327424)
Graduate Degree	0.1582162	0.2068015	0.1058634	0.1769509	0.1347066
	(0.3649440)	(0.4050141)	(0.3076656)	(0.3816284)	(0.3414108)

Note: Summary statistics by Education
Source: Current Population Survey Data.

Table 8: Regression Results by Education Levels

	Employment Status					
	(1)	(2)	(3)	(4)	(5)	(6)
Stringest Policy States	-0.02	-0.00	-0.10	0.08	-0.20	-0.40
	(0.054)	(0.156)	(0.086)	(0.095)	(0.137)	(0.207)
Post March 2020	0.05	0.37***	0.07	0.13*	-0.18*	-0.21
	(0.034)	(0.098)	(0.056)	(0.059)	(0.086)	(0.147)
Treatment × Post	-0.41***	-0.46***	-0.45***	-0.59***	-0.24**	-0.11
	(0.035)	(0.102)	(0.058)	(0.062)	(0.089)	(0.145)
Age	0.02***	0.01***	0.02***	0.02***	0.01***	-0.00
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Female	-0.04**	-0.24***	-0.11***	-0.05	-0.16***	-0.10*
	(0.014)	(0.045)	(0.026)	(0.027)	(0.032)	(0.050)
Black	-0.43***	-0.41***	-0.46***	-0.36***	-0.17**	-0.41***
	(0.023)	(0.077)	(0.040)	(0.041)	(0.059)	(0.084)
Asian	0.05	-0.26**	-0.45***	-0.07	-0.03	-0.02
	(0.027)	(0.095)	(0.055)	(0.058)	(0.048)	(0.066)
Hawaiian/Pacific Islander	-0.18	-0.52	-0.14	0.29	-0.45*	-0.58
	(0.096)	(0.293)	(0.153)	(0.184)	(0.213)	(0.395)
Two or more races	-0.36***	-0.24	-0.43***	-0.25**	-0.37***	-0.29
	(0.046)	(0.140)	(0.079)	(0.081)	(0.099)	(0.205)
Observations	488812	30500	124079	131143	125752	77338

Note: Robust Standard Errors in Parenthesis. All the model used includes state and months as fixed effects.
Source: Current Population Survey Data

Table 9: Regressions Results by Region

	Employment Status				
	(1)	(2)	(3)	(4)	(5)
Stringest Policy States	-0.05	0.00	-0.14	0.20**	-0.25***
	(0.054)	(.)	(0.098)	(0.067)	(0.055)
Post March 2020	0.06	-0.43***	-0.06	-0.03	0.12*
	(0.034)	(0.048)	(0.097)	(0.050)	(0.053)
Treatment × Post	-0.43***	0.00	-0.25*	-0.34***	-0.42***
	(0.035)	(.)	(0.106)	(0.065)	(0.055)
Age	0.01***	0.01***	0.01***	0.02***	0.01***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Female	-0.11***	-0.10***	-0.05	-0.16***	-0.11***
	(0.014)	(0.027)	(0.063)	(0.030)	(0.022)
Black	-0.38***	-0.27***	-0.30*	-0.53***	-0.37***
	(0.024)	(0.041)	(0.139)	(0.037)	(0.050)
Asian	-0.16***	-0.17**	-0.11	-0.38***	-0.10**
	(0.028)	(0.053)	(0.169)	(0.082)	(0.037)
Hawaiian/Pacific Islander	-0.12	-0.86**	1.60	0.42	-0.05
	(0.096)	(0.330)	(1.024)	(0.350)	(0.100)
Two or more races	-0.34***	-0.41***	0.07	-0.45***	-0.31***
	(0.046)	(0.095)	(0.234)	(0.102)	(0.063)
High School Graduate	0.29***	0.31***	-0.06	0.43***	0.25***
	(0.027)	(0.056)	(0.132)	(0.051)	(0.039)
Some College	0.44***	0.43***	0.18	0.64***	0.39***
	(0.028)	(0.057)	(0.133)	(0.053)	(0.040)
Bachelor's Degree	0.89***	0.93***	0.60***	1.12***	0.78***
	(0.029)	(0.058)	(0.139)	(0.058)	(0.042)
Graduate Degree	1.31***	1.39***	1.15***	1.53***	1.17***
	(0.035)	(0.066)	(0.171)	(0.074)	(0.052)
Observations	488812	92185	51387	149793	195447

Note: Robust Standard Errors in Parenthesis. All of the model used includes state and month fixed effects.
Source: Current Population Survey Data