COVID-19 Vaccinations and the Labor Market

Casey Cloutier

Dr. Mary Kaltenberg, Faculty Advisor

Department of Economics, Pace University

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I. Abstract

The recession caused by the COVID-19 pandemic was one of the shortest and most severe in recent history. Millions of Americans lost their jobs, but the labor market has made substantial progress since March of 2020. Many factors have contributed to the improvements made in the labor market, including the introduction of vaccinations against COVID-19 in December of 2020. As more people get vaccinated, more people become confident that they will not become severely ill with COVID-19, and more people are likely to rejoin the labor market and find jobs. This paper seeks to explore how much of the improvements in U-3 unemployment rates in US counties are caused by the increasing vaccination rate against COVID-19. In order to quantify this relationship, various models will be used, including pooled ordinary least squares, fixed effects, and diff-in-diff.

Keywords:

COVID-19, Preventive medicine, Labor, Unemployment, Pandemic Recovery

II. Introduction

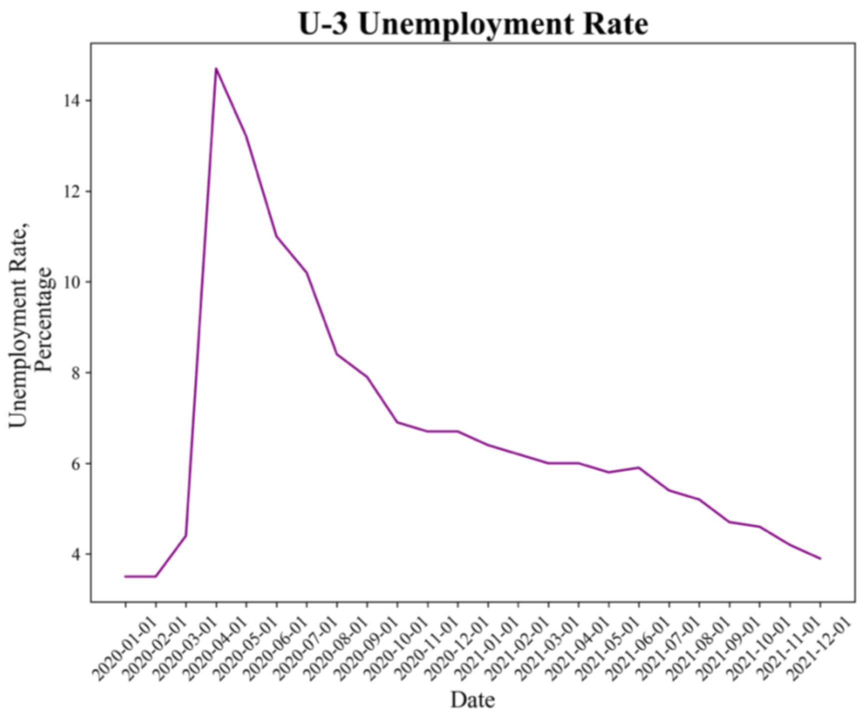
The COVID-19 pandemic caused one of the shortest and deepest recessions in U.S. history, lasting only two months. The pandemic has since changed the way Americans live, work, and spend their leisure time. At the onset of the pandemic, millions of Americans lost their jobs, and workers in high-contact, low-wage industries such as services were especially hard-hit. Though there has been substantial progress in the labor market, many still remain out of the labor force due to pandemic-related factors such as the need to provide child care or fears of the virus (Pitts, 2021). Because of this, the labor market is not likely to fully recover until the effects of the pandemic have largely faded, so it is important to monitor factors affecting the virus in order to properly assess the economic situation.

One such factor is the rollout of vaccinations against COVID-19, which began in late 2020. Because vaccinations are a preventive medical service, it can be predicted that they would be effective in reducing the spread and severity of the virus (Kageleiry & Tefft, 2013). It can also be expected that a decrease in prevalence of COVID-19 should contribute to an increase in employment, as fears of the virus would dissipate and the need for parents to provide childcare would be reduced as schools return to in-person learning.

As seen in Figure 1, though the U-3 unemployment rate had recovered from its peak of 14.7% in April of 2020 to just 3.9% by December of 2021 (U.S. Bureau of Labor Statistics, 2020, 2021), the labor market likely still has a long way to go until full employment is met. Additionally, the overall labor force participation rate as of December of 2021 remained depressed at just 61.9% (BLS, 2021), compared to the pre-pandemic level of 63.3%. before the pandemic in February of 2020, meaning that U-3 unemployment rate readings may be artificially low, and that an increase in labor force participation could lead to an increase in the unemployment rate (Cohen, 2020). It is also expected that labor force participation may not recover for many years due to the cyclical nature of the labor market recovery after recessions (Cajner et al., 2021), which will continue to impact the U-3 measure for some time.

Figure 1

U-3 Unemployment Rate, Jan '20 – Dec '21

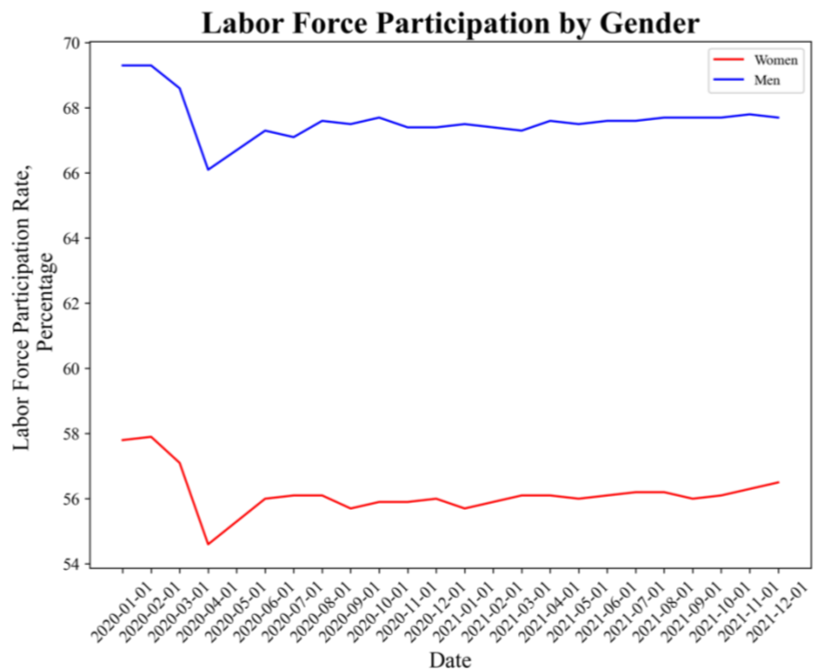


Note. Reproduced from "Unemployment Rate [UNRATE][Dataset]," by BLS 2022.

Also, as seen in Figure 2, the labor force participation rate for women is consistently about ten percentage points below the labor force participation rate for men. Though these rates moved together over the course of the pandemic, there are still significantly less women in the labor force than men. This problem was exacerbated by the onslaught of the pandemic and the movement of schools to an online format, as this created the need for parents to leave the labor market and stay home to care for the family. This has particularly affected the labor force participation rate for women because they are more likely to assume the traditional role of homemaker (Pitts 2021).

Figure 2

Percent Change in Labor Force Participation by Gender, Jan '20 – Dec '21



Note. Reproduced from "Labor Force Participation Rate – Women [LNS11300002] [Dataset]," by BLS, 2021, and from "Labor Force Participation Rate – Men [LNS100001] [Dataset]," by BLS, 2021.

It is expected that the introduction of vaccinations reduces the spread and severity of COVID-19, which could in turn reduce fears of the virus spreading through at-work contact, and potentially reduce unemployment as more people reenter the labor force, especially in high-risk occupations such as services. In order to measure the extent to which COVID-19 vaccinations have caused changes in unemployment rates, I will first used a pooled ordinary least squares model, controlling for the racial, ethnic, gender, and occupational makeup of each county, as well as mask-use, state-level GDP, and access to hospitals. Then, fixed effects models will be used to control for differences over time and by state. In addition, a diff-in-diff model will be employed to examine how unemployment has changed in areas that have or have implemented policy requiring vaccines against COVID-19 in any capacity.

This paper builds upon existing literature by exploring the impact of COVID-19 vaccination rates on unemployment over a 12-month period, from the beginning of the vaccine rollout in the beginning of 2021 to the end of the year. This will then be compared to the unemployment rate in the year 2020 when vaccinations against COVID-19 were non-existent. Because unvaccinated individuals are much more likely to fall ill with more serious cases of COVID-19 and more likely to become hospitalized after becoming infected (Scobie et. al., 2021), they are presumably more likely to be out of work as a result, while vaccinated individuals are less likely to be hospitalized or severely ill from COVID-19.

Furthermore, as the spread of COVID-19 reduces with the aid of vaccines, case numbers should begin to fall. This decrease in cases should lead to an increase of business activities, and regular pre-pandemic activities should resume. One notable change would be the reopening of schools. As children are able to attend school in person once again, this will reduce the need for parents to stay home to provide childcare, which will allow them to return to work. This will especially help women, who are disproportionately affected due to their higher concentration in the service industry than men, and should have a strong positive impact on the labor market recovery (Pitts, 2021, Albanesi & Kim, 2021).

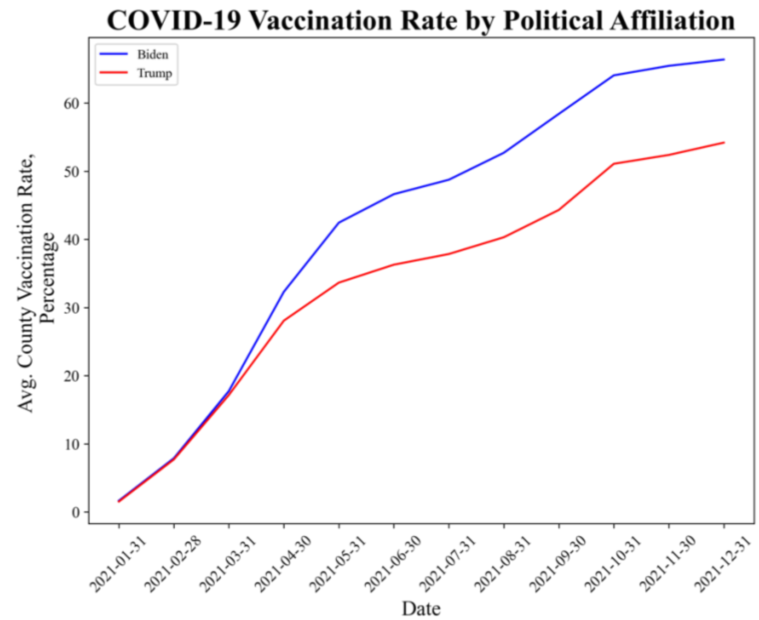
Additionally, the decrease in hospitalizations caused by vaccinations can reduce fears of COVID-19 as well. Improvements in the pandemic recovery may cause certain individuals' confidence that they will not get sick to increase, which may cause them to rejoin the labor force. Vaccinations will also improve confidence in workers who care for at-risk populations such as the elderly or young children at home. If individuals are confident that they will not cause their loved ones to fall ill, they may be more willing to rejoin the labor force. This would first increase unemployment by adding to the size of the labor force, and then decrease unemployment as these individuals find jobs.

As seen in Figures 3 and 4, in general, the vaccination rate has increased as the unemployment rate has decreased across all counties. It now becomes a question of how much of this decrease in unemployment rates has been caused by vaccinations against COVID-19. It is also evident that political affiliation in each county has an association with both vaccination and unemployment rates. Counties that voted for Donald Trump in the 2020 Presidential election have a lower average vaccination rate on average than counties that voted for Joe Biden. This could be due to influence by the presidential candidate and other politicians, as Republican ideals tend to go against vaccination. There is also a political divide in terms of unemployment, where counties that voted for Joe Biden tend to have a higher unemployment rate on average compared to counties that voted for Donald Trump. One reason for this could be that Democratic voters tend to live in cities, which have high concentrations of service workers and have been highly impacted by COVID-19. If service workers lost their jobs during the pandemic, and do not want to find another job in that industry or cannot find another job in that industry, they will likely remain unemployed as they look to change industries.

The rest of the paper will be structured as follows: a review of literature will be followed by a brief discussion of the current situation around COVID-19 and the labor market. Then, data, methodology, and results will be explained.

Figure 3

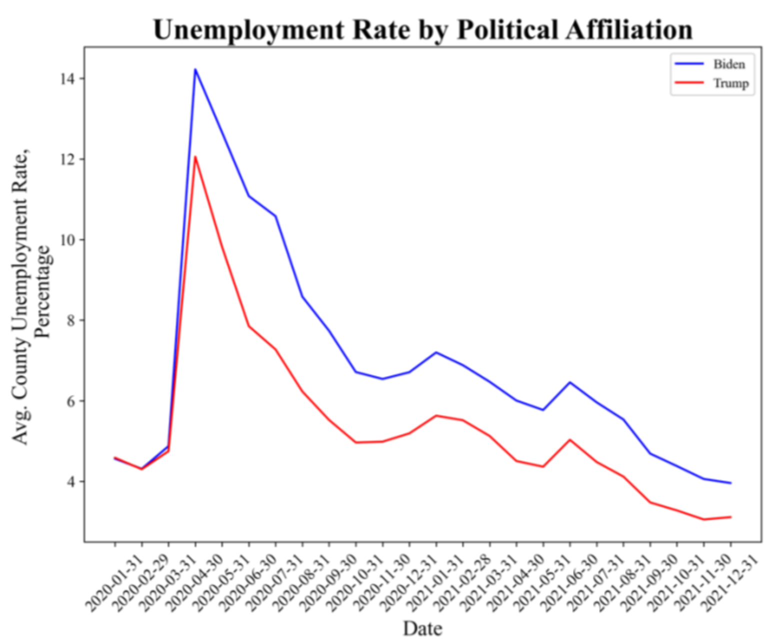
Average County COVID-19 Vaccination Rate by Political Affiliation, Jan ’21 – Dec ‘21



Note. Produced from *COVID-19 vaccinations in the United States, county* [Data set] by CDC (2022) and from *2020 US county level presidential results* [Dataset] by Tony McGovern (2020).

Figure 4

Average County Unemployment Rate by Political Affiliation, Jan ’20 – Dec ‘21



Note. Produced from *Labor force data by county, not seasonally adjusted, latest 14 months* [Data set] by BLS (2021)and from *2020 US county level presidential results* [Dataset] by Tony McGovern (2020).

III. Review of Literature

Existing literature seeks to explore the effects of preventive medical service usage on the labor market. A state-level study by Kageleiry and Tefft found that a 1.58 percent decrease in quantity of preventive medical services used caused a 1 percentage point increase in unemployment rates (2013). The study included multiple types of checkups and tests, including seasonal flu vaccines, but did not focus solely on vaccines. Additionally, Merchant et. al. (2013), in a study of Iowa residents, found preventive care to be positively associated with employment, though their study did not include any kind of vaccination.

These studies are also in agreement with the findings of Luckhaupt et. al. (2014), who attempted to produce population-based estimates of flu-like illness and vaccination rates during the 2009-2010 H1N1 outbreak. This study found that employed persons and those not in the labor force had similar prevalence of flu-like illness (5.5% and 6%, respectively), and a similar prevalence of individuals who had received their H1N1 vaccine (23.7% and 26.5%, respectively). On the other hand, they found the prevalence of flu-like illness to be higher (9.4%) and pH1N1 vaccination coverage to be lower (16.7%) those who were included in the labor force, but were unemployed (Luckhaupt et. al., 2014). Similar results could be expected for COVID-19, as both COVID-19 and H1N1 are airborne viruses that have higher transmission rates when people are in close proximity to one another. In addition, a Canadian study found that increasing the unemployment rate at the provincial level by one percent lead to a reduction in the probability of flu immunization by 0.45 percentage points (Reisman, 2015). Reisman’s models use a binary variable that shows whether or not an individual got their seasonal flu vaccine as the dependent variable. She notes that her results may be due to those who are employed being worried about missing work if they become ill, and the fact that the opportunity cost of becoming ill is lower for unemployed individuals.

On the contrary, in a state-level study of the first 100 days of COVID-19 vaccination rollout, Roghani and Panahi (2021) found a positive relationship between vaccination rates and unemployment using an ordinary least squares regression. However, they emphasize that the early rollout being restricted to certain at-risk groups may have contributed to this positive association. They also found that this relationship became negative when looking at states with unemployment rates greater than 5%. According to the authors, this could indicate that although higher employment is associated with higher vaccination rates in the US, this association might not be consistent in the states with higher unemployment rates (Roghani & Panahi, 2021).

Another potential reason for this positive association during early vaccine rollout could be vaccine hesitancy for reasons such as safety concerns or mistrust. King et. al. (2021), using a representative survey, found that vaccine hesitancy varies widely across occupations, and was around 27.5% for adults ages 18-64 in January of 2021. However, by March, this number had decreased by around 6 percentage points to around 22%. (King et. al., 2021). This hesitancy among occupational groups could potentially be a contributor to increased vaccination rates for the unemployed during the early stages of the vaccine rollout, but can be expected to cause less of an impact as time progresses and vaccination rates increase. Using a similar survey, Shen and Kejriwal (2021) found that 72.4% of White Americans were willing to get the COVID-19 vaccine, compared with non-White Americans, of which only 62.2% affirmed that they would get vaccinated.

Furthermore, Elliott et. al. (2021) found that essential workers are less likely to get vaccinated against COVID-19 than non-essential workers. They also note that this could be due to a variety of outside factors including political views, socioeconomic factors, and influence from medical professionals. It is also important to note that many essential workers, especially service workers, typically receive lower wages than other occupational groups and typically have limited sick time and less work benefits. This limited sick time may mean that service workers are more hesitant to get the vaccine because they fear side effects.

Additional studies have explored the relationships between demographic groups and vaccinations. Abbas et. al. (2018), using a representative survey of US adults over the age of 18, found that certain groups are more likely to get the yearly influenza vaccine than others. Using Rao-Scott's chi-square test, they found that adults over the age of 75 are more likely to get vaccinated than younger groups, with 73.3% of adults over 75 getting their yearly influenza inoculations compared with only 25.5% for those in the 18-24 age group. Additionally, looking at influenza vaccination status by race, they found that 41.8% of White Americans always get their yearly shots, versus only 33.2% of Black Americans.

Looking at political affiliation, Kabir et. al. (2021) found political party affiliation to be highly correlated with COVID-19 vaccination rates on the state level. Looking at each state's political affiliation after the 2020 US Presidential election, they also found that states who voted Republican often had much lower vaccination rates than states who voted for the Democratic candidate as of July of 2021. This aligns with Ye (2021), who found that although average vaccination rates have been largely increasing in each US county, counties who voted Republican had consistently lower average vaccination rates than those who voted Democratic.

To summarize, an increase in quantity preventive medicine is typically associated with decreases in unemployment, possibly due to low opportunity cost for unemployed individuals when getting sick, or changes in access to healthcare when employed versus unemployed.

However, more recent studies of COVID-19 vaccinations have found a positive relationship between vaccination rates and unemployment rates, though this is likely due to limited access to COVID-19 vaccines in the early days of the rollout, or due to hesitancy around getting vaccinated. Furthermore, vaccination and unemployment rates are impacted by other factors, such as demographics, political affiliation, and occupation.

Based on the works of Kageleiry and Tefft (2013) and Merchant et. al. (2013), I expect to see an inverse relationship between vaccination rates and unemployment. I would not expect the results of my estimations to be in line with that of Roghani and Panahi (2021) because they used a much smaller window of time for their study, only 100 days. Additionally, at this time, vaccine eligibility was limited to older individuals and those with underlying medical conditions, who are typically less able to work. By using a wider range of time, the effects of the limited eligibility should not be present in my estimations.

IV. Data and Methodology

To attempt to measure the impact of vaccination rates on unemployment, this paper uses a panel dataset which includes the following variables, measured on the county level: unemployment rates, vaccination rates for 18+ individuals, political affiliation, percent female, percent Black, percent Native American, percent Asian, percent Pacific Islander, percent Hispanic or Latino, mask usage, state GDP, and ratio of COVID-19 vaccine mandates that are present. Twenty-four months of data, from January 2020 through December 2021, are used to produce the estimates.

Unemployment data was collected from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics program, and is aggregated to the county level. The values come from the BLS's Current Population Survey (CPS). Unemployment rates are calculated as the number of unemployed workers as a share of the labor force, which includes employed and unemployed workers who have actively searched for work within the past four weeks.

Data regarding vaccination comes from the Centers for Disease Control (CDC), and is collected by and provided to the CDC by vaccine providers. The vaccination rate for 18+ individuals is calculated by taking the total number of persons over the age of 18 who have received all doses of the COVID-19 vaccine as a share of the total 18+ county population. The total number of doses differs by manufacturer, with Johnson & Johnson requiring only 1 dose, while Pfizer and Moderna require 2 doses to be administered. Vaccination data is reported daily by the CDC, but for the purposes of this paper, only the last day of each month will be used, so as to align with the number of observations from the unemployment data set which is calculated monthly. The 18+ vaccination rate will be used instead of the vaccination rate for all individuals in the county so that individuals ages 0-17 who are not participants in the labor force will not be counted in the vaccination rate.

Data regarding political affiliation was compiled by Tony McGovern using figures from Fox News, Politico, and the New York Times. This paper will use a binary variable where 1 indicates that the county voted for Donald Trump, and 0 indicates that the county voted for Joe Biden. This variable will be used as a control, since both the unemployment rate and the vaccination rate are affected by political affiliation, as previously shown in Figures 3 and 4.

Demographic data was collected from the U.S. Census Bureau's American Community Survey (ACS) from 2019. Data is collected through a mail survey that is sent to 295,000 households in all U.S. counties. Respondents to the survey are encouraged to self-identify information pertaining to demographics. The variables used in this paper include percent female, percent Black, percent Native American, percent Asian, percent Pacific Islander, and percent Hispanic or Latino. Each of these variables is represented as a percentage of each county that has indicated that they identify with each respective group. Because the data is yearly, and from 2019, the values are repeated for each observation in the dataset. It is assumed that the demographic makeup of a county has not materially changed in the two years since the COVID-19 pandemic began. These variables are included as controls because it is likely that each has an association with unemployment or vaccination rates, whether it be due to less women being part of the labor force than men, or differences in access to healthcare for different racial or ethnic groups.

Mask usage data comes from a county-level 2020 survey conducted by the New York Times. Each value represents the percentage of each county that indicated that they wear their masks at different frequencies, including never, rarely, sometimes, frequently, or always. For the purposes of this study, only the variable of those who indicated that they always wear their mask will be included. This variable is included because it has an impact on the spread of COVID-19, and if cases are lower, this may mean that more people have confidence that they will not get sick when they go out in public or go to work. Because this was a one-time survey, the data is repeated for the entirety of the dataset and is time invariable.

State GDP data is calculated by the Bureau of Economic Analysis on a quarterly basis. Because unemployment and vaccination rates are aggregated monthly, the GDP value for each quarter is repeated three times so that each observation has a matching value for state-level GDP. This variable is included as a control because GDP is typically closely associated with unemployment. If GDP is high, that likely means business activity is high and businesses will be able to hire more employees, so unemployment should be lower.

Lastly, data regarding state vaccine mandate policy comes from the CDC, and tells which policies are active in which areas at which times. The variable created for the purposes of this paper is the number of active policies as a share of the total vaccine mandate policies that exist throughout the country. These policies pertain to vaccine mandates on the state level for different groups of individuals (healthcare workers, government workers, higher education students, etc.), and different types of requirements (vaccines required with no exception, vaccines required with religious/healthcare exemptions, or vaccines or regular COVID-19 testing required). There are 16 different policies of this nature that exist across the United States, so the *Policies* variable is the number of policies active in the state at that time divided by 16. This variable has been created to be used in a diff-in-diff model as the "treatment." Dummy variables for state and month have also been created for the purpose of the diff-in-diff model.

Table 1

Summary Statistics Table

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
UR_rate	74,688	5.650	3.233	0.400	3.500	6.800	41.000
Vax_Rate	74,688	17.574	23.974	0	0	38.7	100
trump_True	74,688	0.827	0.378	0	1	1	1
Percent_Female	74,688	49.950	2.316	27.300	49.400	51.100	57.200
Percent_Black	74,688	9.146	14.553	0.000	0.700	10.300	87.200
Percent_AmerInd	74,688	1.700	6.691	0.000	0.200	0.800	93.300
Percent_PacI	74,688	0.085	0.417	0	0	0.1	12
Percent_Asian	74,688	1.341	2.641	0.000	0.300	1.300	42.700
Percent_HisLat	74,688	9.459	13.920	0.000	2.200	9.725	99.200
Mask_Always	74,688	0.508	0.152	0.115	0.394	0.614	0.889
Q_GDP	74,688	510,717.50	565,604.70	26,519.80	171,502.80	554,992.10	2,946,067.00

Note. *See above paragraph for sources.*

To estimate the effects of vaccination rates on the log of the unemployment rate, a pooled OLS model will be employed, with county unemployment rates as the dependent variable and vaccination rates as the independent variable of interest. Political affiliation, gender, racial, ethnic, mask-wearing, quarterly GDP, and service employment variables will be used as controls. The model will be calculated as follows:

$$U\_Rate_{i,t}=\beta_0 + \beta_1 Vax\_Rate_{i,t}+\beta_2 Q\_GDP_{i,t}+Z_i+u_{i,t}$$

Where $U\_Rate_{i,t}$ is the unemployment rate for county i during time t, and $Vax\_Rate_{i,t}$ is the vaccination rate for county i during time t, $Q\_GDP_{i,t}$ is the state GDP for county i during time t, and $Svc\_Emp_{i,t}$ is the number of service employees in county i in state t. Also, Z_i represents control variables that do not change over time within the dataset, such as political affiliation, racial, ethnic, and mask-wearing. One issue that may arise with this model is that the effects of vaccination rates on unemployment rates may not be immediate, so using vaccination and unemployment rates in the same month may not produce the inverse relationship that would be expected. This can be resolved for this in the following model:

$$U\_Rate_{i,t}=\beta_0 + \beta_1 Vax\_Rate_{i,t} + \beta_2 Vax\_Rate_{i,t-1}+\beta_3 Q\_GDP_{i,t}+Z_i+u_{i,t}$$

Where $Vax\_Rate_{i,t-1}$ is the vaccination rate in the month prior. By using this model, it is possible to see different results than the model that does not include lags.

It is important to note that the POLS assumption that there is no heterogeneity, or that $\mathrm{Cov}(a_i, x_{it}) = 0$, fails in this model as seen in Table 2. This is likely because the time invariant variables such as gender and race likely have a large impact on the vaccination rate, as noted by Abbas et. al. (2018) and Elliott et. al. (2021). Because of this, the results of the POLS models are untrustworthy.

Table 2

Correlation Matrix

	Vax_Rate	Trump	%Fem	%Blk	%AmerInd	%PacI	%Asian	%HisLat	Always
Vax_Rate	1								
Trump	-0.066	1							
%Fem	0.028	-0.130	1						
%Blk	-0.032	-0.358	0.118	1					
%AmerInd	0.039	-0.074	-0.016	-0.101	1				
%PacI	-0.019	-0.088	-0.010	-0.045	0.001	1			
%Asian	0.049	-0.423	0.085	0.029	-0.054	0.436	1		
%HisLat	-0.051	-0.157	-0.146	-0.112	-0.017	0.044	0.151	1	
Always	0.025	-0.439	0.096	0.207	-0.106	0.088	0.344	0.330	1

To account for this issue, a fixed effects model will be used. By time-demeaning the terms of the regressions, mathematically the time consistent variables will cancel out so heterogeneity is no longer an issue. Additionally, because the time consistent variables are not included in the calculation, serial correlation should no longer be an issue. The fixed effects model appears as follows:

$$U\_Rate_{i,t} = ß_1 Vax\_Rate_{i,t} + ß_2 Q\_GDP_{i,t} + \lambda_i + \delta_{i,t} + u_{i,t}$$

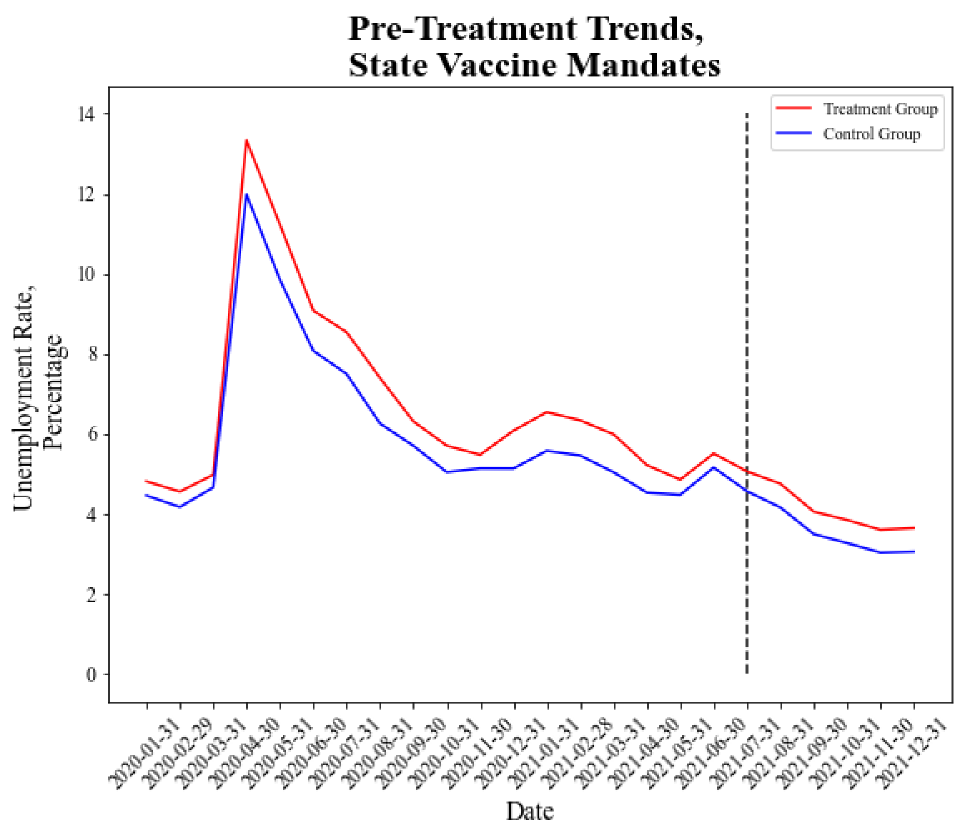
Where Z_i has been omitted because the model has been time-demeaned. In addition, λ_i and $\delta_{i,t}$ represent state and month fixed effects, respectively. The same fixed effects model will be calculated using the vaccination rate in the month prior as the explanatory variable of interest as well:

$$U\_Rate_{i,t} = ß_1 Vax\_Rate_{i,t} + ß_2 Vax\_Rate_{i,t-1} + ß_3 Q\_GDP_{i,t} + \lambda_i + \delta_{i,t}\ u_{i,t}$$

In addition, a diff-in-diff model will be used to examine the effects of vaccine mandate implementation on the state level on the unemployment rate on the county level. As shown in Figure 5, in the time before the vaccine mandates went into place, the unemployment rate in counties in states that had vaccine mandates moved in a similar fashion to counties in states that had no vaccine mandate. Because of this, the parallel trends assumption holds and the effect of vaccine mandates on each group can be compared.

Figure 5

Pre-Treatment Trends for State Vaccine Mandates



Note. Produced from *State-level vaccine mandates* [Dataset] by CDC (2022).

The model will appear as follows:

$$U\_Rate_{i,t} = ß_0 + ß_{DD}Policies_{i,t} + \Sigma\, ß_k\, State_{k,s} + \Sigma\, ß_j\, Month_{j,t} + \Sigma\, \theta_k\, (State_{k,s} * Month_{j,t}) +$$

$$ß_1 Vax\_Rate_{i,t} + ß_2 Q\_GDP_{i,t} + u_{i,t}$$

Where $Policies_{i,t}$ is the percentage of potential vaccine mandate policies that are active in county i during month t, $\Sigma\, ß_k\, State_{k,s}$ is the sum of the dummy variables for each state, $\Sigma\, ß_j\, Month_{j,t}$ is a sum of the dummy variables for each month, and $\Sigma\, \theta_k\, (State_{k,s} * Month_{j,t})$ is sum of the interactions between the state and month variables. Control variables that do not change over time are omitted from the model due to properties of diff-in-diff models.

The same model will then be applied using the vaccination rate in the month prior, which will appear as follows:

$$U\_Rate_{i,t} = ß_0 + ß_{DD}Policies_{i,t} + \Sigma\, ß_k\, State_{k,s} + \Sigma\, ß_j\, Month_{j,t} + \Sigma\, \theta_k\, (State_{k,s} * Month_{j,t}) +$$

$$ß_1 Vax\_Rate_{i,t-1} + ß_2 Q\_GDP_{i,t} + u_{i,t}$$

Lastly, the same diff-in-diff models above will be tabulated without the inclusion of state trends, where the term $\Sigma\, \theta_k\, (State_{k,s} * Month_{j,t})$ will be removed from each.

V. Results

Table 3 shows the results of the above POLS models including clustered robust standard errors. Notably, a one percentage point increase in the vaccination rate causes a .047 percentage point decrease in the unemployment rate, holding all else constant, which is statistically significant at the 99% confidence level. When controlling for political affiliation; racial, ethnic, and gender makeups; state GDP; and the interaction between the vaccination rate and political affiliation, each percentage point increase in the vaccination rate leads to a .046 percentage point decrease in the unemployment rate, holding all else constant. This result is also statistically significant at the 99% confidence level. Using the same controls, but exchanging the concurrent vaccination rate for the vaccination rate in the month prior, the results change. Now, each percentage point increase in the vaccination rate in the month prior causes a .006 percentage point decrease in the unemployment rate, which is much smaller.

Table 3

POLS Regression Results

	Dependent variable:		
		U_Rate	
	(1)	(2)	(3)
Vax_Rate	-0.047***	-0.046***	-0.055***
	(-0.00001)	(-0.00001)	(0.0001)
Lagged_Vax			0.006***
			(-0.0001)
trump_True		-0.615***	-0.690***
		(-0.007)	(-0.008)
Percent_Female		0.023**	0.025**
		(-0.011)	(-0.012)
Percent_Black		0.019***	0.019***
		(0.0003)	(0.0003)
Percent_AmerInd		0.040***	0.040***
		(-0.001)	(-0.001)
Percent_PacI		0.338***	0.332***
		(-0.006)	(-0.006)
Percent_Asian		-0.050***	-0.044***
		(0.001)	(0.001)
Percent_HisLat		0.010***	0.011***
		(-0.0003)	(-0.0003)
ALWAYS		4.338***	4.459***
		(0.032)	(0.034)
log(Q_GDP)		0.121***	0.124***
		(-0.015)	(-0.016)
Vax_Rate:trump_True		-0.003***	
		(0.00001)	
Lagged_Vax:trump_True			-0.001***
			(0.00000)
Constant	6.479***	1.831**	1.793**
	(0.002)	(0.736)	(0.787)

Observations	74,688	74,688	71,576
R^2	0.122	0.219	0.237
Adjusted R^2	0.122	0.219	0.237
F Statistic	10,412.710*** (df = 1; 74686)	1,905.176*** (df = 11; 74676)	1,850.409*** (df = 12; 71563)
Note:			*p**p***p<0.01

It is likely that the small magnitude of the coefficients of the vaccination rates may be attributable to vaccine hesitancy, as explored by King et. al. (2021) and by Shen and Kejriwal (2021). Because the early vaccination rollout was limited only to older individuals and those with health conditions, it can be assumed that these individuals would be out of the labor force, not unemployed (BLS, 2021), and therefore excluded from my models. However, unemployed individuals may still be affected by vaccine hesitancy, which could prevent them from accepting certain jobs.

It is also unsurprising that the coefficient on the vaccination rate in the month prior is larger than the coefficients on vaccination rates in the concurrent month. If people rejoin the labor force after getting vaccinated, it takes time to find a position that aligns with their experience, interest, and comfortability with the virus. This would explain the stronger relationship between vaccination rates in the month prior and unemployment in the current month.

The racial and ethnic controls also have rather small coefficients in both models. Only the percent Asian variable has an inverse relationship with unemployment and, albeit small, all other groups have a positive relationship with unemployment, which could be related to the findings of Abbas et. al. (2018). If other racial and ethnic groups have less access to preventive care, and are more likely to be hesitant about seeking preventive care, this could potentially hinder their performance in the job market. If vaccination rates against COVID-19 are also low in these groups, this may be a cause for the unemployment rate to be higher.

In table 4, the results of the fixed effects estimations are displayed, including clustered robust standard errors. Compared to the results of the POLS models, the coefficients on the vaccination rate in both the concurrent month and the month prior are smaller in magnitude.

Table 4

Fixed Effects Regression Results

	Dependent variable:	
	U_Rate	
	(1)	(2)
Vax_Rate	-0.010***	-0.001***
	(0.00000)	(0.00000)
Lagged_Vax		-0.010***
		(-0.00000)
log(Q_GDP)	-27.368***	-28.576***
	(-0.0001)	(-0.001)
Observations	74,688	71,576
R^2	0.042	0.044
Adjusted R^2	0.0002	0.001
F Statistic	1,573.667*** (df = 2; 71551)	1,058.830*** (df = 3; 68439)
Note:		*p**p***p<0.01

As previously highlighted in Table 2, the vaccination rate and the time invariant controls (including gender, race, ethnicity, political affiliation, and mask-wearing) are correlated. By using fixed effects and time demeaning the terms of the model, because the coefficients on the vaccination rate have increased in the fixed effects models, it is evident that the POLS models contain downward bias and the fixed effects models have reduced this bias.

In the fixed effects models, each percentage point increase in the vaccination rate for each county leads to a .01 percentage point decrease in the unemployment rate, which is statistically significant at the 99% confidence level. Each percentage point increase in the vaccination rate in the month prior also leads to a .01 percentage point decrease in the unemployment rate, which is also significant at the 99% level.

Table 5

Diff-in-Diff Regression Results

	Dependent variable:			
	U_Rate			
	(1)	(2)	(3)	(4)
Policies	-36.805	-41.497	-0.076	-0.104
	(161.217)	(169.344)	(0.202)	(0.271)
Vax_Rate	0.002^{**}	0.015^{***}	-0.005^{***}	0.006^{**}
	(-0.001)	(-0.0004)	(-0.001)	(0.002)
Lagged_Vax		-0.014^{***}		-0.012^{***}
		(-0.001)		(-0.004)
log(Q_GDP)	22.903	30.007	-27.439^{**}	-28.682^{**}
	(-294.168)	(-308.810)	(-12.019)	(-14.358)
Constant	-276.028	-363.227	339.063^{**}	353.970^{**}
	(3,596.846)	(3,775.897)	(146.765)	(175.320)
State Trends	Yes	Yes	No	No
Observations	74,688	71,576	74,688	71,576
R^2	0.718	0.722	0.608	0.615
Adjusted R^2	0.713	0.718	0.608	0.614
Residual Std. Error	1.731 (df = 73487)	1.738 (df = 70424)	2.025 (df = 74612)	2.033 (df = 71500)
F Statistic	155.955^{***} (df = 1200; 73487)	159.212^{***} (df = 1151; 70424)	$1,544.145^{***}$ (df = 75; 74612)	$1,520.043^{***}$ (df = 75; 71500)
Note:				*p**p***p<0.01

Table 5 shows the results of the diff-in-diff regressions including clustered robust standard errors. Based on these results, looking at areas that have implemented COVID-19 vaccine mandates, if all 16 policies are active, this leads to a .076% decrease in the unemployment rate when state trends over time are not included in the model. When state trends are included, all 16 policies being active causes a 36.805% decrease in the unemployment rate, holding all else constant.

When the model contains the vaccination rate in the month prior, all policies being active causes a .104% decrease in the unemployment rate if state trends are not included. After including state trends to in this model, all policies being active causes a 41.497% decrease in the unemployment rate, holding all else constant. The results of the diff-in-diff models are not statistically significant.

In the models where state trends are included, coefficient of the vaccine mandates on the unemployment rate is rather large. This implies that the effects of these policies differ greatly from state to state over time. At the same time, as previously shown in Figure 5, after the first of the vaccine mandates begin to go into effect, both the treatment and control groups continue to move parallel to one another. This indicates that the state-level vaccine mandates have no effect on county-level unemployment rates.

One potential issue that can arise is that the treatment, vaccine mandate policies, are on the state level, whereas the rest of the variables are on the county level. This may cause some inaccuracies within the estimates because there may be counties that have vaccine mandates in areas that have no state-level vaccine mandate active, which would not be counted in this study. This problem arose due to lack of availability of data regarding county level policies.

VI. Conclusion

Based on the results of the fixed effects models, it is clear that the increase in vaccination rates causes a decrease in the unemployment rate. For this reason, individuals should continue to get vaccinated against COVID-19, as the increasing vaccination rate may encourage individuals who have left the labor force to return if they were fearful of the severity of COVID-19.

However, based on the results of the diff-in-diff models and the visualization of pre-treatment trends, it is not likely that the state-level vaccination mandates against COVID-19 have been effective in reducing unemployment. Though the vaccines themselves cause decreases in unemployment, the policy requiring vaccines may not have any effect on unemployment.

Further studies can explore whether or not the vaccine mandates were effective on increasing vaccination rates or not, which could explain why the vaccine mandates did not affect unemployment. Other studies could explore how county vaccine mandates affected county unemployment rates instead of using the state policies, which could potentially yield different results, and a different pre-treatment trends graph. In addition, further studies could include more control variables such as number of workers in each industry, as the employment of individuals in high-contact industries such as services was highly impacted by COVID-19.

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