The Impact of Vaccinations on COVID-19 Case Rates at the State Level

By

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Abstract

This study uses a stepwise regression model to measure the efficacy of vaccination in reducing COVID-19 case rates through 8/10/21. In order to hold other covariants constant, variables like density, poverty, and governmental stringency were also included in the regression tests. The statistical results rigorously show that higher vaccination rates led to significantly lower COVID-19 case rates at the state level. A simulation is presented that estimates the cumulative COVID-19 case rate had vaccinations not been available. With respect to the other variables tested, density was significant in positively affecting case rates in 2021 after not being significant in the last half of 2020. Poverty rates were significant during all periods tested in the study. Surprisingly, governmental stringency as measured by the Oxford Stringency Index was not found significant in reducing COVID-19 case rates in 2021. Finally, no significant evidence of herd immunity was found in 2021.

Keywords: COVID-19; case rates; death rates, vaccine

JEL Codes: C01, C31, C40, C51, I10, I18

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1 Introduction

A number of academic studies have studied the impact of vaccinations on COVID-19 case rates. These studies, however, do not investigate statewide differences and how those differences can be used to estimate the efficacy of COVID-19 vaccination rates.

In Moghadas (Moghadas et al., 2020), the authors conclude that COVID-19 vaccines will be 95 percent effective in preventing disease. Their estimates are a priori in nature and do not include any ex-post tests on the efficacy vaccines. A study that is ex-post and does review statewide reports concludes that fully vaccinated individuals are "unlikely" to get COVID-19 and that vaccines are "highly effective" (Kates et al., 2021). Its major limitation is that the statewide data used are not consistent and are reported by different resources. As the authors conclude:

> *Moving forward, particularly as the more transmissible Delta variant is now the dominant strain of COVID-19 circulating in the U.S., more robust state-level data will help to monitor ongoing vaccine effectiveness and inform discussions about booster vaccinations (Kates et al., 2021, page 4).*

Gostin (Gostin et al., 2021) present an interesting study on how mandatory SARS-CoV-2 vaccinations in K-12 schools, colleges, universities, and businesses may improve the public's health. The examination, however, does not present empirical findings. Rather, it is a review and summary of possible effects. Another study that examines COVID-19 infections at U.S. colleges and universities (Davis and Zacher, 2021, page 1) finds that "infection rates are higher at public institutions." But in spite of the fact that the study covers the 2020-21 academic year, there are no empirical findings relating to the efficacy of vaccinations.

In a study involving 10,813 subjects in Guangdong, China, it was concluded that "full vaccination with inactivated vaccines is effective against pneumonia, severe and critical illness caused by the B.1.617.2 variant (Kang et al., 2021, page 2). The authors use one-way analysis of variance (ANOVA) as well as multivariate logistic regressions to estimate the vaccine's effectiveness. These statistical tools, however, are only used to test the effectiveness of being vaccinated or not with a single sample. The study does not measure the specific effects of increasing vaccination rates.

A study that comes closer to a statewide analysis is one that examines diverging patterns of COVID-19 cases in 7 countries with high vaccination rates (Bukhari et al., 2021). The study concludes somewhat ambiguously that "the number of cases and deaths have declined significantly (with vaccinations $\geq$ 50%), whereas in others they have increased compared to pre-vaccination levels" (Bukhari et al., 2021 page 1). More problematical is the fact that the period of testing in this paper ends on May 30, 2021, and it does not account for covariates that could potentially confound the estimation.

In Singer (Singer et al., 2021), the authors test the effectiveness of a vaccine against the SARS-CoV-2 variant identified through contract tracing in Israel. Although the examination concludes that two doses of the BNT162b2 vaccine confer protection against Beta COVID-19 infection, the testing period ends on March 25, 2021. As in the Kang study in Guangdong, China (Kang et al., 2021), the Singer study does not test the case rates for samples with continuous vaccination rates.

The lack of research on the efficacy of vaccinations at the statewide level is regrettable. With so much attention being given to the success or lack thereof in strategies designed to increase vaccination rates in a state, more academic research at the state level can measure how differing vaccination rates affect COVID-19 case rates.

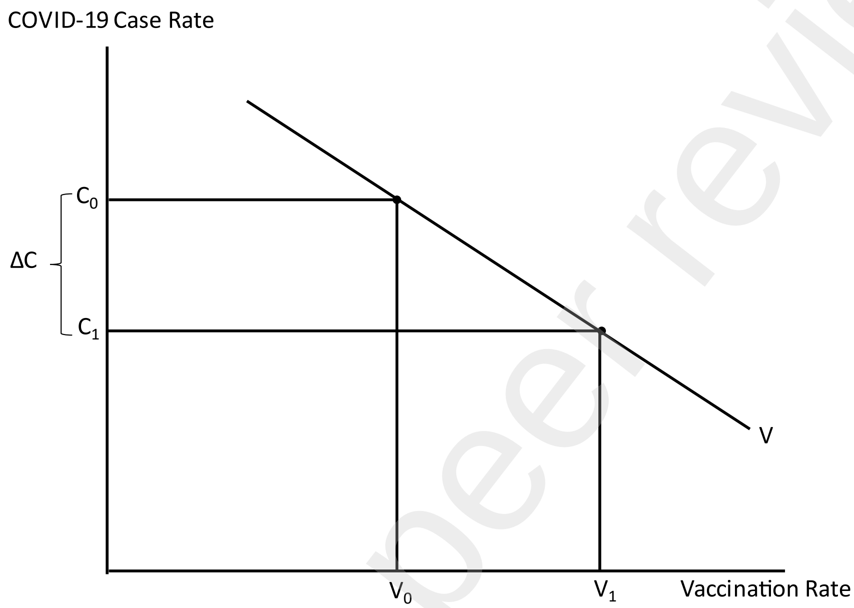
In the study to follow, the efficacy of cumulative vaccination rates from 1/1/21 to 8/10/21 at the state level will be examined. A stepwise regression model similar to that of Doti (*Journal of Bioeconomics,* 2021; *COVID Economics*, 2021) will be used to measure the vaccine's efficacy while holding other covariates like density, poverty, and governmental stringency constant. Such regression tests will have the added benefit of measuring the explanatory impact of these covariates.

This study will also estimate the impact of each state's mean vaccination rate on its mean case rate and carry out a number of "what-if" scenarios. The study also measured the potential impact of herd immunity. It will conclude by extending the research beyond case rates to investigate the impact of vaccinations on COVID-19 mortality rates.

2 Theoretical Model

The benefits of higher vaccination rates are depicted in Figure 1, where the downward sloping, V, points to an inverse relationship between COVID-19 cases and vaccination rates.

FIGURE 1
Benefits of Vaccination



If a state or nation has a mean vaccination rate of V_0, its corresponding rate of COVID-19 cases is C_0. But if that state or nation increased its mean vaccination rate to V_1, it is hypothesized that the COVID-19 case rate for that area will drop to C_1.

In the study to follow, Section 3 will present an empirical model for measuring the impact of different statewide vaccination rates on COVID-19 case rates, as shown by ΔC in Figure 1.

3 Empirical Model

In order to measure the impact of statewide differences in vaccination rates on COVID-19 case rates, it will be necessary to hold constant other variables that influence COVID-19 cases as well as define more precisely the variables to be used in formulating the empirical tests.

Cumulative confirmed COVID-19 cases per 100,000 in state population during the 1/1/21 to 8/10/21 period serves as the dependent variable in the model. A case is defined as a person who meets the clinical and epidemiological criteria for a SARS-CoV-2 infection.

The structural form of the model is shown below in Equation (1).

$$C_{i,t} = b_0 + b_1(x_{1,i}) + b_2(x_{2,i}) + \ldots + b_n(x_{n,i}) \quad (1)$$

where $C_{i,t}$ is the cumulative COVID-19 case rate per 100,000 in state i at the end of some period t. $x_1, \ldots, x_n = 1, \ldots, n$ independent variables in state i. $b_0, b_1, \ldots, b_n = n$ parameters to be estimated.

Note: Display of error terms are suppressed.

Equation (1) can also be estimated in exponential form using natural logs (ln).

In order to control and test for the factors that explain the cumulative COVID-19 case rate by state during some time interval t, the following variables shown below in Equation (2) were selected.

$$case_{i,t} = b_o + b_v\ vaccine_i + \sum_{d=1}^{2} b_{d,t}\ density_i + \sum_{y=1}^{2} b_{y,t}\ income_i + b_t\ stringency_i \quad (2)$$

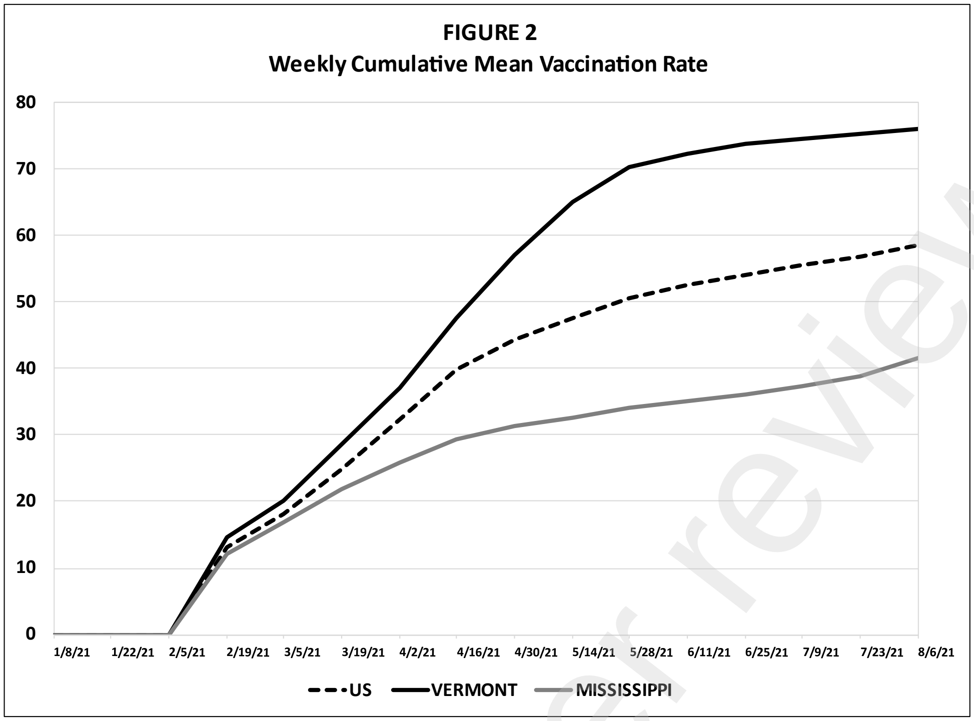
where $case_i$ is the cumulative COVID-19 case rate per 100,000 in state i during some period t. b_o, b_v, b_d, b_y, b_s are parameters to be estimated.

Note: Displays of error terms are suppressed, and the definition and measured statistics for the dependent and independent variables are as shown in Table 2.

The vaccination rate, as defined in Table 2, represents the mean of the single dose or more daily rate from 1/1/21 to 8/10/21. As shown in Table 1, the statewide mean rates over that period range from a high of 53.6 percent in Vermont to a low of 29.6 in Mississippi. Figure 2 shows the weekly U.S. mean cumulative vaccination rate as compared to the outlier states Vermont and Mississippi from 1/1/21 to 8/10/21.

Table 1
Mean Vaccination Rate

	State	Alpha Order From 1/1/21 to 8/10/21		State	In Rank Order from 1/1/21 to 8/10/21
1	Alabama	30.9	1	Vermont	53.6
2	Alaska	40.4	2	Massachusetts	52.2
3	Arizona	38.8	3	Connecticut	51.0
4	Arkansas	33.5	4	Hawaii	50.6
5	California	45.6	5	Maine	50.1
6	Colorado	43.5	6	New Hampshire	49.7
7	Connecticut	51.0	7	New Mexico	48.7
8	Delaware	43.7	8	Rhode Island	48.5
9	Florida	40.2	9	New Jersey	47.9
10	Georgia	32.8	10	Pennsylvania	46.5
11	Hawaii	50.6	11	Maryland	45.7
12	Idaho	31.7	12	California	45.6
13	Illinois	44.3	13	Washington	44.9
14	Indiana	34.6	14	New York	44.7
15	Iowa	40.5	15	Virginia	44.4
16	Kansas	38.9	16	Illinois	44.3
17	Kentucky	38.8	17	Delaware	43.7
18	Louisiana	31.1	18	Minnesota	43.7
19	Maine	50.1	19	Colorado	43.5
20	Maryland	45.7	20	Oregon	43.1
21	Massachusetts	52.2	21	Wisconsin	41.9
22	Michigan	39.4	22	South Dakota	41.4
23	Minnesota	43.7	23	Iowa	40.5
24	Mississippi	29.6	24	Alaska	40.4
25	Missouri	35.0	25	Florida	40.2
26	Montana	38.1	26	Nebraska	40.1
27	Nebraska	40.1	27	Michigan	39.4
28	Nevada	37.9	28	Kansas	38.9
29	New Hampshire	49.7	29	Kentucky	38.8
30	New Jersey	47.9	30	Arizona	38.8
31	New Mexico	48.7	31	Montana	38.1
32	New York	44.7	32	Nevada	37.9
33	North Carolina	36.9	33	Ohio	37.5
34	North Dakota	36.6	34	North Carolina	36.9
35	Ohio	37.5	35	Utah	36.8
36	Oklahoma	36.4	36	North Dakota	36.6
37	Oregon	43.1	37	Oklahoma	36.4
38	Pennsylvania	46.5	38	Texas	36.0
39	Rhode Island	48.5	39	West Virginia	35.3
40	South Carolina	34.5	40	Missouri	35.0
41	South Dakota	41.4	41	Indiana	34.6
42	Tennessee	32.6	42	South Carolina	34.5
43	Texas	36.0	43	Arkansas	33.5
44	Utah	36.8	44	Georgia	32.8
45	Vermont	53.6	45	Tennessee	32.6
46	Virginia	44.4	46	Wyoming	32.3
47	Washington	44.9	47	Idaho	31.7
48	West Virginia	35.3	48	Louisiana	31.1
49	Wisconsin	41.9	49	Alabama	30.9
50	Wyoming	32.3	50	Mississippi	29.6
	Mean	40.7		Mean	40.7
	Coefficient of Variation	15.3		Coefficient of Variation	15.3



As shown in Table 2, there are two density variables where a super density variable was added to the regression test because density, as generally measured, does not adequately measure its impact on COVID-19 cases on a state-level basis (Doti, *Journal of Bioeconomics,* 2021). A state's density (density) is defined as the population of that state divided by its total geographic area in square miles or as shown in Table 2: population density per square mile. Although that measure is relevant for most states, it is not necessarily so for those states where a highly populated metropolitan area exhibits extremely high density. For example, New York City's density is the ratio of its population of 8.2 million (2010 Census) to its land area of 302.6 square miles. The resulting density of New York city of 27,016, compares to New York state's density of 169. Using a state-level density of 169 for New York state would miss the impact of the extraordinarily high rate of density for the city.

In order to capture that impact on a state-level basis, all cities in the nation with a population of 300,000 or more that had a population density of at least 10,000 people per square mile were identified and measured as a ratio of each state's total population. The resulting ratios, in turn, were multiplied by the density of the metropolitan areas that met the selection criteria presented above. In the structural form of the model, this density variable (sdensity) is given by

$$\text{sdensity}_{i,t} = \sum_{k=1}^{n_i} p_{k,i} \;/\; P_{i,t} \;\; * \text{ density}_{i,t}$$

where $p_{k,i}$ is population of the kth city in state i with a population > 300,000 and density > 10,000 per mile^2. n_i is number of cities in state i with population > 300,000and density > 10,000 per mile^2. $P_{i,t}$ is population of state i as of some period t. $\text{density}_{i,t}$ is density of state i as of some period t.

Table 2. Dependent and independent variables used in the study

Description	Name	Mean	SD	CV	Min	Max	Obs.	Source
Dependent variables								
Cumulative COVID-19 case rates from 1/1/21 to 8/10/21	case	4423.30	1131.80	25.59	1775.30	6651.90	50	https://github.com/OxCGRT/USA-covid-policy/blob/master/data/OxCGRT_US_latest.csv
Independent variables								
I. Vaccination Rate								
Mean vaccination rate from 2/13/21 to 8/10/21 (Single dose or more)	vaccine	40.7	6.3	15.5	29.6	53.6	50	https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-United-States-Jurisdi/unsk-b7fc/data
II. Density variables								
Population density per square mile	density	202.7	266.2	131.4	1.3	1207.8	50	https://worldpopulationreview.com/state-rankings/state-densities
Super density per square mile	sdensity	343.0	1610.7	469.6	0.0	11076.0	50	https://en.wikipedia.org/wiki/List_of_United_States_cities_by_population_density
III. Income variables								
Per Capita Personal Income (000)	py	54.5	8.8	16.1	39.4	79.1	50	https://fred.stlouisfed.org/release/tables?rid=151&eid=257197
Poverty rate, percent of persons in poverty	poverty	0.1	0.0	28.6	0.1	0.3	50	https://en.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_poverty_rate
IV. Stringency Variable								
Mean Oxford Stringency Index from 1/1/21 to 8/10/21	stringency	35.1	9.8	27.9	9.3	64.4	50	https://github.com/OxCGRT/USA-covid-policy/blob/master/data/OxCGRT_US_latest.csv

Two income variables, per capita personal income in thousands (py) and the poverty rate (poverty) are included to hold constant the impact of a state's income on that state's COVID-19 case rate.

The efficacy of a state's governmental regualtions that impose various mandates in order to control the spread of COVID-19 is measured by the Oxford daily governmental stringency index (stringency). This index measures the stringency of statewide governmental mandates on a daily basis, using a scale from 1 to 100. The ordinal measures that comprise the Oxford index for every state include in its measurement the following governmental responses to COVID-19:

– School closings
– Workplace closings
– Cancellation of public events
– Restrictions on gathering size
– Closures of public transit
– Stay at home requirements
– Restrictions on internal movements
– Restrictions on international travel
– Public information campaign
– Testing policy
– Contact tracing

The daily Oxford stringency index used in this study was derived by calculating an average stringency index from the daily rates for each state during the 1/1/21 to 8/10/21 period. The derivation is given by:

$$\text{stringency}_{i,t} = \sum_{d=1}^{n} \text{stringency}_{i,d} \,/\, n_t$$

where $\text{stringency}_{i,t}$ is the mean stringency index in state i as of some period t, $\text{stringency}_{i,d}$ is the stringency index in state i as of a particular day, d, and n_t is the number of days during period t.

Table 3 presents the mean stringency index by state in alphabetical and rank order from highest to lowest over the 1/1/21 to 8/10/21 period.

The functional form of the equation that incorporates the impact each state's vaccination rate, density, income and stringency is shown below in Equation (3).

$$\text{case}_i = b_o + b_1 \text{ vaccine}_i + b_2 \text{ density}_i + b_3 \text{ sdensity}_i + b_4 \text{ py}_i + b_5 \text{ poverty}_i + b_6 \text{ stringency}_i \quad (3)$$

where the variables for state i are as defined in Table 2 and $b_0 \ldots\ldots b_6$ are parameters to be estimated.

Note: Error terms are suppressed.

The hypothesized signs of association in Equation (3) are shown in Equation (4):

$$case_i = f\,(\overset{-}{vaccine_i}\,;\ \overset{+}{density_i}\,;\ \overset{+}{sdensity_i}\,;\ \overset{-}{py_i}\,;\ \overset{+}{poverty_i}\,;\ \overset{-}{stringency_i}) \tag{4}$$

Table 3
Mean Oxford Stringency Index Values

	State	Alpha Order From 1/1/21 to 8/10/21		State	In Rank Order from 1/1/21 to 8/10/21
1	Alabama	20.8	1	Hawaii	64.4
2	Alaska	42.4	2	Rhode Island	53.0
3	Arizona	27.4	3	California	49.8
4	Arkansas	31.9	4	Washington	47.9
5	California	49.8	5	Massachusetts	47.6
6	Colorado	33.9	6	New York	47.1
7	Connecticut	43.7	7	Oregon	46.7
8	Delaware	37.2	8	New Mexico	44.3
9	Florida	22.5	9	Vermont	43.9
10	Georgia	30.5	10	Connecticut	43.7
11	Hawaii	64.4	11	Louisiana	43.0
12	Idaho	28.5	12	Minnesota	42.8
13	Illinois	36.4	13	Alaska	42.4
14	Indiana	31.3	14	North Carolina	40.8
15	Iowa	18.5	15	Maryland	37.3
16	Kansas	31.0	16	New Hampshire	37.2
17	Kentucky	33.7	17	Delaware	37.2
18	Louisiana	43.0	18	Texas	36.9
19	Maine	36.1	19	Ohio	36.9
20	Maryland	37.3	20	Michigan	36.7
21	Massachusetts	47.6	21	Illinois	36.4
22	Michigan	36.7	22	Oklahoma	36.2
23	Minnesota	42.8	23	Maine	36.1
24	Mississippi	24.5	24	New Jersey	35.8
25	Missouri	31.4	25	Wisconsin	35.4
26	Montana	31.4	26	Wyoming	35.3
27	Nebraska	21.6	27	Virginia	35.1
28	Nevada	30.8	28	Colorado	33.9
29	New Hampshire	37.2	29	Kentucky	33.7
30	New Jersey	35.8	30	West Virginia	33.1
31	New Mexico	44.3	31	Arkansas	31.9
32	New York	47.1	32	Montana	31.4
33	North Carolina	40.8	33	Missouri	31.4
34	North Dakota	24.5	34	Indiana	31.3
35	Ohio	36.9	35	Kansas	31.0
36	Oklahoma	36.2	36	Nevada	30.8
37	Oregon	46.7	37	Georgia	30.5
38	Pennsylvania	29.4	38	Tennessee	29.9
39	Rhode Island	53.0	39	Pennsylvania	29.4
40	South Carolina	27.0	40	Idaho	28.5
41	South Dakota	9.3	41	Arizona	27.4
42	Tennessee	29.9	42	South Carolina	27.0
43	Texas	36.9	43	Mississippi	24.5
44	Utah	20.2	44	North Dakota	24.5
45	Vermont	43.9	45	Florida	22.5
46	Virginia	35.1	46	Nebraska	21.6
47	Washington	47.9	47	Alabama	20.8
48	West Virginia	33.1	48	Utah	20.2
49	Wisconsin	35.4	49	Iowa	18.5
50	Wyoming	35.3	50	South Dakota	9.3
	Mean	35.1		Mean	35.1
	Coefficient of Variation	27.8		Coefficient of Variation	27.8

4 Impact of Vaccinations and Other Variables on COVID-19 Case Rates

A stepwise model similar to that used by Doti (Doti, *Journal of Bioeconomics*, 2021 and Doti, *COVID Economics*, 2021) added the explanatory variables in groupings from I to IV, as shown in Table 4. The regression results are presented in Regressions 1 to 5, Table 4. Note that explanatory variables were removed if not significant at the $p < 0.10$ level (one-tailed), and the "best" fit regression, Regression (5), Tables 4, is shown as shaded.

Table 4. Regression results, dependent variable definition: mean cumulative case rate (COVID-19 cases per 100,000 people by state) from 1/1/21 to 8/31/21, dependent variable name: cases

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
R-squared	0.06	0.47	0.54	0.53	0.53
Constant	6350.30	8256.13	7424.01	6201.75	6216.81
	(6.15) ***	(9.57) ***	(4.80) ***	(5.16) ***	(5.22) ***
I. Vaccination variable					
vaccine	-47.40	-109.36	-73.19	-80.81	-85.94
	(-1.89) **	(-4.94) ***	(-2.88) ***	(-3.07) ***	(-3.69) ***
II. Density variables:					
density		2.78	2.98	2.69	2.67
		(5.32) ***	(5.34) ***	(5.31) ***	(5.34) ***
sdensity		0.14	0.16	0.13	0.12
		(1.85) **	(2.01) **	(1.69) **	(1.67) **
III. Income variables					
py			-27.59		
			(-1.21)		
poverty			5871.10	8149.38	7996.8
			(1.55) *	(2.38) **	(2.37) **
IV. Policy Intervention					
stringency				-6.31	
				(-0.44)	

Notes: t statistics in parentheses. *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

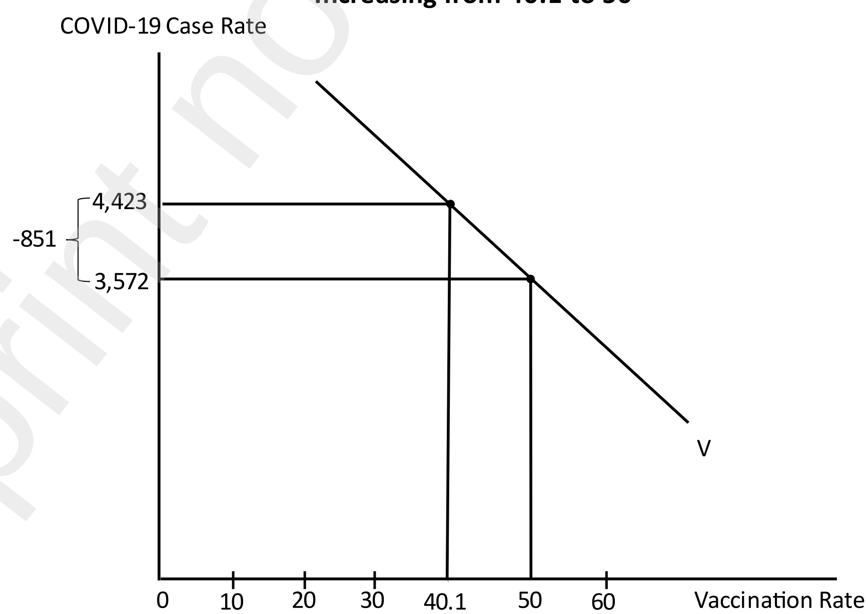
4.1 Vaccination Variable, vaccine

The estimated coefficient of -85.94 for the vaccination coefficient suggests that, on average, a state's COVID-19 case rate decreases by 85.94 cases per 100,000 in a state's population for every increase of 1 percent in a state's average vaccine rate. The measured t statistic of -3.69 for vaccine in Regression 5, Table 4, is highly significant at $p < 0.01$ level (one-tailed).

The empirical findings of Regression 5 can also be used to estimate the "what-if" impact of a higher vaccination rate. Following the theoretical model depicted in Figure 1, Figure 3 shows the estimated change in the COVID-19 case rate that would result if the mean cumulative vaccination rate were 50.0 percent instead of the actual 40.1 over the 1/1/21 to 8/10/21 period. As shown in Figure 3, the estimated coefficient of -85.94 in Regression 5, Table 4 suggests that the COVID-19 case rate per 100,000 in U.S. population would decline by 851 or ([50.0 – 40.1] * -85.94). That, in turn, suggests that the cumulative case rate in the U.S. on 8/10/21 would have been 3,572 or (4,423 – 851) instead of the actual rate of 4,423.

Since the case rate is measured per 100,000 in population, the projected decline in the case rate from 4,423 to 3,572 is equivalent to a cumulative total number of COVID-19 cases on 8/10/21 of 11.8 million at an assumed 50.0 vaccination rate. That compares to 14.6 million cases at the actual vaccination rate of 40.1 for an estimated decline at the 50 percent vaccination rate of 2.8 million cases (14.6 million less 11.8 million).

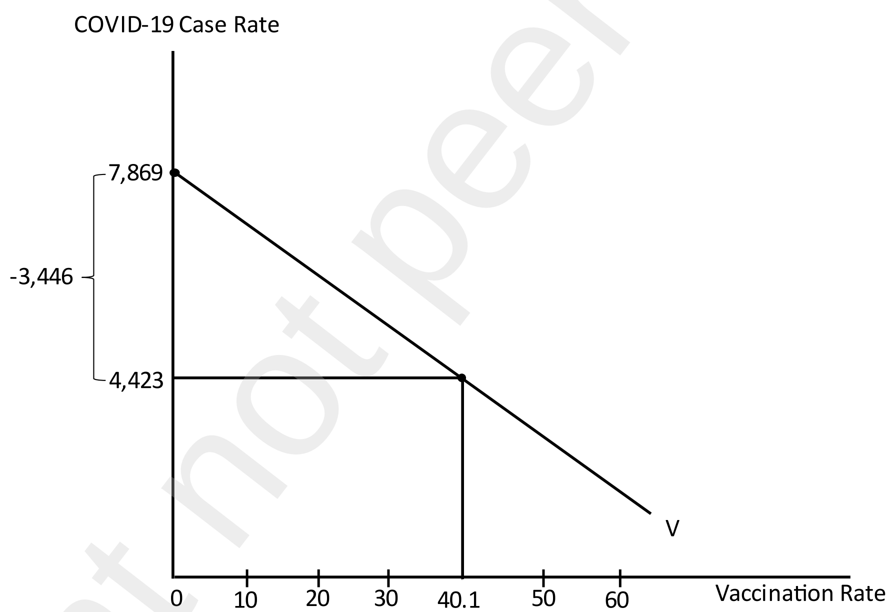
FIGURE 3
Impact of Vaccination Rate
Increasing from 40.1 to 50



The empirical results of Regression 5 can also be used to estimate the "what-if" impact of having no COVID-19 vaccines available and, therefore, a zero vaccination rate. As shown in Figure 4, estimated COVID-19 vaccine case rates per 100,000 in U.S. population would increase by 3,446 or ([0 – 40.1] * -85.94). As a result, the cumulative case rate in the U.S. from 1/1/20 to 8/10/21 would have been 7,869 or (4,423 + 3,446) per 100,000 had no vaccine been available. That compares to the actual rate of 4,423 per 100,000 at an average vaccination rate of 40.1.

Converting from the relative rate of 4,423 cases per 100,000 to 7,869 cases per 100,000 is equivalent to a total number of COVID-19 cases on 8/10/21 of 26.0 million at an assumed vaccination rate of zero and a U.S. population of 330 million. That compares to the 14.6 million cases at the actual average vaccination rate of 40.1 for an estimated increase at a zero percent vaccination rate of 11.4 million cases (26.0 less 14.6).

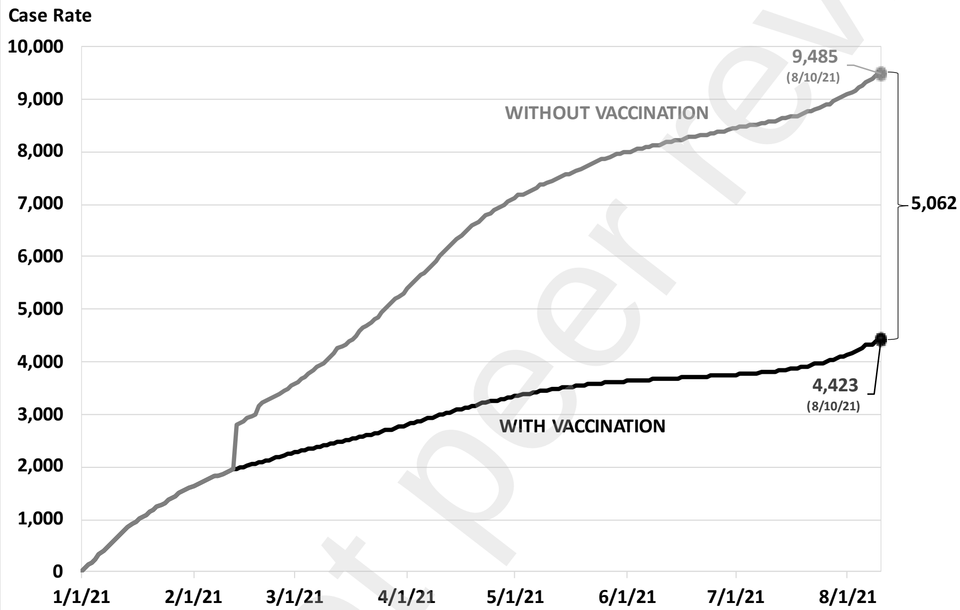
FIGURE 4
Impact of a Zero Vaccination Rate



The above estimate of an increase in the case rate of 3,446 per 100,000 in the U.S. and an increase of 11.4 million total cases is based on the mean vaccination rate of 40.1 from 1/1/21 to 8/10/21. It is also possible to use the estimated coefficient of -85.94 for the vaccination variable in Regression 5 to show the difference in cases on a daily basis. During the 1/1/21 to 8/10/21 period, the mean single dose or more vaccination rate in the U.S. increased from zero on 1/1/21 to 58.9 percent by 8/10/21.

Figure 5 shows a comparison of the actual cumulative case rate as compared to a projected cumulative case rate assuming no vaccinations. By 8/10/21, when the mean vaccination rate hit 58.9 percent, the difference between the cumulative case rate with vaccinations of 4,423 per 100,000 compares to a projected 9,485 per 100,000 with no vaccinations. That difference of 5,062 fewer cases per 100,000 in U.S. population is equivalent to a total reduction of 16.7 million COVID-19 confirmed cases with no vaccinations. This decrease of 16.7 million cases is based on the vaccination rate of 58.9 percent on 8/10/21 as compared to the 11.4 million decrease in the cumulative case rate at a mean vaccination of 40.1 over the 1/1/21 to 8/10/21 period.

FIGURE 5
Comparison of Actual and Estimated Cumulative COVID-19 Case Rates With and Without Vaccination



The estimated coefficient of -85.94 for the vaccine variable in Regression 5, Table 4, can also be used to analyze the implications of the wide disparity in vaccination rates between Vermont and Mississippi, as depicted in Figure 2. Recall that the mean cumulative vaccination rate for the highest vaccinated state, Vermont, was 53.6 percent versus a rate of 29.6 for the lowest vaccinated state, Mississippi.

When Vermont's vaccinated rate of 53.6 is multiplied by the estimated coefficient of -85.94 for the vaccine variable, the resulting estimated decline in Vermont's case rate is -4,607 or (53.6 * -85.94). Multiplying Mississippi's case rate of 29.6 times the vaccine coefficient results in an estimated decline of 2,544 or (29.6 *-85.94). The resulting difference in the estimated case rate for Vermont and Mississippi is 2,063 or (4,607 – 2,544). That difference almost fully accounts for the actual case rate of 5,061 for Mississippi and 2,928 for Vermont since the difference of 2,133 or (5,061 less 2,928) is very close to the difference of 2,063 in the case rates. This suggests that the wide disparity in Vermont and Mississippi case rates is fully explained by the difference in their mean vaccination rates.

Although Figures 3 and 4 are linear, a double logarithmic form of Regression 5, Table 4 was tested. The empirical results of that test (Regression 6) are presented below in Table 5.

Table 5
Regression 6, All Variables Measured in Natural Logs (ln) over the 1/1/21 to 8/10/21 period

	Regression 6	
Dependent Variable Name	lncase	
R-squared	0.43	
Constant	11.03	
	(-13.85)	***
I. Vaccination variable		
lnvaccine	-0.70	
	(-2.77)	***
II. Density variables:		
lndensity	0.09	
	-3.34	***
lnsdensity	0.02	
	(1.46)	*
III. Income variables		
lnpoverty	0.25	
	(1.82)	*

Notes: t statistics in parentheses. *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

Although the R^2 of 0.43 in the double logarithmic form of Regression 5 is lower than the R^2 of 0.53 in the linear form of the equation (Regression 5, Table 4), the measured t statistic for the ln of vaccine (lnvaccine) is still significant at the $p < 0.01$ level. In spite of the lower R^2 value in the double logarithmic form of the equation, the measured coefficients have the desirable quality of representing constant elasticities across different values of the independent variables. That means the -0.70 coefficient for lnvaccine variable represents the constant elasticity of the confirmed case rate with respect to the vaccination rate, which, in turn, suggests a one percent increase in the COVID-19 vaccination rate leads approximately to a 0.70 percent decrease in the COVID-19 case rate.

For comparison purposes, the average elasticity for vaccine in the linear form of the equation is shown in Equation 5.

$$\overline{\mathrm{E}} = \mathrm{b_v}\left[\frac{\overline{\text{vaccine}}}{\overline{\text{case}}}\right] = \text{-}85.94\left[\frac{40.66}{4423.3}\right] = \text{-}0.79 \quad (5)$$

Although the average elasticity of -0.79 in the linear form of the equation compares closely to the constant elasticity of -0.70 in the double logarithmic form of the equation, the elasticity of -0.79 in the linear form of the equation will change as the vaccine variable deviates from its mean value of 40.66.

4.2 Other Explanatory Variables

Table 4 also presents the empirical results for the other explanatory variables used in the stepwise regression model. The coefficients for density, sdensity, and poverty have the hypothesized signs of association as shown in Equation 4 and are all significant in Regression 5, at least at the $p < 0.10$ level. Because they did not pass the $p < 0.10$ significance test, the personal income variable, py, was dropped in Regression 4, and the stringency variable was dropped in Regression 5.

4.2.1 Density Variables

The density and sdensity variables were both significant in Regression 5. In fact, density was the most significant of all the explanatory variables tested. There is empirical evidence, however, that suggests that the impact of the density variables on the case rate changed over time. As shown in Table 6, density and sdensity were the most significant explanatory variables in the first half of 2020. But during the second half of the year, the density variables were no longer significant. These findings suggest that while COVID-19 hit dense states and highly dense urban areas particularly hard during the initial state of the pandemic (1/1/20 to 6/30/20), that impact fell away during the second half of the year (7/1/20 to 12/31/20). This, in turn, suggests that it took about six months before the pandemic to move from densely populated urban areas to more rural areas. Density, however, reared its head again in 2021 as its significance climbed. This is especially the case of the density variable with its measured t of 5.34 as compared to the lower significance of the super density variable, sdensity, with a measured t of 1.67.

4.2.2 Poverty Variable

The poverty variable was significant during all three of the stages shown in Table 6 but particularly so during the early 1/1/20 to 6/30/20 and 1/1/21 to 8/10/21 periods. In the double logarithmic form of the equation reported in Table 5, the constant elasticity of

0.25 suggests that a one percent increase in a state's poverty rate leads to a 0.25 percent increase in its COVID-19 case rate during the 1/1/21 to 8/10/21 period.

4.2.3 Stringency Variable

In analyzing the efficacy of governmental policy mandates, the empirical results shown in Table 6 suggest that the stringency variable was significant throughout 2020 and particularly so during the 7/1/20 to 12/31/20 period. In fact, stringency was the only explanatory variable during the second half of the year that had a $p < 0.05$ or higher level of significance. But in 2021, it exhibited no significance in reducing statewide case rates. Note that its measure t statistic in Regression 4, Table 4 was only -0.44.

A possible explanation for the sharp drop in the significance of the stringency in reducing COVID-19 case rates in 2021 is that states, on average, reduced their use of policy intervention. This can be seen in Figure 6 that shows that the mean weekly stringency score steadily declined from 48.1 on 1/1/21 to 19.9 on 8/10/21. Table 7 shows the statewide changes in mean stringency scores during three periods. Note that the mean stringency score for all states declined from 47.0 during the 7/1/20 to 12/31/20 period to 35.1 in the 1/1/21 to 8/10/21 period.

Table 6
Comparison of Regression Results over Three Different Periods of Time, Dependent Variable: case

Explanatory Variables (excluding vaccine)	1/1/20 to 6/30/20	7/1/20 to 12/31/20	1/1/21 to 8/10/21
Density	1.26	-0.36	2.67
	(-8.25) ***	(-0.39)	(5.34) ***
Super Density	0.11	-0.03	0.12
	(4.73) ***	(0.20)	(1.67) **
Poverty	2184.5	8261.17	7996.8
	(2.30) **	(1.36) *	(2.37) ***
Stringency	-6.47	-120.85	Not
	(-1.94) **	(-5.48) ***	Significant

Notes: t statistics in parentheses. *p‹0.10, **p‹0.05, ***p‹0.01 (one-tailed test)

FIGURE 6
Average Daily Stringency for U.S.

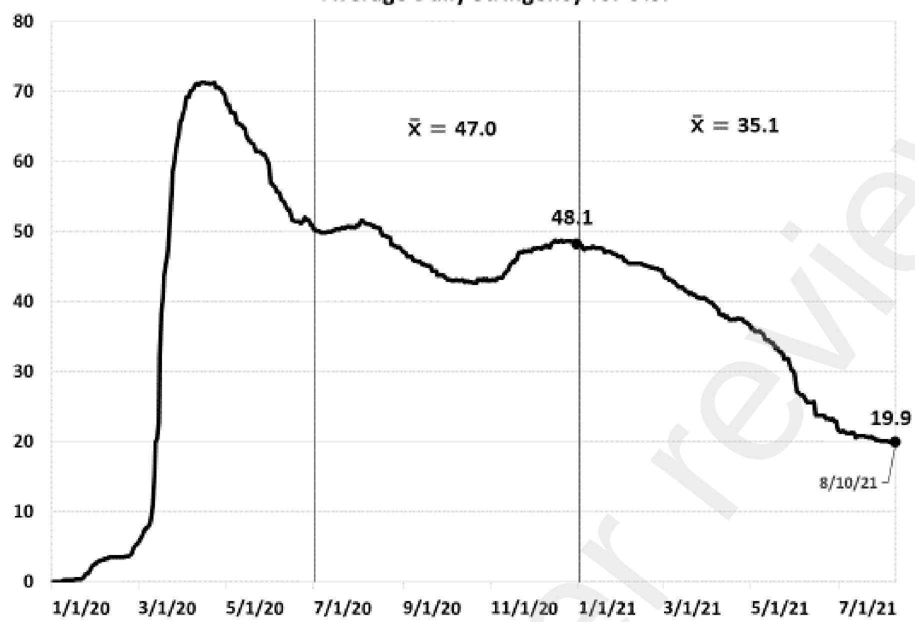
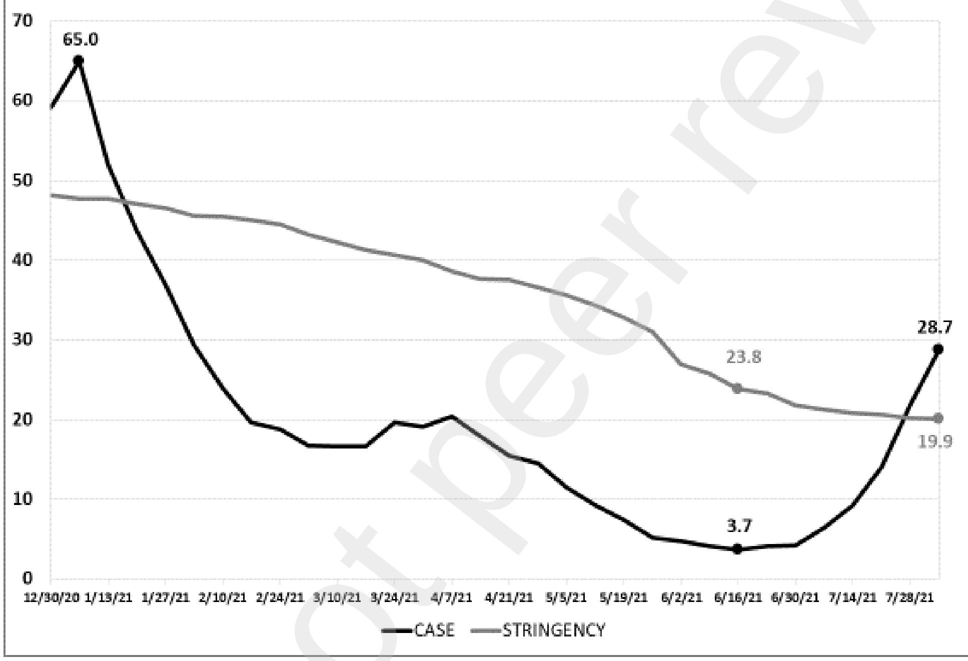


Table 7
Mean Stringency Scores by State Over Three Periods

	State	From 1/1/20 to 6/30/21	From 7/1/20 to 12/31/20	From 1/1/21 to 8/10/21
1	Alabama	30.5	31.6	20.8
2	Alaska	39.6	49.9	42.4
3	Arizona	31.1	39.8	27.4
4	Arkansas	30.9	42.2	31.9
5	California	43.5	59.0	49.8
6	Colorado	38.6	45.8	33.9
7	Connecticut	41.9	59.6	43.7
8	Delaware	46.6	53.4	37.2
9	Florida	40.9	40.3	22.5
10	Georgia	32.8	45.9	30.5
11	Hawaii	41.5	74.8	64.4
12	Idaho	35.2	42.8	28.5
13	Illinois	41.1	48.9	36.4
14	Indiana	35.5	39.1	31.3
15	Iowa	27.6	25.2	18.5
16	Kansas	35.1	41.7	31.0
17	Kentucky	45.6	51.7	33.7
18	Louisiana	33.7	49.1	43.0
19	Maine	46.5	63.2	36.1
20	Maryland	46.1	50.4	37.3
21	Massachusetts	38.8	58.4	47.6
22	Michigan	42.8	51.0	36.7
23	Minnesota	41.0	50.6	42.8
24	Mississippi	32.1	40.9	24.5
25	Missouri	34.1	38.8	31.4
26	Montana	38.3	42.5	31.4
27	Nebraska	35.1	36.0	21.6
28	Nevada	35.8	41.7	30.8
29	New Hampshire	40.6	39.9	37.2
30	New Jersey	38.3	49.1	35.8
31	New Mexico	46.7	74.8	44.3
32	New York	48.2	70.2	47.1
33	North Carolina	37.9	54.8	40.8
34	North Dakota	25.7	30.9	24.5
35	Ohio	43.3	54.4	36.9
36	Oklahoma	30.1	30.2	36.2
37	Oregon	35.7	52.2	46.7
38	Pennsylvania	37.7	48.5	29.4
39	Rhode Island	46.2	64.1	53.0
40	South Carolina	35.5	38.9	27.0
41	South Dakota	22.7	14.1	9.3
42	Tennessee	34.1	43.6	29.9
43	Texas	35.2	49.0	36.9
44	Utah	28.2	36.2	20.2
45	Vermont	41.1	58.9	43.9
46	Virginia	37.8	42.3	35.1
47	Washington	36.8	53.9	47.9
48	West Virginia	39.1	48.2	33.1
49	Wisconsin	33.8	40.0	35.4
50	Wyoming	35.6	42.2	35.3
	Mean	37.4	47.0	35.1
	Standard Deviation	5.8	11.6	9.7

Figure 7 shows the steady decline in the mean weekly stringency score as compared to the mean weekly case rate in the U.S. during the 1/1/21 to 8/10/21 period. The sharp decline in the mean case rate from 65.0 at the beginning of 2021 to 3.7 by mid-June may explain the accompanying decline in the efficacy of the stringency variable during that period. But even though the sharp Delta variant uptick led to an increase in the case rate from 3.7 on 6/16/21 to 28.7 by 8/10/21, the mean stringency score in the U.S. continued to decline over that period from 23.8 to 19.9.

FIGURE 7
Weekly Mean Case Rate Versus Mean Stringency Index



It might be argued that the functional form of the stringency variable changed and that change may account for it being insignificant in 2021. To analyze that possibility, various values of stringency were tested in the model. As an alternative to the stringency variable,stringency, stringencyl, was substituted. The alternative stringency variable measured the absolute change in the mean stringency index value from the 7/1/20 to 12/31/20 period to the mean value during the 1/1/21 to 8/10/21 period. Another stringency variable, stringencyp, was substituted that measured the percentage change in the mean stringency index from the 7/1/20 to 12/31/20 period to the 1/1/21 to 8/10/21 period.

As shown below, all three measured coefficients of stringency were insignificant.

	stringency	**stringencyl**	**stringencyp**
$\hat{b}_s$	-6.31	-9.39	-1.51
t-statistic	(-0.43)	(-0.42)	(-0.14)

5 Impact on Statewide Case Rates

The estimated coefficient for the vaccination rate, vaccine, can be used to estimate the impact of each state's mean vaccination rate on its mean case rate. Those estimates are presented in Table 7 and are based on Regression 5, Table 4. The ΔC term in Equation 6 is represented by the ΔC term shown graphically in Figure 1 where $C_0 - C_1 < 0$.

$$\Delta C = [\text{vaccine}_i] * \hat{b}_v * [P_i / 100{,}000] \tag{6}$$

where ΔC = Reduction in the COVID-19 case rate from 1/1/21 to 8/10/21 as a result of an increase in the vaccination rate
vaccine_i = The mean vaccination rate from 1/1/21 to 8/10/21 for state i
$\hat{b}_v$ = The estimated coefficient for vaccine (see Regression 5, Table 4)
P_i = The population of state i

Note that Equation 6 above requires that the product include $[P_i / 100{,}000]$ in order to convert case rates per 100,000 to the absolute reduction in the number of cases.

After aggregating the state-level results, Table 8 shows that COVID-19 vaccinations reduced the total number of infections in the U.S. by an estimated 10.4 million. As a result, the actual total number of infections dropped from an imputed total of 26.1 million infections (10.4 million + 15.7 million) with no vaccinations to 15.7 million infections, given each state's actual mean vaccination rate. These results are graphically depicted in Figure 8.

Note that the 10.4 million decline in total cases estimated by calculating the aggregate change of all 50 states is close to the 11.4 million cases calculated in Section 4.1 above that was estimated as an average for the U.S. as a whole (see Figure 4).

FIGURE 8
Reduction in the Number of COVID - 19 Cases in the U.S.
Resulting from Each State's Mean Vaccination Rate

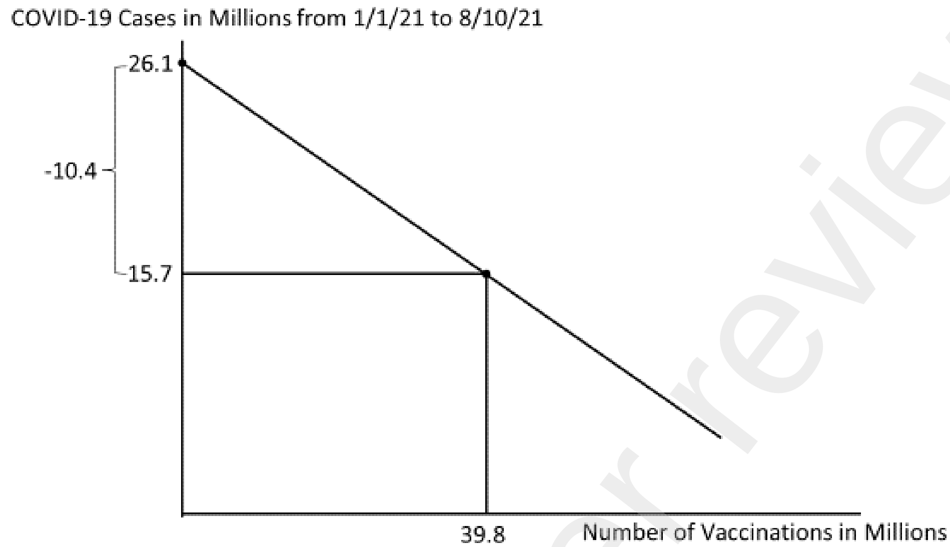


Table 8
The Impact on COVID-19 Cases as a Result of Each State's Mean Vaccination Rate from 1/1/21 to 8/10/21

	1	2	3	4
State	Reduction in the Number of COVID-19 Cases Resulting from State's Mean Vaccination Rate	Actual Number of COVID-19 Cases	Projected Number of COVID-19 Cases with No Vaccinations (sum of column 1 and 2)	Percentage Reduction in COVID-19 Cases as a Result of State's Mean Vaccination Rate ((column 1/ column 3)*100
1 Alabama	88,148	250,161	338,310	26.1
2 Alaska	26,664	31,681	58,345	45.7
3 Arizona	174,575	420,571	595,146	29.3
4 Arkansas	83,098	178,437	261,535	31.8
5 California	1,684,570	1,711,724	3,396,294	49.6
6 Colorado	169,009	248,164	417,173	40.5
7 Connecticut	133,506	173,938	307,443	43.4
8 Delaware	31,530	55,024	86,554	36.4
9 Florida	420,817	1,445,700	1,866,517	22.5
10 Georgia	280,818	553,815	834,633	33.6
11 Hawaii	77,895	24,974	102,869	75.7
12 Idaho	44,807	64,709	109,516	40.9
13 Illinois	393,400	483,739	877,138	44.9
14 Indiana	181,722	270,671	452,393	40.2
15 Iowa	50,324	99,431	149,754	33.6
16 Kansas	77,513	113,085	190,598	40.7
17 Kentucky	129,628	237,429	367,057	35.3
18 Louisiana	171,568	281,274	452,842	37.9
19 Maine	41,852	46,769	88,621	47.2
20 Maryland	193,881	194,936	388,818	49.9
21 Massachusetts	281,914	355,226	637,140	44.2
22 Michigan	314,643	493,045	807,688	39.0
23 Minnesota	208,171	205,305	413,476	50.3
24 Mississippi	62,419	150,149	212,568	29.4
25 Missouri	165,865	267,039	432,904	38.3
26 Montana	29,162	37,204	66,367	43.9
27 Nebraska	36,029	64,191	100,220	35.9
28 Nevada	83,094	140,657	223,750	37.1
29 New Hampshire	43,695	56,277	99,972	43.7
30 New Jersey	273,146	516,688	789,833	34.6
31 New Mexico	80,201	71,636	151,837	52.8
32 New York	783,221	1,184,958	1,968,179	39.8
33 North Carolina	371,683	550,395	922,078	40.3
34 North Dakota	16,089	19,791	35,880	44.8
35 Ohio	370,375	445,512	815,886	45.4
36 Oklahoma	123,706	210,146	333,852	37.1
37 Oregon	170,337	118,508	288,844	59.0
38 Pennsylvania	322,712	591,481	914,193	35.3
39 Rhode Island	48,141	68,586	116,727	41.2
40 South Carolina	120,965	338,338	459,303	26.3
41 South Dakota	7,168	26,433	33,602	21.3
42 Tennessee	177,034	340,210	517,244	34.2
43 Texas	931,790	1,489,471	2,421,261	38.5
44 Utah	56,298	164,509	220,807	25.5
45 Vermont	23,493	18,252	41,744	56.3
46 Virginia	259,082	356,337	615,418	42.1
47 Washington	317,001	248,581	565,582	56.0
48 West Virginia	50,844	82,832	133,676	38.0
49 Wisconsin	177,210	177,021	354,231	50.0
50 Wyoming	17,652	22,915	40,566	43.5
Total	10,378,465	15,697,921.13	26,076,386	39.8

6 Measuring for Herd Immunity

The model developed in this study can be used to measure the impact of herd immunity – resistance to the spread of COVID-19 within a population based on pre-existing immunity from the previous infection for a high proportion of the population.

Since the dependent variable in the model, $case_i$, is the cumulative COVID-19 infection case rate in state i from 1/1/21 to 8/10/21, a proxy for pre-existing immunity from COVID-19 infection can be defined as:

$$precase_{i,t} = \sum_{t=1}^{n} case_{i,t}$$

where $precase_{i,t}$ is the cumulative case rate in state i from 1/1/20 to 12/31/20. Table 9 presents the cumulative case rate for $precase_{i,t}$ by state in alphabetical order and rank order from highest to lowest as of 12/31/20.

The functional form of the equation that incorporates the impact of each states pre-existing immunity as measured by $precase_{i,t}$ is shown below in Equation (7).

$$case_i = b_o + b_1\ vaccine_i + b_2\ density_i + b_3\ sdensity_i + b_4\ poverty_i + b_5\ precase_i \qquad (7)$$

where the variables for state i are as defined in Table 2, $precase_i$ is as defined above and $b_0 \ldots b_5$ are parameters to be estimated.

Note: Error terms are suppressed.

The hypothesized signs of association in Equation (7) are shown below in Equation (8).

$$case_i = f\ (\overset{+}{vaccine};\ \overset{+}{density};\ \overset{+}{sdensity};\ \overset{+}{poverty};\ \overset{-}{precase}) \qquad (8)$$

The empirical results of testing Equation (7) are presented below in Table 10.

As in the empirical results of Regression 5, all of the variables except for $precase_i$ are significant and have the hypothesized signs of association. The variable serving as a proxy for the impact of herd immunity, $precase_i$, has the hypothesized negative sign, but p= 0.21 is just short of passing a one-tailed 0.10 significance test.

This empirical finding does not necessarily mean there is no herd immunity resulting from the COVID-19 pandemic. More likely, the mean cumulative case rate of 6,336 per 100,000 for all states as of 12/31/20 (See Table 9) may not be high enough to lead to a significant resistance response during the 1/1/20 to 8/10/21 period.

Table 9
Cumulative COVID case rate as of 12/31/20 (precase)

	State	Alpha Order		State	Rank Order
1	Alabama	7,340	1	North Dakota	12,086
2	Alaska	6,430	2	South Dakota	11,108
3	Arizona	7,010	3	Wisconsin	8,923
4	Arkansas	7,429	4	Iowa	8,905
5	California	5,907	5	Nebraska	8,609
6	Colorado	5,753	6	Tennessee	8,521
7	Connecticut	5,221	7	Utah	8,511
8	Delaware	5,822	8	Rhode Island	8,320
9	Florida	6,089	9	Kansas	7,729
10	Georgia	6,223	10	Idaho	7,722
11	Hawaii	1,564	11	Illinois	7,654
12	Idaho	7,722	12	Wyoming	7,626
13	Illinois	7,654	13	Indiana	7,572
14	Indiana	7,572	14	Montana	7,547
15	Iowa	8,905	15	Arkansas	7,429
16	Kansas	7,729	16	Minnesota	7,341
17	Kentucky	5,925	17	Alabama	7,340
18	Louisiana	6,787	18	Oklahoma	7,315
19	Maine	1,792	19	Mississippi	7,274
20	Maryland	4,569	20	Missouri	7,165
21	Massachusetts	5,442	21	Nevada	7,161
22	Michigan	5,304	22	Arizona	7,010
23	Minnesota	7,341	23	Louisiana	6,787
24	Mississippi	7,274	24	New Mexico	6,783
25	Missouri	7,165	25	Alaska	6,430
26	Montana	7,547	26	Georgia	6,223
27	Nebraska	8,609	27	Florida	6,089
28	Nevada	7,161	28	Texas	6,038
29	New Hampshire	3,285	29	Ohio	5,990
30	New Jersey	5,956	30	New Jersey	5,956
31	New Mexico	6,783	31	Kentucky	5,925
32	New York	5,062	32	California	5,907
33	North Carolina	5,090	33	South Carolina	5,893
34	North Dakota	12,086	34	Delaware	5,822
35	Ohio	5,990	35	Colorado	5,753
36	Oklahoma	7,315	36	Massachusetts	5,442
37	Oregon	2,686	37	Michigan	5,304
38	Pennsylvania	5,056	38	Connecticut	5,221
39	Rhode Island	8,320	39	North Carolina	5,090
40	South Carolina	5,893	40	New York	5,062
41	South Dakota	11,108	41	Pennsylvania	5,056
42	Tennessee	8,521	42	West Virginia	4,781
43	Texas	6,038	43	Maryland	4,569
44	Utah	8,511	44	Virginia	4,069
45	Vermont	1,189	45	New Hampshire	3,285
46	Virginia	4,069	46	Washington	3,207
47	Washington	3,207	47	Oregon	2,686
48	West Virginia	4,781	48	Maine	1,792
49	Wisconsin	8,923	49	Hawaii	1,564
50	Wyoming	7,626	50	Vermont	1,189
	Mean	6,336		Mean	6,336
	Coefficient of Variation	33.69		Coefficient of Variation	33.69

Table 10
Regression 7 - Regression test of Equation (7) that includes a variable representing pre-existing case (precase)

	Regression 7	
Dependent Variable	case	
R-squared	0.54	
Constant	7455.27	
	(4.83)	***
Independent Variables		
vaccine	-102.93	
	(-3.83)	***
density	2.76	
	-5.49	***
sdensity	0.12	
	-1.67	*
poverty	7539.80	
	-2.24	**
precase	-0.08	
	(-1.25)	

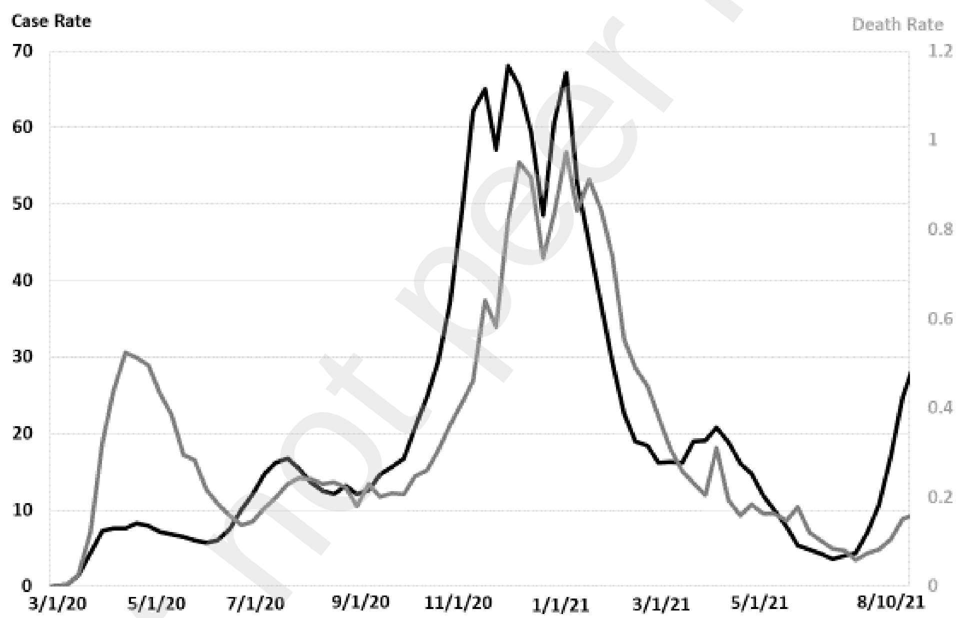
Notes: t statistics in parentheses. *p<0.10, **p<0.05, ***p<0.01 (one-tailed test)

7 The Impact of Vaccination in reducing the COVID-19 Death Rate

The focus of this study has been on measuring the efficacy of increasing vaccination rates on reducing confirmed cases of COVID-19. It might be argued that in addition to reducing the confirmed case rate, vaccinated people have a better chance of surviving after being infected with the virus. That argument can be tested by comparing mortality rates pre- and post-vaccination periods. The mortality rate is defined as the ratio of the COVID-19 death rate to the COVID-19 case rate.

Figure 9 shows a comparison of weekly COVID-19 case rates and death rates from 3/1/20 to 8/10/21 and suggests the presence of a lag before changes in the case rate affect the death rate.

FIGURE 9
Comparison of Weekly COVID-19 Case Rates and Death Rates



The timing of that lag can be analyzed by comparing correlation coefficients between weekly COVID-19 death rates and various weekly lags of confirmed case rates. As shown in Table 11, the highest correlation coefficient of 0.886 suggests a lag of 3 weeks before changes in case rates affect death rates. This finding is also supported by correlation coefficients that measure the lag measured in days rather than weeks. The highest correlation coefficient of 0.843 when using a lag of 21 days supports the finding that a lag of 3 weeks before case rates affect death rates.

Table 11

Correlation Coefficients (r-values) that Measure the Lag in Weeks and Days between COVID-19 Case Rates and Death Rates from 3/1/20 to 8/10/21

Weeks		Days	
	r-value		r-value
Case (-0)	0.803	Case (-18)	0.700
Case (-1)	0.857	Case (-19)	0.766
Case (-2)	0.881	Case (-20)	0.827
Case (-3)	0.886	Case (-21)	0.843
Case (-4)	0.863	Case (-22)	0.779

The presence of a lag of three weeks or 21 days before the case rate affects the death rate needs to be considered when measuring the COVID-19 mortality rate. That measure, defined as the ratio of the COVID-19 death rate to the case rate lagged three weeks, can be expressed in percentage terms as follows:

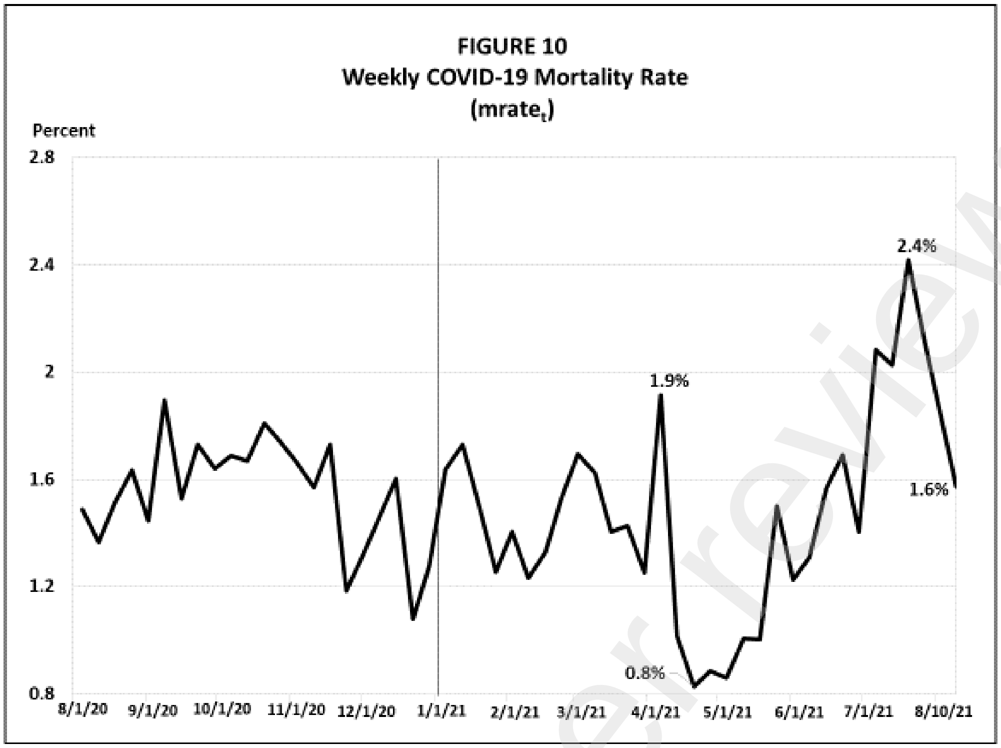
$$mrate_t = [drate_t / crate_{t-3}] * 100$$

where $mrate_t$ = Mean COVID-19 mortality rate during week t
$drate_t$ = Mean COVID-19 death rate during week t
$crate_{t-3}$ = Mean COVID-19 case rate lagged 3 weeks

A graphical representation of the weekly COVID-19 mortality rate, as measured by mrate is shown in Figure 10. That figure shows that the mortality rate, mrate, hovered within a range of 1.2 to 1.6 percent through 4/1/21. Then after peaking at 1.9 percent on 4/7/21, the mortality rate dropped sharply to 0.8 percent by 4/21/21. Perhaps because of the COVID-19 Delta variant, the mortality rate subsequently increased to 2.4 percent by 7/21/21 and thereafter declined sharply to 1.6 percent by 8/10/21.

The mean mortality rate, mrate, from 8/1/20 to 12/31/20, was 1.55 percent versus 1.46 percent during the 1/1/21 to 8/10/21 period, an interval of time when vaccines became available and the vaccination rate steadily increased. But in spite of the increase in the vaccination rate, the decrease in the mean weekly mortality rate from 1.55 to 1.46 was not significant. The measured t statistic for a two-sample hypothesis test, assuming unequal variances was an insignificant +0.99 with a one-tailed $p = 0.16$. These empirical results suggest that vaccinations had no significant impact in reducing the COVID-19 mortality rate, at least when comparing the 8/1/20 to 12/31/20 period with the 1/1/21 to 8/10/21 period.

Although no significant impact was found in the mortality rate, it should be noted that this study points to a sharp decline in the number of deaths as a result of vaccinations. Given a mortality rate of 1.46 during the 1/1/21 to 8/10/21 period and an estimated total decline of 16.7 million cases through 8/10/21 (see Figure 5), the total estimated decline in COVID-19 deaths from vaccinations is about 245,000 lives or (16.7 million * 0.0146).



8 Conclusion

Much controversy has arisen over the efficacy of COVID-19 vaccinations and the efforts taken or not taken by state governments to increase their mean vaccination rates. In spite of this, no academic papers have been published that examine statewide differences in COVID-19 vaccination rates and case rates. This study hopes to fill that gap by presenting a stepwise regression test that measures the hypothesized impact of vaccinations and other explanatory variables on each state's COVID-19 case rate.

The empirical findings presented in Table 4 show that the vaccination rate, two measures of density, and the poverty rate are all significant at the $p < 0.05$ (one-tailed) level or higher and have the hypothesized signs of association. The measured t statistic of -3.67 for the state's vaccination rate is highly significant at the $p < 0.01$ level (one-tailed). On average, the regression findings suggest a state's COVID-19 case rate changes by -85.94 cases per 100,000 in population for every increase of 1 percent in a state's vaccine rate. That, in turn, suggests that the mean cumulative case rate in the U.S. of 40.1 per 100,000 on 8/10/21 resulted in a decline of 3,446 cases per 100,000 or (40.1 * -85.94). That represents a decrease in the total number of cases in the U.S. of 11.4 million COVID-19 confirmed cases as a result of the various COVID-19 vaccines.

A "what-if" scenario had the mean vaccination rate been 50 instead of 40.1 points to a further decline of 851 cases per 100,000, or a total reduction of 2.8 million confirmed COVID-19 cases.

The analysis was also extended to compare actual and estimated cumulative COVID-19 case rates with and without vaccination over the 1/1/21 to 8/10/21 period (see Figure 5). Based on a mean cumulative vaccination rate of 58.9 percent, the findings point to a difference of 5,062 fewer cases per 100,000 in the U.S. That is equivalent to a total reduction of 16.7 million cases through 8/10/21. Assuming a COVID-19 death rate of 1.46 percent (see Section 7), that suggests that about 245,000 lives have been saved because of vaccines.

A constant rate elasticity of -0.70 was estimated in a double logarithmic version of the best-fit equation. That estimate compared closely to the average elasticity of -0.79 in the linear version of the best-fit equation.

Density was the most significant variable tested over the 1/1/21 to 8/1/21 period. Empirical evidence, however, suggests that the impact of density on cumulative COVID-19 cases changed over time. While it was highly significant in the first half of 2020, its significance evaporated during the second half. These findings suggest that COVID-19 hit dense states hard during the initial stage of the pandemic (1/1/20 to 6/30/20), but that impact fell away during the second half. But density returned as being a highly significant variable from 1/1/21 to 8/10/21.

The poverty variable that measured the mean poverty rate in each state was significant during all three periods tested in the study. A constant elasticity of 0.25 for the variable over the 1/1/21 to 8/10/21 period suggests that a one percent increase in a state's poverty rate leads to a 0.25 percent increase in its COVID-19 case rate.

In analyzing the efficacy of governmental policy mandates, the empirical results shown in Table 6 suggest that the stringency variable was significant throughout 2020 and particularly so during the 7/1/20 to 12/31/20 period. In fact, stringency was the only explanatory variable during the second half of 2020 that had a $p < 0.05$ or higher level of significance. But in 2021, it exhibited no significance in reducing statewide case rates. This finding may have resulted from the sharp decline in the use of mandates in 2021.

Table 8 on page 24 presents the estimated impact on each state's mean vaccinated rate and the actual number of cases, given each state's mean vaccination rate over the 1/1/20 to 8/10/21 period.

In testing for the presence of herd immunity in 2021, the empirical results had the hypothesized sign of association, but its significance ($p = 0.21$) was short of passing a one-tailed 0.10 significance test.

Finally, the empirical findings of this study point to a 21-day or 3-week lag before COVID-19 case rates affect COVID-19 death rates. The presence of that lag was used to test the relationship between cases and deaths over several time periods. The empirical results suggest that unlike the highly significant impact of vaccinations in reducing COVID-19 case rates, they had no significant impact in reducing the COVID-19 mortality rates, at least when comparing the 8/1/20 to 12/31/20 period with the 1/1/21 to 8/10/21 period.

Future research should be directed at extending the study through September 2021 in order to better measure the impact of the recent surge in COVID-19 cases and deaths from the Delta variant on the other variables tested in this study. The model can also be extended to directly examine the impact of the vaccinations and other variables on the COVID-19 death rate rather than the indirect test used in the final section of this study.

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