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Abstract

This study analyzes the benefits of statewide policy intervention in reducing COVID-19 deaths and the costs of that intervention in lost jobs and lower real gross state product (RGSP). Policy interventions are measured by the Oxford stringency index which places a daily numerical value on the level of a state's policy intervention.

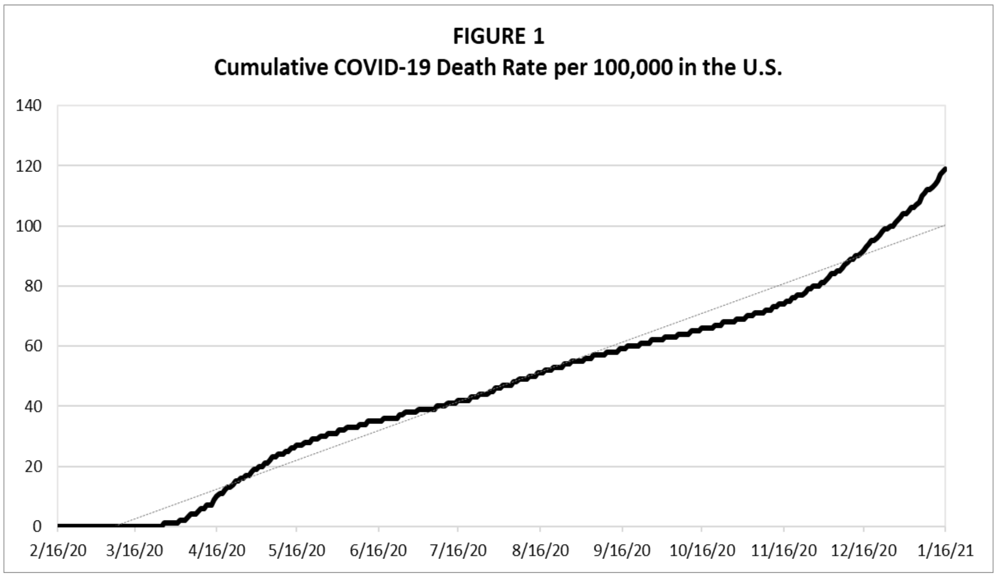
Empirical evidence is provided that shows policy interventions have reduced COVID-19 deaths by 375,000 lives in 2020. On the cost side, it was found that policy intervention resulted in a loss of 7.3 million jobs and a decline of $410 billion in RGSP.

The study concludes by integrating the findings related to the benefits and costs of policy interventions to the economic cost per life saved for every state, as well as an estimate of the national average cost per life of $1.1 million. That figure is compared to an age-adjusted value of statistical life (VSL) calculated in the study of $4.4 million for COVID-19 fatalities.

Keywords: *COVID-19, empirical, benefits and costs, policy intervention, Oxford stringency index, jobs, real gross state product, VSL.*

1. Introduction

Understanding the benefits and costs associated with policy interventions designed to reduce the infection and death rates of COVID-19 is critically important. COVID-19 is the most significant health threat of our time. As shown below in Figure 1, the COVID-19 death rate in the U.S. continues to increase and towards the end of 2020 has begun to increase at a faster rate.



Several academic studies have attempted to study the benefits and costs related to policy interventions to contain the spread of the COVID-19 virus and reduce its death rate. Unfortunately, most of these studies were conducted during the early months of the pandemic. Even these early studies, though, do not address the impact at the state level or examine the economic impact of policy interventions on jobs or spending.

In a study by Robinson, Sullivan, and Shogren, for example, the inquiry focuses on the relationship between age and the value of a statistical life (VSL) (Robinson, Sullivan, and Shogren, 2020). They use various approaches in measuring VSL to examine the empirical findings cited in other studies, but they do not independently measure the benefits and costs related to policy intervention.

One of the studies they cite is “The Benefits and Costs of Using Social Distancing to Flatten the Curve for COVID-19” (Thunstrom et al., 2020). The authors of this study use estimates of the impact of social distancing used by Australia in controlling the spread of the 1918 Spanish flu to measure the impact of social distancing in reducing the mortality risk of COVID-19. Not only is the use of data relating to the Spanish flu suspect, but these data relate only to social distancing rather than the full range of policy interventions. As they conclude, “While there may be other combinations of policies that could be adopted for this pandemic or in the future, we leave those for future work.” (Thunstrom et al., 2020, page 193).

Greenstone and Nigam also focus their investigation on the impact of social distancing on COVID-19 deaths. No other policy interventions are considered. There is also no analysis relating to the cost side of the equation.

Dave et al. examine how shelter-in-place orders affect COVID-19 during the early months of the pandemic. The focus is on measuring the effectiveness of the timing of the orders on the virus, not to the costs and benefits of policy intervention (Dave et al., 2020).

In "A Cost-Benefit Analysis of the COVID-19 Disease," Rowthorn and Maciejowski's interest is "in the cost-benefit analysis of large-scale interventions such as lockdowns" (Rowthorn ad Maciejowski, 2020, page 539). The only intervention evaluated is that of lockdowns, and the analysis relates to Britain – not the U.S.

Spiegel and Tookes create their own measure relating to business restrictions for every county in the U.S. and use those measures to forecast the impact on COVID-19 deaths (Spiegel and Tookes, 2020). They state, "We focus on fatalities rather than cases because of substantial variation on testing capacity over time and region." The authors find that policy intervention at the county level predicts lower 4 to 6 weeks ahead fatality growth. This study, however, as impressive as it is in attempting to measure the extent of policy intervention at the county level, does not analyze the costs of the interventions.

In the study to follow, the emphasis will be on measuring the benefits and costs of statewide policy interventions in reducing the rate of COVID-19 deaths. Policy interventions are measured by using the Oxford stringency index. The costs of policy intervention will measure the impact on each state's jobs and real gross state product. The period of analysis will be the full calendar year 2020.

There are several important areas of benefits and costs that will not be addressed in this study. It will not examine the benefits that might occur if policy interventions help prevent the health care system from being overwhelmed with COVID-19 patients. Neither does it consider the costs relating to increasing death rates, mental health, or other health problems associated with people not getting needed health care because they are discouraged from seeking medical treatment.

While these benefits and costs are relevant and important, this study's aim is to focus on how policy interventions at the state level benefit society by reducing death rates but, in doing so, incur costs relating to lost jobs and income. The study will conclude by estimating the economic cost per life saved for each state resulting from policy interventions and compare that cost to an age-adjusted value of statistical life (VSL).

2. Theoretical Model

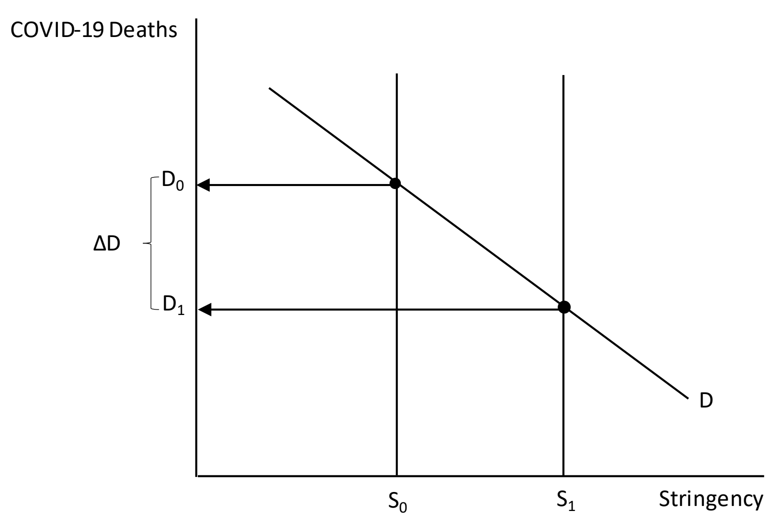
2.1 Benefits from Policy Intervention

The benefits from policy intervention are depicted graphically in Figure 2, where the downward sloping, D, points to an inverse relationship between COVID-19 deaths and stringency, where stringency measures the degree to which individuals protect themselves from being infected by the virus.

Even in a world with no policy intervention, it is reasonable to assume that individuals would voluntarily self-protect themselves from infection. Self-protection might include wearing a mask, distancing themselves from others, and avoiding crowds. Such voluntary levels of stringency where there is no policy intervention can be depicted in Figure 2 at an average stringency level of S_0. At that level, the intersection of S_0 and D points to COVID-19 deaths of D_0.

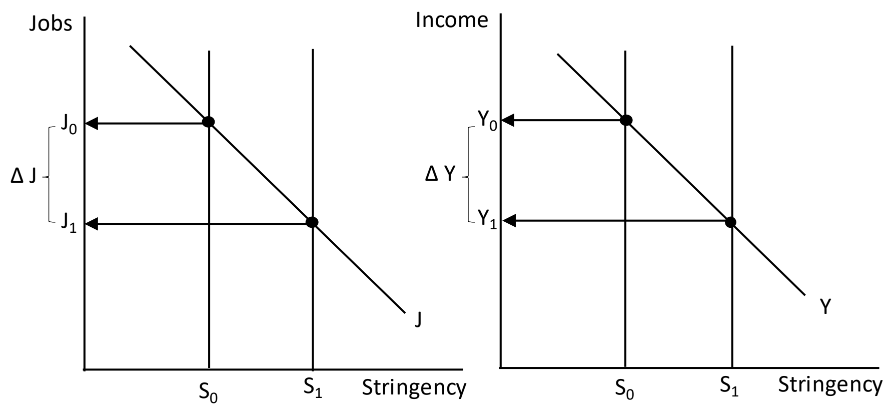
If public policy intervention results in a shift to a higher level of stringency, S_1, the intersection of S_1 and D points to a decline in the death rate from D_0 to D_1.

FIGURE 2
Benefits of Policy Intervention



The costs of policy intervention on jobs (J) and income (Y) are graphically shown in the two graphs in Figure 3. As in Figure 2, S_0 represents the average voluntary level of stringency with no public intervention. As stringency increases from S_0 to S_1, as a result of policy intervention, the costs to the economy are reflected by a decline in jobs from J_0 to J_1 and a decline in RGSP from Y_0 to Y_1.

FIGURE 3
Costs of Policy Intervention



In the study to follow, Section 3 will address how an increase in policy intervention such as that shown in the above figures by the shift from S_0 to S_1 can be measured. Section 3 will also present an empirical model for estimating the change in the number of deaths, Δ D, from policy intervention (see Figure 2). Section 4 will examine how greater stringency as shown by S_0 to S_1 results in lower jobs, Δ J, while section 5 shows how it results in lower income, Δ Y (see Figure 3). Before concluding, Section 6 will construct an age-adjusted dollar value of a statistical life for a person dying from COVID-19 and compare that value to the cost per life saved as estimated in this study.

3. Measuring the Benefits – Changes in Deaths, Δ D, Resulting from Policy Intervention

3.1 Empirical Model

The cumulative COVID-19 death rate per 100,000 people by state from January 1, 2020, to January 1, 2021, serves as the dependent variable in a cross-section model tested in this study. These death rates by state in alphabetical and rank order from highest to lowest are shown in Table 1. Note that the unweighted average COVID-19 death rate of all states is different from the death rate for the U.S. shown in Figure 1.

Policy interventions are measured by the Oxford daily government stringency index. Using a scale from 1 to 100, the ordinal daily measures that comprise the Oxford index include the following eleven government policy interventions relating to COVID-19:

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

The daily Oxford stringency index in this study was derived by calculating an annual average from the daily index values for each state during the 1/1/20 to 12/31/20 period. The average Oxford stringency index values for all states in alphabetical order and rank order from highest to lowest over the 1/1/20 to 12/31/20 period are shown in Table 2. Since the average stringency index, $\overline{S}$, equals 42.12 in calendar year 2020, the shift from S_0 to S_1 shown graphically in Figures 2 to 3 can be represented numerically as a shift from 0 to 42.12.

Figure 4 shows the daily Oxford stringency index values for the U.S., and for comparison, it also shows the state with the highest average index (New Mexico) and the state with the lowest (South Dakota). **Error! Bookmark not defined.**

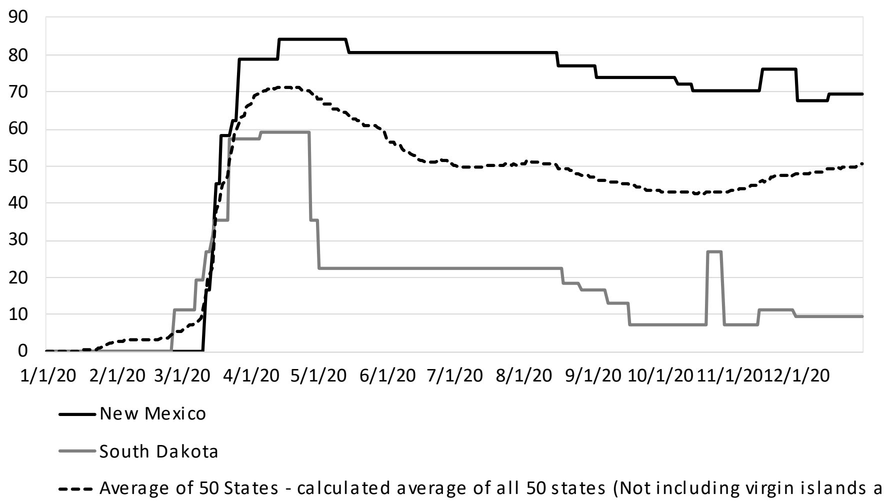
TABLE 1
COVID Death Rates in the U.S. by State
Per 100,000 people

Alphabetical order		**Rank Order**	
State	**1/1/2021**	**State**	**1/1/2021**
Alabama	99	New Jersey	216
Alaska	29	New York	197
Arizona	124	Massachussetts	183
Arkansas	124	North Dakota	172
California	67	Connecticut	171
Colorado	86	South Dakota	171
Connecticut	171	Rhode Island	168
Delaware	96	Mississippi	164
Florida	102	Louisiana	162
Georgia	103	Illinois	145
Hawaii	20	Michigan	133
Idaho	81	Pennsylvania	127
Illinois	145	Indiana	126
Indiana	126	Iowa	125
Iowa	125	Arizona	124
Kansas	99	Arkansas	124
Kentucky	61	New Mexico	122
Louisiana	162	South Carolina	106
Maine	27	Georgia	103
Maryland	99	Nevada	103
Massachussetts	183	Tennessee	103
Michigan	133	Florida	102
Minnesota	97	Alabama	99
Mississippi	164	Kansas	99
Missouri	93	Maryland	99
Montana	91	Texas	98
Nebraska	86	Minnesota	97
Nevada	103	Delaware	96
New Hampshire	57	Missouri	93
New Jersey	216	Montana	91
New Mexico	122	Wisconsin	90
New York	197	Colorado	86
North Carolina	66	Nebraska	86
North Dakota	172	Idaho	81
Ohio	78	Ohio	78
Oklahoma	64	West Virginia	77
Oregon	36	Wyoming	76
Pennsylvania	127	California	67
Rhode Island	168	North Carolina	66
South Carolina	106	Oklahoma	64
South Dakota	171	Kentucky	61
Tennessee	103	Virginia	60
Texas	98	New Hampshire	57
Utah	41	Washington	45
Vermont	22	Utah	41
Virginia	60	Oregon	36
Washington	45	Alaska	29
West Virginia	77	Maine	27
Wisconsin	90	Vermont	22
Wyoming	76	Hawaii	20
Average	101.76	Average	101.76

TABLE 2
Average Oxford Stringency Index Values from 1/1/20 to 12/31/20

Alphabetical Order		Rank Order	
State	Average Stringency Score Jan 1, 2020 - Dec 31, 2020	State	Average Stringency Score Jan 1, 2020 - Dec 31, 2020
Alabama	30.60	New Mexico	60.70
Alaska	44.69	Hawaii	58.55
Arizona	35.76	New York	58.26
Arkansas	36.09	Maine	55.35
California	51.29	Rhode Island	55.24
Colorado	45.25	California	51.29
Connecticut	50.76	Connecticut	50.76
Delaware	49.15	Vermont	50.03
Florida	40.99	Delaware	49.15
Georgia	39.96	Kentucky	48.96
Hawaii	58.55	Maryland	48.25
Idaho	39.75	Ohio	47.54
Illinois	45.04	Massachusetts	47.44
Indiana	37.86	North Carolina	46.90
Iowa	26.39	Minnesota	46.53
Kansas	38.27	Washington	46.25
Kentucky	48.96	Colorado	45.25
Louisiana	41.41	Illinois	45.04
Maine	55.35	Alaska	44.69
Maryland	48.25	Oregon	43.98
Massachusetts	47.44	West Virginia	43.49
Michigan	42.14	Texas	42.73
Minnesota	46.53	Pennsylvania	42.47
Mississippi	36.54	Michigan	42.14
Missouri	36.08	New Jersey	41.95
Montana	40.38	Virginia	41.63
Nebraska	35.88	Louisiana	41.41
Nevada	38.17	Florida	40.99
New Hampshire	40.22	Montana	40.38
New Jersey	41.95	New Hampshire	40.22
New Mexico	60.70	Georgia	39.96
New York	58.26	Idaho	39.75
North Carolina	46.90	Wyoming	38.78
North Dakota	28.30	Tennessee	38.49
Ohio	47.54	Kansas	38.27
Oklahoma	29.61	Nevada	38.17
Oregon	43.98	Indiana	37.86
Pennsylvania	42.47	Wisconsin	36.89
Rhode Island	55.24	Mississippi	36.54
South Carolina	34.18	Arkansas	36.09
South Dakota	18.38	Missouri	36.08
Tennessee	38.49	Nebraska	35.88
Texas	42.73	Arizona	35.76
Utah	32.34	South Carolina	34.18
Vermont	50.03	Utah	32.34
Virginia	41.63	Alabama	30.60
Washington	46.25	Oklahoma	29.61
West Virginia	43.49	North Dakota	28.30
Wisconsin	36.89	Iowa	26.39
Wyoming	38.78	South Dakota	18.38
Average	42.12	Average	42.12

FIGURE 4
Oxford Stringency Index for the U.S., New Mexico and South Dakota



The annual average of the Oxford daily stringency index will serve in this study as a proxy for each state's policy interventions. But in measuring the explanatory impact of policy interventions, it will be necessary to control and test for other demographic and socioeconomic variables that may significantly affect COVID-19 death rates.

Following a functional form similar to that used by Doti (Doti, *Journal of Bioeconomics*, 2021), Equation (1) shown below was tested.

$$d_i = b_o + b_m s_i + \sum_{d=1}^{3} b_{d,} \text{ Density}_i + \sum_{y=1}^{2} b_y \text{ Income}_i +$$

$$\sum_{r=1}^{3} b_r \text{ Racial/Ethnic}_i + \sum_{h=1}^{4} b_h \text{ Age/Health}_i \qquad (1)$$

All the dependent and independent variables are defined in Table 3.

The subscript i refers to state i.

b_o, b_m, b_d, b_y, b_r, b_h = Parameters to be estimated

Note: Displays of error terms are suppressed.

TABLE 3. Dependent and independent variables used in Equation (1) and Equations 1 - 6, Table 4

	Description	Name	Mean	SD	CV	Min	Max	Obs.	Source
Dependent variables									
	COVID-19 cumulative death rates through 12/31/20	d	101.76	46.66	45.85	20.00	216.00	50	https://www.statista.com/statistics/1109011/coronavirus-covid19-death-rates-us-by-state/
Independent variables									
	I. Policy Intervention								
	Mean Oxford Stingency Index from 1/1/20 to 12/31/20	s	42.12	8.25	19.61	18.38	60.70	50	https://github.com/OxCGRT/USA-covid-policy/blob/master/data/OxCGRT_US_latest.csv
	II. Density Variables								
	Population density per square mile	density	202.65	266.24	131.38	1.30	1207.80	50	https://worldpopulationreview.com/state-rankings/state-densities
	Super density per square mile	sdensity	342.98	1610.69	469.62	0.00	11076.00	50	https://en.wikipedia.org/wiki/List_of_United_States_cities_by_population_density
	Urban population as a percentage of the total population	urbanpop	0.74	0.15	20.27	0.39	0.95	50	https://en.wikipedia.org/wiki/Urbanization_in_the_United_States
	III. Income Variables								
	Per Capita Personal Income (000)	py	54.50	8.80	16.15	39.36	79.09	50	https://fred.stlouisfed.org/release/tables?rid=151&eid=257197
	Poverty rate, percent of persons in poverty	poverty	0.14	0.04	28.57	0.07	0.27	50	https://en.wikipedia.org/wiki/List_of_U.S._states_and_territories_by_poverty_rate
	IV. Racial/Ethnic Variables								
	Black or African American Population as a percentage of the total population	afram	10.51	9.55	90.87	0.40	37.60	50	https://worldpopulationreview.com/states/states-by-race
	Hispanic population as a percentage of the total population	hispanic	11.74	10.34	88.07	1.50	48.54	50	https://worldpopulationreview.com/state-rankings/hispanic-population-by-state
	Asian population as a percentage of the total population	asian	4.18	5.53	132.30	0.76	37.75	50	https://worldpopulationreview.com/state-rankings/asian-population
	V. Age/Health Variables								
	Percentage of population aged 65 or over	age65	16.49	1.88	11.40	11.10	20.60	50	https://www.prb.org/which-us-states-are-the-oldest/
	Obesity rate	obesity	30.75	3.73	12.13	22.60	38.10	50	https://worldpopulationreview.com/state-rankings/obesity-rate-by-state
	Diabetes mortality rate	diabetes	21.95	4.39	20.00	14.60	36.20	50	https://www.cdc.gov/nchs/pressroom/sosmap/diabetes_mortality/diabetes.htm
	Smoking Rate	smokers	17.33	3.50	20.20	8.90	26.00	50	https://worldpopulationreview.com/state-rankings/smoking-rates-by-state

3.2 Empirical Findings

A step-wise regression model similar to that used by Doti (Doti, *Journal of Bioeconomics*, 2021) added explanatory variables in groupings from I to IV, as shown in Table 3. The regression results are presented in Equations 1 to 6, Table 4. Note that except for the policy intervention variable, s, in Equation 1, Table 4, other variables were removed if not significant at the $p < 0.10$ level (one-tailed). The rationale for retaining the policy intervention variable, s, in Equation 2, Table 4 is that the significance tests for s in Equation 1, Table 4 may be spurious since there are no other control variables in the equation. Indeed, when the density variables, density, and sdensity, were added to Equation 2, Table 4, the measured t statistic for s was significant at the $p < 0.01$ level (one-tailed).

Note also that the "best" fit equation, Equation 6, Table 4, is shown as shaded.

3.2.1 Policy Intervention Variable, s

Although a great deal of controversy has arisen over the efficacy of statewide policy interventions to control the spread of COVID-19 (*Boston Review*, 2020; *Healthline*, 2020; *Wall Street Journal*, 2020), more rigorous studies have shown that such interventions significantly reduce COVID-19 deaths (Doti, *Journal of Bioeconomics*, 2021).

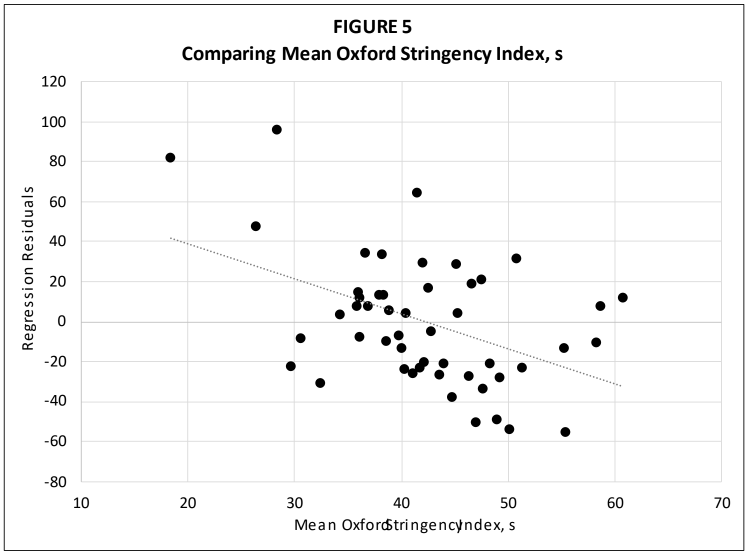
The empirical results shown in Table 4, which extend the tests through the end of 2020, confirm Doti's earlier findings of a highly significant inverse relationship between policy interventions as measured by the Oxford stringency index and COVID-19 death rates by state (Doti, *Journal of Bioeconomics*, 2021). The measured t statistic of -4.30 for s in Equation 6, Table 4, is highly significant at $p < 0.01$ (one-tailed). Its estimated coefficient of -2.48 suggests that, on average, a state's COVID-19 death rate, d, decreases by 2.48 deaths per 100,000 for every increase of 1 point in a state's average Oxford stringency index, s.

In a regression equation (not reported here), the R^2 term for Equation 6, Table 4, when the policy intervention variable, s_i, is excluded from the equation, drops from 0.67 to 0.53. A scatter diagram that compares the residuals from the equation where s is excluded is shown in Figure 5.

TABLE 4. Regression results, dependent variable definition: cumulative deathrate (COVID-19 deaths per 100,000 people by state) from 1/1/20 to 1/1/21, dependent variable name: d

	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5	Equation 6
R-squared	0.02	0.54	0.66	0.68	0.67	0.67
Constant	136.29	198.07	91.31	131.45	157.81	126.27
	(-3.97) ***	(-5.59) ***	(-1.69) *	(-4.79) ***	(-2.30) **	(-4.68) ***
I. Policy Intervention						
s	-0.82	-2.77	-2.86	-2.64	-2.61	-2.48
	(-1.02)	(-4.36) ***	(-5.16) ***	(-4.42) ***	(-3.94) ***	(-4.30) ***
II. Density Variables						
density		0.11	0.11	0.12	0.12	0.12
		(5.23) ***	(5.44) ***	(6.75) ***	(6.34) ***	(7.27) ***
sdensity		0.01	0.01	0.01	0.01	0.01
		(3.65) **	(3.66) ***	(3.99) ***	(3.83) ***	(4.05) ***
urbanpop		-9.13				
		(-0.23)				
III. Income Variables						
py			0.66			
			(0.88)			
poverty			494.54	380.14	401.95	408.23
			(3.66) ***	(3.05) ***	(3.19) ***	(3.79) ***
III. Racial/Ethnic Variables						
afram				-0.01		
				(-0.01)		
hispanic				0.53		
				(1.20)		
Asian				-1.39	-1.27	-1.26
				(-1.68) **	(-1.40) *	(-1.55) *
V. Age/Health Variables						
$age65_i$					-0.39	
					(-0.16)	
$obesity_i$					-1.36	
					(-0.61)	
$diabetes_i$					-0.21	
					(-0.14)	
$smoker_i$					1.57	
					(-0.69)	

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



Although Figure 5 suggests a linear trendline, a double logarithmic form of Equation 6, Table 4 was tested. The empirical results of that test are presented below:

TABLE 5
Equation 6, Table 4 with All Variables Measured in Natural Logs (ln)

	Equation 6
R-squared	0.45
Constant	9.06
	(-7.20) ***
I. Policy Intervention	
s	-1.05
	(-3.24) ***
II. Density Variables	
density	0.17
	(3.11) ***
sdensity	0.06
	(2.38) ***
III. Income Variables	
poverty	0.66
	(2.68) ***
III. Racial/Ethnic Variables	
Asian	-0.13
	(-1.43) *

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

Although the R^2 of 0.45 in the double logarithmic form of the Equation is lower than the R^2 of 0.62 in the linear form of the equation (Equation 6, Table 4), the measured t statistic for the ln of s 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 coefficients have the desirable quality of representing constant elasticities across different values of the independent variables. That means that the -1.05 coefficient for the ln of s represents the constant elasticity of d with respect to s, which, in turn, suggests that a one percent increase in the Oxford stringency index, s, leads approximately to a one percent decline in COVID-19 deaths, d. For comparison purposes, the average elasticity for s in the linear form is shown in Equation (2).

$$\overline{E}_i = b_m \left[\frac{\bar{s}}{\bar{d}} \right] = -2.48 \left[\frac{42.12}{101.76} \right] = -1.03 \qquad (2)$$

Although the average elasticity of -1.03 in the linear form of the equation compares closely to the constant elasticity of -1.05 in the double logarithmic form of the equation, the elasticity of -1.03 in the linear form of the equation will change as s deviates from its mean value of 42.12.

3.2.2 Other Explanatory Variables

A super density variable, sdensity, was added as a variable to measure the impact on COVID-19 deaths for those states where a highly populated metropolitan area like New York City exhibits extremely high density. In those instances, the true nature of a metropolitan area's density is obscured when dividing by the entire land area of a state. To capture that impact, a sdensity variable was added as defined in Equation (3).

$$\text{sdensity}_{i,t} = \sum_{k=1}^{n_i} p_{k,i} \,/\, P_{i,t} \; * \text{density}_{i,t} \qquad (3)$$

where $p_{k,i}$ = Population of the kth city in state i with a population >300,000 and density >10,000 per sq. mile

n_i = Number of cities in state i with population >300,000 and density >10,000 per sq. mile

$P_{i,t}$ = Population of state i as of some period t

$\text{density}_{i,t}$ = Density of state i as of some period t

As shown in Equation 6, Table 3, both the sdensity and density variables were significant at the $p < 0.01$ level (one-tailed) and supportive of the theory that higher density facilitates virus transmission.

The poverty variable in Equation 6, Table 3, was also highly significant. Its positive coefficient suggests that poverty is associated with higher rates of COVID-19 deaths. In the double logarithmic form of the equation reported in Table 5, the constant elasticity of 0.66 suggests that a one percent increase in a state's poverty rate leads to a 0.66 percent increase in its COVID-19 death rate.

The only Racial/Ethnic variable that tested as significant was that represented by the percentage of Asian-Americans. Its negative coefficient of -1.26 suggests that an increase of one in the percentage of Asian-Americans living in a state is associated with a 1.26 percent decline in its COVID-19 death rate. While the relationship was significant, it was at a relatively low $p < 0.10$ level (one-tailed). As pointed out by Doti (Doti, *Journal of Bioeconomics*, 2021), a possible explanation for this is anecdotal evidence that Asian-Americans responded more quickly in adopting safe-distancing and mask-wearing before such preventive measures were mandated by governments (Magnier, *South China Morning Post*, 2020). This explanation received empirical support in the Doti study (Doti, *Journal of Bioeconomics*, 2021) that showed that the asian variable was only significant during the first half of 2020.

The fact that the percentage of African-Americans (afram) and Hispanics (Hispanic) in a state was found to have no significant impact on COVID-19 deaths runs counter to other studies that suggest a positive causal relationship (Mangier, 2020, APM Research, 2020). It is likely, though, that those studies did not adequately control for the impact of other explanatory variables. When, for example, a variable measuring the poverty rate is omitted from Equation 6, Table 4, the coefficients for the African-American variable (afram) and Hispanic variable (Hispanic) are both significant, as shown below in Table 6. These empirical results suggest that studies that have found a positive relationship between COVID-19 deaths and the percentage of African-Americans and Hispanics in a state or metropolitan area may be experiencing identification error.

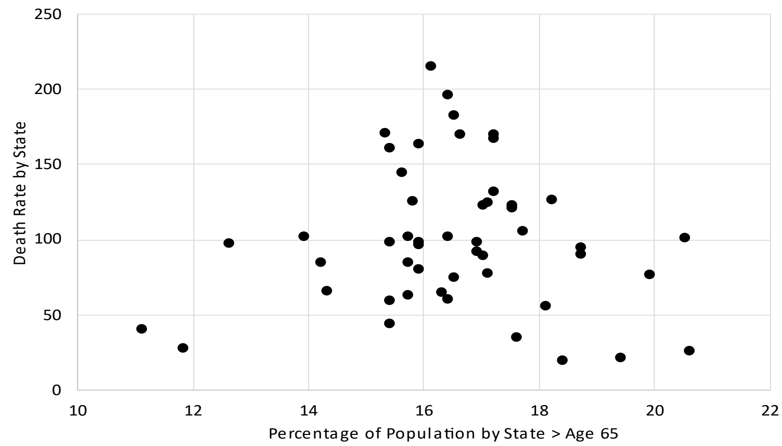
TABLE 6
Equation 6, Table 4 with afram and hispanic added to the equation and poverty removed

	Equation 6	
R-squared	0.61	
Constant	173.23	
	(6.69)	***
I. Policy Intervention		
s	-2.57	
	(-3.95)	***
II. Density Variables		
density	0.11	
	(5.66)	***
sdensity	0.01	
	(3.69)	***
III. Income Variables		
lpoverty	Removed form Equation 6, Table 4	
III. Racial/Ethnic Variables		
afram	0.70	
	(1.41)	*
hispanic	0.93	**
	(2.00)	
asian	-1.60	**
	(-1.77)	

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

None of the coefficients for the Age/Health variables were significant. Although these results may seem surprising, especially for the age65 variable, it is likely that there is not enough dispersion in the Age/Health variables for the regression equation to pick up any significant explanatory power at the state level. As shown in Figure 4, higher death rates at the state level occurred near the average of 16.49 percent > Age65 for all states rather than at higher outlying values (Doti, *Journal of Bioeconomics*, 2021).

FIGURE 6
Death Rate for Age 65 or Over Population at the State Level



3.2.3 Impact of Policy Intervention on COVID-19 Lives Saved or Lost

The estimated coefficient for the stringency variable, sjanjul can be used to estimate the change in the number of deaths ($\Delta D_{i,t}$) as a result of a state having a stringency index above zero. Those estimates are presented in Table 7 and are based on Equation (4). The ΔD_i term in Equation (4) is the same ΔD term shown graphically in Figure 2 where $D_0 - D_1 < 0$.

$$\Delta D_i = \left[s_{i,} \right] * \hat{b}_m * \left[P_i / 100{,}000 \right] \qquad (4)$$

where ΔD_i = Change in the number of COVID-19 deaths in 2020 in state i as a result of policy intervention

s_i = The average stringency index in 2020 for state i

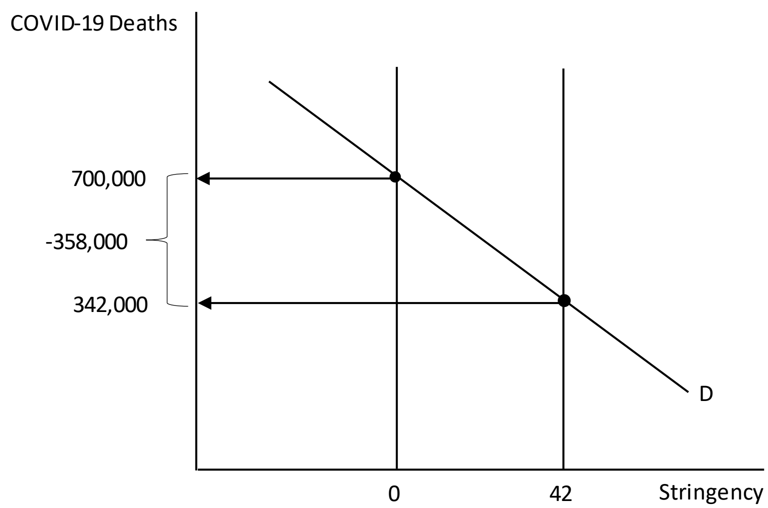
$\hat{b}_m$ = The estimated coefficient for the stringency index value (See Equation 6, Table 4)

P_i = The population of state i in 2020

Note that the above equation requires that the product include [$P_{i,t}$ / 100,000] to convert death rates per 100,000 to the absolute number of lives saved or less.

As shown in Table 7, the estimated reduction in the total number of COVID-19 deaths in all states as a result of each state's policy intervention is -358,000. Since the total number of actual COVID-19 deaths in the U.S. in 2020 was 342,000, the estimated decrease of about 358,000 deaths suggests that the actual number of deaths would have been about double the actual level (342,000 + 358,000 = 700,000) had there been no intervention beyond $S_0 = 0$. These results are shown graphically in the following Figure 7.

FIGURE 7
Benefits of Policy Intervention



Section 4 that follows will examine economic costs associated with the impact of policy intervention on each state's jobs.

TABLE 7
The impact on COVID-19 Llives Saved as a Result of Each State's Level of Policy Intervention

	State	Change in the Number of COVID-19 Deaths
1	Alabama	-3,721
2	Alaska	-811
3	Arizona	-6,455
4	Arkansas	-2,701
5	California	-50,258
6	Colorado	-6,463
7	Connecticut	-4,488
8	Delaware	-1,187
9	Florida	-21,831
10	Georgia	-10,522
11	Hawaii	-2,056
12	Idaho	-1,762
13	Illinois	-14,155
14	Indiana	-6,322
15	Iowa	-2,065
16	Kansas	-2,765
17	Kentucky	-5,425
18	Louisiana	-4,775
19	Maine	-1,845
20	Maryland	-7,234
21	Massachusetts	-8,110
22	Michigan	-10,438
23	Minnesota	-6,508
24	Mississippi	-2,697
25	Missouri	-5,492
26	Montana	-1,070
27	Nebraska	-1,721
28	Nevada	-2,915
29	New Hampshire	-1,356
30	New Jersey	-9,240
31	New Mexico	-3,157
32	New York	-28,109
33	North Carolina	-12,199
34	North Dakota	-535
35	Ohio	-13,781
36	Oklahoma	-2,905
37	Oregon	-4,600
38	Pennsylvania	-13,483
39	Rhode Island	-1,451
40	South Carolina	-4,365
41	South Dakota	-403
42	Tennessee	-6,519
43	Texas	-30,727
44	Utah	-2,571
45	Vermont	-774
46	Virginia	-8,812
47	Washington	-8,734
48	West Virginia	-1,933
49	Wisconsin	-5,327
50	Wyoming	-557
	Total	-358,000

4. Measuring the Costs – Change in Jobs, Δ J, Resulting from Policy Intervention

4.1 Empirical Model

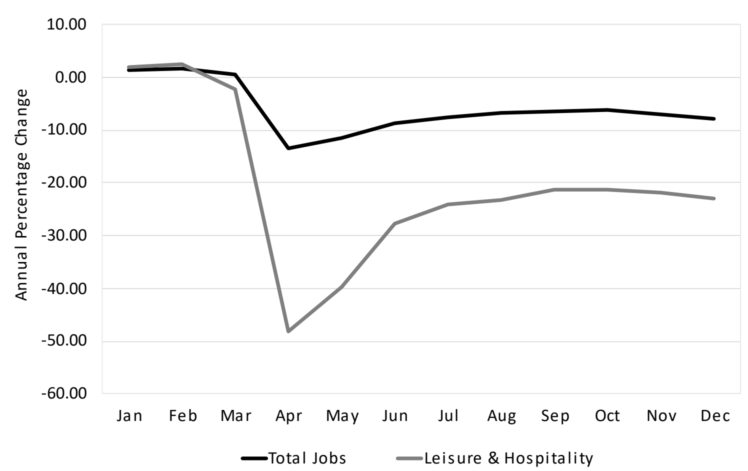
In order to measure the impact of policy intervention as measured by the Oxford stringency index on jobs, it will be necessary to hold constant other variables that exert an influence on job growth. Although more restrictive policy interventions to control the spread of COVID-19 would be expected to reduce jobs, the impact on each state's jobs will also depend on other factors.

To isolate the impact of policy interventions on jobs in 2020, one must hold constant each state's natural economic growth rate. Two states with the same stringency index but exhibiting different economic trends are likely to experience different rates of job loss. Unless those differing trends are accounted for in a regression test, the coefficients that measure the impact of differing levels of policy intervention will be biased.

A straightforward approach to account for each state's economic growth potential is to assume that annual job growth in 2020 would be similar to that which otherwise would have occurred in 2019 if COVID-19 had not occurred. West Virginia, for example, lost about 1 percent of its jobs in 2019. Because of that relatively weak economic performance, West Virginia would be expected to lose more jobs than other states in 2020, not necessarily because of its policy response to COVID-19 but because its economy is weaker than other states. Similarly, one would expect that Utah's relatively strong job growth of nearly 3 percent in 2019 will have a positive impact on its job performance in 2020.

Another state-specific economic factor that needs to be held constant is the proportion of its total jobs in leisure & hospitality. As shown in Figure 8, that sector took the brunt of the COVID-19 hit in the U.S., losing almost 50 percent of its jobs in April 2020. That compares to a much lower annual loss of about 13 percent for all jobs.

FIGURE 8
Comparison of Job Growth in the U.S.



The functional form of an equation that incorporates the impact of each state's policy intervention, its underlying economic strength, and its dependence on the leisure & hospitality job sector is shown below Equation (5).

$$pj_i = b_0 + b_j (s_i) + b_n (pj19_i) + b_h (jlh19_i) \tag{5}$$

where pj_i = Annual percentage change in jobs in 2020 in state i
s_i = Average Oxford stringency index in 2020 in state i
$pj19_i$ = Annual percentage change in jobs in 2019 in state i
$jlh19_i$ = Average proportion of total jobs in leisure & hospitality in 2019 in state i

b_o, b_j, b_n, b_h are parameters to be estimated

Note: Displays of error terms are suppressed.

The hypothesized signs of association in Equation (5) are shown in Equation (6):

$$pj_i = f(\overset{-}{s_i};\ \overset{+}{pj19_i};\ \overset{-}{jlh19_i}) \tag{6}$$

4.2 Empirical Findings

Table 8 presents the empirical results for the regression tests of Equation (5). Note that all of the coefficients for the above variables have the hypothesized signs of association shown in Equation (6) and are all significant at either the $p < 0.1$ or $p < 0.01$.

TABLE 8
Regression Results for Equation 5

Dependent Variable		
pj_i		
R-squared	0.58	
Constant	-1.30	
	(-1.17)	
Independent Variables		
s_i	-0.11	
	(-5.62)	***
$pj19_i$	1.01	
	(4.88)	***
$jlh19_i$	-12.02	
	(-1.62)	*

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

The coefficient of -0.11 for s suggests that a one point increase (decrease) in the stringency index, s, leads to a 0.11 decrease (increase) in job growth in 2020 (pj).

4.2.1 Impact of Policy Interventions on the Number of Jobs (ΔJ_i)

As in this study's analysis of the impact of policy intervention on COVID-19 deaths presented in Section II, a similar methodology can be used to measure the impact of policy intervention on jobs. The number of jobs saved by having stringency index values above zero is given by Equation (7). The ΔJ_i term is the same ΔJ term shown graphically in Figure 3 where $J_0 - J_1 < 0$.

$$\Delta J_{i,} = \left[\, s_i \,\right] * \left[\hat{b}_j / 100\right] * j19_i \tag{7}$$

where ΔJ_i = Number of jobs lost (-) or saved (+) in 2020 in state i
s_i = The average stringency index in 2020 for state i
$J19_i$ = Average number of jobs in 2019 in state i
$\hat{b}_j$ = The estimated coefficient of -0.11 for the policy intervention variable, s_i, as shown in Table 8

Note that the above equation requires that the estimated coefficient, $\hat{b}_j$, be divided by 100 to convert from percentage to decimal changes. The estimates based on Equation (7) above are presented in Table 9.

As shown in Table 9, the estimated loss in jobs in all states as a result of each state's policy intervention is about -7.3 million. Since the average number of jobs in 2020 was 142 million, the estimated loss of 7.3 million jobs suggests that the actual number of jobs would have been 149.3 million (142 million + 7.3 million) had there been no policy intervention beyond S_0. These results are shown graphically in the following Figure 9.

In percentage terms, the loss of 7.3 million jobs represents a decline of 4.8 percent from the job total in 2019. That compares to an actual decline in jobs of 6.3 percent. The ratio of the 4.8 decline in jobs resulting from policy intervention to the actual total decline of 6.3 percent is 0.75. That, in turn, suggests that the increase in stringency from S_0 to S_1 or 0 to 42 accounts for 75 percent of the total loss of jobs in 2020.

FIGURE 9
Costs of Policy Intervention

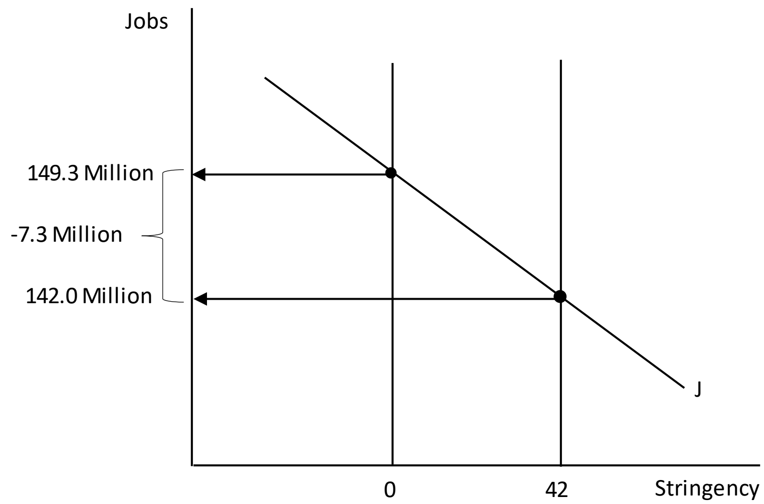


TABLE 9
The Impact on Jobs Lost as a Result of Each State's Level of Policy Intervention

	State	Δj_i (Change in the Number of Jobs)
1	Alabama	-70,241
2	Alaska	-16,302
3	Arizona	-116,315
4	Arkansas	-51,010
5	California	-989,672
6	Colorado	-139,590
7	Connecticut	-94,812
8	Delaware	-25,345
9	Florida	-406,322
10	Georgia	-204,163
11	Hawaii	-42,511
12	Idaho	-33,417
13	Illinois	-305,163
14	Indiana	-132,755
15	Iowa	-46,346
16	Kansas	-60,309
17	Kentucky	-105,122
18	Lousiana	-91,207
19	Maine	-38,948
20	Maryland	-147,928
21	Massachusetts	-193,853
22	Michigan	-206,868
23	Minnesota	-153,432
24	Mississippi	-46,877
25	Missouri	-115,937
26	Montana	-21,629
27	Nebraska	-40,808
28	Nevada	-59,923
29	New Hampshire	-30,476
30	New Jersey	-194,866
31	New Mexico	-57,597
32	New York	-631,344
33	North Carolina	-237,572
34	North Dakota	-13,764
35	Ohio	-294,117
36	Oklahoma	-55,844
37	Oregon	-94,511
38	Pennsylvania	-285,164
39	Rhode Island	-30,806
40	South Carolina	-82,875
41	South Dakota	-8,966
42	Tennessee	-133,082
43	Texas	-605,738
44	Utah	-55,906
45	Vermont	-17,514
46	Virginia	-187,102
47	Washington	-177,675
48	West Virginia	-34,655
49	Wisconsin	-121,806
50	Wyoming	-12,433
	Total	-7,320,623

To measure the impact of policy intervention on total spending, the following Section IV focuses on changes in real gross state product (RGSP). That analysis will allow for estimating the dollar cost of each life saved or lost, resulting from a state's policy intervention.

5. Measuring the Costs – Change in Income, Δ Y, Resulting from Policy Intervention

5.1 Empirical Model

A version of the model presented in Section 4 for measuring the impact of policy intervention on jobs can be used in this section to measure the impact on real gross state product (RGSP). As in Section 4, differences in a state's Oxford average stringency index in 2020 is used to measure the impact of policy intervention. Instead of using percentage changes in jobs in 2019 to measure the underlying job-producing strength of a state before COVID-19 hit, percentage changes in RGSP in 2019, py19, serve as a proxy for the income-producing potential of a state's economy.

In the national income accounts, an "Art, Entertainment, Accommodations and Food Services" category is used to measure spending in leisure & hospitality. Similar to Section 4, where the proportion of leisure & hospitality jobs is used to measure a state's dependence on the job sector hardest hit by COVID-19, the proportion of RGSP in "Art, Entertainment, Accommodation and Food Services" will serve as a proxy for that variable.

The functional form of an equation explaining each state's RGSP as a function of policy intervention, a state's underlying economic strength, and its dependence on the Arts, Entertainment, Accommodation, and Food Services sector of the economy is shown in Equation (8).

$$py_i = b_0 + b_g (s_i) + b_y (py19_i) + b_a (ae19_i) \tag{8}$$

where py_i = Annual percentage change in RGSP in 2020 in state i
s_i = Average Oxford stringency index in 2020 in state i
$py19_i$ = Annual percentage change in RGSP in 2019 in state i
$ae19_i$ = Average proportion of total RGSP in arts, entertainment, accommodation and food services in 2019 in state i

b_o, b_g, b_y, b_a are parameters to be estimated.

Note: Displays of error terms are suppressed.

The hypothesized signs of association in Equation (8) are shown below in Equation (9):

$$py_i = f(\overset{-}{s_i};\ \overset{+}{py19_i};\ \overset{-}{ae19_i}) \tag{9}$$

5.2 Empirical Findings

Table 10 presents the empirical results for the regression test of Equation (8). Note that all of the coefficients for the variables in Equation (8) have the hypothesized signs of association shown in Equation (9) and are all significant at the $p < 0.01$ (one-tailed test).

TABLE 10
Regression Results for Equation 8

Dependent Variable		
py_i		
R-squared	0.48	
Constant	-1.70	
	(-2.56)	***
Independent Variables		
s_i	-0.05	
	(-2.99)	***
$py19_i$	0.64	
	(5.60)	***
$ae19_i$	-14.45	
	(-2.31)	***

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

The estimated coefficient of -0.05 for s suggests that a one-point increase (decrease) in the stringency index (s) leads to a 0.05 decrease (increase) in RGSP growth in 2020 (py). This result is about half the -0.11 estimated coefficient for s in Section 3, explaining percentage changes in jobs, pj (see Table 8). These findings are intuitively plausible since changes in stringency are likely to have a greater percentage impact on jobs than income. Jobs in leisure-related activities have a lower value-added than other job categories. As a result, the impact of disproportionately large leisure-related job losses will be muted when measuring the income effect.

5.2.1 Impact of Policy Intervention on the level of RGSP

The increase or decrease in a state's RGSP by having stringency index values lower or higher than average is given by Equation (10).

$$\Delta Y_i = \left[s_i \right] * \left[\hat{b}_m / 100 \right] * Y19_i \qquad (10)$$

where ΔY_i = Change in the level of RGSP in 2020 in state i
s_i = The average stringency index in 2020 for state i
$\hat{b}_m$ = The estimated coefficient of -0.05 for the policy intervention variable as shown in Table 10
$Y19_i$ = Average RGSP in 2019 in state i

and all other variables are as defined in Equation 10.

Note that the above equation requires that the estimated coefficient, $\hat{b}_m$, be divided by 100 to convert from percentage to decimal changes. The estimates for ΔY_i based on Equation (10) above are presented in Table 11.

As shown in Table 11, the estimated loss in RGSP for all states as a result of each state's policy intervention is about $410 billion. Since RGSP in 2020 was about $18,500 billion, the estimated loss of $410 billion suggests that RGSP would have been about $18,900 (18,500 billion + 410 billion) had there been no policy intervention beyond S_0. These results are shown graphically in Figure 10.

In percentage terms, the loss of $410 billion represents a decline of 2.2 percent in RGSP in 2020. As expected, given that the negative impact of the COVID-19 recession will be greater on jobs than income, the 2.2 percent decline in RGSP is roughly half the decline of 4.8 percent in jobs as estimated in Section 4.2.1.

Recall that policy intervention was also shown in Section 4.2.1 to account for 75 percent of the total loss in jobs in 2020. Similarly, the 2.2 percent decline in RGSP resulting from policy intervention is about 75 percent of the actual decline of 3 percent in 2020.

FIGURE 10
Costs of Policy Intervention

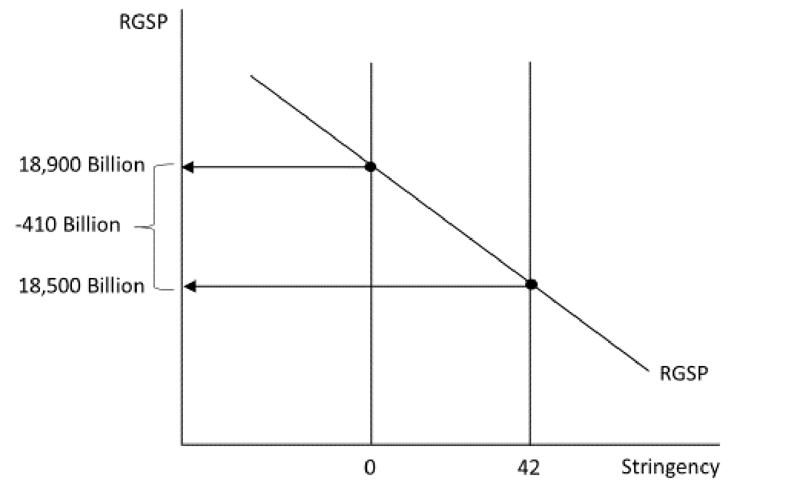


TABLE 11

The Impact on RGSP as a Result of Each State's Level of Policy Intervention

	State	Δy_i Change in RGSP (In Milions)
1	Alabama	-2,998
2	Alaska	-1,141
3	Arizona	-5,737
4	Arkansas	-2,069
5	California	-70,325
6	Colorado	-7,961
7	Connecticut	-6,150
8	Delaware	-1,526
9	Florida	-19,274
10	Georgia	-10,684
11	Hawaii	-2,270
12	Idaho	-1,472
13	Illinois	-16,807
14	Indiana	-6,214
15	Iowa	-2,234
16	Kansas	-2,984
17	Kentucky	-4,524
18	Louisiana	-4,752
19	Maine	-1,574
20	Maryland	-8,822
21	Massachusetts	-11,933
22	Michigan	-9,505
23	Minnesota	-7,685
24	Mississippi	-1,828
25	Missouri	-5,026
26	Montana	-945
27	Nebraska	-2,070
28	Nevada	-2,823
29	New Hampshire	-1,490
30	New Jersey	-11,280
31	New Mexico	-2,931
32	New York	-41,399
33	North Carolina	-11,729
34	North Dakota	-740
35	Ohio	-14,134
36	Oklahoma	-2,785
37	Oregon	-4,845
38	Pennsylvania	-14,864
39	Rhode Island	-1,425
40	South Carolina	-3,549
41	South Dakota	-429
42	Tennessee	-6,054
43	Texas	-36,551
44	Utah	-2,715
45	Vermont	-712
46	Virginia	-9,966
47	Washington	-12,588
48	West Virginia	-1,497
49	Wisconsin	-5,468
50	Wyoming	-720
	Total	-410,000

6. Estimated Economic Cost Per Life Saved

Table 12 presents an estimated economic cost per life saved based on the total loss in RGSP presented in Table 11 and the total number of lives saved (fewer deaths) in Table 7 in Section 3.2.3. These findings, as shown in Table 12, point to an average loss in RGSP of \$1,145,000 per life saved because of policy interventions. That cost per life saved ranges from a low of \$677,813 in Mississippi to a high of \$1,472,821 in New York state. A question that arises is whether the per capita costs in Table 12 are reasonable or not. That question turns on the difficult question regarding the value of a human life.

A great deal of empirical research has been conducted regarding the value of a statistical life (VSL) (Robinson, Sullivan, and Shogren; 2020, Murphy and Topel, 2006). Both the U.S. Environmental Protection Agency (U.S. EPA, 2016 update) and the U.S. Department of Health and Human Services (U.S. HHS, 2016) include VSL estimates in their benefit-cost analyses.

As a standard tool in analyzing benefits and costs, VSL estimates are generally based on the values economists measure for the willingness of people to pay for a slight reduction in the probability of death (Murphy and Topel, 2006). For example, if a person is willing to pay \$8,000 to reduce the probability of death by 0.1 percent, the resulting VSL for that person is \$8,000/0.001 or \$8 million. Note that this empirical approach captures not only the potential lifetime earnings of an individual but the consumption of non-market goods like leisure time.

VSL is sometimes held at a constant value that does not vary with age (Robinson, Sullivan, and Shogren; 2020). Although most governmental agencies follow that approach, as noted by Robinson, Sullivan, and Shogren, "… the HHS (U.S. HHS; 2016) guidance recommends adjustments in sensitivity analysis when the risk changes disproportionately to the old or the very young." (Robinson, Sullivan, and Shogren; 2020, page 3).

That is certainly the case in terms of COVID-19 deaths. As shown below in Table 13, roughly 80 percent of the deaths through year-end 2020 occurred at ages 65 years and above. The grouped median age of a COVID-19 death was 78.4. Using age-adjusted VSL (Greenstone and Nigam; 2020) and adjusting the age intervals to conform with the age groupings shown in Table 13 makes it possible to calculate a weighted average age-adjusted VSL of \$4.2 million, as shown in Table 14.

The age-adjusted VSL estimate of \$4.2 million presented in Table 14 compares closely with the \$4.47 million estimated by Robinson, Sullivan, and Shogren (2020, page 7) using a similar approach.

The fact that the \$4.47 million calculated in Table 14 is significantly above the estimated average cost per life saved of \$1.15 million, as shown in Table 12, suggests that the cost of policy intervention is not excessive, at least when using a VSL methodology to place a dollar value on a human life.

TABLE 12
The Total Estimated Cost in RGSP Per Life Saved Resulting from a Stringency Index Above or Below the Mean Index

State	$\Delta RGSP20_i$ In Millions (See Table 11)	Change in Deaths Resulting from Policy Interventions Above or Below the Mean Index (See Table 7)	Economic Cost per Life Saved
Alabama	1,128	1,400	805,617
Alaska	-66	-47	1,407,729
Arizona	1,020	1,148	888,784
Arkansas	346	451	766,027
California	-12,574	-8,986	1,399,269
Colorado	-551	-448	1,231,730
Connecticut	-1,047	-764	1,370,242
Delaware	-218	-170	1,285,549
Florida	533	604	882,907
Georgia	577	569	1,015,454
Hawaii	-637	-577	1,104,075
Idaho	88	105	835,728
Illinois	-1,091	-919	1,187,318
Indiana	698	710	982,987
Iowa	1,331	1,230	1,081,879
Kansas	300	278	1,078,972
Kentucky	-633	-758	833,917
Louisiana	81	81	995,240
Maine	-376	-441	853,037
Maryland	-1,120	-919	1,219,652
Massachusetts	-1,339	-910	1,471,493
Michigan	-6	-6	910,576
Minnesota	-729	-617	1,180,852
Mississippi	279	411	677,813
Missouri	841	919	915,129
Montana	41	46	883,085
Nebraska	360	299	1,202,480
Nevada	292	302	968,257
New Hampshire	70	64	1,098,238
New Jersey	46	37	1,220,731
New Mexico	-897	-966	928,688
New York	-11,471	-7,788	1,472,821
North Carolina	-1,196	-1,244	961,454
North Dakota	361	261	1,383,264
Ohio	-1,612	-1,572	1,025,586
Oklahoma	1,177	1,228	958,670
Oregon	-205	-195	1,053,076
Pennsylvania	-122	-111	1,102,387
Rhode Island	-339	-345	982,144
South Carolina	824	1,013	813,137
South Dakota	555	521	1,064,902
Tennessee	570	614	928,625
Texas	-523	-440	1,189,531
Utah	821	777	1,055,714
Vermont	-113	-122	919,446
Virginia	117	103	1,130,883
Washington	-1,124	-780	1,441,195
West Virginia	-47	-61	774,593
Wisconsin	774	755	1,026,325
Wyoming	62	48	1,293,556
Average	-410,000	-358,000	1,145,000

TABLE 13
Deaths Associated with COVID-19 by Age Group in the U.S.
December 30, 2020

Age Group	No. of Deaths	Percent of Deaths	Death rate per 100,000 people
Under 1	32	0.01	0.85
1 - 4	19	0.01	0.12
5 - 14	51	0.02	0.12
15 - 24	483	0.16	1.13
25 - 34	2,087	0.69	4.54
35 - 44	5,398	1.79	12.96
45 - 54	14,496	4.81	35.46
55 - 64	35,981	11.93	84.76
65 - 74	64,355	21.33	204.41
75 - 84	82,646	27.40	517.51
85 and over	96,131	31.87	1,455.44
Total	301,679	100	91.91

TABLE 14
Calculating an Age-Adjusted VSL of COVID-19 Deaths

Age Group	VSL (In Millions)	Percent of Deaths (See Table 13)	VSL * Percent of Deaths
Under 1	14.70	0.01	0.15
1 - 4	14.70	0.01	0.15
5 - 14	15.00	0.02	0.30
15 - 24	15.70	0.17	2.51
25 - 34	15.90	0.73	10.97
35 - 44	14.80	1.88	26.49
45 - 54	12.00	5.00	57.72
55 - 64	8.50	12.23	101.40
65 - 74	4.80	21.41	102.39
75 - 84	2.60	27.08	71.24
85 and over	1.50	31.47	47.80
		Sum =	421.11

Age-adjusted VSL = 421.11/100 = $4.2 million

7. Conclusion

Although there has been much controversy over the efficacy of policy interventions taken to reduce the infection and death rates of COVID-19, no studies have systematically measured their benefits and costs at the state level. This study fills that gap by presenting cross-section regression analyses that measure how policy interventions, as measured by the Oxford stringency index, reduce COVID-19 death rates. It also examines how those interventions increase costs in terms of greater job losses and lower RGSP.

The study provides empirical support for the belief that policy interventions have resulted in lower COVID-19 death rates. It does this by measuring the impact of policy interventions while holding other explanatory variables constant. The findings suggest that the COVID-19 death rate decreases by 2.48 deaths per 100,000 in population for every increase of 1 point in the Oxford stringency index. That relationship is used to estimate that COVID-19 deaths decreased by 358,000 lives (Table 7) as a result of each state's level of policy intervention.

On the cost side of the equation, various economic factors are held constant in order to measure the impact of policy intervention on jobs and RGSP for every state. It was found that policy intervention resulted in a loss of about 7.3 million jobs (Table 9) and a decline of $410 billion in RGSP for all 50 states (see Table 11).

Because this study measures lives saved or lost as well as the gains or losses to RGSP, it was possible to derive an average cost per life saved in the U.S. of $1,145,000, a cost that ranges from a high of $1,472,000 in New York state to a low of $677,000 for Mississippi.

The study concluded by producing a weighted average age-adjusted value of a statistical life (VSL) of $4.2 million, a value significantly above the estimated $1.145 million average cost per U.S. life saved.

Future research should be directed at updating the empirical finding in this study as more data become available. This will be particularly valuable in light of both the recent surge in infection and death rates as well as the timing of future decreases in infection and death rates as more vaccinations take place. The findings of this study would also be more complete by confronting the empirical challenges involved in removing the assumptions laid out in the introduction of this study.

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