informs
https://pubsonline.informs.org/journal/serv
SERVICE SCIENCE
Vol. 15, No. 3, September 2023, pp. 188–211
ISSN 2164-3962 (print), ISSN 2164-3970 (online)

Health and Economic Impacts of Lockdown Policies in the Early Stage of COVID-19 in the United States

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Received: November 20, 2021
Revised: June 10, 2022; December 2, 2022
Accepted: January 25, 2023
Published Online in Articles in Advance: March 17, 2023

https://doi.org/10.1287/serv.2023.0321

Abstract. Lockdown policies, such as stay-at-home orders, are known to be effective in controlling the spread of the novel coronavirus disease 2019. However, concerns over economic burdens of these policies rapidly propelled U.S. states to move toward reopening in the early stage of the pandemic. Decision making in most states has been challenging, especially because of a dearth of quantitative evidence on health gains versus economic burdens of different policies. To assist decision makers, we study the health and economic impacts of various lockdown policies across U.S. states and shed light on policies that are most effective. To this end, we make use of detailed data from 50 U.S. states plus the District of Columbia on various factors, including number of tests, positive and negative results, hospitalizations, ICU beds and ventilators used, residents' mobility obtained from cellphone data, and deaths. Our analyses allow quantifying the total cost versus the total quality-adjusted life year (QALY) associated with various lockdown policies. We utilize a compartmental model with Markov chain Monte Carlo simulation to estimate the spread of disease. To calibrate our model separately for each U.S. state, we make use of empirical data on the intensity of intervention policies, age, ratio of Black/Hispanic populations, per capita income, residents' mobility, and number of daily tests and feed them to a longitudinal mixed-effect model. Finally, we utilize a microsimulation model to estimate the total cost and total QALY for each state and perform cost-effectiveness analysis to identify policies that would have worked best. Our results show that, compared with no intervention during March–June 2020, the policies undertaken across the United States saved, on average, about 41,284.51 years' worth of QALY (per 100K capita), incurring $164.01 million (per 100K capita). Had the states undertaken more strict policies during the same time frame than those they adopted, these values would be 44,909.41 years and $117.28 million, respectively. By quantifying the impact of various lockdown policies separately for each state, our results allow federal and state authorities to avoid following a "one size fits all" strategy and instead enact policies that are better suited for each state. Specifically, by studying the trade-offs between health gains and economic impacts, we identify the particular states that would have benefited from implementing more restrictive policies. Finally, in addition to shedding light on the impact of lockdown policies during our study period (March–June 2020), our results have important implications on curbing future fast-spreading variants of the coronavirus or other related potential epidemics.

Supplemental Material: The online appendix is available at https://doi.org/10.1287/serv.2023.0321.

Keywords: COVID-19 • lockdown policies • SEIRS model • Markov chain Monte Carlo • longitudinal mixed-effect model

1. Introduction

The novel coronavirus disease 2019 (COVID-19) has wreaked havoc around the globe ever since its onset in November 2019. Based on some estimates, 14.9 million excess deaths occurred in 2020–2021 worldwide that were all associated with COVID-19 (World Health Organization 2022). In the United States, as of November 4, 2022, more than 97 million total cases and more than one million total deaths have been confirmed (Centers for Disease Control and Prevention 2022). In response to the COVID-19 pandemic and in order to curb the progression of the disease, U.S. states each scrambled to implement various lockdown policies in the early stage of the pandemic, including stay-at-home executive orders, nonessential business closures, large-gathering bans, and school closures. These policies have been shown to be effective in lowering the growth rates of COVID-19 (see, e.g., Courtemanche et al. 2020). However, they often bear economic implications, such as the cost of lost income and productivity (see, e.g., Shretta 2020), which might have propelled states to proceed toward reopening prematurely (RAND Corporation

2020). As a result of reopening segments of the economy, some states observed spikes in new cases and were forced to exert new lockdowns, delay their reopening plans, or impose other restrictive policies (Gamio 2020, Reuters 2020). In light of the challenges faced by the states, we aim to provide quantitative evidence and, for the first time (to our knowledge), investigate both the health and economic impacts of various lockdown policies that were or could have been implemented by each of the states. Our main goal is to shed light on policies that are most effective in trading off the underlying health gains versus the potential economic burdens.

To this end, we provide an extensive analysis of the policies implemented in the early stage of the pandemic in each state, compare their performance with a hypothetical no-intervention scenario as well as a set of counterfactual policies that could have been imposed. We do so by first developing a compartmental model that captures the dynamics of the disease progression over time. Utilizing data of 50 U.S. states plus the District of Columbia (DC) on various factors (e.g., number of COVID-19 tests, infections, hospitalizations, ICU bed and ventilation usage, and deaths), we exclusively estimate our model parameters for each state via Markov chain Monte Carlo (MCMC) simulation. We then develop a longitudinal mixed-effect model to quantify the impact of different policies on potential reductions in disease transmission rates. Here, we adjust our analysis for each state by considering policies, their duration, sociodemographic/economic factors (e.g., age, race, income), number of daily tests, and residents' mobility, which we obtain from cellphone data.

Specifically, we take into account the effect of race because Black or Hispanic populations are reported to be more vulnerable against the health/economic impacts of COVID-19 (Artiga et al. 2020). We also take into account the effect of residents' mobility as compliance of residents to adhere with policies imposed by their state can play an important role in controlling the disease (Bodas and Peleg 2020). However, information on the level of adherence is only available via limited surveys, which are not fully reliable. Instead, we make use of cellphone data to directly gauge the mobility of individuals in each state, and this can effectively approximate their level of compliance (Charoenwong et al. 2020). These allow us to perform high-fidelity simulation analyses and compare the lockdown policies that were followed with potential policies that could have been imposed by each state.

Our measurements of the impact of lockdown policies include the total cost incurred as well as the total quality-adjusted life years (QALYs) saved, albeit with respect to certain factors considered in this study. To quantify the cost, we include both direct and indirect costs. Specifically, we consider (1) the direct cost of either utilizing existing hospital resources (e.g., beds and ventilators) or expanding these resources in case there is a limited supply of them and (2) the indirect cost of lost income as well as that incurred when infected individuals have to quarantine. To quantify QALY, we consider how quality of life is impacted by different stages of the disease (e.g., healthy, infected, hospitalized, dead, etc.). Finally, in addition to quantifying both the costs incurred and the QALYs saved, we perform cost-effectiveness (CE) analyses to further shed light on suitable lockdown policies that could have been enacted in each state.

1.1. Policy Insights and Implications

Our results allow the government and public health authorities not only to observe the impact of their existing policies retrospectively, but also to adopt more effective policies for future pandemics. Specifically, our results indicate the following:

- Compared with no intervention, the lockdown policies imposed across the United States during March–June 2020 increased (on average and per 100K capita) the total QALY and cost 41,284.51 years and \$164.01 million, respectively. Moreover, more strict policies (i.e., enacting lockdowns for a longer period than what were actually implemented) in the United States could have saved (on average and per 100K capita) 44,909.41 years of total QALY, costing \$117.28 million.
- For subpopulations who are at higher risk (e.g., age ≥65 and Black/Hispanic race), compared with no intervention, the policies enacted across the United States during March–June 2020 saved (on average and per 100K capita) 64,185.49 years' worth of QALY and incurred \$11.03 million. Under more strict policies, these outcomes would have been 69,389.41 years and −\$49.69 million.
- We find a significant amount of heterogeneity in the total QALY saved and the extra total cost across states. For example, we observe that New Jersey and New York have much higher total QALY gains and extra costs compared with states with a higher population, such as California and Texas. As one of the potential reasons, this might be associated with the number of infections, hospitalizations, and deaths averted under lockdown policies in these states. For example, we find that, under more strict policies (compared with no intervention), a maximum of 100 and 50 daily deaths per 100K capita would have been averted in New Jersey and New York, respectively, whereas this number in California and Texas is about 6 and 0.4, respectively.
- Our results show that, for the majority of the states, the more restrictive counterfactual policies we study are typically more cost-effective than the policies that were implemented. This means that they could have saved more QALYs per dollar imposed to the society. Thus, federal and state authorities should have followed such more restrictive policies instead of what they enacted. However, we find that, in some states,

such as California and New Jersey, the enacted policies were quite comparable to such counterfactual policies.

• Regardless of the lockdown policy, lowering residents' mobility beyond 10 miles from their residence could be viewed as an effective strategy in that it tangibly improves the total QALY gains. Furthermore, the impact of lowering residents' mobility is much higher under the policies implemented across the states than those more strict ones that could have been followed. This suggests that lowering mobility and imposing (lifting) restrictive policies have substitutive (complementary) effects.

1.2. Related Literature

Our work is among the first to examine the state-wide differential impact of various lockdown policies in terms of both health gains and economic burdens for all U.S. states. For related studies, we refer interested readers to Debata et al. (2020), Ghaffarzadegan and Rahmandad (2020), Holtz et al. (2020), Lin and Meissner (2020), Lyu and Wehby (2020), Wilson and Stimpson (2020), Ziedan et al. (2020), Berry et al. (2021), Brauner et al. (2021), Chernozhukov et al. (2021), Donnelly and Farina (2021), and Rahmandad et al. (2022).

Furthermore, regarding the type of health outcomes considered in this study, we note that the majority of studies analyze more direct outcomes, such as number of infections, hospitalizations, and deaths. Whereas we reflect on these outcomes in our numerical results, we measure the QALY metric as our primary health outcome. For some of studies that incorporate this metric in the COVID-19 domain, one can refer to Briggs and Vassall (2021), Ferreira et al. (2021), Reif et al. (2021), Malik et al. (2022), Wouterse et al. (2022), and references therein.

There are also specific studies in the operations research/management (OR/OM) literature that are relevant to our work. Kaplan (2020) analyzes the timing of a specific policy (e.g., university opening). Blackmon et al. (2021) analyze the problem of food insecurity amid the pandemic and develop a decision support system to improve the underlying decisions. Shen et al. (2021) propose a game-theoretic approach to address the impact of mask distribution in controlling the spread of the disease. Birge et al. (2022) develop an optimization model based on residents' mobility to identify targeted policies for business closures. We also refer interested readers to studies that analyze the impact of lifting nonpharmacologic interventions (see, e.g., Chhatwal et al. 2021, Linas et al. 2022), the impact of testing and compliance to quarantine after a positive test on disease transmission (see, e.g., Yu et al. 2022), resource allocation for COVID-19 vaccines (see, e.g., Kim et al. 2021), simultaneous impact of nonpharmacologic interventions and COVID-19 vaccines on health outcomes (see, e.g., Patel et al. 2021), and the effect of balancing service waiting times and disease infection rates (see, e.g., Mondschein et al. 2022). Finally, for reviews of problems attributed to COVID-19 that can be addressed by OR/OM methods, we refer to Choi (2021), Gupta et al. (2022), and the references therein. In Table 1, we compare our work with some existing studies that evaluate related policy interventions in the COVID-19 domain.

The rest of this paper is organized as follows. In Section 2, we present our data and methodology. In Section 3, we provide our numerical results and main findings, insights, and implications from our results. In Section 4, we discuss the limitations and future research directions and conclude the paper.

2. Data and Methodology

2.1. Data

Our study is focused on lockdown policies that were implemented in the early stages of the COVID-19 pandemic (March–June 2020). For part of our analyses, we make use of the Star Schema data (Foldi and Csefalvay 2020), which has the following data attributes: 50 U.S. states plus DC, date, number of daily total COVID tests, positive and negative results, hospitalizations, ICU beds used, ventilators used, and deaths in each state.[1] The beginning date for each state in this data set varies, but the end date for all states is June 7, 2020. The second data that we utilize in our analysis are the timeline of the lockdown policies undertaken in each state, hereafter referred to as current policies for simplicity. In our study, these lockdown policies consist of three main interventions: stay-at-home order and nonessential business closures, large-gathering ban, and school closures. For details regarding the current policies and the data we collected, see Table 2. We also utilize the data of projected infections provided by the Institute for Health Metrics and Evaluation (2020) in order to test and validate our estimations (see Section 3.1.2). Finally, we make use of cellphone data (Cuebiq 2020) to obtain information on individuals' mobility in each state.

2.2. An Epidemiologic Model

To analyze the spread of disease, we utilize an epidemiologic compartmental model known as SEIRS that considers *susceptible*, *exposed*, *infected*, and *recovered* populations. One of the main assumptions in this model is that an immunity obtained upon recovery will not be lifelong in the absence of treatments (see, e.g., Altmann et al. 2020), which was the case during the timeline of our study (American Journal of Managed Care 2021). To properly reflect on the problem under consideration, we make the following adjustments in our SEIRS model (the model is shown in Figure 1):

• We note that being exposed to the disease can be the beginning of the presymptomatic period (see, e.g., World Health Organization 2020). Therefore, we do not

Table 1. Summary of Some Existing Literature on the Evaluation of COVID-19 Policy Interventions

Study	Study period	Study location	Policy type	Outcome measure(s)	Methodology/model
Ghaffarzadegan and Rahmandad (2020)	Feb–Mar 2020	Iran	Current lockdowns[a]	# infections # deaths	SEIR compartmental MCMC simulation
Holtz et al. (2020)	Mar-Apr 2020	United States	Current lockdowns	Geographic/social network spillovers across the United States	Difference-in-differences (DID)
Kaplan (2020)	2020 (month not specified)	United States (Connecticut)	Crowd-size restrictions Hospital surge planning University opening	# infections # hospitalizations	Mathematical models
Lyu and Wehby (2020)	Mar–May 2020	United States 15 states	Mask mandates	Infection transmission rate	DID
Ziedan et al. (2020)	Apr 2019–Apr 2020	United States	Current lockdowns	Non-COVID-19 healthcare utilization	DID
Berry et al. (2021)	Mar–May 2020	United States	Current lockdowns	# infections # deaths	DID
Brauner et al. (2021)	Feb–May 2020	41 countries (not including the United States)	Current lockdowns	Infection transmission rate	Bayesian hierarchical
Chhatwal et al. (2021)	Mar 2020–Dec 2021	United States	Current lockdowns Mask mandates	# infections # hospitalizations # deaths	SEIR compartmental Simulation
Chernozhukov et al. (2021)	Mar–May 2020	United States	Mask mandates Counterfactual mandates	# infections # deaths	Structural equations
Ferreira et al. (2021)	Mar–Apr 2020	Portugal	Current lockdowns	Health-related quality of life Anxiety level	Survey analysis
Kim et al. (2021)	Not specified	United States	Vaccines resource allocations	Infection attack rate	SIR-D compartmental
Reif et al. (2021)	Mar 2020–Mar 2021	United States	Not specified	QALYs lost	State-transition microsimulation
Birge et al. (2022)	Apr 2020	United States (New York)	Current lockdowns	# infections	Optimization
Wouterse et al. (2022)	2020 (month not specified)	Netherlands	Not specified	QALYs lost	Simulation
Yu et al. (2022)	Not specified	United States	Testing capacity and compliance	Infection transmission rate	SIR compartmental Simulation
Our study	Mar–Jun 2020	United States All 51 states	Current lockdowns Counterfactual lockdowns No intervention	QALY Cost[b]	SEIRS compartmental MCMC simulation

[a]"Current" refers to the time during the study period when the corresponding policy was implemented.
[b]Both measures are estimated based on the number of infected, hospitalized, and dead individuals under different policies.

differentiate between exposed and presymptomatic conditions.

• We allow transmissions between (a)symptomatic infected and hospitalized populations.

• Among hospitalizations, we account for demand for common beds, ICU beds alone, or ICU beds with mechanical ventilators.

• We assume a ventilator is only used with an ICU bed (not a common bed), which is consistent with the medical literature (see, e.g., Gracey 1995, Wunsch et al. 2013).

• For hospitalized patients who are discharged, we also consider the possibility of being infected (i.e., carrier) postdischarge (Modern Healthcare 2020).

• For the current policies in each state, we consider the fact that there are overlaps between interventions resulting in different time frames. For example, for Alabama, we observed four time frames: March 7–April 3, April 4–30, May 1–11, and May 12–June 7 (see Table 2). Because of the type/number of interventions undertaken in each time frame, this can result in a potentially different disease transmission rate. We account for this

Table 2. Timelines of current intervention policies and data collected

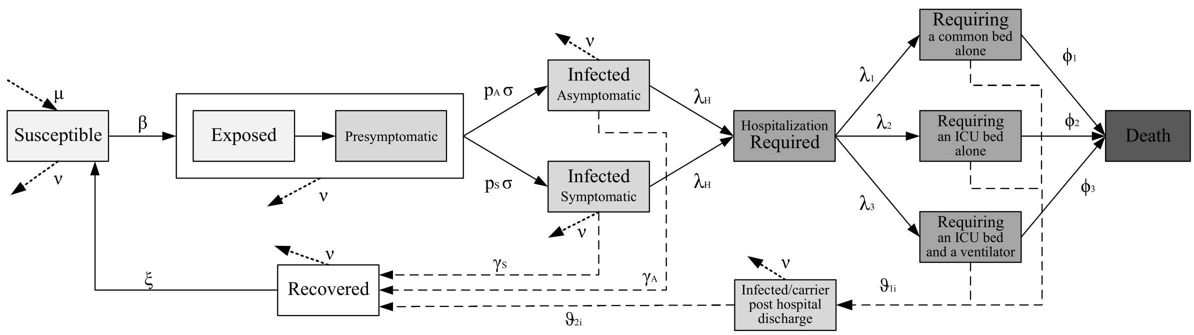
State	Intervention 1[a]		Intervention 2[a]		Intervention 3[a]		Data	
	Start	End	Start	End	Start	End	Start	End
Alabama	04-Apr	30-Apr	04-Apr	11-May	04-Apr	ROSY[b]	07-Mar	07-Jun
Alaska	28-Mar	20-May	28-Mar	IND[c]	28-Mar	ROSY	06-Mar	07-Jun
Arizona	31-Mar	15-May	17-Mar	16-May	15-Mar	ROSY	04-Mar	07-Jun
Arkansas	—[d]	—	06-Apr	IND	06-Apr	ROSY	06-Mar	07-Jun
California	19-Mar	IND	19-Mar	IND	19-Mar	ROSY	04-Mar	07-Jun
Colorado	26-Mar	30-Apr	26-Mar	IND	26-Mar	ROSY	05-Mar	07-Jun
Connecticut	23-Mar	20-May	23-Mar	20-Jun	23-Mar	ROSY	07-Mar	07-Jun
Delaware	24-Mar	31-May	24-Mar	IND	24-Mar	ROSY	06-Mar	07-Jun
District of Columbia	01-Apr	29-May	01-Apr	IND	01-Apr	ROSY	05-Mar	07-Jun
Florida	03-Apr	04-May	03-Apr	IND	03-Apr	ROSY	04-Mar	07-Jun
Georgia	03-Apr	30-Apr	03-Apr	IND	03-Apr	ROSY	04-Mar	07-Jun
Hawaii	25-Mar	31-May	25-Mar	IND	25-Mar	ROSY	07-Mar	07-Jun
Idaho	25-Mar	30-Apr	25-Mar	30-Apr	—	—	07-Mar	07-Jun
Illinois	21-Mar	31-May	21-Mar	31-May	21-Mar	ROSY	04-Mar	07-Jun
Indiana	24-Mar	01-May	24-Mar	IND	24-Mar	ROSY	06-Mar	07-Jun
Iowa	17-Mar	15-May	17-Mar	IND	17-Mar	ROSY	06-Mar	07-Jun
Kansas	30-Mar	03-May	30-Mar	04-May	30-Mar	ROSY	06-Mar	07-Jun
Kentucky	26-Mar	IND	26-Mar	IND	26-Mar	ROSY	06-Mar	07-Jun
Louisiana	23-Mar	15-May	23-Mar	IND	23-Mar	ROSY	07-Mar	07-Jun
Maine	02-Apr	31-May	01-May	31-May	02-Apr	ROSY	07-Mar	07-Jun
Maryland	30-Mar	15-May	30-Mar	IND	30-Mar	ROSY	05-Mar	07-Jun
Massachusetts	24-Mar	18-May	24-Mar	18-May	24-Mar	ROSY	12-Mar	07-Jun
Michigan	24-Mar	12-Jun	24-Mar	01-Jun	24-Mar	ROSY	01-Mar	07-Jun
Minnesota	27-Mar	18-May	27-Mar	18-May	27-Mar	ROSY	06-Mar	07-Jun
Mississippi	03-Apr	27-Apr	03-Apr	IND	03-Apr	ROSY	07-Mar	07-Jun
Missouri	06-Apr	03-May	06-Apr	03-May	06-Apr	ROSY	07-Mar	07-Jun
Montana	28-Mar	24-Apr	28-Mar	IND	28-Mar	07-May	07-Mar	07-Jun
Nebraska	10-Apr	30-Apr	10-Apr	04-May	10-Apr	ROSY	05-Mar	07-Jun
Nevada	01-Apr	01-May	01-Apr	IND	01-Apr	ROSY	05-Mar	07-Jun
New Hampshire	27-Mar	15-Jun	27-Mar	15-Jun	27-Mar	ROSY	04-Mar	07-Jun
New Jersey	21-Mar	IND	21-Mar	IND	21-Mar	ROSY	05-Mar	07-Jun
New Mexico	24-Mar	15-May	24-Mar	IND	24-Mar	ROSY	06-Mar	07-Jun
New York	22-Mar	15-May	22-Mar	IND	22-Mar	ROSY	04-Mar	07-Jun
North Carolina	30-Mar	08-May	30-Mar	IND	30-Mar	ROSY	04-Mar	07-Jun
North Dakota	27-Mar	30-Apr	—	—	27-Mar	ROSY	07-Mar	07-Jun
Ohio	23-Mar	29-May	23-Mar	IND	23-Mar	ROSY	05-Mar	07-Jun
Oklahoma	28-Mar	06-May	28-Mar	IND	28-Mar	ROSY	07-Mar	07-Jun
Oregon	23-Mar	15-May	23-Mar	IND	23-Mar	ROSY	04-Mar	07-Jun
Pennsylvania	01-Apr	08-May	01-Apr	IND	01-Apr	ROSY	06-Mar	07-Jun
Rhode Island	28-Mar	08-May	28-Mar	IND	28-Mar	ROSY	01-Mar	07-Jun
South Carolina	07-Apr	04-May	07-Apr	IND	07-Apr	ROSY	04-Mar	07-Jun
South Dakota	—	—	06-Apr	31-May	06-Apr	ROSY	07-Mar	07-Jun
Tennessee	31-Mar	30-Apr	31-Mar	IND	30-Mar	ROSY	05-Mar	07-Jun
Texas	02-Apr	30-Apr	02-Apr	IND	02-Apr	ROSY	04-Mar	07-Jun
Utah	27-Mar	01-May	27-Mar	IND	27-Mar	ROSY	07-Mar	07-Jun
Vermont	24-Mar	15-Jun	24-Mar	IND	24-Mar	ROSY	06-Mar	07-Jun
Virginia	30-Mar	10-Jun	30-Mar	IND	30-Mar	ROSY	05-Mar	07-Jun
Washington	23-Mar	31-May	23-Mar	IND	23-Mar	ROSY	22-Jan	07-Jun
West Virginia	24-Mar	04-May	24-Mar	IND	24-Mar	ROSY	06-Mar	07-Jun
Wisconsin	25-Mar	26-May	25-Mar	26-May	25-Mar	ROSY	04-Mar	07-Jun
Wyoming	25-Mar	01-May	25-Mar	IND	25-Mar	ROSY	07-Mar	07-Jun

Notes. Timelines of interventions, sources: Kates et al. (2020), Wu et al. (2020), and Treisman (2020). Timelines of data, source: Foldi and Csefalvay (2020).

[a]Intervention 1: stay-at-home order and/or nonessential business closures. Intervention 2: large-gathering ban. Intervention 3: school closures.
[b]ROSY: remainder of school year.
[c]IND: indefinitely (at the time of data collection, June 7, 2020).
[d]An executive order was not issued in that state.

by solving piecewise ordinary differential equations (ODEs) in our SEIRS model. As a result, the disease transmission rate in our setting depends on time. Of note, because transmission rates also affect other factors in our model (e.g., hospitalization and death rates), such factors are also time-dependent in our analyses.

Figure 1. The SEIRS Compartmental Model



Notes. Dashed and dotted arrows represent recovery/discharge flows and vital dynamics, respectively. For graphic simplicity, "infected/carrier posthospital discharge" is shown with one compartment (there are three of them). "Hospitalization required" is only shown for illustrative purposes and is not among the compartments.

As shown in Figure 1, the outputs in our SEIRS model are the number of people in each compartment on each day, for example, susceptible, exposed, infected symptomatic/asymptomatic, hospitalized with common bed, ICU bed, or ventilator, and death. We solve our model using the following ODEs (for the notation used, see Table 3):

$$\frac{dS(t)}{dt} = \frac{-\beta(t)S(t)\sum_{i\in\{A,S,H,PD\}} I_i(t)}{S(t)+E(t)+\sum_{i\in\{A,S,H,PD\}} I_i(t)+R(t)} + \xi R(t) + \mu\left(S(t)+E(t)+\sum_{i\in\{A,S,PD\}} I_i(t)+R(t)\right) - \nu S(t), \tag{1a}$$

$$\frac{dE(t)}{dt} = \frac{\beta(t)S(t)\sum_{i\in\{A,S,H,PD\}} I_i(t)}{S(t)+E(t)+\sum_{i\in\{A,S,H,PD\}} I_i(t)+R(t)} - (\sigma+\nu)E(t), \tag{1b}$$

$$\frac{dI_A(t)}{dt} = p_A\sigma E(t) - (\lambda_H+\gamma_A+\nu)I_A(t), \tag{1c}$$

$$\frac{dI_S(t)}{dt} = p_S\sigma E(t) - (\lambda_H+\gamma_S+\nu)I_S(t), \tag{1d}$$

$$\frac{dI_{HRi}(t)}{dt} = \lambda_H(I_A(t)+I_S(t))\lambda_i - (\vartheta_{1i}+\phi_i)I_{HRi}(t) \quad \text{for } i\in\{1,2,3\}, \tag{1e}$$

$$\frac{dI_{PDi}(t)}{dt} = \vartheta_{1i}I_{HRi}(t) - (\vartheta_{2i}+\nu)I_{PDi}(t) \quad \text{for } i\in\{1,2,3\}, \tag{1f}$$

$$\frac{dR(t)}{dt} = (\gamma_A I_A(t)+\gamma_S I_S(t)) + \sum_{i=1}^{3}\vartheta_{2i}I_{PDi}(t) - (\xi+\nu)R(t), \tag{1g}$$

$$S(0)=N(0)-e_0, E(0)=e_0, I_A(0)=I_S(0)=I_H(0) = I_{PD}(0)=R(0)=0. \tag{1h}$$

2.3. Potential Lockdown Policies

In addition to analyzing the performance of current policies, we study the impact of some potential policies that

Table 3. Summary of Notations for the SEIRS Model

t	Time index (in days), $t=0,1,\ldots,T$ (T: time horizon)
$S(t)$	# susceptible (#: number of people)
$E(t)$	# exposed to the virus
e_0	# initially exposed (at the onset of disease)
$P(t)$	# presymptomatic, $P(t)=E(t)$
$I_A(t)$	# infected and asymptomatic (not developing symptoms)
$I_S(t)$	# infected and symptomatic
$I_H(t)$	# infected needed to be hospitalized, $I_H(t)=\sum_{i=1}^{3} I_{HRi}(t)$
$I_{HRi}(t)$	# requiring hospital resources, $i\in\{1:$ Common/non-ICU bed, $2:$ ICU bed alone, $3:$ ICU bed with ventilator$\}$
$I_{PDi}(t)$	# infected/carrier of the disease posthospital discharge for index $i\in\{1,2,3\}$, $I_{PD}(t)=\sum_{i=1}^{3} I_{PDi}(t)$
$D(t)$	# deaths from COVID-19
$R(t)$	# recovered from the disease
$N(t)$	Total number of people (sum of numbers in all compartments at time t)
l_I	Incubation period (time between exposure/being presymptomatic and appearance of signs/symptoms of disease)
	$\sigma=1/l_I$: rate of becoming infected postexposure/presymptomatic period
l_{Rk}	recovery period for $k\in\{$A: asymptomatic, S: symptomatic$\}$
	γ_k: recovery rate for $k\in\{$A: asymptomatic, S: symptomatic$\}$, $\gamma_k=1/l_{Rk}$
l_W	Immunity waning period
	ξ: waning rate, $\xi=1/l_W$
LOS_i	Hospital length of stay for index $i\in\{1,2,3\}$ (see above for description of index i)
	ϑ_{1i}: hospital discharge rate for index $i\in\{1,2,3\}$, $\vartheta_{1i}=1/\text{LOS}_i$
	ϑ_{2i}: full recovery rate after a hospital discharge for index $i\in\{1,2,3\}$, $\vartheta_{2i}=1/\max\{l_R-\text{LOS}_i,0\}$
$\beta(t)$	Transmission rate at time t (rate at which the disease is transmitted between a susceptible and an exposed individual)
p_S	Probability of a symptomatic infection
p_A	Probability of an asymptomatic infection, $p_A=1-p_S$
λ_H	Rate of hospitalization
λ_i	Rate of hospitalization for index $i\in\{1,2,3\}$, $\sum_{i=1}^{3}\lambda_i=1$
ϕ_i	Covid-related death rate for index $i\in\{1,2,3\}$
μ	Vital dynamics (natural birth rate; not occurred during hospitalization)
ν	Vital dynamics (natural death rate; not occurred during hospitalization)

Note. Compartments indices 1–12 refer to S, E, I_A, I_S, I_{HRi} and I_{PDi} for $i\in\{1,2,3\}$, R and D compartments, respectively.

could have been followed by states (see Table 4) as well as a hypothetical no-intervention policy. These potential policies are set based on the current lockdown policies with the exception that we typically explore a longer duration, representing more strict policies compared with the current policies. Because most states initiated their policies in March and the end date in our data are June 7, we analyze these policies for March through June of 2020. These policies are labeled such that they are ordered in their degree of leniency. Thus, policy 3 (1) in Table 4 is the most (least) strict policy. Our assumptions on the way the states would have transitioned between these policies (e.g., first implementing all interventions, then lifting the stay-at-home order, and so on) is consistent with what has been reported by the authorities for each state (see Table 2).

2.4. Adjusting Disease Transmission Rates

As we estimate the disease transmission rates in our SEIRS model, there exist underlying factors that could affect the dynamics of the disease but are not reflected in the SEIRS model, for example, population's age and race (Artiga et al. 2020), income (Smialek 2020), compliance to following policies (Bodas and Peleg 2020), and number of daily tests (Pitzer et al. 2021). As a result, we cannot directly apply these estimated transmission rates to examine the impact of potential lockdown policies. To address this, we develop a longitudinal mixed-effect regression model, which allows us to measure the impact of policies on potential reductions in transmission rates. For each state, we adjust our analysis by duration and intensity of interventions, age, the ratio of Black or Hispanic populations, per capita income, and number of daily tests. In addition, we make use of the shelter-in-place analysis data (Cuebiq 2020) on the ratio of mobile devices moving within 1 mile, between 1 and 10 miles, or more than 10 miles from home in each state. Also, for the number of daily tests, we make use of the Star Schema data (Foldi and Csefalvay 2020). Table 5 shows the summary of the independent variables used in our longitudinal regression model (for details about this model, see Section 3.2).

2.5. Measuring Health and Economic Impacts

2.5.1. Health Outcomes. Under each policy, we measure health outcomes by making use of QALYs. This quantifies the number of years an individual can accrue depending on the individual's health status; for example, full health (death) accounts for one (zero) year(s) of quality of life accrued, and a medical condition such as infection yields a value that is strictly between zero and one over one year. In our setting, the SEIRS model has 12 compartments, each representing a different stage of the disease (see Section 2.2 for more details). Let $X(t) = (X_1(t), \ldots, X_{12}(t))$ represent the state of the model at time t, where $X_i(t)$ denotes the number of people estimated to be in compartment $i \in \{1, 2, \ldots, 12\}$ at time t. Let $q_i \in [0, 1]$ represent the quality-of-life (qol) score for compartment i. This is a number between zero and one, and one (zero) represents full health (death) based on a one-year time frame. Also let Q_i be the terminal qol score that a patient accrues at the end of the time horizon for the rest of the patient's life. We quantify total QALY as the quality-adjusted life years that a population can accrue over the time horizon:

$$\text{Total QALY} = \sum_{t=1}^{T-1} \sum_{i=1}^{12} q_i X_i(t) + \sum_{i=1}^{12} Q_i X_i(T). \tag{2}$$

As mentioned in Section 2.4, we adjust the disease transmission rate based on age, ratio of underrepresented populations, per capita income, people's mobility, number of daily tests, and type and duration of policies. As a result, the number of people in different compartments and, hence, our measure of QALY reflects these factors. Of note, Equation (2) reveals a linear function that accounts for between-compartment distribution of health benefits. However, it does not account for within-compartment distribution, such as subpopulations with specific health conditions (e.g., obesity, diabetes, immunodeficiency, etc.) that might be more susceptible to COVID-19. Because our data does not include such granular information for each state, we focus on broader sociodemographic information in Table 5. We also perform a sensitivity analysis on the estimated qol scores (and, hence, QALY values) to

Table 4. Summary of Potential Intervention Policies

Policy	Stage 1	Stage 2	Stage 3	Number of time frames
P1	Start: 01-Mar, end: 30-Apr Duration: 61 days Interventions 1/2/3[a]	Start: 01-May, end: 31-May Duration: 31 days Interventions 2/3	Start: 01-Jun, end: 30-Jun Duration: 30 days Intervention 3	3
P2	Start: 01-Mar, end: 31-May Duration: 92 days Interventions 1/2/3	Start: 01-Jun, end: 30-Jun Duration: 30 days Interventions 2/3	—	2
P3	Start: 01-Mar, end: 30-Jun Duration: 122 days Interventions 1/2/3	—	—	1

[a]Intervention 1: stay-at-home order and nonessential business closures; intervention 2: large-gathering ban; intervention 3: school closures.

Table 5. Summary of Sociodemographics and Mobility Information

State	Average PCI, $[a,b]	Median Age[b]	Race Ratio[b,c]	Mobility ratio[e]			
				Time frame 1[d]	Time frame 2	Time frame 3	Time frame 4
Alabama	25,746	38.7	0.30	(0.315,0.298,0.386)	(0.396,0.281,0.321)	(0.319,0.290,0.390)	(0.311,0.281,0.406)
Alaska	35,065	33.9	0.10	—	—	—	—
Arizona	27,964	37.2	0.36	(0.335,0.359,0.305)	(0.461,0.308,0.230)	(0.485,0.301,0.213)	(0.407,0.329,0.263)
Arkansas	24,426	37.9	0.23	(0.343,0.302,0.354)	(0.344,0.296,0.359)	—	—
California	33,128	36.1	0.44	(0.328,0.364,0.306)	(0.470,0.301,0.227)	—	—
Colorado	34,845	36.5	0.26	(0.420,0.273,0.306)	(0.554,0.230,0.214)	(0.438,0.263,0.297)	—
Connecticut	41,365	40.8	0.27	(0.331,0.362,0.306)	(0.508,0.294,0.196)	(0.392,0.343,0.263)	—
Delaware	32,625	39.8	0.30	(0.316,0.351,0.332)	(0.474,0.295,0.230)	(0.370,0.328,0.301)	—
District of Columbia	50,832	33.9	0.56	—	—	—	—
Florida	28,774	41.8	0.41	(0.360,0.310,0.329)	(0.466,0.277,0.255)	(0.368,0.302,0.328)	—
Georgia	28,015	36.4	0.41	(0.321,0.288,0.390)	(0.422,0.268,0.309)	(0.313,0.281,0.404)	—
Hawaii	32,511	38.8	0.12	—	—	—	—
Idaho	25,471	35.9	0.14	(0.397,0.283,0.318)	(0.481,0.265,0.253)	(0.379,0.290,0.329)	—
Illinois	32,924	37.7	0.31	(0.285,0.306,0.408)	(0.434,0.266,0.298)	(0.328,0.288,0.382)	—
Indiana	27,305	37.5	0.16	(0.308,0.310,0.381)	(0.474,0.267,0.258)	(0.355,0.297,0.346)	—
Iowa	30,063	38.1	0.09	(0.284,0.290,0.425)	(0.441,0.252,0.305)	(0.353,0.270,0.375)	—
Kansas	29,600	36.3	0.17	(0.392,0.247,0.360)	(0.478,0.240,0.280)	(0.382,0.254,0.362)	—
Kentucky	25,888	38.6	0.12	(0.314,0.305,0.380)	(0.391,0.287,0.321)	—	—
Louisiana	26,205	36.4	0.37	(0.268,0.313,0.418)	(0.408,0.284,0.306)	(0.303,0.295,0.400)	—
Maine	29,886	44.3	0.03	(0.390,0.298,0.311)	(0.492,0.268,0.239)	(0.394,0.295,0.310)	(0.346,0.308,0.345)
Maryland	39,070	38.5	0.39	(0.364,0.314,0.321)	(0.509,0.267,0.223)	(0.408,0.300,0.291)	—
Massachusetts	39,913	39.4	0.19	(0.393,0.389,0.217)	(0.553,0.308,0.138)	(0.435,0.372,0.192)	—
Michigan	28,938	39.6	0.19	(0.337,0.308,0.353)	(0.501,0.257,0.240)	(0.367,0.294,0.338)	—
Minnesota	34,712	37.9	0.11	(0.367,0.271,0.360)	(0.478,0.240,0.281)	(0.377,0.261,0.361)	—
Mississippi	22,500	36.9	0.41	(0.315,0.275,0.408)	(0.412,0.267,0.320)	(0.309,0.277,0.413)	—
Missouri	28,282	38.4	0.15	(0.367,0.283,0.349)	(0.425,0.268,0.305)	(0.326,0.283,0.390)	—
Montana	28,706	39.8	0.04	(0.481,0.224,0.293)	(0.569,0.205,0.224)	(0.450,0.238,0.311)	—
Nebraska	29,866	36.3	0.15	(0.419,0.234,0.345)	(0.463,0.233,0.304)	(0.405,0.247,0.347)	(0.378,0.240,0.380)
Nevada	28,450	37.7	0.38	(0.436,0.292,0.271)	(0.512,0.261,0.226)	(0.435,0.280,0.284)	—
New Hampshire	36,914	42.7	0.05	(0.350,0.321,0.327)	(0.468,0.290,0.241)	(0.367,0.320,0.312)	—
New Jersey	39,069	39.6	0.34	(0.301,0.398,0.300)	(0.541,0.286,0.172)	—	—
New Mexico	25,257	37.3	0.51	(0.376,0.332,0.291)	(0.493,0.294,0.211)	(0.428,0.312,0.259)	—
New York	35,752	38.4	0.33	(0.323,0.352,0.323)	(0.529,0.267,0.203)	(0.424,0.307,0.268)	—
North Carolina	28,123	38.4	0.31	(0.310,0.315,0.375)	(0.418,0.292,0.289)	(0.340,0.302,0.357)	—
North Dakota	34,256	35.1	0.07	(0.446,0.211,0.341)	(0.507,0.204,0.288)	(0.391,0.230,0.378)	—
Ohio	29,011	39.3	0.16	(0.292,0.330,0.376)	(0.443,0.285,0.271)	(0.321,0.317,0.362)	—
Oklahoma	26,461	36.3	0.18	(0.328,0.273,0.398)	(0.414,0.267,0.318)	(0.315,0.275,0.409)	—
Oregon	30,410	39.2	0.15	(0.373,0.344,0.282)	(0.496,0.287,0.215)	(0.427,0.308,0.263)	—
Pennsylvania	31,476	40.7	0.18	(0.395,0.321,0.283)	(0.509,0.280,0.209)	(0.399,0.316,0.284)	—
Rhode Island	33,315	39.9	0.22	(0.347,0.387,0.265)	(0.536,0.310,0.153)	(0.419,0.372,0.208)	—
South Carolina	26,645	39.0	0.32	(0.324,0.304,0.370)	(0.400,0.291,0.308)	(0.314,0.302,0.383)	—
South Dakota	28,761	36.8	0.06	(0.438,0.238,0.323)	(0.484,0.234,0.280)	(0.385,0.251,0.362)	—
Tennessee	27,277	38.6	0.22	(0.306,0.305,0.388)	(0.411,0.288,0.300)	(0.306,0.300,0.392)	—
Texas	28,985	34.3	0.52	(0.357,0.263,0.378)	(0.457,0.250,0.292)	(0.363,0.264,0.372)	—
Utah	26,907	30.5	0.15	(0.379,0.317,0.303)	(0.476,0.283,0.240)	(0.381,0.311,0.307)	—
Vermont	31,917	42.8	0.03	(0.340,0.306,0.353)	(0.476,0.268,0.255)	—	—
Virginia	36,268	38.0	0.29	(0.346,0.309,0.344)	(0.420,0.285,0.293)	—	—
Washington	34,869	37.6	0.17	(0.342,0.354,0.302)	(0.483,0.291,0.225)	(0.401,0.318,0.280)	—
West Virginia	24,774	42.2	0.05	(0.320,0.325,0.354)	(0.478,0.276,0.245)	(0.367,0.302,0.329)	—
Wisconsin	30,557	39.2	0.13	(0.331,0.309,0.359)	(0.459,0.266,0.273)	(0.349,0.295,0.355)	—
Wyoming	31,214	37.0	0.10	(0.392,0.346,0.261)	(0.497,0.298,0.203)	(0.393,0.333,0.272)	—

Note. For number of daily tests, we use the data in Foldi and Csefalvay (2020).

[a]PCI: Per capita income/year. PCI and median age are obtained from Mathematica, Wolfram Research, Inc. (see Online Appendix A).

[b]In our simulation, we consider a $\pm 10\%$ variation for this measure (based on the point estimate reported here).

[c]Ratio of Black or Hispanic population (Henry J. Kaiser Family Foundation 2018).

[d]Mobility information is obtained from Cuebiq (2020). Numbers in (.) represent the average ratio of mobile devices moving within 1 mile, between 1 and 10 miles, and more than 10 miles from home, respectively. Mobility data for Alaska/District of Columbia/Hawaii was not available. For these states, we take the average mobility rates from other states.

[e]For characterization of time frames, see Sections 2.1 and 2.2.

test the validity of our main findings (see Section 3.4.2). Finally, in addition to reporting the total QALY per 100K capita, we also evaluate the QALY values by focusing on high-risk subpopulations formed by people 65 years or older or those with Black/Hispanic race.

2.5.2. Economic Outcomes. We measure economic impacts using the sum of direct and indirect costs (see, e.g., Meltzer et al. 1999). The direct costs entail the costs related to utilizing existing healthcare resources, such as common beds, ICU beds, and ventilators, as well as expanding these resources when facing higher demands for them. Following the notation introduced in Table 6, the total direct cost is measured as

$$\begin{aligned}\text{Total direct cost} = \sum_{t=1}^{T}[&c_1X_5(t) + c_2X_6(t) + c_3X_7(t)\\ &+ \hat{c}_1\max\{0, X_5(t) - C_1(t)\}\\ &+ \hat{c}_2\max\{0, X_6(t) - C_2(t)\}\\ &+ \hat{c}_3\max\{0, X_7(t) - C_3(t)\}],\end{aligned} \tag{3}$$

where the first (second) line represents the daily cost of utilizing (expanding) resources.

The indirect costs, however, relate to other expenses, such as those associated with lost income/productivity and quarantining. Using the notation introduced in Table 6, the total indirect cost is measured as

$$\begin{aligned}\text{Total indirect cost} = \text{PCI} \times \eta \times \sum_{t=1}^{T}[&\text{lost income } (t)\\ &+ \text{quarantine cost } (t)],\end{aligned} \tag{4}$$

where

$$\begin{aligned}\text{lost income } (t) = \sum_{j=1}^{4} p_j(t)\theta_j \sum_{i=1}^{11}[&X_i(t) + X_{12}(t)\\ &(365 \times (\max\{0, 65 - \text{Age}\} - t + 1))],\end{aligned} \tag{5a}$$

$$\begin{aligned}\text{quarantine cost } (t) = (&I_A^N(t)d_A + I_S^N(t)d_S)\\ &\times (q_Hc_H + q_Fc_F) \times \gamma,\end{aligned} \tag{5b}$$

where the first sum on the right-hand side (RHS) in (5a) captures the percentage of lost income. The second sum on the RHS in (5a) calculates the number of people who lost their income in the population. This is measured separately for death ($i = 12$) and other compartments in the SEIRS model. Of note, when an individual dies, the income is lost for the rest of the individual's working life. Assuming the working life ends at 65 years of age for an alive person, the number of days income is lost for a person who dies on day t is measured as $365 \times (\max\{0, 65 - \text{Age}\} - t + 1)$. Furthermore, the first factor in (5b) reveals the number of individuals quarantining adjusted by the duration of their quarantine period (in days), and the second factor represents the cost of quarantining per person per day. Of note, our calculations differentiate between asymptomatic and symptomatic infections because they often have different quarantine periods (see, e.g., Centers for Disease Control and Prevention 2021). Finally, γ is the proportion of people who have to quarantine when infected. Whereas we set this parameter exogenously, we conduct sensitivity analyses on this (and many other parameters and assumptions) in our robustness checks.

Using Equations (2)–(5b), we compare the total QALY saved and the total cost incurred under different lockdown policies compared with a hypothetical no-intervention scenario. Further details about our estimation of QALY and costs parameters can be found in Online Appendix C. Moreover, in Section 3.4, we perform extensive sensitivity analyses to test the robustness of our main findings against the estimated parameters.

Finally, we also compare the cost-effectiveness of different policies by measuring the incremental

Table 6. Summary of Notations for the Economic Outcomes

Cost: direct	c_i	Operating cost (\$/day) of a unit of existing resource i, i =1 (common bed), 2 (ICU bed), 3 (ICU bed & ventilator)
	$\hat{c}_i$	One-time cost (\$) for adding a unit of resource i
	$X_k(t)$	# in compartment j on day t, $k = 5$ (hosp w common bed), 6 (hosp w ICU bed), 7 (hosp w ICU bed & ventilator)
	$C_i(t)$	Current capacity of resource i on day t (updated on a daily basis)
Cost: lost income	PCI	Per capita income per day
	η	Employment rate
	$p_j(t)$	% of working population who lose between $0.25(j-1)$ and $0.25j$ of their income, $j = 1, \ldots, 4$
	θ_j	% of lost income for individuals who lose between $j-1$ and j quartiles of their income, $\theta_j \in [0.25(j-1), 0.25j]$
	$X_i(t)$	# in compartment i on day t (patients in compartments $i = 1, \ldots, 11$ are alive)
	$X_{12}(t)$	# patients who die on day t
Cost: quarantine	q_H	Probability of a quarantining person doing that at home
	q_F	Probability of a quarantining person doing that at a facility (e.g., hotel), $q_F = 1 - q_H$
	c_H	Cost (\$/day) for quarantining at home
	c_F	Cost (\$/day) for quarantining at a facility
	d_A	# days of quarantine if asymptomatic
	d_S	# days of quarantine if symptomatic
	$I_A^N(t)$	# new asymptomatic infections on day t
	$I_S^N(t)$	# new symptomatic infections on day t
	γ	% of people who do quarantine when infected (set exogenously, subject to sensitivity analysis)

cost-effectiveness ratio (ICER) (see, e.g., Drummond et al. 2015):

$$\begin{aligned}\text{ICER} &= \frac{\text{Incremental total cost (\$)}}{\text{Incremental total QALY (years)}}\\ &= \frac{\begin{array}{c}\text{Total cost (potential policy)}\\ -\text{ Total cost (current policy)}\end{array}}{\begin{array}{c}\text{Total QALY (potential policy)}\\ -\text{ Total QALY (current policy)}\end{array}}.\end{aligned} \tag{6}$$

Let WTP represent the willingness to pay defined as the maximum amount that the society is willing to pay to obtain one extra QALY (in years). Then, a potential policy intervention is said to be more cost-effective than the current policy if ICER ≤ WTP (see, e.g., Drummond et al. 2015).

3. Numerical Results and Analyses

3.1. Parameter Estimations and Model Validation

3.1.1. Estimations. Table 7 shows the estimated parameters of our SEIRS model in terms of their 95% confidence intervals (CIs). To estimate these parameters, we conduct an MCMC simulation via the Metropolis–Hastings algorithm (Chib and Greenberg 1995).[2] The MCMC simulation generates the posterior estimates of parameters based on observed data of the number of infections, hospitalizations, and deaths. Following Bayesian inference, we first construct a log-likelihood function of the observed data conditional on model parameters (prior), in which the log likelihood is based on Poisson distributions for the number of infections, hospitalizations, and deaths (see, e.g., Bootsma and Ferguson 2007, Ghaffarzadegan and Rahmandad 2020). For a given U.S. state, we denote by $v_D = [v_{D,t}]_{t\in F}$ the vector of a statistic (e.g., infections, hospitalizations, or deaths) observed from our data over time frame F. We let $v_E = [v_{E,t}]_{t\in F}$ be the corresponding vector whose values (e.g., infections, hospitalizations, and deaths) are obtained by running the deterministic Equations (1a)–(1h) in the SEIRS model. After assuming a uniform prior $U[0,1]$ for all parameters that are defined as rates (Bootsma and Ferguson 2007) and different uniform distributions for other parameters (e.g., length of stay), we then form the Poisson log-likelihood function as (Taboga 2021)

$$\log L(v_D, v_E) = \sum_{t\in F}[-v_{D,t} - \log(v_{E,t}!) + \log(v_{D,t})v_{E,t}]. \tag{7}$$

Using the log-likelihood function in (7), we resort to the MCMC simulation to iteratively construct the posterior distribution of parameters given the observed data. We run multiple chains to avoid wide CIs, which are typically idiosyncratic to MCMC simulations with a single chain. In addition, for the convergence of the Metropolis–Hastings algorithm, we use the modified potential scale reduction factor (Brooks and Gelman 1998) (further details are provided in Online Appendix C.6). Finally, to identify the burn-in period (i.e., number of initial iterations of the algorithm to discard), we visually inspect the variations in estimated parameters over iterations to detect nonstationary behavior. For further details about the Metropolis–Hastings algorithm, we refer to Robert (2015) and Van Ravenzwaaij et al. (2018).

3.1.2. Validation. To validate our model, we compare our predictions of number of infections, hospitalizations, and deaths with those observed in the data (see Online Appendix B). For each state, we iterate our SEIRS model 1,000 times, and in each iteration, we randomly select a value for each parameter from the respective CI reported in Table 7. From our results, we observe that the values we observe from the data are within the corresponding CIs from our predictions, and in most cases, the mean value of our predictions closely mimics that of the data.

3.2. Mixed-Effect Longitudinal Model

The disease transmission rate that we estimate in Section 3.1 is obtained based on the data gathered under the actual lockdown policies undertaken across the United States. However, we also aim to analyze some counterfactual policies, in which their intensity and duration differ from the one under which the data are gathered (see Table 4). Therefore, we need to adjust the transmission rate accordingly. To accomplish this, we develop a longitudinal mixed-effect regression model to quantify how much the transmission rates are impacted by intervention policies, their durations, population age, ratio of Black or Hispanic populations, per capita income, mobility rates, and number of daily tests in each state. The outcome is the amount of reduction in transmission rate at any given time compared with the baseline rate (i.e., when there is no intervention). Using the notations in Table 8, our first model is as follows:

$$\begin{aligned}\text{Model 1}: \beta_0 - \beta_i = {} & b_0 + b_1 * policy_i + b_2 * duration_i\\ & + b_3 * mobility_i^1 + b_4 * mobility_i^2\\ & + b_5 * tests_i + b_6 * median\ age\\ & + b_7 * race\ ratio + b_8 * PCI.\end{aligned} \tag{8}$$

We also make use of two nonlinear models (labeled as models 2 and 3), in which we consider all pairwise and/or triplewise interactions between variables in (8). Comparing these models in Table 9, we observe that performance measures are not unanimous in favoring one model. For example, model 1 results in better Bayesian information criterion values, whereas model 3 yields better Akaike information criterion and log likelihood values. Because of its simplicity and its quality that is fairly comparable with models 2 and 3, we select model 1 in order to perform our simulation analyses (see Section 3.3). From Table 10, we observe that increasing the intensity and duration of lockdown policies as well as

Table 7. Summary of Estimated SEIRS Parameters

State	$N(0)^{a}$	μ^{b}	ν^{b}	$e_0{}^{a}$	$\beta_0{}^{c}$	$\beta_1{}^{c}$	$\beta_2{}^{c}$	$\beta_3{}^{c}$	σ^{d}	$\gamma_S{}^{e}$	ξ^{f}
Alabama	4,849,377	1.18	1.11	$(0.75,2.67)*10^{3}$	(0.35,5.14)	(0.64,5.56)	(1.06,10.16)	(0.70,6.31)	(6.77,18.78)	(1.96,4.66)	(0.28,0.52)
Alaska	736,732	1.36	0.65	$(10^{-6},221.56)$	(4.66,17.84)	$(10^{-6},5.93)$	$(10^{-6},4.88)$	—	(4.07,13.42)	(2.56,5.55)	(0.26,0.49)
Arizona	6,731,484	1.22	0.90	$(1.18,3.50)*10^{3}$	(1.52,6.03)	(1.64,9.08)	(2.52,10.92)	(0.18,4.99)	(4.01,13.86)	(1.93,4.32)	(0.27,0.50)
Arkansas	2,966,369	1.24	1.06	$(0.15,0.38)*10^{3}$	(9.10,23.47)	(1.72,7.65)	—	—	(2.02,7.79)	(2.11,3.79)	(0.27,0.49)
California	38,802,500	1.19	0.73	$(9.03,43.54)*10^{3}$	(3.52,12.83)	$(10^{-6},5.28)$	—	—	(3.43,13.90)	(2.02,3.84)	(0.27,0.49)
Colorado	5,355,866	1.21	0.73	$(5.22,10.30)*10^{3}$	(3.28,10.10)	(0.86,3.91)	(0.10,1.86)	—	(5.68,17.59)	(2.25,5.48)	(0.27,0.49)
Connecticut	3,590,886	0.96	0.87	$(5.61,23.05)*10^{3}$	(7.24,21.67)	$(10^{-6},3.05)$	$(10^{-6},1.59)$	—	(3.01,11.78)	(1.88,3.85)	(0.27,0.50)
Delaware	935,614	1.14	1.01	$(0.67,3.11)*10^{3}$	(5.75,12.98)	(0.10,1.75)	(0.07,0.11)	—	(3.45,13.36)	(2.05,3.81)	(0.26,0.49)
District of Columbia	658,893	1.44	0.86	$(0.45,1.64)*10^{3}$	(6.58,21.57)	$(10^{-6},4.19)$	$(10^{-6},3.31)$	—	(3.78,13.60)	(2.06,3.98)	(0.27,0.50)
Florida	19,893,297	1.11	1.06	$(0.87,5.51)*10^{3}$	(4.01,15.57)	(1.00,4.59)	(0.90,6.29)	—	(4.66,16.64)	(2.26,5.72)	(0.26,0.48)
Georgia	10,097,343	1.27	0.86	$(3.18,7.87)*10^{3}$	(3.73,17.02)	(1.39,5.94)	(0.12,2.97)	—	(4.94,16.35)	(2.43,5.83)	(0.26,0.49)
Hawaii	1,431,603	1.18	0.90	$(0.41,1.31)*10^{2}$	(0.12,7.78)	$(10^{-6},5.68)$	$(10^{-6},2.36)$	—	(14.41,21.64)	(5.98,7.51)	(0.27,0.50)
Idaho	1,654,930	1.34	0.80	$(0.15,3.48)*10^{3}$	(8.29,23.84)	$(10^{-6},2.98)$	$(10^{-6},3.10)$	—	(6.92,17.66)	(3.70,6.87)	(0.27,0.49)
Illinois	12,859,995	1.12	0.86	$(9.55,31.70)*10^{3}$	(3.57,21.38)	(0.01,4.51)	(0.11,2.06)	—	(3.67,11.33)	(2.02,3.67)	(0.27,0.50)
Indiana	6,596,855	1.22	0.94	$(5.45,14.09)*10^{3}$	(0.87,4.50)	(0.90,8.81)	(0.58,2.30)	—	(3.98,14.54)	(2.41,5.79)	(0.26,0.49)
Iowa	3,107,126	1.21	0.93	$(0.95,2.26)*10^{3}$	(1.31,5.94)	(2.86,9.80)	$(10^{-6},2.59)$	—	(3.70,13.43)	(2.01,4.78)	(0.26,0.49)
Kansas	2,904,021	1.22	0.87	$(0.19,0.59)*10^{3}$	(5.07,20.71)	$(10^{-6},4.80)$	$(10^{-6},4.92)$	—	(5.45,16.68)	(2.87,6.33)	(0.27,0.50)
Kentucky	4,425,092	1.21	1.04	$(0.44,3.02)*10^{3}$	(3.84,19.44)	(0.85,3.59)	—	—	(2.84,12.45)	(2.06,3.48)	(0.27,0.50)
Louisiana	4,649,676	1.26	1.00	$(6.10,20.44)*10^{3}$	(3.29,18.65)	$(10^{-6},3.54)$	$(10^{-6},3.58)$	—	(4.15,14.81)	(2.17,4.99)	(0.27,0.50)
Maine	1,330,089	0.91	1.08	$(0.93,3.81)*10^{2}$	(1.81,10.03)	(0.89,10.96)	$(10^{-6},4.01)$	$(10^{-6},8.35)$	(3.51,13.68)	(1.99,4.60)	(0.27,0.50)
Maryland	5,976,407	1.17	0.86	$(4.31,17.54)*10^{3}$	(1.62,12.88)	(0.33,3.39)	(0.74,3.97)	—	(5.44,17.07)	(2.25,5.29)	(0.27,0.50)
Massachusetts	6,794,422	1.04	0.86	$(23.34,46.21)*10^{3}$	(4.00,18.14)	(0.90,2.46)	(0.71,2.73)	—	(3.82,15.34)	(1.97,4.96)	(0.26,0.48)
Michigan	9,909,877	1.11	0.97	$(10.58,20.57)*10^{3}$	(3.97,18.37)	$(10^{-6},1.85)$	$(10^{-6},0.44)$	—	(4.94,16.03)	(1.98,3.92)	(0.25,0.47)
Minnesota	5,489,594	1.23	0.79	$(0.56,5.06)*10^{3}$	(1.30,5.27)	(4.27,9.30)	(0.21,2.27)	—	(3.73,12.37)	(2.10,4.25)	(0.26,0.49)
Mississippi	2,994,079	1.20	1.05	$(0.44,3.98)*10^{3}$	(4.44,16.36)	(1.43,7.05)	(1.85,7.67)	—	(4.53,16.24)	(2.98,6.90)	(0.27,0.48)
Missouri	6,083,672	1.17	0.99	$(0.63,4.52)*10^{3}$	(3.22,14.23)	(1.76,7.44)	(1.18,4.87)	—	(5.08,16.20)	(2.75,6.49)	(0.27,0.50)
Montana	1,023,579	1.14	0.96	$(0.23,1.47)*10^{2}$	(2.25,10.21)	(1.82,5.11)	(0.16,3.75)	$(10^{-6},3.67)$	(4.37,16.03)	(2.93,6.26)	(0.27,0.50)
Nebraska	1,881,503	1.35	0.83	$(0.12,0.42)*10^{3}$	(4.46,12.70)	(3.81,10.58)	(3.47,10.31)	$(10^{-6},5.02)$	(4.64,15.99)	(1.96,3.94)	(0.27,0.50)
Nevada	2,839,099	1.27	0.90	$(0.78,3.09)*10^{3}$	(4.50,15.01)	(0.17,3.10)	$(10^{-6},1.77)$	—	(5.69,17.92)	(2.12,5.86)	(0.26,0.47)
New Hampshire	1,326,813	0.91	0.91	$(0.08,14.28)*10^{2}$	(7.06,18.34)	(0.16,3.00)	(0.18,1.73)	—	(3.40,13.06)	(2.00,3.47)	(0.27,0.51)
New Jersey	8,944,469	1.11	0.85	$(37.94,51.73)*10^{3}$	(6.64,18.05)	(0.38,2.26)	—	—	(3.70,15.42)	(2.21,3.00)	(0.27,0.49)
New Mexico	2,085,572	1.11	0.88	$(0.61,1.98)*10^{3}$	(4.20,17.83)	(0.19,5.58)	(0.05,2.87)	—	(4.06,10.12)	(2.08,4.74)	(0.27,0.50)
New York	19,746,227	1.13	0.84	$(3.90,14.53)*10^{4}$	(7.96,22.56)	(0.20,2.14)	(0.01,1.66)	—	(4.15,14.71)	(2.28,4.71)	(0.26,0.49)
North Carolina	10,042,802	1.19	0.94	$(0.56,4.50)*10^{3}$	(4.26,15.44)	(1.95,5.43)	(0.26,4.68)	—	(4.59,16.17)	(2.10,5.51)	(0.27,0.48)
North Dakota	756,927	1.39	0.83	$(0.45,3.57)*10^{2}$	(1.61,3.65)	(4.68,12.74)	(0.02,1.52)	—	(4.13,12.77)	(2.47,5.89)	(0.27,0.51)
Ohio	11,594,163	1.16	1.02	$(4.57,11.31)*10^{3}$	(4.78,14.97)	(0.38,4.37)	(0.81,5.00)	—	(4.02,14.64)	(2.20,5.60)	(0.26,0.49)
Oklahoma	3,878,051	1.26	1.04	$(0.61,3.17)*10^{3}$	(4.22,16.24)	(0.28,3.45)	(0.01,1.87)	—	(5.08,16.20)	(2.75,6.49)	(0.27,0.50)
Oregon	3,970,239	1.09	0.92	$(0.34,1.71)*10^{3}$	(3.51,14.12)	(0.14,5.97)	(0.40,5.60)	—	(4.14,15.52)	(2.89,6.58)	(0.26,0.49)
Pennsylvania	12,787,209	1.06	1.04	$(5.69,21.37)*10^{3}$	(7.19,20.02)	(0.25,3.98)	(0.03,2.91)	—	(4.05,12.97)	(2.48,6.09)	(0.26,0.49)
Rhode Island	1,056,298	0.99	0.93	$(0.37,1.19)*10^{3}$	(8.47,20.21)	(0.23,5.42)	(0.08,2.41)	—	(6.40,18.00)	(2.04,4.66)	(0.26,0.50)
South Carolina	4,896,146	1.15	1.04	$(0.59,1.54)*10^{3}$	(6.79,17.41)	(0.14,2.20)	(3.24,8.76)	—	(4.02,14.71)	(2.28,6.15)	(0.27,0.50)
South Dakota	858,469	1.39	0.86	$(10^{-6},223.95)$	(8.97,20.15)	(0.41,4.96)	(3.20,9.48)	—	(5.82,18.47)	(1.97,4.54)	(0.27,0.50)
Tennessee	6,549,352	1.23	1.04	$(0.31,1.19)*10^{3}$	(5.54,17.44)	(0.07,5.78)	(1.52,9.07)	—	(5.85,17.55)	(2.60,6.53)	(0.26,0.48)
Texas	26,956,958	1.41	0.75	$(4.21,11.11)*10^{3}$	(3.66,9.14)	(2.72,8.67)	(1.75,7.05)	—	(5.23,15.70)	(2.39,6.45)	(0.27,0.49)

Table 7. (Continued)

State	$N(0)^a$	μ^b	ν^b	e_0^a	β_0^c	β_1^c	β_2^c	β_3^c	σ^d	γ_S^e	ξ^f
Utah	2,942,902	1.65	0.59	$(0.16,1.23)*10^3$	(1.01,5.81)	(3.15,8.73)	(2.90,7.66)	—	(5.40,17.49)	(2.42,6.13)	(0.26,0.49)
Vermont	626,562	0.89	0.90	$(1.28,3.57)*10^2$	(4.26,19.29)	(0.02,1.04)	—	—	(3.69,13.69)	(1.93,4.01)	(0.27,0.50)
Virginia	8,326,289	1.18	0.84	$(0.31,5.35)*10^3$	(5.67,19.15)	(0.51,5.65)	—	—	(4.50,14.61)	(2.03,3.86)	(0.27,0.50)
Washington	7,061,530	1.25	0.83	$(1.23,3.17)*10^2$	(5.97,17.90)	(0.04,3.13)	(0.02,1.46)	—	(5.01,17.72)	(2.06,4.11)	(0.27,0.50)
West Virginia	1,844,128	0.97	1.22	$(1.63,6.44)*10^2$	(5.34,19.78)	(0.13,3.85)	(0.01,2.45)	—	(5.13,15.74)	(3.32,6.85)	(0.27,0.50)
Wisconsin	5,771,337	1.10	0.87	$(1.05,6.21)*10^3$	(10^{-6},10.45)	(10^{-6},5.61)	(0.02,1.55)	—	(3.60,13.51)	(2.09,4.76)	(0.26,0.47)
Wyoming	584,153	1.13	0.85	$(0.18,1.36)*10^2$	(6.02,18.15)	(2.00,7.80)	(0.03,2.63)	—	(5.96,18.53)	(4.16,7.23)	(0.26,0.48)

State	p_S^a	λ_H^c	λ_1^c	λ_2^c	ϕ_1^b	ϕ_2^b	ϕ_3^b	LOS_1^g	LOS_2^g	LOS_3^g
Alabama	(12.97,74.13)	(0.12,0.32)	(47.63,87.33)	(10^{-6},0.93)	(0.32,0.67)	(0.52,2.68)	(1.96,5.14)	(4.81,9.10)	(6.77,11.02)	(10.1,18.82)
Alaska	(13.30,69.02)	(0.77,10.74)	(50.66,95.71)	(10^{-6},2.75)	(10^{-6},0.96)	(10^{-6},1.87)	(10^{-6},4.22)	(5.05,9.37)	(6.91,11.24)	(10.02,18.69)
Arizona	(14.41,66.80)	(1.78,5.92)	(47.44,84.77)	(10^{-6},0.78)	(0.02,0.35)	(0.30,1.03)	(2.67,5.51)	(5.19,9.61)	(6.94,11.26)	(10.24,18.86)
Arkansas	(13.11,59.94)	(10^{-6},5.14)	(45.22,79.38)	(10^{-6},1.09)	(10^{-6},0.09)	(10^{-6},0.86)	(10^{-6},8.71)	(4.94,9.07)	(6.92,11.23)	(10.40,18.89)
California	(14.66,74.08)	(0.77,11.16)	(46.46,79.41)	(10^{-6},1.04)	(10^{-6},0.22)	(10^{-6},0.48)	(10^{-6},4.97)	(4.81,8.89)	(6.81,11.02)	(10.53,19.05)
Colorado	(13.92,67.90)	(10^{-6},8.42)	(45.98,77.98)	(10^{-6},0.19)	(0.07,1.41)	(0.12,3.55)	(3.67,13.17)	(4.83,9.06)	(6.91,11.19)	(10.31,18.93)
Connecticut	(13.06,69.81)	(10^{-6},9.70)	(44.55,75.87)	(10^{-6},1.27)	(10^{-6},5.53)	(10^{-6},8.40)	(10^{-6},31.36)	(4.92,9.11)	(6.97,11.19)	(10.63,18.97)
Delaware	(12.36,69.51)	(0.56,7.66)	(45.41,80.62)	(10^{-6},6.95)	(10^{-6},0.16)	(10^{-6},0.31)	(10^{-6},9.72)	(4.83,8.85)	(6.80,11.08)	(10.80,19.25)
District of Columbia	(17.22,72.45)	(2.53,7.65)	(46.01,77.35)	(10^{-6},3.68)	(10^{-6},1.24)	(10^{-6},2.68)	(0.51,8.16)	(4.94,9.19)	(6.90,11.21)	(10.50,19.22)
Florida	(14.95,72.25)	(10^{-6},1.02)	(45.55,77.74)	(10^{-6},1.66)	(0.04,0.60)	(0.57,1.20)	(2.00,9.54)	(4.75,8.70)	(6.94,11.23)	(10.16,18.54)
Georgia	(12.96,53.69)	(10^{-6},4.16)	(46.09,82.58)	(10^{-6},1.28)	(10^{-6},2.11)	(10^{-6},4.23)	(10^{-6},16.52)	(4.96,9.27)	(6.97,11.24)	(10.33,18.86)
Hawaii	(13.44,58.36)	(10^{-6},0.52)	(48.52,89.56)	(10^{-6},0.49)	(0.02,0.31)	(0.21,0.92)	(0.75,5.45)	(4.84,8.90)	(6.99,11.29)	(9.50,17.86)
Idaho	(13.09,71.65)	(10^{-6},0.66)	(51.41,94.23)	(10^{-6},3.34)	(1.15,1.27)	(2.41,7.79)	(7.75,15.87)	(4.84,8.97)	(6.88,11.15)	(9.69,17.91)
Illinois	(11.48,57.86)	(10^{-6},12.46)	(45.5,76.99)	(10^{-6},1.40)	(10^{-6},1.88)	(10^{-6},3.48)	(10^{-6},9.58)	(4.78,8.66)	(6.87,11.04)	(10.61,19.07)
Indiana	(14.45,74.94)	(10^{-6},8.38)	(45.26,81.77)	(10^{-6},0.58)	(0.14,0.23)	(0.31,1.64)	(2.64,10.77)	(4.94,9.07)	(7.15,11.42)	(10.64,19.01)
Iowa	(15.71,76.67)	(10^{-6},12.56)	(46.05,83.30)	(10^{-6},1.95)	(0.63,3.96)	(2.48,7.87)	(3.30,16.63)	(4.77,8.85)	(6.86,11.18)	(10.70,19.22)
Kansas	(11.29,69.32)	(10^{-6},0.78)	(46.91,83.50)	(10^{-6},2.59)	(0.74,2.01)	(0.53,5.92)	(1.41,12.24)	(4.88,9.15)	(6.84,10.99)	(10.48,19.09)
Kentucky	(13.00,63.80)	(10^{-6},13.85)	(45.84,82.29)	(10^{-6},1.80)	(10^{-6},0.15)	(10^{-6},0.50)	(10^{-6},9.22)	(4.93,9.00)	(6.76,11.04)	(10.27,18.88)
Louisiana	(11.08,68.34)	(10^{-6},10.59)	(46.27,80.05)	(10^{-6},1.29)	(10^{-6},0.57)	(10^{-6},3.11)	(10^{-6},11.91)	(4.92,9.11)	(6.88,11.10)	(10.34,19.06)
Maine	(14.99,71.10)	(0.79,5.37)	(47.72,86.84)	(10^{-6},0.81)	(0.04,0.72)	(0.06,0.95)	(0.21,3.57)	(4.86,9.23)	(6.76,11.06)	(10.78,19.09)
Maryland	(12.70,65.26)	(10^{-6},6.22)	(45.9,80.22)	(10^{-6},1.50)	(0.03,0.62)	(0.73,1.21)	(2.56,9.50)	(4.81,8.83)	(6.89,11.08)	(10.33,19.03)
Massachusetts	(15.59,61.59)	(10^{-6},8.98)	(46.60,74.30)	(10^{-6},1.44)	(0.10,1.19)	(0.14,4.30)	(2.30,14.08)	(4.85,8.86)	(6.89,11.13)	(10.02,18.18)
Michigan	(12.75,73.61)	(10^{-6},8.94)	(47.22,84.63)	(10^{-6},0.59)	(0.27,1.44)	(0.48,3.02)	(6.40,16.60)	(4.92,8.95)	(6.82,10.90)	(10.06,18.51)
Minnesota	(11.55,60.88)	(10^{-6},8.25)	(46.64,84.29)	(10^{-6},1.98)	(0.19,2.30)	(0.23,6.43)	(4.89,17.69)	(4.73,8.80)	(6.93,11.12)	(10.32,18.70)
Mississippi	(12.12,69.38)	(10^{-6},10.63)	(45.44,77.72)	(10^{-6},0.83)	(0.04,0.41)	(0.18,0.80)	(2.19,6.49)	(4.90,9.11)	(7.02,11.41)	(11.08,19.54)
Missouri	(19.08,79.39)	(0.50,4.66)	(45.51,80.73)	(10^{-6},0.74)	(10^{-6},0.13)	(10^{-6},0.44)	(0.59,4.95)	(4.75,8.43)	(6.90,10.99)	(10.61,19.30)
Montana	(11.95,64.38)	(1.85,7.75)	(50.57,93.05)	(10^{-6},1.17)	(0.04,0.51)	(0.42,1.52)	(2.73,12.15)	(4.65,8.49)	(6.94,11.21)	(9.29,16.93)
Nebraska	(12.21,72.35)	(10^{-6},11.90)	(48.76,88.48)	(10^{-6},2.78)	(0.03,0.42)	(0.36,1.03)	(1.53,7.63)	(4.96,9.01)	(6.94,11.17)	(9.95,18.41)
Nevada	(14.38,73.37)	(10^{-6},12.70)	(45.8,76.33)	(10^{-6},1.75)	(0.02,0.34)	(10^{-6},0.25)	(1.36,3.26)	(4.92,8.99)	(6.88,11.21)	(10.70,19.35)
New Hampshire	(11.1,65.64)	(10^{-6},5.64)	(45.57,78.65)	(10^{-6},7.63)	(10^{-6},0.31)	(10^{-6},2.90)	(10^{-6},8.62)	(4.78,8.91)	(6.85,11.08)	(10.47,18.83)
New Jersey	(11.65,67.36)	(0.85,6.87)	(45.96,76.38)	(10^{-6},0.20)	(10^{-6},0.98)	(10^{-6},3.28)	(2.38,17.13)	(4.86,9.07)	(6.89,11.09)	(10.15,18.73)
New Mexico	(14.01,69.86)	(10^{-6},5.22)	(45.41,80.56)	(10^{-6},3.72)	(10^{-6},0.20)	(10^{-6},2.63)	(10^{-6},11.39)	(4.67,8.63)	(6.91,11.22)	(10.87,19.37)
New York	(16.20,67.48)	(10^{-6},7.65)	(45.74,78.03)	(10^{-6},1.76)	(10^{-6},0.71)	(10^{-6},2.20)	(3.69,12.19)	(4.91,9.12)	(6.89,11.19)	(11.10,19.38)
North Carolina	(13.35,69.05)	(10^{-6},7.54)	(45.45,80.85)	(10^{-6},0.70)	(10^{-6},0.34)	(10^{-6},0.66)	(1.84,8.74)	(5.19,9.32)	(6.86,11.07)	(10.86,19.24)
North Dakota	(14.12,67.79)	(10^{-6},6.88)	(48.64,91.71)	(10^{-6},0.42)	(0.22,0.38)	(0.17,0.44)	(2.66,9.59)	(5.02,9.28)	(6.99,11.39)	(10.39,19.05)

Table 7. (Continued)

State	p_S[a]	λ_H[c]	λ_1[c]	λ_2[c]	ϕ_1[b]	ϕ_2[b]	ϕ_3[b]	LOS_1[g]	LOS_2[g]	LOS_3[g]
Ohio	(13.82,57.80)	(10^{-6},6.03)	(46.43,84.30)	(10^{-6},0.14)	(0.49,0.96)	(0.07,2.24)	(1.57,10.97)	(4.74,8.73)	(6.95,11.28)	(10.30,18.75)
Oklahoma	(19.08,79.39)	(0.09,1.66)	(45.51,80.73)	(10^{-6},0.74)	(10^{-6},0.13)	(10^{-6},1.44)	(0.59,8.15)	(4.75,8.43)	(6.90,10.99)	(10.61,19.30)
Oregon	(15.00,58.95)	(8.27,22.49)	(47.33,87.43)	(10^{-6},3.44)	(10^{-6},0.20)	(10^{-6},0.31)	(10^{-6},7.22)	(5.20,9.50)	(6.88,11.10)	(9.73,18.41)
Pennsylvania	(15.24,51.58)	(10^{-6},6.82)	(45.26,85.33)	(10^{-6},0.48)	(0.33,0.67)	(0.15,3.47)	(1.69,8.55)	(4.61,8.48)	(6.84,11.04)	(10.17,18.63)
Rhode Island	(12.32,60.51)	(10^{-6},6.83)	(47.46,84.58)	(10^{-6},3.70)	(10^{-6},0.29)	(10^{-6},1.44)	(4.83,18.51)	(4.91,8.96)	(6.75,10.86)	(10.44,18.61)
South Carolina	(12.14,65.74)	(10^{-6},6.22)	(45.3,80.72)	(10^{-6},0.35)	(10^{-6},0.41)	(10^{-6},0.63)	(0.49,8.65)	(4.94,9.22)	(6.82,10.98)	(10.96,19.55)
South Dakota	(16.81,75.45)	(10^{-6},16.98)	(51.63,94.44)	(10^{-6},1.14)	(10^{-6},0.17)	(10^{-6},0.52)	(10^{-6},6.44)	(4.85,9.09)	(6.73,10.81)	(9.79,18.15)
Tennessee	(14.55,72.11)	(10^{-6},1.10)	(46.13,82.04)	(10^{-6},0.89)	(0.02,0.24)	(0.76,1.22)	(1.92,6.00)	(4.79,9.06)	(6.75,10.91)	(9.81,18.37)
Texas	(14.44,55.98)	(2.58,3.52)	(44.58,82.21)	(10^{-6},1.25)	(0.38,0.69)	(0.16,0.28)	(0.79,6.48)	(4.98,9.17)	(6.96,11.12)	(10.61,19.30)
Utah	(12.62,64.50)	(10^{-6},9.45)	(48.72,92.7)	(10^{-6},0.13)	(10^{-6},0.28)	(10^{-6},0.61)	(0.22,4.83)	(4.94,9.31)	(6.99,11.33)	(10.38,18.92)
Vermont	(14.80,70.65)	(10^{-6},14.53)	(50.06,92.23)	(10^{-6},1.54)	(10^{-6},0.57)	(10^{-6},4.83)	(10^{-6},12.54)	(4.93,9.13)	(6.94,11.24)	(10.19,18.49)
Virginia	(12.39,67.52)	(10^{-6},9.65)	(45.06,75.78)	(10^{-6},4.17)	(10^{-6},0.18)	(10^{-6},0.70)	(10^{-6},6.69)	(4.81,8.90)	(6.83,11.08)	(10.45,19.00)
Washington	(14.38,59.54)	(10^{-6},6.76)	(45.79,83.03)	(10^{-6},2.59)	(10^{-6},0.55)	(10^{-6},1.97)	(1.62,9.38)	(4.87,9.08)	(6.99,11.30)	(10.47,19.06)
West Virginia	(13.51,70.88)	(10^{-6},16.50)	(47.88,87.97)	(10^{-6},8.63)	(10^{-6},1.02)	(10^{-6},2.18)	(10^{-6},6.44)	(4.98,9.34)	(7.03,11.28)	(10.29,18.89)
Wisconsin	(13.37,66.74)	(10^{-6},11.73)	(45.93,85.75)	(10^{-6},0.43)	(10^{-6},0.53)	(10^{-6},0.88)	(10^{-6},6.42)	(4.69,8.60)	(6.87,11.06)	(11.11,19.63)
Wyoming	(15.12,63.78)	(10^{-6},11.42)	(49.62,90.28)	(10^{-6},1.69)	(10^{-6},1.17)	(10^{-6},1.12)	(10^{-6},3.50)	(4.99,9.25)	(6.72,10.95)	(10.23,18.75)

Notes. The unit for all rates is 1/100 days (or %/day) (except μ/ν). Values in (…) represent 95% confidence intervals (negative values are replaced by 10^{-6}). For brevity, values are shown with two decimal places.

[a]$N(0)$: # initial population, e_0: # initially exposed. p_S: Prob of a symptomatic infection. Prob of an asymptomatic infection: $p_A = 1 - p_S$.

[b]Natural birth and death rates (unit: $1/(100^* \times 365$ days)). ϕ_i: covid-related death rate for index i (for description of index i, see Table 3).

[c]β_i's: Disease transmission rates in different time frames. β_0: baseline transmission rate (when there is no-intervention). "—" implies no time frame (no transmission rate). λ_H: rate of hospitalization. λ_1: rate of hospitalization with a common bed. λ_2: rate of hospitalization with an ICU bed. Rate of hospitalization with an ICU bed and a ventilator: $\lambda_3 = 1 - (\lambda_1 + \lambda_2)$.v

[d]Infection rate postexposure.

[e]Recovery rate for infected symptomatic. Recovery rate for infected asymptomatic: $\gamma_A = \gamma_S +$ Random Uniform[10, 20]; that is, asymptomatic ones are reported to take between 5 and 10 fewer days to recover compared with symptomatic ones (Centers for Disease Control and Prevention 2022).

[f]Immunity waning rate. In the absence of treatments, the waning period takes $1/\xi$ days. For example, for $\xi = 0.5\%$, this period lasts 1,000/5 = 200 days.

[g]LOS_i: hospital length of stay (in days) for index i.

Table 8. Summary of Notations for the Mixed-Effect Regression Models

β_0	Baseline transmission rate (when there is no intervention)[a]
β_i	Disease transmission rate when there is a policy intervention in time frame i (unique under each policy)[a]
$policy_i$	Intervention policy in time frame i, $p_i \in \{0,3,2,1\}$ (i.e., categorical variable)[b]
	$p_i = 0$: no-intervention policy
	$p_i = 3$: three lockdown policies in time frame i (stay-at-home order, large-gatherings ban, and school closures)
	$p_i = 2$: two lockdown policies in time frame i (large-gatherings ban and school closures)
	$p_i = 1$: one lockdown policy in time frame i (school closures)
$duration_i$	Duration of time frame i under the current policies[c]
$mobility_i^1$	Average rate of mobility in time frame i (within 1 mile from home)[d]
$mobility_i^2$	Average rate of mobility in time frame i (within 1 and 10 miles from home)[d]
$tests_i$	Average number of daily tests in in time frame i[e]
median age	Median age in each state[d]
race ratio	Ratio of state's population with Black or Hispanic race[d]
PCI	Average per capita income in each state[d]

[a]For estimations of β_0 and β_is, see Table 7.
[b]Order of intervention policies is set as $0 \to 3 \to 2 \to 1$.
[c]Obtained from information in Table 2.
[d]Information presented in Table 5. Also, to avoid collinearity, we do not consider mobility rates of more than 10 miles from home.
[e]Obtained from the Star Schema data (Foldi and Csefalvay 2020).

Table 9. Performance Measures for the Mixed-Effect Regression Models

Model	Akaike information criterion	Bayesian information criterion	Log likelihood
1	771.62	810.04	−372.81
2	790.95	944.66	−343.48
3	728.11	1,005.96	−270.06

number of daily tests is associated with more reductions in transmission rates (statistically significant). Furthermore, increasing per capita income and reducing the ratio of Black/Hispanic populations could also potentially improve the transition rates, but we do not observe any statistically significant results in this regard. Finally, our estimated coefficients presented in Table 10 indicate that increasing the mobility rate within 10 miles from home (compared with the distance beyond that) can positively impact reductions in transmission rates. However, our results do not provide any statistically significant evidence on this potential impact of mobility.

Because mobility, race ratio, and per capita income have large P-values, the predicted difference in disease transmission rates could have large variance when analyzed over these specific covariates. This can be caused, for example, by the relatively large standard error of the estimated coefficients for these three covariates. However, this is not the case for the other covariates in Table 10. Overall, our results in Online Appendix C.7 show that our estimates for disease transmission rates are fairly robust and not sensitive to potential misestimations (see Online Appendix C. 7 for more details).

3.2.1. Endogenous Transmission Rates and Costs. As mentioned earlier, we aim to compare our proposed policies and the current policies with a hypothetical no-intervention scenario. There is empirical evidence in the literature that, even without societal interventions, people would not have endangered themselves and taken the risk of going out (see, e.g., Abouk and Heydari 2021). This implies that the transmission rate would naturally decline based on the risk perception about the negative outcomes of the pandemic in the population (e.g., number of infections, hospitalizations, or deaths). This results in the transmission rate under the no-intervention policy to be endogenous.[3] For each state separately, we accommodate this

Table 10. Results of Mixed-Effect Model (8)

Variable[a]	Estimate, %	Standard error, %	t-value	P-value
Intercept	−10.128	6.137	−1.650	0.1054
$policy_i: 0 \to 3$	5.463	1.555	3.514	0.0007***
$policy_i: 0 \to 3 \to 2$	5.945	0.775	7.671	< .00001***
$policy_i: 0 \to 3 \to 2 \to 1$	5.761	1.153	4.996	< .00001***
$duration_i$	2.541	1.510	1.683	0.0953$^+$
$mobility_i^1$	3.190	8.842	0.361	0.7189
$mobility_i^2$	19.28	14.74	1.308	0.1959
$tests_i$	7.335	2.896	2.533	0.0129*
median age	4.468	2.760	1.619	0.1125
race ratio	−0.195	3.595	−0.054	0.9573
per capita income	0.069	2.120	0.033	0.9738

Note. Results are obtained by the "lmer" function in the R computing package.
[a]For notations, see Table 8.
Significance: ***0.001, **0.01, *0.05, $^+$0.1.

endogeneity as follows:

$$\hat{\beta}_0 = \beta_0 + \alpha \times \frac{\bar{I}}{\text{state's population}} \quad \text{for} \quad \alpha \leq 0, \tag{9}$$

where $\hat{\beta}_0$ is the new transmission rate under no intervention, β_0 is the baseline transmission rate that we already estimate (see Table 7), α is an exogenous parameter that characterizes the level of risk perception, and $\bar{I}$ is the daily average number of infections under no intervention (this is obtained from the SEIRS model). As can be seen from (9), $\hat{\beta}_0$ is modeled endogenously because it decreases as the number of infections increases. Furthermore, the amount of decrease depends on the level of risk perception, α.[4]

In addition to considering an endogenous disease transition rate, we also account for the endogenous cost of staying home because of the perception that attending work might cause infection even though there is no government policy intervention (e.g., a stay-at-home order). We measure this by $\sum_{t=1}^{T}\sum_{i=1}^{11} X_i(t) \times mobility_1 \times \xi \times \mathrm{PCI} \times \eta$, where the first factor denotes the total number of people alive during the time horizon, the second factor is the percentage of people who stay home (we account for this via the rate of residents' mobility within < 1 mile from their home), ξ is an exogenous parameter that represents the percentage of people who would lose income when staying home, and $\mathrm{PCI} \times \eta$ is the per capita income adjusted by the population's employment rate. For the no-intervention policy, we add this cost to the corresponding direct and indirect costs measured by Equations (3)–(5b). In our robustness checks, we perform various sensitivity analyses on the aforementioned parameters and evaluate their impact.

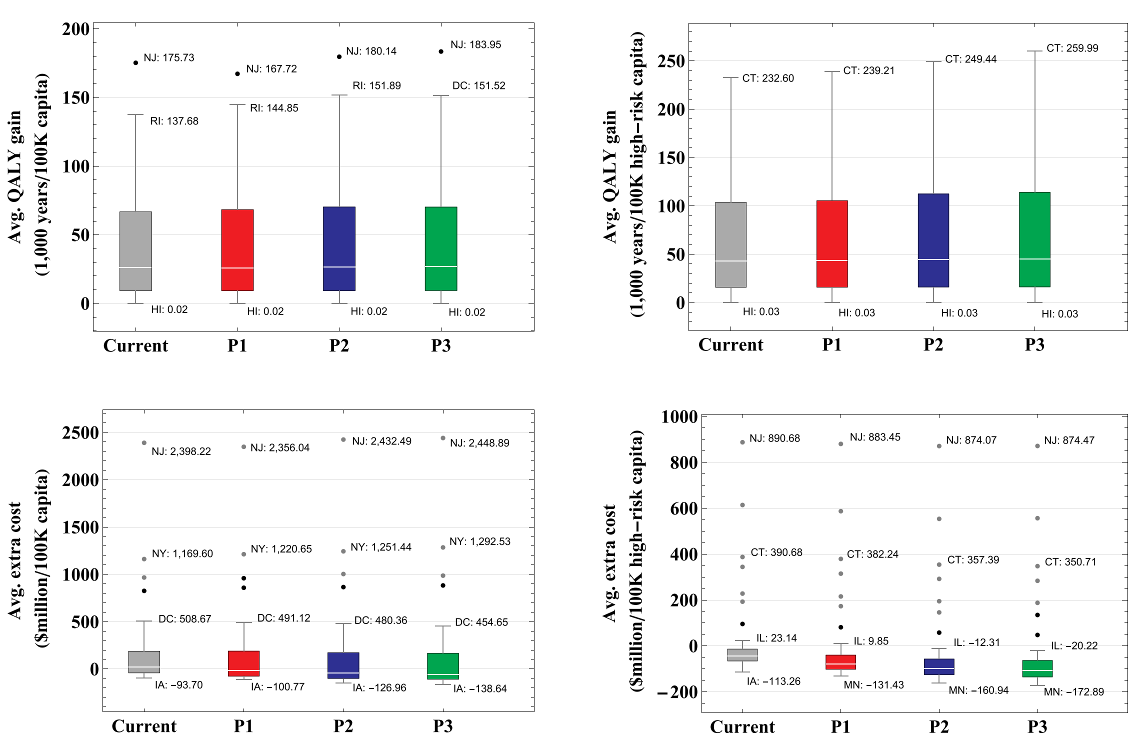
3.3. Comparison of Intervention Policies

3.3.1. Microsimulation Model. We compare the performance of the current policies and our counterfactual policies in each state against a hypothetical no-intervention benchmark. We make this comparison based on the total QALY accrued and total costs incurred throughout the time horizon of March 1 through June 30, 2020. To account for variations in the estimated values of various parameters for each state, we iterate our calculations of the QALY and the cost obtained under each policy 10,000 times. The details of this microsimulation model are provided in Online Appendix D.1.

3.3.2. QALY and Cost Comparisons. We now analyze the total QALY accrued and the total cost incurred for each state under various policies and report these measures per 100K capita. Figure 2 shows the results, based on which we make the following observation.

Observation 1. Compared with no intervention during March–June 2020, the average increase in the total

Figure 2. Distribution of Average Outcomes Across States



Notes. Outcomes are obtained when comparing intervention policies with no intervention. Current: the current policies undertaken in each state during the timeline of our study. See Table 4 for intervention policies P1/P2/P3. Complete results for each state are provided in Online Appendix D.3.

QALY and cost per 100K capita across the U.S. states is

i. 41,284.51 years and \$164.01 million under the current policy.
ii. 42,178.04 years and \$141.05 million under policy 1.
iii. 43,885.49 years and \$124.25 million under policy 2.
iv. 44,909.41 years and \$117.28 million under policy 3.

Observation 1 reveals that imposing the counterfactual policies we study (policies 1–3) would result in higher total QALY gains and decrease the total cost (compared with the current policy). Of note, the potential policies we study are typically more strict than what states imposed. Hence, these policies are able to better control the spread of the disease and yield improvements in QALY. Moreover, fewer infections implies less cost of quarantining. They also result in fewer hospitalizations, which, in turn, lowers the cost of utilization and potential expansion of beds and ventilators in hospitals. Finally, we observe that more restrictive policies reduce the indirect cost of lost income that is incurred because of deaths. More restrictive policies, however, increase the lost income in the population because they prevent individuals from attending their work and engaging in their daily activities. Overall, combining the positive and negative effects, we find that more strict policies could have reduced the total extra cost.

In addition to the average results, we observe a significant amount of heterogeneity in the QALY gained or extra cost incurred when the same lockdown policy is undertaken across different states. Notably, our results reveal that an improvement in the total QALY or an increase in the total cost is not necessarily proportional to a state's population (see Figure 2). For example, in Michigan, the average QALY gain per 100K capita under policy 1 compared with no intervention is 102,000 years, whereas in New Jersey with about 1 million fewer residents than Michigan, this gain under the same policy is 167,720 years. Similarly, whereas New York and Florida have a similar number of residents, our results show that the impact of imposing policy 2 on QALY and costs compared with no intervention is vastly different for these two states (139,570 years and \$1251.440 million for New York but 12,440 years and −\$97.070 million for Florida).

An important factor that can be associated with these variations in the total QALY and cost across states is the number of infections, hospitalizations, and deaths averted in those states under different lockdown policies. The higher these aversions, the higher the total QALY saved and the lower the cost of utilization or expansion of beds/ventilators and quarantine (see our results in Online Appendix D.5). The ability of lockdown policies to increase these aversions, in turn, depends on various geographic and demographic factors that differ across states. Among all such factors, it is especially important to understand how policies affect the high-risk population within each state. Thus, we next focus our attention on high-risk populations within each state and rerun our analyses for this population.

3.3.3. Impact on High-Risk Population.

It is known that some subpopulations are more susceptible to COVID-19 complications. These include individuals with older age, minority race, diabetes, obesity, cancer, and immunodeficiency (Artiga et al. 2020, Mayo Clinic 2020). As a result, their QALY could be more severely impacted compared with the average population. Furthermore, differences in the percentage of such individuals in states can contribute to the heterogeneous impact of policies we find across states. To gain a better understanding, we now estimate the total QALY saved and the total extra cost under different lockdown policies for subpopulations formed by individuals 65 years or older and with Black/Hispanic race (further details are provided in Online Appendix D.2). Of note, our data does not include more granular information on other risk factors in each state (e.g., cancer and immunodeficiency rates), and hence, we defer analyzing such factors to future research.

Our results related to individuals 65 years or older and with Black/Hispanic race are presented in Figure 2. We make the following observation based on our results.

Observation 2. Among individuals 65 years or older and with Black/Hispanic race compared with no intervention during March–June 2020, the average increase in the total QALY and cost per 100K capita across the U.S. states is

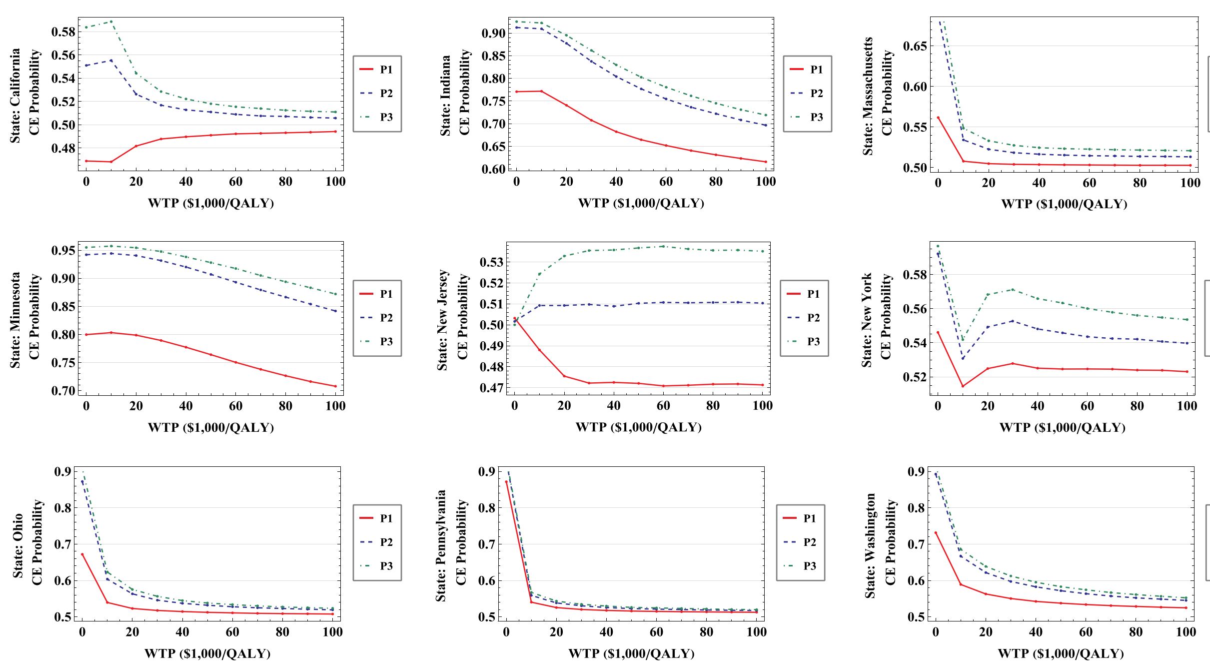
i. 64,185.49 years and \$11.03 million under the current policy.
ii. 65,638.82 years and −\$19.28 million under policy 1.
iii. 67,625.69 years and −\$41.32 million under policy 2.
iv. 69,389.41 years and −\$49.69 million under policy 3.

Observation 2 shows that QALY gain (extra cost) per 100K capita in the high-risk population is higher (lower) than that obtained for the average population (see Observation 1). One reason for this observation is the fact that the number of infections, hospitalizations, and deaths averted under lockdown policies for the high-risk population is also higher than that for the average population. This not only improves the total QALY saved, but also reduces the extra cost incurred by lowering the cost of utilizing/expanding resources (as well as the cost of quarantining). Also, this high-risk population comprises senior people, and hence, the impact of lost income is lower in this group than the average population. We also observe a high variation across states in terms of these outcomes; for example, in Michigan (New Jersey), the average QALY gain per 100K high-risk capita under policy 1 compared with no intervention is 130,950 (212,610) years. Thus, our earlier results that (1) states with a similar total population can see significantly different impacts of the same lockdown policy and (2) the impacts of policies are not necessarily higher in more populous states are likely a result of the differences in the percentage of high-risk population. However, other factors, such as the population density of each state and a variety of sociopolitical differences across states, can also play a role. A deep analysis of such factors is outside the scope of our work, and hence, we leave it to future research to study their effect.

3.3.4. Cost-Effectiveness of Intervention Policies. We make use of Equation (6) and measure the CE of a potential policy compared with the current policy via the probability that ICER ≤ WTP (for more details, see Online Appendix D.1). The higher this probability, the higher the cost-effectiveness of the potential policy compared with the current policy. To gain more insight into the cost-effectiveness of these policies, we consider a range of WTP values between \$0 and \$100K per QALY, which is consistent with the literature (see, e.g., Echazu and Nocetti 2020). Our results in Figure 3 reveal that, within this WTP range, the potential policies we study are typically more cost-effective than the current policies adopted by states. This is expected because our earlier result in Observation 1 shows that more strict policies could improve the QALY saved and incur less extra cost compared with the current policies. We also observe that the potential policies are particularly more attractive when state authorities are less willing to pay to gain one extra year's worth of QALY (e.g., WTP ≤ \$20K compared with WTP > \$20K). This impact, however, is not uniform across states. Specifically, our results show that the cost-effectiveness of the more restrictive policies for low WTP values is much more pronounced in states such as Indiana, Minnesota, Pennsylvania, and Washington than other states such as California, Massachusetts, New Jersey, and New York. This is yet another indication of the heterogeneity of health and economic outcomes across the states.

In closing this section, we emphasize that caution should be exercised in interpreting our cost-effectiveness results. Our findings are based on data from the early stage of this pandemic (March to June 2020). As the pandemic evolves (e.g., as the number of new cases rises, new variants of COVID-19 arrive, and vaccinations become more available), the numbers presented here will change as well. Decision making on what policies to impose, however, has been challenging for authorities, mainly because of a lack of quantitative evidence on health gains versus economic burdens of different lockdown policies. To the best of our knowledge, our findings are among the first to shed light on the heath versus economic impacts of COVID-19 lockdown policies separately for each state, and we hope they could facilitate the decision-making process for COVID-19 and future epi-demics.

Figure 3. Cost-Effectiveness Probability of Potential Policies Compared with Current Policies



Notes. Results for other states are provided in Online Appendix D.4. A drop in the CE probability implies an improvement in the performance of the current policies compared with the potential policies.

3.4. Robustness Checks and Relevant Managerial Implications

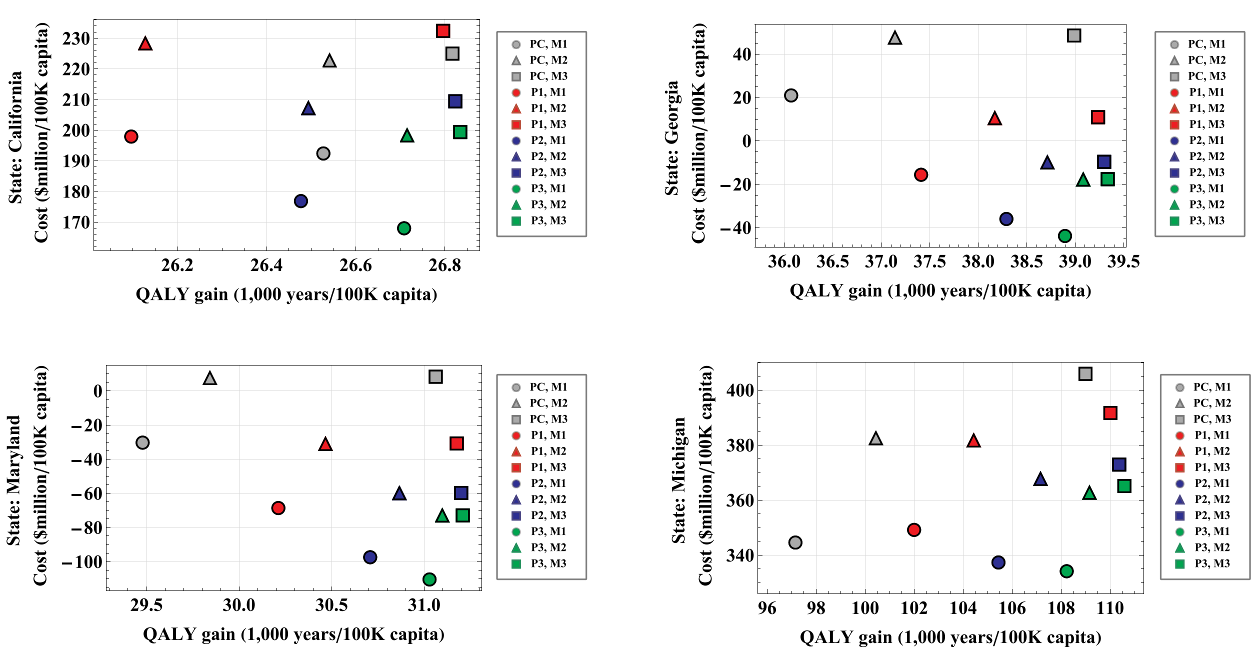
To test the robustness of our main results, we now perform extensive sensitivity analyses on various parameters, including residents' mobility, qol scores and QALY values, the proportion of population losing their income, projected infections, the population level of risk perception (about the negative outcomes of the pandemic), the proportion of individuals who would lose their income when staying home (under no intervention), the proportion of infected individuals who quarantine, and the level of capacity of hospital resources.

3.4.1. Mobility. In our baseline comparisons of policies in Section 3.3, we utilize the actual mobility rates observed from cellphone data separately for each state. Under this actual scenario (referred to as M1, hereafter), the average mobility rates over all states for moving within 1 mile, between 1 and 10 miles, and more than 10 miles from home are about 0.4, 0.3, and 0.3, respectively (see Table 5 for more details). We now consider two hypothetical scenarios: a 10% reduction in movements within 1 mile from home (M2) and no movement beyond 10 miles from home (M3). That is, under M2 and M3, we allow the rates for moving within 1 mile, between 1 and 10 miles, and more than 10 miles from home to be 0.5, 0.3, and 0.2 and 0.5, 0.5, and 0.0, respectively. From the results in Figure 4, we observe that, under any intervention policy, lowering residents' mobility beyond 10 miles from home would increase the total QALY gains (compared with no intervention). This typically comes at the expense of higher extra cost incurred compared with no intervention. However, we also observe that, in states such as New York, reduced mobility would result in lower extra cost. Furthermore, in a consistent fashion across the states, the less strict a lockdown policy, the more improvement in the total QALY gain under that policy when we reduce the residents' mobility beyond 10 miles. These results highlight the importance of individuals' compliance to lockdown policies in managing the pandemic.

3.4.2. qol Scores and QALY Values. We consider two alternative scenarios for qol scores (and, hence, the estimated QALY values) in which they are selected from either higher or lower ranges compared with our baseline scenario. The results are provided in Online Appendix E.1. We observe that, as we lower qol scores (i.e., when health conditions across all compartments deteriorate), the savings in the total QALY from current/potential policies increases compared with no intervention. This result supports the notion that more strict policies are better suited for populations with worse health conditions. Furthermore, we observe no consistent impact on the extra cost across states when changing qol scores. Overall, our results give us confidence that our findings are relatively robust to the estimates used in our main analysis for qol and QALY values.

3.4.3. Proportion of Population with Lost Income. We consider two alternative scenarios for the portion of the working population who have lost their income. Details

Figure 4. Average Outcomes Under Different Intervention Policies and Mobility Scenarios



Notes. Intervention policies are compared with no intervention. See Table 4 for intervention policies P1/P2/P3. M1: mobility observed in each state (see Table 5). M2/M3: other mobility scenarios used for robustness check.

are provided in Online Appendix E.2. From our results, we observe that, as the ratio of the population who lost more than 50% of their income increases, the extra total cost incurred by current/potential policies compared with no intervention ramps up. However, as expected, we do not observe consistent changes in the QALY outcomes across states when changing the ratio of population with lost income.

3.4.4. Projected Infections. Because of factors such as limited capacity of COVID-19 tests (Gao and Rosenlof 2020) and low (high) chance of false positive (negative) tests (Surkova et al. 2020, Watson et al. 2020), the number of observed positive cases could differ drastically from the true number of infected cases. Furthermore, it is reported that up to 40%–80% of people showing up for tests are asymptomatic (Gómez-Ochoa et al. 2020, Heneghan et al. 2020). In the absence of symptoms, the likelihood that a person tests positive could be a fraction of a randomly selected member of the population. Based on this premise, in our sensitivity analyses, we project the number of true daily infections in each state as follows:

$$\begin{aligned}\text{Projected infections} &= \text{rate of observed infections}\\ &\quad \times \text{fraction of total population}\\ &\quad \times \text{population size}\\ &= \frac{\#\,\text{positive tests}}{\#\,\text{total tests}}\\ &\quad \times \text{fraction of total population}\\ &\quad \times \text{population size.}\end{aligned} \tag{10}$$

For the fraction of total population in each state, we perform a sensitivity analysis by considering scenarios in which the fraction is varied by setting it to either 10% or 50%. For example, in a state with 1 million residents, if the numbers of positive and total tests are 2,000 and 20,000 on a given day, respectively, then the projected number of infections under these values is 10,000 and 50,000, respectively.

From our results in Online Appendix E.3, we observe that, as the projected number of true infections increases, the extra cost incurred under more strict lockdown policies (compared with no intervention) is typically reduced. This is because higher projected infections result in higher hospitalizations/deaths, which can be averted under more strict policies. As a result, the cost of utilizing/expanding resources as well as the cost of quarantining would decrease. Furthermore, when projected infections are higher, more QALY can be saved under more strict lockdown policies (compared with no intervention) in states such as Arizona, California, and Texas. However, this effect is not consistent across all states (e.g., in Georgia, the QALY saved would decrease).

3.4.5. Population Risk Perception. In Section 3.2.1, we introduce the parameter $\alpha \leq 0$ that captures the population level of risk perception. In our baseline setting, we consider $\alpha = -0.1$, and for alternative scenarios, we use $\alpha \in \{-0.2, -0.5\}$. We also consider the case in which the risk perception does not play any role. We do so by setting $\alpha = 0$. As can be seen from our results in Online Appendix E.4, when people become more risk-averse against the negative outcomes of the pandemic under no intervention, the QALY saved under more strict lockdown policies decreases. This is expected because fewer people would take the risk of going out and potentially harming themselves, which, in turn, helps reduce the disease transmission rate absent any lockdown. Furthermore, we notice that more risk aversion could lower the extra cost incurred under lockdown policies (compared with no intervention) in states such as Massachusetts, Michigan, and New York. However, we do not find this to be consistent across all states. For example, we observe a curvilinear impact in states such as California and Pennsylvania. One reason for this finding is that, although more risk aversion could control the spread of the disease (thus reducing the costs related to hospitalization) under no intervention, the amount of lost income resulting from staying home can increase.

3.4.6. Proportion Losing Income. In our baseline scenario, we assume that 50% of people who would not take the risk of going out under no intervention would lose their income. As alternative scenarios, we consider 25% and 75% of individuals suffering from this under no intervention. Results are presented in Online Appendix E.5. We observe that, when this rate increases, the extra cost incurred under more strict lockdown policies (compared with no intervention) would typically increase. Whereas this is expected, we also notice that changing this proportion would have a little to no impact on the QALY saved under more strict policies.

3.4.7. Proportion Quarantining. In our baseline scenario, we assume that 50% of infected individuals quarantine. We now consider two alternative scenarios in which this proportion is changed to 25% and 75%. Based on our results in Online Appendix E.6, we observe that, when a higher percentage of infected individuals quarantine, the extra cost incurred under more strict lockdown policies (compared with no intervention) would increase in states such as California, Georgia, and Massachusetts. However, we also observe that, in states such as Michigan and New York, the extra cost would be lowered when the quarantine rate increases. This might be because the number of infections is typically reduced under more strict policies, and hence, there are fewer individuals who have to quarantine. Furthermore, we observe that, in states such as Maryland, Massachusetts, and Michigan, when the quarantine rate increases, the QALY saved under more strict policies (compared with no intervention) would decrease. This implies that quarantining would have more promise under less strict policies, mainly because of the higher number of resulting infections.

3.4.8. Capacity Level of Hospital Resources. In our baseline scenario, we consider the current number of beds and ventilators available in each state. As our alternative scenarios, we consider 50% and 150% of the existing capacities of these resources. Our results in Online Appendix E.7 show that, if the states had more beds/ventilators in place, they would have born less extra cost under more strict policies (compared with no intervention). This is because these states would not have to pay for capacity expansion (this is noticeable in states such as California, Maryland, and Michigan). That said, we also notice that having a higher capacity might have a little to no impact on the extra cost incurred in some states (e.g., New York) and a curvilinear impact in others (e.g., Massachusetts). One justification for this observation is the fact that infections/hospitalizations/deaths would be already down under more strict policies, and hence, the higher cost of capacity expansion may be offset by the lower cost of resource utilization, lost income, or quarantining. Finally, we observe no tangible difference in the QALY saved when increasing the capacity of resources.

Overall, our various robustness checks give us confidence about the validity of our main findings and reveal that the various calibration and validation steps we have taken (see, e.g., Section 3.1.2) are sufficient. In particular, we observe that the outputs of our SEIRS models as well as the recommendations obtained from our policy comparisons are not that sensitive to our estimation of the main input parameters.

4. Discussion, Limitations, Future Research, and Conclusion

4.1. Discussion

Since the onset of COVID-19, U.S. states have undertaken various societal intervention policies. Despite their effectiveness in controlling the spread of disease (Courtemanche et al. 2020), many states eased the lockdown policies within a few weeks to months since their enactment. The driving force behind this is the economic burdens of these policies, for example, lost income and productivity (RAND Corporation 2020, Shretta 2020). However, premature reopening has contributed to some states observing the resurgence of COVID-19 cases, which forced states to retract their reopening decisions (Gamio 2020, Reuters 2020). Although the trade-off between health and economic impacts of lockdown policies is a well-known concept, what makes adopting effective policies currently challenging is the lack of quantitative evidence on this trade-off.

To provide such evidence, in the first part of our study, we develop a compartmental SEIRS model to capture the dynamics of COVID-19 infections over time. We estimate the parameters of this model for each state by conducting an MCMC simulation. To this end, we employ data of 50 U.S. states plus DC reporting on number of tests, infections, hospitalizations, ICU bed and ventilation usage, and deaths between early March and June 7. We also make use of cellphone data to estimate individuals' mobility in each state. After calibrating our models with these data, we analyze the impact of various lockdown policies on potential reductions in the disease transmission rates via a longitudinal mixed-effect regression model. Our results reveal that an increase in the strictness of policies, their duration, number of tests, per capita income, and the residents' mobility rate within 10 miles from their homes (compared with the distance beyond that) as well as a decrease in the ratio of Black/Hispanic populations are associated with more reductions in the COVID-19 transmission rates (albeit, not all of these effects are statistically significant).

In the second part of our study, we conduct an extensive simulation analysis to measure the QALY gained versus the cost incurred for both the current policy in place in each state (back in March–June 2020) and some counterfactual policies. Our findings provide quantitative evidence and important implications that can help public health authorities to not only evaluate the existing policies retrospectively, but also enact more effective policies prospectively. Furthermore, our extensive robustness checks on parameters such as residents' mobility rates, qol scores and QALY values, proportions of population with lost income, projected infections, population level of risk perception (about the negative outcomes of the pandemic), the proportion of people who would lose their income when staying home (under no intervention), the proportion of infected individuals who quarantine, and the capacity level of hospital resources reveal that our main findings on the performance of lockdown policies are relatively robust to variations in these parameters. In particular, we observe that, even if our estimated values for such parameters are not perfectly accurate, the recommendations we provide through our policy comparisons remain fairly intact. Thus, authorities can make use of our main recommendations without concerns over potential inaccuracies in estimating such parameters.

Finally, we note that the entire human life is typically valued at \$8–\$11 million, which accounts for \$100K–\$125K per year (Yakusheva et al. 2022). Albeit erring on the side of optimism, our estimate of the cost incurred per QALY saved (≈\$4,000/QALY on average under the current lockdown policies) is close to some estimates reported by the literature (see, e.g., Cutler and Summers 2020). The main reason for our low estimate is the fact that we not only measure QALY during our study period, we also account for a patient's quality of life had the patient stayed in a specific disease state for a long time/permanently. This is consistent with what is reported about the health implications of "long COVID" (see, e.g., U.S. Department of Health and Human Services 2021). Of note, for cost, the only long-term effect we consider is the cost of lost income for a dead person over the person's remaining working lifetime.

4.2. Limitations

Although we analyze a range of variations for the ratio of population with lost income, this ratio may be impacted by various demographic and socioeconomic risk factors (Selden and Berdahl 2020), which can warrant further investigation. Also, we note that our estimations and results are obtained based on our specific data sources and time frames as well as the specific methodology we employ. An alternative model and/or new data source may result in different outcomes. Nevertheless, our study provides a reliable quantitative framework to streamline the process of analyzing and comparing different lockdown policies.

4.3. Future Research and Conclusion

In addition to addressing the limitations we discuss in the previous section, as the pandemic evolves and new data becomes available, future research can enhance our study through the following avenues. However, it is important to note that most of the factors discussed (e.g., public vaccination, contact tracing, etc.) were not widely in place during our study period (i.e., the early stages of COVID), and hence, data on them mainly exists outside our study period.

1. In addition to factors that we account for in this study, future research can incorporate other driving forces, such as the cost associated with COVID-19 tests, the benefits attained via public vaccination, or second order impacts of COVID-19 on patients whose non-COVID-19 care is delayed or avoided (for reasons such as state mandates or limited capacity of healthcare settings).
2. Future research can make further adjustments in the disease transmission rate based on various factors, such as the type of infection (e.g., symptomatic and quarantined versus undetected asymptomatic), the type of test results leading to detection (e.g., purely symptomatic testing, random asymptomatic testing, and contact tracing), and vaccination status.
3. Future research can also examine the impact of other intervention policies (e.g., mandating wearing face masks). It should be noted, however, that such policies can only be impactful in the presence of more strict intervention policies (Lyu and Wehby 2020).
4. Future research can make use of more detailed mobility data and better adjust for mobility in rural areas, where people typically travel longer distances for daily activities.
5. In the absence of viable treatments or vaccination, a recovery from COVID-19 does not necessitate permanent immunity. Given the time between the presumed onset of COVID-19 in the United States and the projected drug delivery, a recovered person can become susceptible/infected again. For example, our estimation for California shows that the average immunity rate is 0.38% (see Table 7), which implies an average immunity period of 10,000/38 = 263.16 days. Such scenarios can aggravate the landscape of pandemics and may warrant even more strict lockdown policies. Evaluating the cost-effectiveness of policies under such circumstances would be another interesting avenue for future research.

Our study provides a detailed quantitative framework to analyze health versus economic impacts of these lockdown policies. In particular, for each state, we account for the direct costs of utilizing healthcare resources (e.g., beds and ventilators) or expanding them, the indirect costs of lost income and productivity, the indirect cost of quarantining, and the population's quality of lives that could be saved under more restrictive policies. The results and insights provided in this study can help federal and state agencies to not only evaluate their policies retrospectively, but also make better decisions on these policies to curb the spread of disease in the future. Finally, it is important to note that, whereas our work is focused on the COVID-19 pandemic, some of our policy recommendations and the insights generated might be valuable for curbing inevitable future pandemics.

Acknowledgments

The authors are grateful for helpful comments they received from members of the State of Vermont COVID-19 modeling team as well as conversations and data received from Bahrain's undersecretary of national economy and Bahrain's director of the planning and economic studies directorate. These all helped the authors to better calibrate their models and provide more actionable results.

Endnotes

[1] In addition to the database used in this study, there are several premier and widely used databases on U.S. state policies (see, e.g., Inter-University Consortium for Political and Social Research 2021).

[2] MCMC simulation is used for estimating the dynamics of infectious disease (see, e.g., Bootsma and Ferguson 2007, Ghaffarzadegan and Rahmandad 2020, Paul et al. 2020). For more details, see Van Ravenzwaaij et al. (2018).

[3] For other studies incorporating an endogenous transmission rate and also why some CDC models might have failed in providing good predictions, see, for example, Ghaffarzadegan and Rahmandad 2020, Institute for Health Metrics and Evaluation COVID-19 Forecasting Team 2021, and Rahmandad et al. 2022.

[4] We set α such that the transmission rate under no intervention would not fall below that under lockdown policies. Nevertheless, we also conduct sensitivity analyses on α to better gage its impact.

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