COVID-19: Health and Economic Impacts of Societal Intervention Policies in the U.S.

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Problem definition: Intervention policies such as stay-at-home orders are known to be effective in controlling the spread of the novel Coronavirus Disease 2019 (COVID-19). However, concerns over economic burdens of these policies rapidly propelled U.S. states to move towards reopening. We study the health and economic impacts of various intervention policies across U.S. states, and shed light on policies that are most effective.

Academic/practical relevance: Decision-making in most states has been challenging, especially because of a dearth of quantitative evidence on health gains versus economic burdens of different intervention policies. To assist decision-makers, we make use of detailed data from 50 U.S. states plus District of Columbia on various factors, including number of tests, positive and negative results, hospitalizations, ICU beds and ventilators used, residents' mobility obtained from cell phone data, and death. Our analyses, for the first time, allow quantifying the total cost versus the total quality-adjusted life year (QALY) associated with various intervention policies.

Methodology: 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, and residents' mobility, 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.

Results: Our results show that, compared to no intervention during March-June 2020, the policies undertaken across the U.S. on average saved about 168.85 years worth of QALY (per 100k capita) while incurring \$130.61 million (per 100k capita). Had the states undertaken more strict policies during the same time frame than those they adopted, these values would be 186.52 years and \$186.15 million, respectively.

Managerial implications: By quantifying the impact of various intervention 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 intervention 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.[1]

Key words: COVID-19; societal intervention policies; SEIRS model; Markov chain Monte Carlo; longitudinal mixed-effect model

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1. Introduction

The novel Coronavirus Disease 2019 (COVID-19) has wreaked havoc around the globe ever since its onset in January 2020. In the United States, as of February 14, 2021, 27,417,468 total cases and 482,536 total deaths have been confirmed (CDC 2020). In response to the COVID-19 pandemic and in order to curb the progression of the disease, U.S. states have each scrambled to implement various intervention policies, including stay-at-home executive orders, non-essential 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 (Shretta 2020, Wall Street Journal 2020), which might have propelled states to proceed towards reopening prematurely (RAND 2020). As a result, some states have observed spikes in new cases (Associated Press 2020, New York Times 2020a) and may be forced to exert new lockdowns, delay their reopening plans, or impose other restrictive policies (Reuters 2020, Washington Post 2020b). Despite these challenges, there exist limited quantitative evidence on evaluating the health and economic impacts of various intervention policies in each state. Thus, it is not clear which intervention policies are more effective in better trading off the underlying health gains versus the potential economic burdens.

In this study, for the first time, we provide an extensive analysis of the intervention policies implemented in each state, compare their performance with a hypothetical no-intervention scenario as well as a set of counterfactual intervention 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 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 simulation. We then develop a longitudinal mixed-effect model to quantify the impact of different intervention policies on potential reductions in the disease transmission rates. Here, we adjust our analysis for each state by considering intervention policies, their duration, sociodemographic/economic factors (e.g., age, race, and income), and residents' mobility which we obtain from cell phone data.

Specifically, we take into account the effect of race, because Black or Hispanic populations are reported to be more vulnerable against health/economic impacts of COVID-19 (KFF 2020a). 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 cell phone data to directly gauge the mobility of individuals in each state, which can effectively approximate their level of compliance (Charoenwong et al. 2020). These allow us to perform high-fidelity simulation analyses and compare the current policies with other potential policies that could have been imposed by each state. For each state, we report the total cost as well as the total quality-adjusted life years (QALYs) obtained under such policies per 100k capita. The former includes the direct cost of healthcare resources utilization (e.g., beds and ventilators) and the indirect cost of lost income. The latter captures a population's quality of life impacted by different stages of the disease (e.g., healthy, infected, hospitalized, dead, etc.). Finally, in addition to reporting these outcomes, we perform cost-effectiveness analyses to further shed light on the impact of intervention policies that could have been enacted in each state.

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

- Compared to a hypothetical no-intervention scenario, the policies imposed across the U.S. during March-June 2020 increased (on average and per 100k capita) the total QALY and cost 168.85 years and \$130.61 million, respectively. Moreover, more strict policies in the U.S. could have saved (on average and per 100k capita) 186.52 years of total QALY while costing \$186.15 million.
- For sub-populations who are at higher risk (e.g., age ≥ 65 and Black/Hispanic race), compared to no intervention, the policies enacted across the U.S. during March-June 2020 saved (on average and per 100k capita) 243.25 years worth of QALY while incurring \$155.90 million. Under more strict policies, these outcomes would have been about 270.04 years and \$215.49 million, respectively.
- 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 lower extra costs compared to states with a higher population such as California and Texas. Our further analyses reveal that this might be associated with the number of infections, hospitalizations, and deaths averted under intervention policies in these states. For example, we find that under more strict policies (compared to no intervention), a maximum of 100 and 50 daily deaths per 100k capita would have been averted in New Jersey and New York, respectively, while this number in California and Texas is only about 5 and 0.4, respectively.

- Our results show that, at willingness to pay (WTP) values within \$20,000–\$50,000 per QALY gain, current policies implemented across states are typically more cost-effective than the more restrictive counterfactual policies we study. However, we find that federal and state authorities should have followed such more restrictive policies instead of what they enacted, if they are willing to accept higher WTP values.
- Regardless of the intervention 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 without significantly increasing the total cost incurred. 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.

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

2. Data and Methodology

2.1. Data

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. The beginning date for each state in this dataset varies, but the end date for all states is June 7, 2020. The second data that we utilize in our analysis is the timeline of societal intervention policies undertaken in each state, hereafter referred to as *current* policies for simplicity. In this study, we consider three main interventions: stay-at-home order and non-essential business closures, large-gathering ban, and school closures. For details regarding the current intervention policies and the data we have collected, see Table 1. We also utilize the data of projected infections provided by IHME (2020) in order to test and validate our estimations (see §3.1.2). Finally, we make use of cell phone data (CUEBIQ 2020) to obtain information on individuals' mobility in each state.

2.2. An Epidemiological Model

To analyze the spread of disease, we utilize an epidemiological compartmental model known as SEIRS that considers *susceptible*, *exposed*, *infected*, and *recovered* populations.[2] One of the main assumptions in this model is that an immunity obtained upon recovery will not be life-long in the absence of treatments (see, e.g., Altmann et al. (2020)). To properly reflect on the problem we want to study, we make the following adjustments in our SEIRS model (see Figure 1):

- We allow transmissions between asymptomatic infected, symptomatic infected, and hospitalized populations.
- Among hospitalizations, we account for demand for common beds, ICU beds alone, or ICU beds with mechanical ventilators.
- For hospitalized patients who are discharged, we also consider the possibility of being infected (i.e., *carrier*) post-discharge (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 have observed four time frames: 03/07–04/03, 04/04–04/30, 05/01–05/11, and 05/12–06/07 (see Table 1). Due to the type/number of interventions undertaken in each time frame, this can result in a potentially different disease transmission rate. We account for this 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, since transmission rates also affect other factors in our model (e.g., hospitalization and death rates), such factors are also time-dependent in our analyses.
- We note that being exposed to the disease can be the beginning of the presymptomatic period (see, e.g., WHO (2020)). Therefore, we do not differentiate between exposed and infected presymptomatic conditions.

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[2] For other models that can be used to analyze the timing of societal intervention policies (e.g., university opening), we refer to Kaplan (2020) and the references therein.

Table 1 Timelines of current intervention policies and data collected[a]

State	Intervention 1[b]		Intervention 2[b]		Intervention 3[b]		Data	
	Start	End	Start	End	Start	End	Start	End
Alabama	04-Apr	30-Apr	04-Apr	11-May	04-Apr	ROSY[c]	07-Mar	07-Jun
Alaska	28-Mar	20-May	28-Mar	IND[d]	28-Mar	ROSY	06-Mar	07-Jun
Arizona	31-Mar	15-May	17-Mar	16-May	15-Mar	ROSY	04-Mar	07-Jun
Arkansas	—[e]	—	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
Dist. of Col.	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

[a] Timelines of interventions, source: KFF (2020b), NBC News (2020), NPR (2020). Timelines of data, source: Foldi and Csefalvay (2020). [b] Intervention 1: stay-at-home order and/or non-essential business closures,
Intervention 2: large-gathering ban, Intervention 3: school closures. [c] ROSY: remainder of school year.
[d] IND: indefinitely (at the time of data collection, June 7, 2020). [e] An executive order was not issued in that state.

- 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)).

As shown in Figure 1, the outputs in our SEIRS model are the number of people in each compartment on each day; e.g., 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 2):

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

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

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

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

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

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

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

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

2.3. Potential Intervention Policies

In addition to analyzing the performance of current policies, we study the impact of some potential intervention policies that could have been followed by states (see Table 3). Since most states initiated their policies in March and the end date in our data is June 07, 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 3 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 stay-at-home order, and so on) is consistent with what has been reported by the authorities for each state (see Table 1).

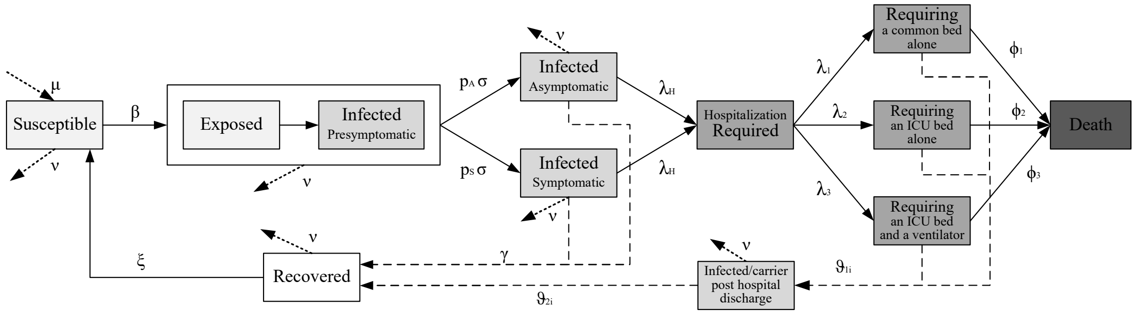

Figure 1 **The SEIRS compartmental model**
Notes. See Table 2 for the notation used. All rates are between 0 and 1. Dashed and dotted arrows represent recovery/discharge flows and vital dynamics, respectively. For graphical simplicity, "infected/carrier post hospital discharge" is shown with one compartment (there are three of them). "Hospitalization Required" is only shown for illustrative purposes and is not among compartments.

Table 2 **Summary of notations for the SEIRS model**†

T	time horizon
t	time index (in days), $t = 0, 1, \ldots, T$
$S(t)$	# susceptible (#: number of people)
$E(t)$	# exposed to the virus
e_0	# initially exposed (at the onset of disease)
$I_P(t)$	# infected and presymptomatic (have yet to develop symptoms), $I_P(t) = E(t)$
$I_A(t)$	# 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, $i \in \{1 : \text{Common/non-ICU bed}, 2 : \text{ICU bed alone}, 3 : \text{ICU bed with ventilator}\}$
$I_{PDi}(t)$	# infected/carrier of the disease post hospital discharge for index $i \in \{1, 2, 3\}$, $I_{PD}(t) = \sum_{i=1}^{3} I_{PDi}(t)$
$D(t)$	# death 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/presymptomatic infection and appearance of signs/symptoms of disease)
LOS_i	hospital length of stay for index $i \in \{1, 2, 3\}$ (see above for description of index i)
l_R	recovery period
l_W	immunity/waning period
$\beta(t)$	transmission rate at time t (rate at which the disease is transmitted between a susceptible and an exposed individual)
σ	rate of becoming infected post exposure/presymptomatic period, $\sigma = 1/l_I$
p_S	probability of symptomatic infection
p_A	probability of asymptomatic infection, $p_A = 1 - p_S$
λ_H	rate of hospitalizations
λ_i	rate of hospitalizations for index $i \in \{1, 2, 3\}$, $\sum_{i=1}^{3} \lambda_i = 1$
ϕ_i	covid-related death rate for index $i \in \{1, 2, 3\}$
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 $i \in \{1, 2, 3\}$, $\vartheta_{2i} = 1/\max\{l_R - \text{LOS}_i, 0\}$
γ	recovery rate, $\gamma = 1/l_R$
ξ	waning rate, $\xi = 1/l_W$
μ	vital dynamics (natural birth rate; not occurred during hospitalization)
ν	vital dynamics (natural death rate; not occurred during hospitalization)

† The SEIRS model has 12 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.

Table 3 Summary of potential intervention policies

Policy	Stage 1	Stage 2	Stage 3	# Time Frames
1[†]	Start: 01-Mar, end: 30-Apr Duration: 61 days Interventions 1/2/3[‡]	Start: 01-May, end: 31-May Duration: 31 days Interventions 2/3	Start: 01-Jun, end: 30-Jun Duration: 30 days Intervention 3	3
2	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
3	Start: 01-Mar, end: 30-Jun Duration: 122 days Interventions 1/2/3	—	—	1

[†] These policies are referred to as P1, P2, and P3, respectively.

[‡] Interventions 1: stay-at-home order and non-essential business closures, 2: large-gathering ban, 3: school closures.

2.4. Adjusting Disease Transmission Rates

As we estimate the disease transmission rates in our SEIRS model, there exist underlying conditions that could affect the dynamics of the disease, but are not reflected in the SEIRS model; e.g., population's age and race (KFF 2020a), income (New York Times 2020b), and compliance to following policies (Bodas and Peleg 2020). As a result, we cannot directly apply the estimated transmission rates that we have obtained from the SEIRS model to examine the impact of intervention policies. To address this, we develop a longitudinal mixed-effect regression model, which allows us to measure the impact of intervention policies on potential reductions in transmission rates (for details, see §3.2). For each state, we adjust our analysis by duration of interventions, age, the ratio of Black or Hispanic populations, and per capita income. 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. Table 4 shows the summary of the independent variables used in our longitudinal regression model.[3]

2.5. Measuring Health and Economic Impacts

2.5.1. Health Outcomes. For each intervention policy, we measure health outcomes by making use of *quality-adjusted life years* (QALY), which quantifies the number of years an individual can accrue depending on his/her health status; e.g., full health (death) accounts for 1 (0) year of quality of life accrued, and a medical condition such as infection yields

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[3] Regarding income, it has been reported that income losses as a result of COVID-19 have less impacted people with higher socio-economic status (New York Times 2020b). Therefore, in our analysis, we do not target top percentiles of income. Instead, we consider the average per capita income. Nevertheless, in our simulation, we consider a range for this measure by allowing a ±10% variation (based on the reported values in Table 4).

Table 4 Summary of socio-demographics and mobility information

State	**PCI ($)**[a]	**Median Age**	**Race Ratio**[b]	**Mobility Ratio**[c]			
				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)	—
Dist. of Col.	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)	—

[a] Per capita income per year. PCI and median age are obtained from Mathematica, Wolfram Research, Inc. (see Appendix A).
[b] Ratio of Black or Hispanic population (KFF 2018c). [c] 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. [d] For characterization of time frames, see §2.1-2.2.

a value that is strictly between 0 and 1 over one year. In our setting, the SEIRS model has 12 main compartments each representing a different stage of the disease (see §2.2 for more details). Let $X(t) = (X_1(t), \dots, X_{12}(t))$ represent the state of the model at time t, where $X_i(t)$ denotes the number of people estimated to be in compartment i at time t. Also, let $q_i \in [0,1]$, $i \in \{1,2,\dots,12\}$, represent the *quality-of-life* (qol) score attributed to compartment i. This is a number between 0 and 1, where 1 (0) represents full health (death) based on a one-year time frame. We quantify total QALY as the quality-adjusted life years that a population can accrue over the time horizon (i.e., T days):

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

As mentioned in §2.4, we adjust the disease transmission rate based on age, the ratio of underrepresented populations, per capita income, people's mobility, and type and duration of intervention policies. As a result, the number of people in different compartments (and hence our measure of QALY in Equation (2)) reflects these factors. Of note, Equation (2) reveals a linear function that accounts for between-comparment distribution of health benefits. However, it does not account for within-compartment distribution such as sub-populations with specific health conditions (e.g., obesity, diabetes, immunodeficiency, etc.) that might be more susceptible to COVID-19. Since our data does not include such granular information for each state, we (a) focus on broader socio-demographic information (see, e.g., Table 4), and (b) perform various sensitivity analyses on the estimated qol scores (and hence, QALY values) to test the validity of our main findings (see, e.g., §3.4.3). Finally, in addition to reporting the total QALY per 100k capita, we also evaluate the QALY values by focusing on high-risk sub-populations 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 healthcare resources such as common beds, ICU beds, and ventilators. Following the notations in §2.5.1, let $X_5(t)$, $X_6(t)$, and $X_7(t)$ represent the number of hospitalized infected patients who are using common beds, ICU beds, and ICU beds with ventilators at time t, respectively. Also, let C_1, C_2, and C_3 represent the daily operating costs for using one unit of these resources, respectively. Then, total direct cost is measured as:

$$\text{Total direct cost} = \sum_{t=1}^{T} \big[C_1 X_5(t) + C_2 X_6(t) + C_3 X_7(t)\big]. \tag{3}$$

The indirect costs, however, relate to the expenses associated with lost income and productivity. It has been reported that 48%, 20%, 14%, and 18% of people in the U.S. have lost less than 25%, between 25% and 50%, between 50% and 75%, and more than 75% of their income, respectively (Statista 2020). Thus, to measure the indirect costs, we let $p_j(t)$, $j = 1, \ldots, 4$, represent the portion of working population who lose between $(j-1) * 0.25$ and $j * 0.25$ of their income. Furthermore, let PCI represent per capita income per day, η be the employment rate, and $\theta_j \in [(j-1) \times 0.25, j \times 0.25]$ denote the percentage of lost income for individuals who lose between $j-1$ and j quartiles of their income. Then, the total indirect cost can be measured as:

$$\text{Total indirect cost} = \text{PCI} \times \eta \times \sum_{t=1}^{T} \Bigg[\underbrace{\sum_{i=1}^{11} \big[X_i(t) + X_{12}(t)\,(T-t+1)\big]}_{\substack{\text{population size subject to lost income}\\ \text{per day}}} \; \underbrace{\sum_{j=1}^{4} p_j(t)\theta_j}_{\text{\% of lost income}} \Bigg]. \tag{4}$$

The third factor in (4) calculates the number of days income is lost for the population. This is done separately for $i = 12$ (death) and other compartments in the SEIRS model. This is because when an individual dies on day t, we assume that the income is lost during the rest of the horizon $(T - t + 1)$. The fourth factor in (4) captures the percentage of lost income. In our main analyses, we make use of Equation (4) to approximate and gauge the impact of the total indirect cost. In §3.4.4, we perform sensitivity analyses and alter our estimated values to test the robustness of our main findings. Finally, using the results from Equations (2)-(4), we measure Incremental Cost-Effectiveness Ratio (ICER) to compare the cost-effectiveness of different policies (see, e.g., Drummond et al. (2015)):

$$\begin{aligned}\text{ICER} &= \frac{\text{Incremental total cost (\$)}}{\text{Incremental total QALY (years)}} \\ &= \frac{\text{Total cost (potential policy)} - \text{Total cost (current policy)}}{\text{Total QALY (potential policy)} - \text{Total QALY (current policy)}}.\end{aligned} \tag{5}$$

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 $\leq$ WTP (see, e.g., Drummond et al. (2015)). Further details about QALY and costs parameters that we use can be found in Online Appendix C.

3. Numerical Results and Analyses

3.1. Parameter Estimations and Model Validation

3.1.1. Estimations. To estimate the parameters of our SEIRS model, we conduct a Markov chain Monte Carlo (MCMC) simulation[4] via the *Metropolis–Hastings* algorithm (Chib and Greenberg 1995). The MCMC simulation generates the posterior estimates of parameters based on prior distributions. In our estimation, we use uniform priors for all parameters (Bootsma and Ferguson 2007). Furthermore, we assume that daily number of infections, hospitalizations, and deaths (i.e., information available from our data) each follow a Poisson process, based on which we form the log-likelihood functions to run the Metropolis–Hastings algorithm. We run multiple chains to accommodate narrow confidence intervals (CIs) for estimations (typically idiosyncratic to MCMC simulations with a single chain). In each of these chains, we select a different prior for each parameter in our model. In addition, we use the *modified potential scale reduction factor* to check the convergence of the Metropolis–Hastings algorithm (Brooks and Gelman 1998). 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 a nonstationary behavior. Table 5 shows the estimated parameters.

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 have iterated our SEIRS model 1,000 times, where in each iteration we randomly select a value for each parameter from the respective CI reported in Table 5. 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.

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[4] MCMC simulation is well-known and widely used for estimating the dynamics of infectious disease (see, e.g., Bootsma and Ferguson (2007), Ghaffarzadegan and Rahmandad (2020), Paul et al. (2020)). For a general description of MCMC simulation, we refer to Van Ravenzwaaij et al. (2018).

Table 5 Summary of SEIRS parameters estimated from the MCMC simulation

State	$N(0)$	μ	ν	e_0	β_0	β_1	β_2	β_3	σ	γ	ξ	p_S	λ_H	λ_1	λ_2	ϕ_1	ϕ_2	ϕ_3	LOS$_1$	LOS$_2$	LOS$_3$
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)	(0.7,6.31)	(6.77,18.78)	(1.96,4.66)	(0.28,0.52)	(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)	(4.81,9.1)	(6.77,11.02)	(10.1,18.82)
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)	(13.3,69.02)	(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	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)	(0.27,0.5)	(14.41,66.8)	(1.78,5.92)	(47.44,84.77)	(10^{-6},0.78)	(0.02,0.35)	(0.3,1.03)	(2.67,5.51)	(5.19,9.61)	(6.94,11.26)	(10.24,18.86)
Arkansas	2,966,369	1.24	1.06	$(0.15,0.38)*10^3$	(9.1,23.47)	(1.72,7.65)	—	—	(2.02,7.79)	(2.11,3.79)	(0.27,0.49)	(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)	(10.4,18.89)
California	38,802,500	1.19	0.73	$(9.03,43.54)*10^3$	(3.52,12.83)	(10^{-6},5.28)	—	—	(3.43,13.9)	(2.02,3.84)	(0.27,0.49)	(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	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)	(13.92,67.9)	(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	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)	(0.27,0.5)	(13.06,69.81)	(10^{-6},9.70)	(44.55,75.87)	(10^{-6},1.27)	(10^{-6},5.53)	(10^{-6},8.4)	(10^{-6},31.36)	(4.92,9.11)	(6.97,11.19)	(10.63,18.97)
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)	(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)	(6.8,11.08)	(10.8,19.25)
Dist. of Col.	658,893	1.44	0.86	$(0.45,1.64)*10^3$	(6.58,21.57)	(10^{-6},4.19)	(10^{-6},3.31)	—	(3.78,13.6)	(2.06,3.98)	(0.27,0.5)	(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)	(6.9,11.21)	(10.5,19.22)
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)	(14.95,72.25)	(10^{-6},1.02)	(45.55,77.74)	(10^{-6},1.66)	(0.04,0.6)	(0.57,1.2)	(2,9.54)	(4.75,8.7)	(6.94,11.23)	(10.16,18.54)
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)	(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	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)	(0.27,0.5)	(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)	(4.84,8.9)	(6.99,11.29)	(9.5,17.86)
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)	(3.7,6.87)	(0.27,0.49)	(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	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)	(0.27,0.5)	(11.48,57.86)	(10^{-6},12.46)	(45.5,76.99)	(10^{-6},1.4)	(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	6,596,855	1.22	0.94	$(5.45,14.09)*10^3$	(0.87,4.50)	(0.9,8.81)	(0.58,2.30)	—	(3.98,14.54)	(2.41,5.79)	(0.26,0.49)	(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	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)	—	(3.7,13.43)	(2.01,4.78)	(0.26,0.49)	(15.71,76.67)	(10^{-6},12.56)	(46.05,83.3)	(10^{-6},1.95)	(0.63,3.96)	(2.48,7.87)	(3.3,16.63)	(4.77,8.85)	(6.86,11.18)	(10.7,19.22)
Kansas	2,904,021	1.22	0.87	$(0.19,0.59)*10^3$	(5.07,20.71)	(10^{-6},4.8)	(10^{-6},4.92)	—	(5.45,16.68)	(2.87,6.33)	(0.27,0.5)	(11.29,69.32)	(10^{-6},0.78)	(46.91,83.5)	(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	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)	(0.27,0.5)	(13.0,63.8)	(10^{-6},13.85)	(45.84,82.29)	(10^{-6},1.8)	(10^{-6},0.15)	(10^{-6},0.5)	(10^{-6},9.22)	(4.93,9)	(6.76,11.04)	(10.27,18.88)
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)	(0.27,0.5)	(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)	(6.88,11.1)	(10.34,19.06)
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)	(1.99,4.6)	(0.27,0.5)	(14.99,71.1)	(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	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)	(0.27,0.5)	(12.7,65.26)	(10^{-6},6.22)	(45.9,80.22)	(10^{-6},1.5)	(0.03,0.62)	(0.73,1.21)	(2.56,9.5)	(4.81,8.83)	(6.89,11.08)	(10.33,19.03)
Massachusetts	6,794,422	1.04	0.86	$(23.34,46.21)*10^3$	(4,18.14)	(0.9,2.46)	(0.71,2.73)	—	(3.82,15.34)	(1.97,4.96)	(0.26,0.48)	(15.59,61.59)	(10^{-6},8.98)	(46.6,74.3)	(10^{-6},1.44)	(0.1,1.19)	(0.14,4.3)	(2.3,14.08)	(4.85,8.86)	(6.89,11.13)	(10.02,18.18)
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)	(12.75,73.61)	(10^{-6},8.94)	(47.22,84.63)	(10^{-6},0.59)	(0.27,1.44)	(0.48,3.02)	(6.4,16.6)	(4.92,8.95)	(6.82,10.9)	(10.06,18.51)
Minnesota	5,489,594	1.23	0.79	$(0.56,5.06)*10^3$	(1.3,5.27)	(4.27,9.3)	(0.21,2.27)	—	(3.73,12.37)	(2.1,4.25)	(0.26,0.49)	(11.55,60.88)	(10^{-6},8.25)	(46.64,84.29)	(10^{-6},1.98)	(0.19,2.3)	(0.23,6.43)	(4.89,17.69)	(4.73,8.8)	(6.93,11.12)	(10.32,18.7)
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)	(2.98,6.9)	(0.27,0.48)	(12.12,69.38)	(10^{-6},10.63)	(45.44,77.72)	(10^{-6},0.83)	(0.04,0.41)	(0.18,0.8)	(2.19,6.49)	(4.9,9.11)	(7.02,11.41)	(11.08,19.54)
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)	—	(5.08,16.2)	(2.75,6.49)	(0.27,0.5)	(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)	(6.9,10.99)	(10.61,19.3)
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)	(0.27,0.5)	(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	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)	(0.27,0.5)	(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	2,839,099	1.27	0.90	$(0.78,3.09)*10^3$	(4.5,15.01)	(0.17,3.10)	(10^{-6},1.77)	—	(5.69,17.92)	(2.12,5.86)	(0.26,0.47)	(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)	(10.7,19.35)
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)	—	(3.4,13.06)	(2,3.47)	(0.27,0.51)	(11.1,65.64)	(10^{-6},5.64)	(45.57,78.65)	(10^{-6},7.63)	(10^{-6},0.31)	(10^{-6},2.9)	(10^{-6},8.62)	(4.78,8.91)	(6.85,11.08)	(10.47,18.83)
New Jersey	8,944,469	1.11	0.85	$(37.94,51.73)*10^3$	(6.64,18.05)	(0.38,2.26)	—	—	(3.7,15.42)	(2.21,3)	(0.27,0.49)	(11.65,67.36)	(0.85,6.87)	(45.96,76.38)	(10^{-6},0.2)	(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	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)	(0.27,0.5)	(14.01,69.86)	(10^{-6},5.22)	(45.41,80.56)	(10^{-6},3.72)	(10^{-6},0.2)	(10^{-6},2.63)	(10^{-6},11.39)	(4.67,8.63)	(6.91,11.22)	(10.87,19.37)
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)	(16.2,67.48)	(10^{-6},7.65)	(45.74,78.03)	(10^{-6},1.76)	(10^{-6},0.71)	(10^{-6},2.2)	(3.69,12.19)	(4.91,9.12)	(6.89,11.19)	(11.1,19.38)
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)	(2.1,5.51)	(0.27,0.48)	(13.35,69.05)	(10^{-6},7.54)	(45.45,80.85)	(10^{-6},0.7)	(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	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)	(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)
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)	(2.2,5.6)	(0.26,0.49)	(13.82,57.8)	(10^{-6},6.03)	(46.43,84.3)	(10^{-6},0.14)	(0.49,0.96)	(0.07,2.24)	(1.57,10.97)	(4.74,8.73)	(6.95,11.28)	(10.3,18.75)
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)	—	(5.08,16.2)	(2.75,6.49)	(0.27,0.5)	(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)	(6.9,10.99)	(10.61,19.3)
Oregon	3,970,239	1.09	0.92	$(0.34,1.71)*10^3$	(3.51,14.12)	(0.14,5.97)	(0.4,5.60)	—	(4.14,15.52)	(2.89,6.58)	(0.26,0.49)	(15,58.95)	(8.27,22.49)	(47.33,87.43)	(10^{-6},3.44)	(10^{-6},0.2)	(10^{-6},0.31)	(10^{-6},7.22)	(5.2,9.5)	(6.88,11.1)	(9.73,18.41)
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)	(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	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)	—	(6.4,18)	(2.04,4.66)	(0.26,0.5)	(12.32,60.51)	(10^{-6},6.83)	(47.46,84.58)	(10^{-6},3.7)	(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	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)	(0.27,0.5)	(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	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)	(0.27,0.5)	(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	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)	(2.6,6.53)	(0.26,0.48)	(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)	(4.79,9.06)	(6.75,10.91)	(9.81,18.37)
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)	—	(5.23,15.7)	(2.39,6.45)	(0.27,0.49)	(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)	(10.61,19.3)
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)	—	(5.4,17.49)	(2.42,6.13)	(0.26,0.49)	(12.62,64.5)	(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	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)	(0.27,0.5)	(14.8,70.65)	(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	8,326,289	1.18	0.84	$(0.31,5.35)*10^3$	(5.67,19.15)	(0.51,5.65)	—	—	(4.5,14.61)	(2.03,3.86)	(0.27,0.5)	(12.39,67.52)	(10^{-6},9.65)	(45.06,75.78)	(10^{-6},4.17)	(10^{-6},0.18)	(10^{-6},0.7)	(10^{-6},6.69)	(4.81,8.9)	(6.83,11.08)	(10.45,19)
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)	(0.27,0.5)	(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)	(6.99,11.3)	(10.47,19.06)
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)	(0.27,0.5)	(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	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)	—	(3.6,13.51)	(2.09,4.76)	(0.26,0.47)	(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)	(4.69,8.6)	(6.87,11.06)	(11.11,19.63)
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)	(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},3.5)	(4.99,9.25)	(6.72,10.95)	(10.23,18.75)

For notations, see Table 2. All columns except the first four represent 95% confidence intervals. All rates are in %. LOSs are in days. Negative values are replaced by 10^{-6}. Values are shown with 2 decimal places. For information about $N(0)$, μ, and ν, see Online Appendix A.

For each time frame in each state, there is one transmission rate β_i. "—" implies no time frame, and hence, no transmission rate. β_0: baseline transmission rate pre-intervention. β_1: transmission rate during the first intervention time frame.

3.2. Mixed-Effect Longitudinal Model

We develop a longitudinal mixed-effect regression model to quantify how much the disease transmission rates are impacted by intervention policies, their durations, population age, ratio of Black or Hispanic populations, per capita income, and mobility rates in each state. The outcome is the amount of reduction in transmission rate at any given time compared to the baseline rate (i.e., pre-intervention). Using the notation in Table 6, our first model is as follows:

$$\begin{aligned}\text{Model 1: } \beta_0 - \beta_i = {} & b_0 + b_1 * policy_i + b_2 * duration_i + b_3 * mobility_i^1 + b_4 * mobility_i^2 \\ & + b_5 * median\ age + b_6 * race\ ratio + b_7 * per\ capita\ income.\end{aligned} \tag{6}$$

We also make use of two other models (labeled as Models 2 and 3), where we consider all pairwise and/or triplewise interactions between variables. Comparing these models in Table 7, we observe that performance measures are not unanimous in favoring one model. For example, Model 1 results in better Akaike information criterion and Bayesian information criterion values, whereas Model 3 yields better mean square error and mean absolute error values. Due to its simplicity and its quality that is fairly comparable with Model 3, we select Model 1 in order to perform our simulation analyses (see §3.3). From Table 8, we observe that increasing the intensity and duration of interventions 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 statically significant results in this regard. Finally, our estimated coefficients presented in Table 8 indicate that increasing the mobility rate within 10 miles from home (compared to 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.

3.3. Comparison of Intervention Policies

3.3.1. Micro-Simulation Model. We compare the performance of our counterfactual intervention policies against the current policies in each state and a hypothetical no-intervention benchmark. We make this comparison based on the total QALY accrued and total costs incurred throughout the time horizon of 01-March through 30-June. To account for sensitivity to the estimated values of various parameters in our setting, for each state,

Table 6 Summary of notations for the mixed-effect regression models

β_0	baseline transmission rate (pre-intervention)[a]
i	time frame
β_i	disease transmission rate in time frame i [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
	$p_i = 3$: 3 intervention policies in time frame i (stay-at-home order, large gatherings ban, and school closures)
	$p_i = 2$: 2 intervention policies in time frame i (large gatherings ban and school closures)
	$p_i = 1$: 1 intervention 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]
median age	median age in each state[e]
race ratio	ratio of state's population with Black or Hispanic race[e]
per capita income	per capita income in each state[e]

[a] β_i's are obtained from our estimation (see Table 5). [b] Order of intervention policies is set as: $0 \to 3 \to 2 \to 1$.
[c] Obtained from information in Table 1. [d] Information presented in Table 4. To avoid collinearity, we do not consider mobility rates of more than 10 miles from homes. [e] Information presented in Table 4.

Table 7 Performance measures for the mixed-effect regression models

Model	AIC	BIC	Log likelihood	MSE	MAE
1	-474.89	-448.95	246.45	0.00168	0.03025
2	-464.69	-409.92	251.34	0.00160	0.02950
3	-458.63	-392.33	252.32	0.00159	0.02894

AIC: Akaike information criterion. BIC: Bayesian information criterion. MSE: mean square error. MAE: mean absolute error. MSE/MAE are obtained by 5 two-fold cross validations across states.

Table 8 Results of mixed-effect model 1

Variable[a]	Estimate (%)	Std. Error (%)	df	t value	P value	Code[b]
Intercept	-22.05	8.634	4.892*10^1	-2.554	0.013815	*
$policy_i:\ 0 \to 3$	6.212	1.556	1.059*10^2	3.993	0.000121	***
$policy_i:\ 0 \to 3 \to 2$	6.989	0.6686	9.856*10^1	10.452	$< .00001$	***
$policy_i:\ 0 \to 3 \to 2 \to 1$	6.108	1.168	1.297*10^2	5.231	$< .00001$	***
$duration_i$	0.03325	0.02024	1.065*10^2	1.642	0.10354	.
$mobility_i^1$	3.021	9.040	9.348*10^1	0.334	0.739128	
$mobility_i^2$	16.78	15.06	5.900*10^1	1.114	0.269797	
median age	0.3455	0.2032	4.486*10^1	1.700	0.096055	.
race ratio	-2.042	3.572	4.639*10^1	-0.572	0.570084	
per capita income	4.284*10^{-5}	1.135*10^{-4}	4.803*10^1	0.377	0.707834	

Results are obtained by the "lmer" function in the R computing package.
To use these result for making predictions, we use "predict()" function in the R computing package.
[a] For notations, see Table 6. [b] Significance codes: '***' 0.001; '**' 0.01; '*' 0.05; '.' 0.2.

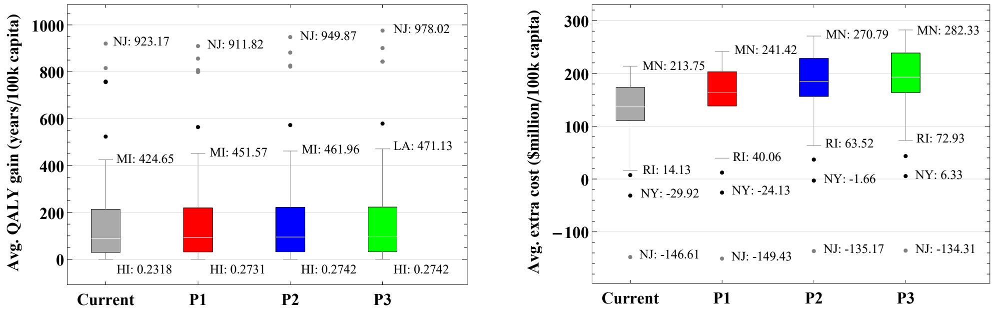
we iterate our calculations of the QALY and the cost obtained under each policy 10,000 times. The details of this micro-simulation model are provided in Appendix D.1.

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

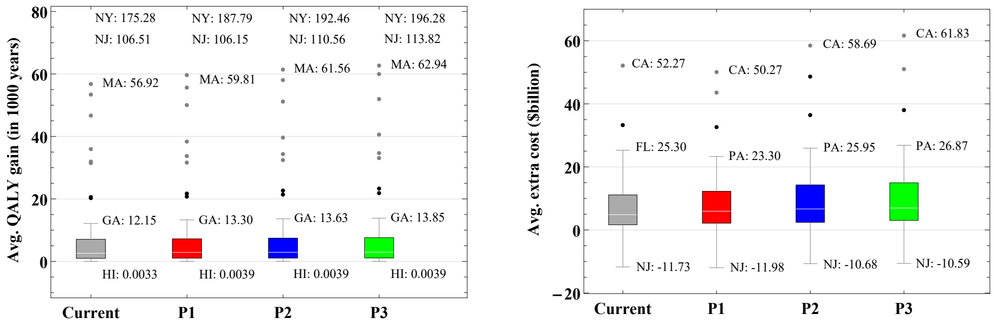
Observation 1. *Compared to no intervention during March-June 2020, the average increase in the total QALY and cost per 100k capita across the U.S. states is*
(i) 168.85 years and \$130.61 million under the current policy,
(ii) 177.73 years and \$155.24 million under Policy 1,
(iii) 182.69 years and \$177.44 million under Policy 2, and
(iv) 186.52 years and \$186.15 million under Policy 3.

Observation 1 reveals that imposing the counterfactual policies we study (Policies 1, 2, and 3) would result in higher total QALY gains while increasing the total cost (compared to the current policy). This is expected since the potential policies we study are typically more strict than what states imposed. Hence, these potential policies are able to better control the spread of the disease and yield improvements in QALY. These improvements, however, are offset by higher total costs (mainly due to the indirect cost of lost income). While these average effects are expected, we observe a significant amount of heterogeneity in the QALY gained or extra cost incurred when the same intervention 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 2b). For example, in Michigan, the overall QALY gain under Policy 1 compared to no intervention is 50,210 years, whereas in New Jersey which has about 1 million fewer residents than Michigan, this gain under the same policy is 106,146 years. Similarly, while 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 to no intervention is vastly different for these two states (192,459 years and \$1.639 billion for New York, but 6,837 years and \$36.637 billion for Florida).

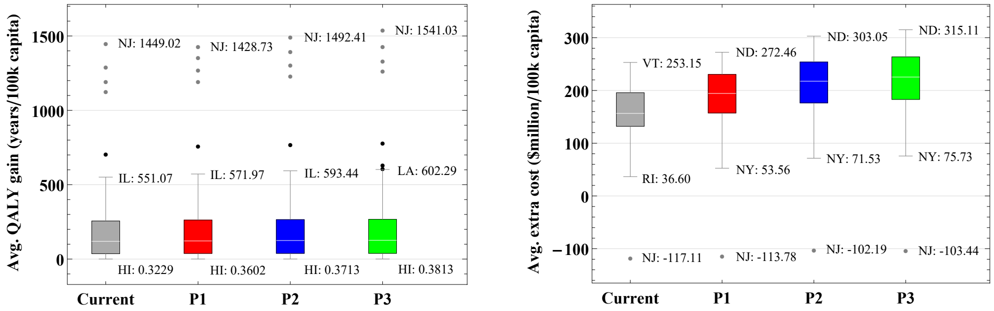
An important factor that is associated with these variations in the total QALY and cost across states is the number of infections, hospitalizations, and deaths averted in those



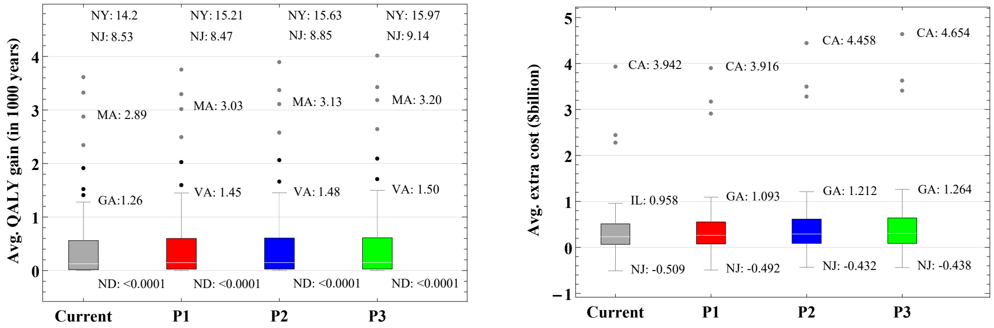
(a) Results: per 100k capita in each state



(b) Results: total population in each state



(c) Results: per 100k high-risk capita in each state



(d) Results: total high-risk population in each state

Figure 2 Distribution of outcomes across states

Notes. Intervention policies are compared with no intervention. See Table 3 for intervention policies P1/P2/P3. Complete results for parts (a)-(d) are provided in Appendix D.3, Tables D.2-D.5, respectively.

states under different intervention policies. The higher these aversions, the higher the total QALY saved and the lower the direct cost of beds/ventilators utilization (see our results in Online Appendix D.4). The ability of intervention policies to increase these aversions, in turn, depends on various geographical and demographical factors that differ across states. Among all such factors, it is especially important to understand how intervention policies affect the high-risk population within each state. Thus, we next focus our attention on high-risk population within each state and re-run our analyses for this population.

3.3.3. Impact on High-Risk Population. It is known that some sub-populations are more susceptible to COVID-19 complications. These include individuals with older age, minority race, diabetes, obesity, cancer, and immunodeficiency (KFF 2020a, Mayo Clinic 2020). As a result, their QALY could be more severely impacted compared to the average population. Furthermore, differences in 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 intervention policies for sub-populations formed by individuals 65 years or older and with Black/Hispanic race. 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 the individuals 65 years or older and with Black/Hispanic race are presented in Figure 2c (further details are provided in Appendix D.2). We make the following observation based on our results:

OBSERVATION 2. *Among individuals 65 years or older and with Black/Hispanic race, compared to 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) 243.25 years and \$155.90 million under the current policy,
(ii) 256.48 years and \$185.57 million under Policy 1,
(iii) 264.09 years and \$207.32 million under Policy 2, and
(iv) 270.04 years and \$215.49 million under Policy 3.

Observation 2 shows that QALY gains and extra cost per 100k capita in the high-risk population are both higher than those obtained for the average population (see Observation 1). Furthermore, our results reveal that the total QALY gains and extra cost for the high-risk population account for about 5.33% and 4.69% of the outcomes obtained for the whole population, respectively.[5] While this high-risk population constitute on average 3.80% of the whole population in the U.S. (see, e.g., KFF (2018b,c)), there is a high variation across states in terms of this percentage. Thus, our earlier results that (a) states with a similar total population can see significantly different impacts of the same intervention policy, and (b) the impacts of intervention policies are not necessarily higher in more populous states are likely due to the differences in the percentage of high-risk population. However, other factors such as the population density of each state and a variety of socio-political differences across states can play a role. A deep analysis of such factors are 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 (5), and measure the cost-effectiveness (CE) of a potential policy compared to the current policy via the probability that ICER $\leq$ WTP (for more details, see Appendix D.1). The higher this probability, the higher the cost-effectiveness of the potential policy compared to the current policy. To gain more insights 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, current policies adopted by states are typically more cost-effective than the other potential policies we study. Due to their more strict nature, the potential policies would considerably elevate the total QALY. However, these improvements in QALY are offset by higher total costs (mainly impacted by the indirect cost of lost income). When implementing such strict policies, concerns about indirect costs could be mitigated, if state authorities utilize other mechanisms (e.g., external funding sources for lost income or economic productivity of their residents). We also observe that these potential policies become more attractive as state authorities increase their WTP values (e.g., WTP = \$100,000 compared to \$50,000). This impact of increasing WTP values, however, is not uniform across states. Specifically, our results show that increasing the WTP value has a

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[5] The impact on extra cost is less noticeable than that on QALY gains. One reason for this observation is the fact that, although the high-risk population is at higher risk of economic impacts of lost income (thus increasing the indirect cost), the number of infections, hospitalizations, and deaths averted under intervention policies for this population is also higher (thus decreasing the direct cost).

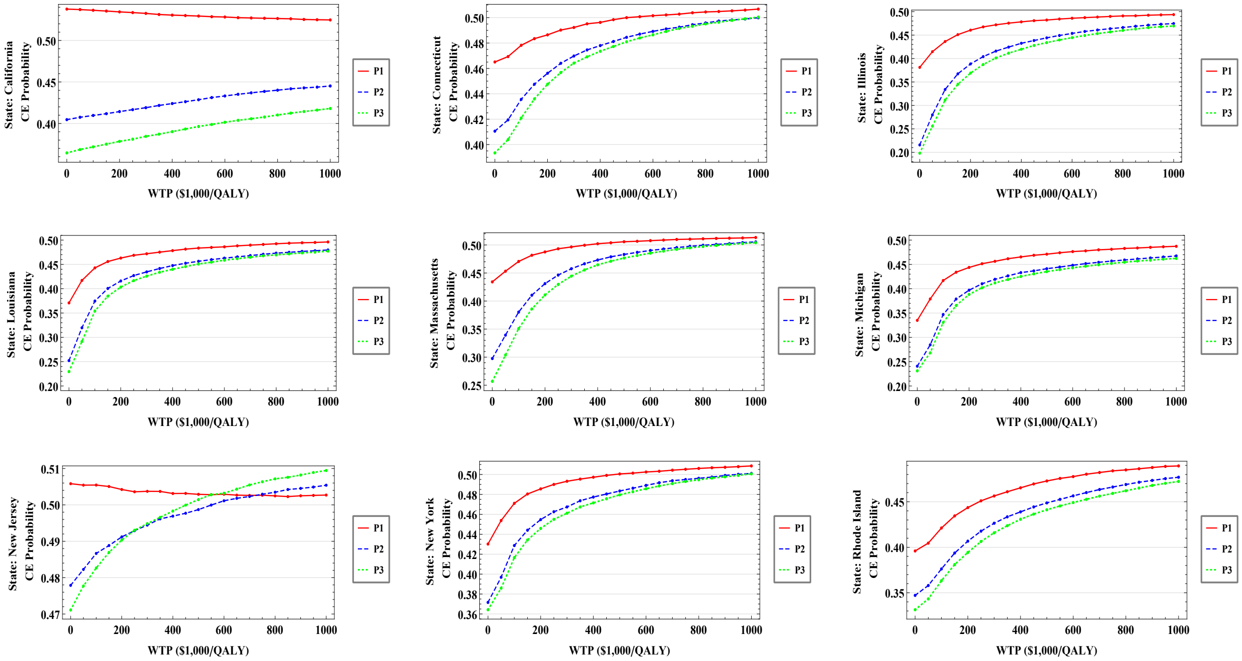

Figure 3 **(Color online) Cost-effectiveness probability of potential policies compared to the current policies**

Notes. See Table 3 for intervention policies P1/P2/P3. Results for other states are provided in Appendix D.5. Unlike other states, the cost-effectiveness of policy P1 will be dropped in states such as California and New Jersey when we increase WTP. This is because the current policy observed in these states are typically more strict than policy P1.

much more pronounced impact on the cost-effectiveness of the more restrictive policies we study in states such as Illinois, Louisiana, Massachusetts, Michigan, and New York than other states such as Arizona, California, Washington, and Wisconsin. This is yet another indication of the heterogeneity of health/economic outcomes in this pandemic.

In closing this section, we emphasize that caution should be exercised in interpreting our cost-effectiveness results. First, although our results indicate that at typical WTP rates more restrictive intervention policies might not be cost-effective for some specific states, they do not promote the idea that the costs are not worth the benefits. In a pandemic like COVID-19, the ultimate objective should be to control the number of infections, hospitalizations, and deaths (as our earlier results attest). External funding sources such as government relief bills (e.g., the government's Coronavirus Aid, Relief, and Economic Security (CARES) Act) might be used to mitigate some of the cost-related measures we study. Second, our findings are based on data from March 2020 to June 2020. The number of new cases in the U.S., however, soared up in December 2020-January 2021 (New York

Times 2021).[6] As a result, we expect that the more strict policies we study could have saved more lives and yielded higher QALY gains than what we report based on our study period. Finally, imposing more strict policies may be inevitable, especially as states face the risk of fast-spearing variants of the coronavirus (Nature 2020) and/or tangible delays in rollout of the COVID19 vaccine (BMJ 2021). Decision-making on what policies to impose, however, has been challenging for the authorities, mainly because of lack of quantitative evidence on health gains versus economic burdens of different intervention policies. To the best of our knowledge, our findings provide the first set of quantitative values on the heath versus economic impact of COVID-19 policies separately for each state, and we hope they could facilitate the decision-making process for COVID-19 and future epidemics.

3.4. Robustness Checks

To test the robustness of our main results, we now perform extensive sensitivity analyses on various parameters, including residents' mobility, WTP, qol scores and QALY values, and the proportion of population losing their income.

3.4.1. Mobility. In our baseline comparisons of policies in §3.3, we utilized the actual mobility rates observed from cell phone 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 4 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 to no intervention) without significantly increasing the total cost. Furthermore, in a consistent fashion across the states, the less strict an intervention 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 societal intervention policies in managing the pandemic.

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[6] For example, on April 9, 2020, 34,699 new cases were identified in the U.S., while this number changed to 300,594 on Jan 8, 2021 (New York Times 2021).

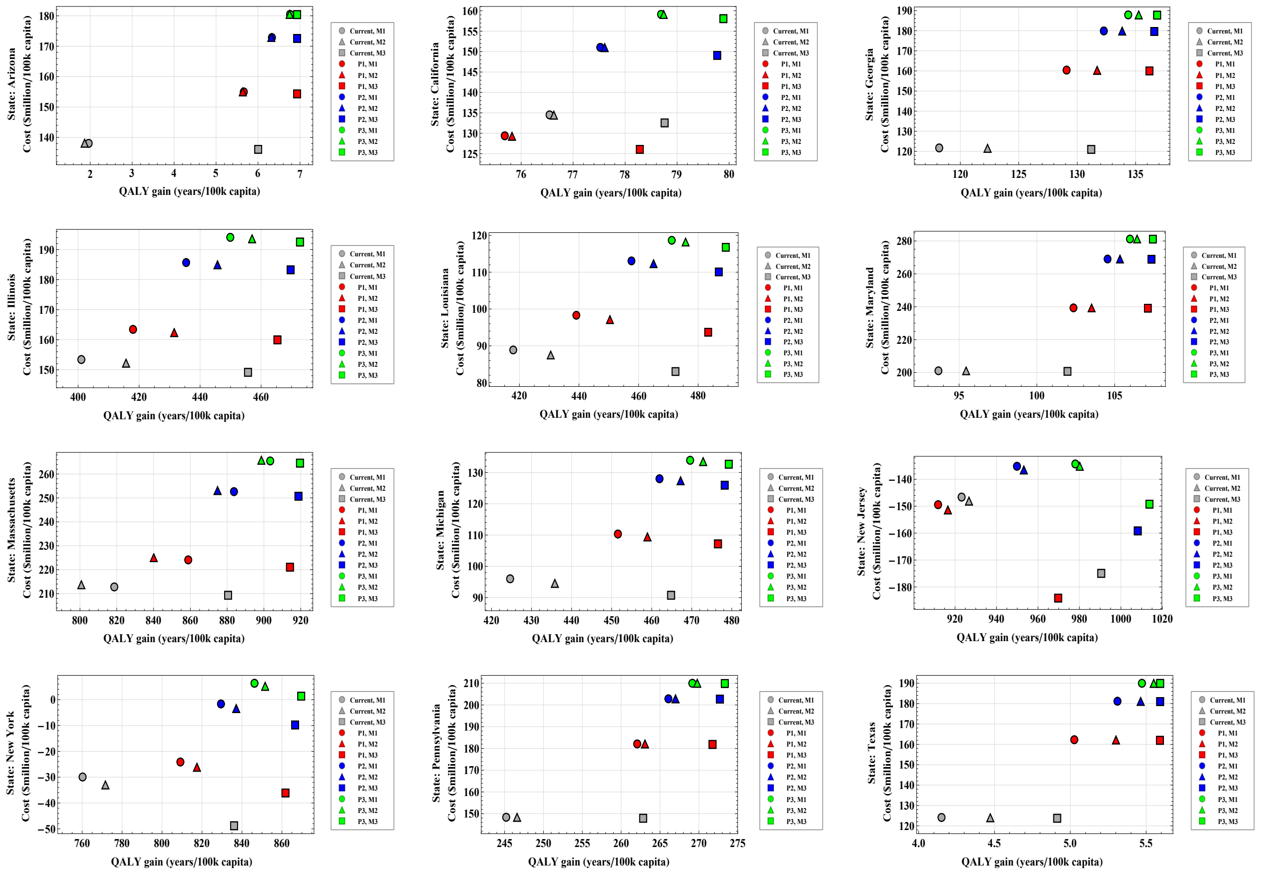

Figure 4 **(Color online) Average outcomes under different intervention policies and mobility scenarios**
Notes. Intervention policies are compared with no intervention. See Table 3 for intervention policies P1/P2/P3. M1: mobility observed in each state (see Table 4). M2/M3: other mobility scenarios used for robustness check.

3.4.2. WTP. In our robustness check, we alter the value of WTP beyond $100,000/QALY. As states become willing to pay more for one extra year of QALY, we would expect the potential policies—advocating more strict interventions—to become more cost-effective. Our results in Figure 3 verify this conjecture. However, they also reveal that the story surrounding the impact of WTP is more nuanced. For example, we find that increasing WTP can have both linear and concave effects on the cost-effectiveness of societal intervention policies we study. In particular, while we observe a linear effect in states such as California, Iowa, and Oregon, we find a concave effect in other states such as Michigan, New York, and New Hampshire. Also, in a few states such as Hawaii, Minnesota, North Dakota, and Utah, the variations in cost-effectiveness is not sensitive to that in WTP. Furthermore, we find that despite the difference between potential Policies 2 and 3 (recall that stay-at-home order and non-essential business closures are lifted one month earlier under Policy 2 than Policy 3), their cost-effectiveness are quite comparable regardless of the WTP value. Finally, in the state of New Jersey, our results show that the cost-effectiveness of Policy 3 would drastically surpass that of Policies 1 and 2 when we increase WTP, although the former is more strict than the latter. This is consistent with what we observed earlier regarding the total QALY gain and extra total cost estimated for this state (see §3.3.2).

3.4.3. qol Scores and QALY Values. We consider two alternative scenarios for qol scores (and hence, the estimated QALY values) where they are selected from either higher or lower ranges compared to 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 get deteriorated), the saving in the total QALY from current/potential policies increases compared to no intervention. This result supports the notion that more strict policies are better suited for populations with worse health conditions. Furthermore, we observe no tangible difference in the total cost 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.

3.4.4. Proportions of Population with Lost Income. We consider two alternative scenarios for the portion of working population who have lost their income. Details are provided in Online Appendix E.2. From our results, we observe that, as the ratio of population who lost more than 50% of their income increases, the extra total cost incurred by current/potential policies compared to no intervention ramps up. However, as expected, we do not observe changes in the QALY outcomes when chaning the ratio of population with lost income.

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., §3.1.2) have been sufficient. In particular, we observe that the outputs of our SERIS 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 intervention policies within a few weeks to months since their enactment. The deriving force behind this has been the economic burdens of these policies; e.g., lost income and productivity (RAND 2020, Shretta 2020, Wall Street Journal 2020). However, premature reopening has contributed to some states observing the resurgence of COVID-19 cases (Associated Press 2020, New York Times 2020a), which may force states to retract their reopening decisions (Reuters 2020, Washington Post 2020b). Although the trade-off between health and economic impacts of intervention 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 cell phone data to estimate individuals' mobility in each state. After calibrating our models with these data, we analyze the impact of various intervention 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 interventions, their duration, per capita income, and the residents' mobility rate within 10 miles from their homes (compared to 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 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. Finally, our extensive robustness checks on parameters such as residents' mobility rates, WTP values, qol scores and QALY values, and proportions of population with lost income reveal that our main findings on the performance of intervention 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.

4.2. Limitations

Strict interventions can “flatten” curves for COVID-19 cases, hospitalizations, and deaths (see, e.g., Boloori and Saghafian (2020), Lyu and Wehby (2020b)). Similar effects can be achieved by relaxing hospitals’ limited capacities on available beds and ventilators (Adelman 2020). Since capacity expansion mechanisms often bear extra direct costs, they could alter some of our results. However, to the best of our knowledge, there is currently no reliable data source on costs associated with such capacity expansions in each state. We leave it to future research to study the interplay between capacity expansion mechanisms and the cost-effectiveness of societal intervention policies. Furthermore, although we have analyzed 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 investigations. Finally, 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 employed. 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 societal intervention policies.

4.3. Future Research and Conclusion

In addition to addressing the limitations we discussed in the previous section, as the pandemic evolves and new data becomes available, future research can enhance our study through three main avenues:

(1) In addition to factors that we have accounted for in this study, future research can corporate 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 have been delayed or avoided (due to reasons such as state’s mandates or limited capacity of healthcare settings).

(2) 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 2020a).

(3) In the absence of viable treatments or vaccination, a recovery from COVID-19 does not necessitate permanent immunity. At the time of writing this paper, no fully studied treatment has become available that could be used for the mass population, and the ones promised for this purpose, as well as mass delivery of potential vaccines, are well behind the schedule (CNN 2020). Given the time between the presumed onset of COVID-19 in the U.S. 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 5), which implies an average immunity period of 263 days. This scenario can aggravate the COVID-19 landscape and may warrant even more strict intervention policies. Evaluating the cost-effectiveness of policies under such circumstances would be another interesting avenue for future research.

To briefly conclude, we note that while financial ramifications of intervention policies instigate resistance against their long-term enactment, imposing them may be inevitable depending on how this pandemic pans out. Recent promising news about the development and future availability of vaccines for the mass population could also alter the path for this pandemic. Nevertheless, our study provides important qunatitative insights that can help the federal government as well as the authorities in each state to make better decisions through a more detailed understanding of the health and cost consequences of societal intervention policies that can be used to curb the infection rates. Finally, it is important to note that while 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.

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Online Appendices

APPENDIX A. Summary of Socio-Demographic Information Retrieved from Mathematica

Table A.1 Summary of other socio-demographics information[a]

State	Population[b]	Annual Birth[b]	Annual Death[b]	Employment[c]
Alabama	4,849,377	57,313	53,879	2,618,073
Alaska	736,732	10,031	4,819	445,031
Arizona	6,731,484	81,942	60,523	3,520,657
Arkansas	2,966,369	36,640	31,322	1,606,087
California	38,802,500	462,617	282,520	21,245,509
Colorado	5,355,866	64,524	39,116	3,215,903
Connecticut	3,590,886	34,567	31,149	2,235,248
Delaware	935,614	10,683	9,454	548,130
Dist. of Col.	658,893	9,493	5,677	813,734
Florida	19,893,297	221,695	211,692	10,679,883
Georgia	10,097,343	127,873	86,319	5,559,982
Hawaii	1,431,603	16,878	12,748	873,157
Idaho	1,654,930	22,220	13,308	947,483
Illinois	12,859,995	144,299	110,004	7,608,799
Indiana	6,596,855	80,711	62,175	3,727,784
Iowa	3,107,126	37,672	28,809	2,034,878
Kansas	2,904,021	35,457	25,230	1,855,548
Kentucky	4,425,092	53,471	46,074	2,438,265
Louisiana	4,649,676	58,498	46,343	2,517,085
Maine	1,330,089	12,073	14,335	830,221
Maryland	5,976,407	70,091	51,453	3,437,502
Massachusetts	6,794,422	70,419	58,564	4,198,813
Michigan	9,909,877	109,472	95,983	5,454,613
Minnesota	5,489,594	67,642	43,200	3,562,386
Mississippi	2,994,079	35,978	31,536	1,568,063
Missouri	6,083,672	71,297	60,141	3,663,291
Montana	1,023,579	11,618	9,870	647,427
Nebraska	1,881,503	25,343	15,582	1,245,362
Nevada	2,839,099	35,932	25,610	1,666,531
New Hampshire	1,326,813	12,004	12,125	848,016
New Jersey	8,944,469	99,501	75,723	5,128,341
New Mexico	2,085,572	23,125	18,388	1,115,677
New York	19,746,227	222,924	164,817	11,039,874
North Carolina	10,042,802	119,203	94,312	5,460,841
North Dakota	756,927	10,536	6,250	487,337
Ohio	11,594,163	134,291	117,750	6,829,647
Oklahoma	3,878,051	48,759	40,266	2,159,540
Oregon	3,970,239	43,305	36,563	2,320,043
Pennsylvania	12,787,209	135,190	133,439	7,304,947
Rhode Island	1,056,298	10,481	9,802	615,347
South Carolina	4,896,146	56,353	50,744	2,507,978
South Dakota	858,469	11,911	7,337	564,481
Tennessee	6,549,352	80,239	67,977	3,746,010
Texas	26,956,958	378,664	202,786	14,157,309
Utah	2,942,902	48,642	17,443	1,673,907
Vermont	626,562	5,581	5,634	427,422
Virginia	8,326,289	98,403	69,729	4,936,137
Washington	7,061,530	87,950	58,587	3,948,743
West Virginia	1,844,128	17,888	22,567	921,898
Wisconsin	5,771,337	63,712	50,393	3,595,084
Wyoming	584,153	6,601	4,971	389,776

[a] Information is obtained by Mathematica, Wolfram Research, Inc. (see the codes below). Information for per capita income and median age is provided in the main body (see Table 4). [b] This information is used to measure the initial population, $N(0)$, and vital dynamics μ and ν used in the SEIRS model. $N(0)$=Population, μ=(1/365)*(Annual Birth/Population), ν=(1/365)*(Annual Death/Population). [c] This is used to obtain the employment rate in each state (see Appendix C.3).

Sample of Mathematica codes to retrieve demographic and cost information (shown for the state of Michigan)

Per capita income: `AdministrativeDivisionData[Entity["AdministrativeDivision","Michigan","UnitedStates"],"PerCapitaIncome"]`

Population: `AdministrativeDivisionData[Entity["AdministrativeDivision","Michigan","UnitedStates"],"Population"]`

Birth: `AdministrativeDivisionData[Entity["AdministrativeDivision","Michigan","UnitedStates"],"AnnualBirths"]`

Death: `AdministrativeDivisionData[Entity["AdministrativeDivision","Michigan","UnitedStates"],"AnnualDeaths"]`

Median age: `AdministrativeDivisionData[Entity["AdministrativeDivision","Michigan","UnitedStates"],"MedianAge"]`

Employment: `AdministrativeDivisionData[Entity["AdministrativeDivision","Michigan","UnitedStates"],"PerCapitaIncome"]`

APPENDIX B. Model Validation

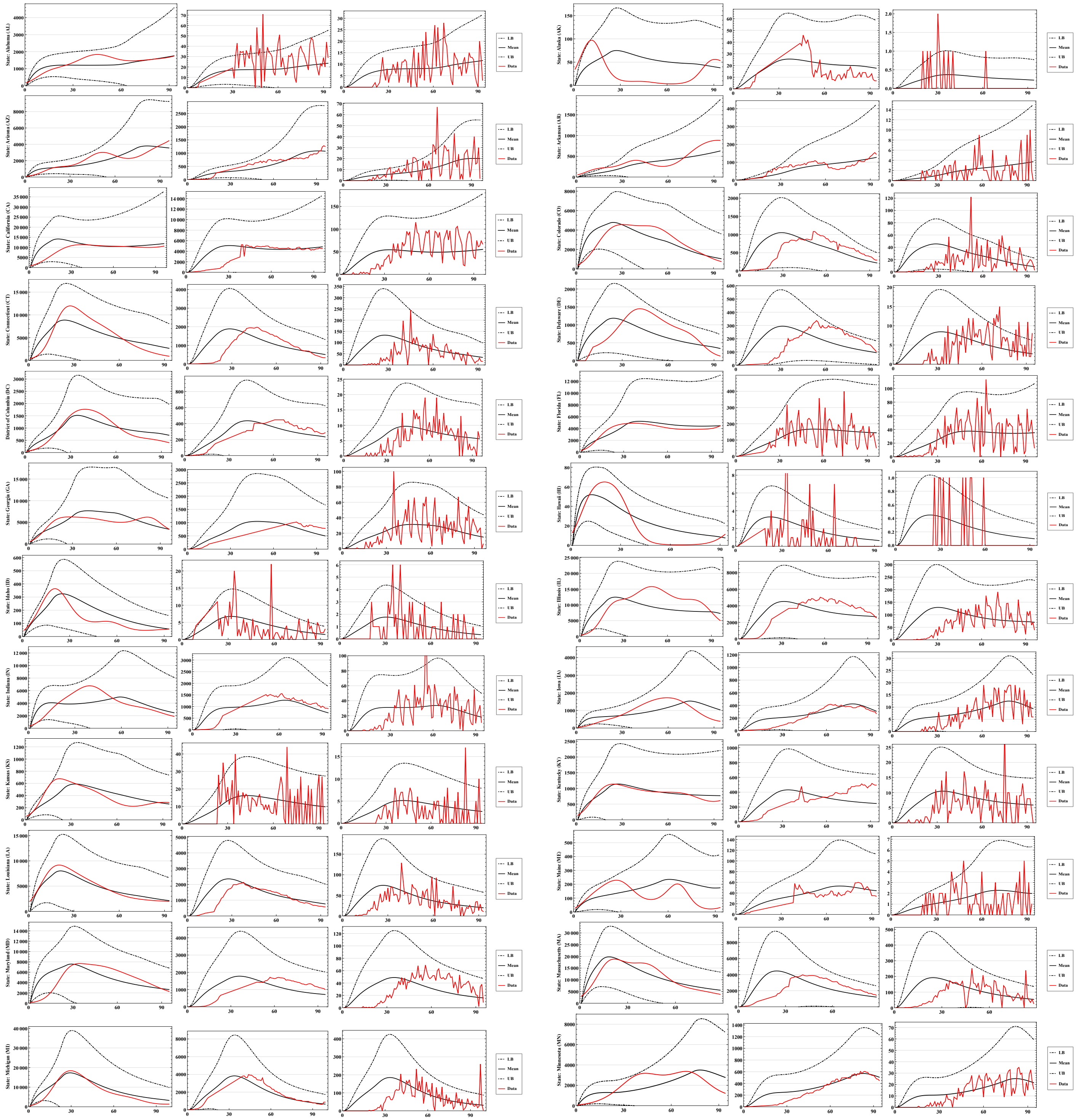

Figure B.1 (Color online) SEIRS model validation: comparison of our predictions with the data

Notes. Data of projected infections comes from IHME (2020). Data of projected hospitalizations and deaths comes from Foldi and Csefalvay (2020). For each state, columns from left to right represent results for the total number of projected infections, hospitalizations, and deaths, respectively. x-axis represents time (days). For each state, day 0 is different (see Table 1, column "Data"). LB/UB: Lower/upper bounds represent 90% CIs for each outcome. Not visible lower bounds imply negative values.

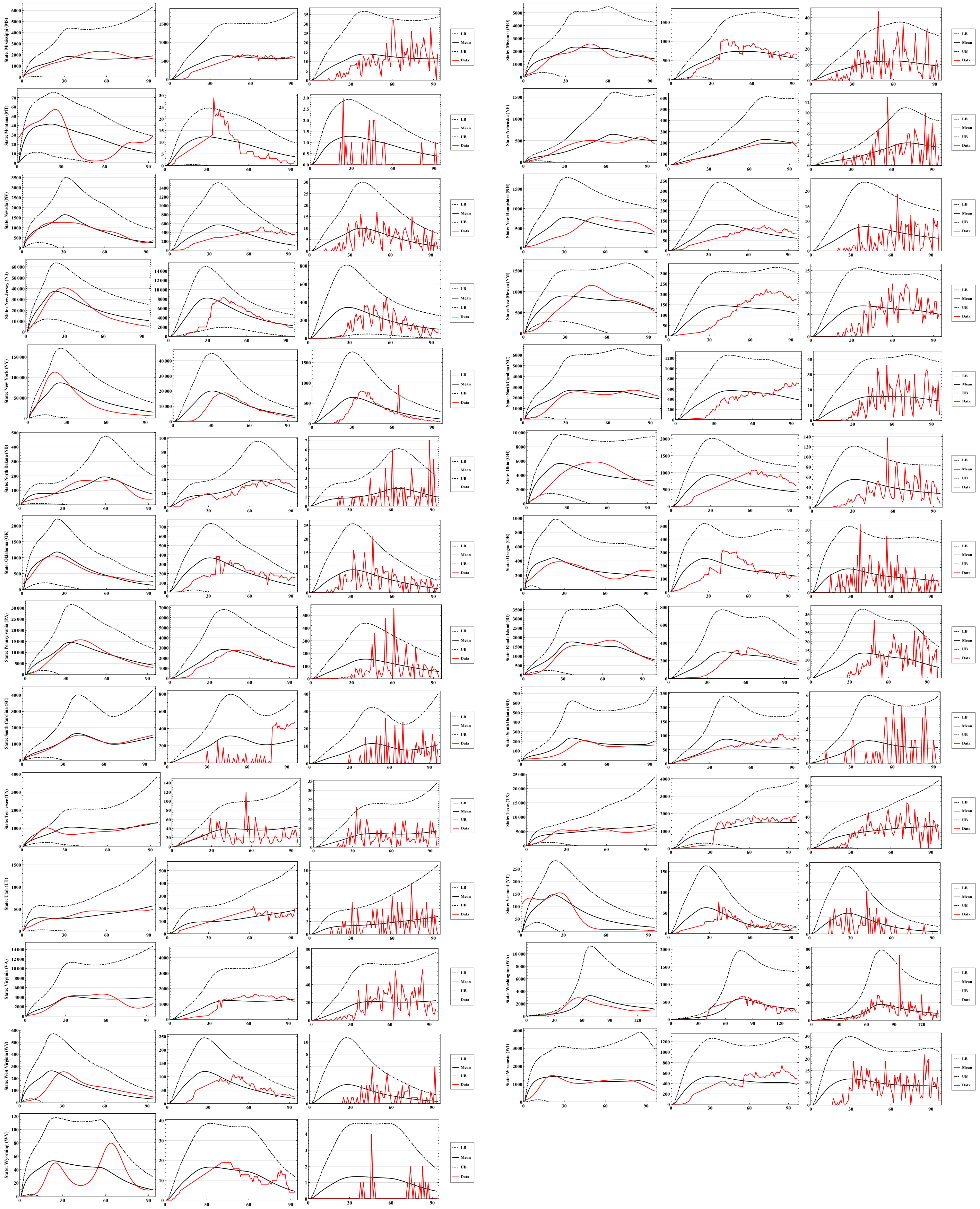

Figure B.1 **Continued**

APPENDIX C. Parameter Estimations (related to QALY and Cost)

C.1. Quality-of-life Scores. Following §2.5 in the main body, we characterize qol scores as follows:

$$q_i = \begin{cases} 1.0, & \text{if } i \in \{1,11\} \quad \text{Compartment(s): susceptible, recovered,} \\ x \in [0.8,1.0], & \text{if } i = 2 \quad \text{Compartment(s): exposed/presymptomatic,} \\ x \in [0.7,0.9], & \text{if } i = 3 \quad \text{Compartment(s): infected asymptomatic,} \\ x \in [0.6,0.8], & \text{if } i = 4 \quad \text{Compartment(s): infected symptomatic,} \\ x \in [0.5,0.7], & \text{if } i = 5 \quad \text{Compartment(s): infected hospitalized (common bed),} \\ x \in [0.3,0.5], & \text{if } i = 6 \quad \text{Compartment(s): infected hospitalized (ICU bed),} \\ x \in [0.1,0.3], & \text{if } i = 7 \quad \text{Compartment(s): infected hospitalized (ICU bed \& ventilator),} \\ x \in [0.7,0.9], & \text{if } i = 8 \quad \text{Compartment(s): carrier post discharge (was hospitalized common bed),} \\ x \in [0.6,0.8], & \text{if } i = 9 \quad \text{Compartment(s): carrier post discharge (was hospitalized ICU bed),} \\ x \in [0.5,0.7], & \text{if } i = 10 \quad \text{Compartment(s): carrier post discharge (was hospitalized ICU bed \& ventilator),} \\ 0.0, & \text{if } i = 12 \quad \text{Compartment(s): dead.} \end{cases} \tag{EC.1}$$

Regarding our notion in Equation (EC.1), we note the following points:

- Since we measure QALY per single day, we divide the qol scores in Equation (EC.1) by 365 to account for the daily counterparts.
- To the best of our knowledge, qol scores for majority of these compartments are not reported by the literature. Therefore, we consider a range of variation for these scores. For example, for patients with infection that are hospitalized in a common bed, we select the range [0.5,0.7]. Of note, this range is very close to the average qol score of 0.6 reported in the medical literature for the same category of patients (Liu et al. 2020).
- We set up these ranges such that the qol scores for different compartments would properly reflect on their relative severity. For example, the average qol score for an infected hospitalized patient (in a common bed) is 0.6, whereas its counterpart for an infected hospitalized patient (in an ICU bed) is 0.4.
- For cases that are still carriers of the disease post hospital discharge, we assume that their health will be improved compared to when they were hospitalized. Of note, this improvement is more noticeable for patients who had been hospitalized in an ICU bed and with a ventilator.
- These ranges allow us to account for variations in qol scores for different compartments. Nevertheless, in our robustness checks, we will consider two alternative scenarios for qol scores where they are selected from either higher or lower ranges (see Appendix E.1).

C.2. Direct Cost. Through the following steps, we take a back-of-the-envelope calculation to estimate the operating costs of a common bed, an ICU bed, and an ICU bed with a ventilator per day.

1. We obtain the costs of using an ICU bed or an ICU bed with a ventilator per day (Dasta et al. 2005). We then use the U.S. healthcare inflation rate to prorate the corresponding values from 2005 to 2020 (YCHARTS 2020).
2. To measure the operating cost of a common non-ICU bed, we use the average ratio of cost of an ICU bed to that of a non-ICU bed reported to be 5.85 (Norris et al. 1995).
3. The costs obtained via steps 1-2 are used for the state of Washington that is reported to have the highest inpatient expenses per day KFF (2018a). For other states, we adjust costs based on the ratio of inpatient expenses in each state compared to that in the state of Washington KFF (2018a).
4. Table C.1 shows the results of these estimations. To account for potential variations, in our simulation, we consider a range for each of these costs by allowing a ±10% variation based on the reported values.

C.3. Indirect Cost. In Equation (4) in the main body, we used $p_j(t)$, $j = 1, \ldots, 4$, to represent the proportion of working population who have lost less than 25%, between 25% and 50%, between 50% and 75%, and more than 75% of their income, respectively. Also, according to Statista (2020), we let $p_1(t) = 48\%$, $p_2(t) = 20\%$, $p_3(t) = 14\%$, $p_4(t) = 18\%$; e.g., 48% of people in the survey have lost less than 25% of their income. Despite this evidence, the survey study reported in Statista (2020) does not account for the number and intensity of societal intervention policies. Indeed, to the best of our knowledge, there is no

Table C.1 Cost of healthcare resources utilization ($/day)

State	Common bed	ICU bed	ICU bed & ventilator
Alabama	470.29	2,751.20	3,892.49
Alaska	668.88	3,912.98	5,536.21
Arizona	818.44	4,787.87	6,774.04
Arkansas	572.63	3,349.91	4,739.56
California	1,075.82	6,293.55	8,904.33
Colorado	927.48	5,425.78	7,676.58
Connecticut	863.82	5,053.37	7,149.68
Delaware	925.35	5,413.31	7,658.93
Dist. of Col.	1,057.85	6,188.42	8,755.59
Florida	674.06	3,943.27	5,579.07
Georgia	561.97	3,287.54	4,651.32
Hawaii	805.34	4,711.25	6,665.64
Idaho	972.25	5,687.72	8,047.17
Illinois	802.90	4,697.00	6,645.47
Indiana	789.19	4,616.81	6,532.02
Iowa	487.04	2,849.20	4,031.15
Kansas	586.34	3,430.09	4,853.01
Kentucky	595.78	3,485.33	4,931.16
Louisiana	618.32	3,617.19	5,117.72
Maine	802.90	4,697.00	6,645.47
Maryland	857.42	5,015.95	7,096.74
Massachusetts	925.35	5,413.31	7,658.93
Michigan	731.02	4,276.48	6,050.50
Minnesota	724.62	4,239.06	5,997.56
Mississippi	417.59	2,442.94	3,456.35
Missouri	719.14	4,206.98	5,952.18
Montana	485.52	2,840.29	4,018.54
Nebraska	631.42	3,693.81	5,226.12
Nevada	606.44	3,547.69	5,019.40
New Hampshire	798.94	4,673.83	6,612.70
New Jersey	848.59	4,964.28	7,023.63
New Mexico	865.65	5,064.06	7,164.81
New York	876.31	5,126.43	7,253.04
North Carolina	680.46	3,980.69	5,632.01
North Dakota	560.14	3,276.85	4,636.20
Ohio	861.69	5,040.90	7,132.03
Oklahoma	600.35	3,512.06	4,968.98
Oregon	1,046.88	6,124.27	8,664.83
Pennsylvania	769.09	4,499.21	6,365.63
Rhode Island	855.60	5,005.26	7,081.61
South Carolina	626.85	3,667.08	5,188.31
South Dakota	469.98	2,749.42	3,889.97
Tennessee	653.96	3,825.66	5,412.68
Texas	793.15	4,639.98	6,564.80
Utah	893.97	5,229.78	7,399.26
Vermont	801.99	4,691.65	6,637.91
Virginia	633.85	3,708.06	5,246.29
Washington	1,081.91	6,329.19	8,954.75
West Virginia	552.22	3,230.52	4,570.65
Wisconsin	770.01	4,504.56	6,373.20
Wyoming	436.48	2,553.41	3,612.65

data reporting on this specific information. To accommodate this, we take the following steps to adjust our estimations:

1. When all three interventions are in place (including stay-at-home order and non-essential business closures, large-gathering ban, and school closures), we resort to the survey in in Statista (2020) and let $p_1(t) = 48\%,\ p_2(t) = 20\%,\ p_3(t) = 14\%,\ p_4(t) = 18\%$. This is a reasonable assumption, because the foregoing survey was conducted in May 2020, when most states had undergone these three interventions (see Table 1 in the main body).
2. Recall that, when we transition between our counterfactual policies, we relax one intervention at a time (see Table 3 in the main body). When this happens, we drop the corresponding p_j's for $j = 2, 3, 4$ by 5% and add them to quantile 1. Based on this premise, we have (for description of Policies 1/2/3, see Table 3 in the main body):

$$(p_1(t), p_2(t), p_3(t), p_4(t)) = \begin{cases} (48\%, 20\%, 14\%, 18\%)\,, & \text{under Policy 1: if } 1 \le t \le 61, \\ (63\%, 15\%, 9\%, 13\%)\,, & \text{under Policy 1: if } 62 \le t \le 92, \\ (78\%, 10\%, 4\%, 8\%)\,, & \text{under Policy 1: if } 93 \le t \le 122, \\ (48\%, 20\%, 14\%, 18\%)\,, & \text{under Policy 2: if } 1 \le t \le 92, \\ (63\%, 15\%, 9\%, 13\%)\,, & \text{under Policy 2: if } 93 \le t \le 122, \\ (48\%, 20\%, 14\%, 18\%)\,, & \text{under Policy 3: if } 1 \le t \le 122, \end{cases} \tag{EC.2}$$

3. Despite these adjustments, the resulting values may not be exactly representive of reality. We account for this via two routes:
   (a) First, in our simulation, we consider a ±10% variation based on the resulting values for p_j's.
   (b) Then, in our robustness checks, we consider two alternative scenarios for p_j's (see Appendix E.2).

Finally, we obtain the employment rate η by the ratio Employment/Population, where the latter two measures were already introduced in Table A.1.

APPENDIX D. Comparison of Intervention Policies (continued from main body, §3.3)

D.1. Micro-Simulation Model

Table D.1 A pseudocode for the micro-simulation model

```
Input: all information related to each state, type and duration of conterfactual policies 1-3 (see Table 3)
1  for each state
2    for iteration $k$=1 to 10,000
3      for each parameter in the SEIRS model
4        randomly select a value from the corresponding CI // see Table 5$^{a}$
5      for each compartment in the SEIRS model
6        randomly select a qol score from the corresponding range // see Appendix C.1, Equation (EC.1)
7      for each hospital resource
8        randomly select an operation cost from the corresponding range // see Appendix C.2
9      for each quantile $j$ of population losing their income$^{c}$
10       randomly select a ratio of lost income per day for this quantile, $\theta_j \in [(j-1)*0.25, j*0.25]$
11       randomly select a portion of population for this quantile from the corresponding range // see Appendix C.3, Equation (EC.2)
12     for each counterfactual policy
13       predict transmission rates $\beta_1$-$\beta_3$ // using Equation (6)
14       run the SEIRS model (Equations (1a)-(1h)) to obtain the number of people in each compartment over the time horizon,
         $X_i(t)$ for $i \in \{1,\dots,12\}$ and $t=1,\dots,122$ // using information from lines 3-4 and 13, 122 days: 01-March through 30-June
15       obtain the total QALY and cost // using information from lines 5-11 and 14 in Equations (2)-(4)
16     for the current policy
17       run the SEIRS model (Equations (1a)-(1h)) to obtain the number of people in each compartment over the time horizon,
         $X_i(t)$ for $i \in \{1,\dots,12\}$ and $t=1,\dots,122$ // using information from lines 3-4
18       obtain the total QALY and cost // using information from lines 5-11 and 17 in Equations (2)-(4)
19     for the hypothetical no-intervention policy
20       run the SEIRS model (Equations (1a)-(1h)) to obtain the number of people in each compartment over the time horizon,
         $X_i(t)$ for $i \in \{1,\dots,12\}$ and $t=1,\dots,122$ // using information from lines 3-4
21       obtain the total QALY and cost // using information from lines 5-11 and 20 in Equations (2)-(4)
22   return the average and std. dev. of total QALY and cost from each policy // using lines 2, 15, 18, and 21
```

[a] For $N(0)$, μ, and ν, there is no need to randomly select a value.

[c] $j=1,\dots,4$; losing less than 25%, between 25% and 50%, between 50% and 75%, and more than 75% of their income, respectively.

Measuring the Cost-Effectiveness Probability. From our discussion in §2.5 (in the main body), recall that a potential policy is said to be more cost-effective than the current policy if ICER≤WTP. Since, in our simulation, we run 10,000 iterations under each policy, there will be $10^4 \times 10^4 = 10^8$ comparisons of ICER with WTP. To this end, the cost-effectiveness (CE) probability of a potential policy compared to the current policy is measured as the percentage of these 10^8 comparisons where ICER $\leq$ WTP.

D.2. Accounting for High-Risk Population.

Older people and minority races typically have lower qol scores compared to the average population. As reported by the literature, a person aging one year older could drop his/her qol score about 0.00343 per year compared to the same person one year younger. Similarly, a person with a minority race could drop the qol score about 0.01 per year compared to White people (see, e.g., Dyrbye et al. (2007), Grassi et al. (2020)). To address this in our analysis, we take the following steps:

1. We consider the ranges [0.001,0.005] and [0.005,0.2] for the drops in the qol score for each extra year a person ages and for Black/Hispanic races, respectively.
2. In our simulation, we generate random values from these two ranges and subtract their average from the qol scores that we have already used in our baseline comparisons; see Equation (EC.1).

Of note, the high-risk population is also impacted from the economic standpoint. Indeed, compared to White people, Black/Hispanic populations are reported to be, on average, 15% more exposed to financial repercussions caused by COVID-19 (see, e.g., Saenz and Sparks (2020)). Thus, when accounting for the proportion of lost income in our simulation, we consider an increase in this proportion across all quantiles of lost income (see Equation (EC.2)). This increase is from the range [2%,5%], which is also consistent with the findings in the literature (see, e.g., Parker et al. (2020)).

D.3. Increase in QALY and Cost. In this section, we report on the average and standard deviation of QALY gains and extra cost obtained under different intervention policies compared to no intervention.

Table D.2 Results: per 100k capita

State	**Current**	**Potential intervention policy**		
	Policy	**P1**	**P2**	**P3**
Alabama	1.1889 (0.0249)	1.7851 (0.1243)	1.9111 (0.1953)	1.9414 (0.1112)
	99.938 (0.7197)	150.417 (0.9201)	169.0003 (0.8758)	176.8958 (1.2961)
Alaska	34.5109 (1.5006)	36.3539 (7.982)	37.2408 (4.8299)	37.8845 (6.3911)
	186.2986 (2.802)	212.9493 (2.4144)	240.1858 (1.1485)	250.8313 (0.958)
Arizona	1.9643 (0.0807)	5.661 (0.235)	6.3311 (0.3133)	6.7635 (0.2865)
	138.0669 (1.4549)	154.9727 (1.3786)	172.8467 (1.0723)	180.4707 (1.0501)
Arkansas	50.3899 (5.4979)	51.1226 (7.1109)	51.1675 (6.2877)	51.1975 (4.7047)
	125.3991 (0.9315)	142.063 (1.1063)	159.2282 (0.2906)	167.367 (2.0319)
California	76.5462 (3.6798)	75.685 (7.0698)	77.5215 (6.8192)	78.6912 (9.7688)
	134.5055 (5.7161)	129.3818 (4.4763)	151.0426 (9.1807)	159.1241 (7.5613)
Colorado	37.3894 (4.3593)	40.5347 (2.5274)	41.3325 (1.0555)	41.7862 (3.5407)
	176.1548 (2.2984)	209.9596 (2.0241)	236.1213 (0.6952)	247.7443 (3.5709)
Connecticut	759.7085 (22.6067)	800.8986 (29.6873)	824.4195 (11.9382)	845.6433 (38.1282)
	8.307 (29.2894)	13.0149 (24.4491)	38.2849 (8.7506)	44.9289 (9.8612)
Delaware	213.9733 (16.494)	219.6798 (20.8353)	221.8743 (18.6245)	223.225 (5.7912)
	72.7662 (7.4858)	82.758 (12.6286)	105.8682 (13.3857)	116.0495 (9.2958)
District of Columbia	263.0158 (20.0426)	313.3399 (3.7717)	336.0518 (23.5878)	356.4364 (14.9066)
	140.3108 (12.0498)	160.3769 (17.9862)	191.0840 (10.4426)	194.4692 (11.2773)
Florida	30.8426 (4.1609)	32.9236 (4.7211)	33.3702 (5.6879)	33.6681 (5.1098)
	127.1502 (1.2835)	165.3542 (0.6858)	184.1546 (1.0065)	191.8918 (1.4227)
Georgia	118.1892 (5.822)	129.0925 (2.1413)	132.2778 (2.6066)	134.3655 (11.1955)
	121.7096 (0.3359)	160.4149 (0.4819)	179.8957 (2.168)	187.9028 (2.9814)
Hawaii	0.2318 (0.0055)	0.2731 (0.0062)	0.2742 (0.0156)	0.2742 (0.0152)
	199.4169 (1.2367)	213.1152 (0.4571)	238.9378 (0.891)	249.3891 (1.8969)
Idaho	210.6182 (6.7329)	215.3366 (4.3386)	218.0078 (19.6291)	219.9565 (12.5194)
	138.317 (1.2692)	157.5195 (0.8226)	176.1185 (0.772)	183.3995 (1.1125)
Illinois	401.0637 (7.1648)	418.0043 (18.2987)	435.4295 (40.3176)	449.8997 (35.7729)
	153.386 (15.9931)	163.4188 (16.7142)	185.6861 (4.5809)	194.0827 (12.9475)
Indiana	4.8061 (0.1987)	5.8894 (0.1211)	6.026 (0.0792)	6.0276 (0.327)
	144.7189 (1.1065)	164.0959 (0.7206)	185.1833 (0.3434)	193.9282 (2.2912)
Iowa	2.9621 (0.1647)	4.5626 (0.1121)	4.962 (0.1351)	5.1157 (0.1899)
	205.8914 (2.1224)	211.9575 (1.9962)	236.699 (0.3612)	247.4263 (2.6673)
Kansas	114.6543 (4.0531)	120.1744 (21.2464)	122.3505 (11.5146)	123.8352 (18.749)
	169.4741 (1.615)	205.133 (1.3509)	229.3194 (1.7029)	239.3294 (2.6517)
Kentucky	162.1128 (8.0749)	161.6976 (19.2134)	167.4444 (10.5056)	171.832 (12.6156)
	134.8662 (6.6725)	137.2935 (6.6454)	155.5503 (7.5482)	162.6792 (2.3501)
Louisiana	417.9386 (7.2019)	439.117 (13.4763)	457.6127 (41.971)	471.1281 (20.9787)
	88.873 (13.5604)	98.2933 (14.2305)	113.0626 (14.1647)	118.6556 (11.1615)
Maine	7.0526 (0.1416)	10.5486 (0.5379)	10.9978 (0.115)	11.305 (0.9)
	158.3814 (1.4402)	196.6493 (1.7233)	220.02 (2.0757)	229.5359 (2.1791)
Maryland	93.6734 (4.2371)	102.3538 (9.3706)	104.5452 (9.4398)	105.9828 (9.7253)
	201.0499 (2.32)	239.3226 (3.3808)	269.0177 (2.105)	281.1914 (3.63)
Massachusetts	818.6499 (40.2312)	858.8553 (36.217)	883.7123 (8.9219)	903.421 (19.1315)
	212.7984 (4.1037)	224.0991 (5.9395)	252.6364 (2.3759)	265.4569 (3.8149)
Michigan	424.6499 (10.1509)	451.5707 (20.4967)	461.9561 (14.0592)	469.602 (10.2701)
	96.0045 (2.8043)	110.3333 (7.8126)	128.0079 (8.4058)	133.9047 (13.9201)
Minnesota	2.5338 (0.0408)	3.5751 (0.1276)	3.8325 (0.1391)	3.8733 (0.1776)
	213.751 (0.839)	241.4228 (1.6895)	270.7877 (0.3179)	282.3298 (1.3173)

For each state, the first and second rows indicate QALY gain (years) and extra cost ($million), respectively.
See Table 3 for intervention policies P1/P2/P3.

Table D.2 Continued

State	Current	Potential intervention policy		
	Policy	P1	P2	P3
Mississippi	79.2546 (6.0507)	85.5185 (11.3028)	87.938 (12.8894)	89.4949 (8.9987)
	83.364 (1.0728)	108.8265 (1.4463)	123.5515 (1.389)	129.1472 (0.4276)
Missouri	38.9706 (4.2423)	43.0134 (2.6077)	44.1404 (4.643)	44.8516 (3.0202)
	119.0241 (3.6725)	159.041 (2.3075)	180.6207 (1.303)	189.1151 (2.0325)
Montana	127.866 (18.9575)	147.236 (13.2849)	151.7295 (3.9044)	154.4235 (5.4266)
	140.0596 (0.955)	196.6916 (0.2631)	220.7487 (1.23)	230.2729 (2.187)
Nebraska	29.2209 (0.719)	40.09 (0.8113)	41.8504 (3.4919)	43.0018 (1.4527)
	117.6601 (0.959)	203.3231 (1.6956)	228.0819 (2.7986)	238.2375 (3.76)
Nevada	111.0626 (6.8394)	117.7067 (2.636)	119.2316 (15.0793)	120.2167 (2.1739)
	130.1518 (2.8692)	166.7047 (0.5318)	187.7024 (3.7218)	196.638 (4.199)
New Hampshire	209.6681 (16.2196)	217.2183 (13.36)	219.5659 (25.8457)	221.2791 (10.2244)
	182.6276 (6.6818)	208.463 (8.1622)	238.7645 (6.3208)	251.8574 (9.8433)
New Jersey	923.1667 (27.2476)	911.8189 (46.0089)	949.8689 (15.345)	978.019 (7.3449)
	-146.6065 (5.6346)	-149.4335 (13.2744)	-135.1693 (26.4944)	-134.3085 (5.3966)
New Mexico	98.0857 (1.5836)	105.6471 (10.9168)	107.8358 (10.7953)	109.4576 (3.5479)
	118.1744 (3.7742)	131.0302 (2.7618)	148.398 (2.7073)	156.0052 (3.1072)
New York	760.2323 (36.3077)	809.1661 (14.3157)	829.4769 (10.2419)	846.2468 (9.8848)
	-29.9188 (4.3835)	-24.1253 (26.4407)	-1.6555 (13.3274)	6.3315 (25.1145)
North Carolina	48.8059 (8.1941)	51.8119 (8.3877)	52.7345 (9.4082)	53.3281 (2.8118)
	130.7145 (2.7324)	161.1973 (1.7362)	180.3622 (2.5112)	188.5607 (0.9179)
North Dakota	0.4189 (0.0209)	0.5137 (0.0349)	0.5532 (0.0352)	0.5542 (0.0404)
	198.4032 (1.0185)	233.7083 (2.181)	259.8519 (2.732)	271.4984 (1.235)
Ohio	94.2865 (9.5392)	96.8719 (12.3053)	98.6322 (10.77)	99.838 (10.1002)
	167.7057 (1.4898)	179.6968 (1.5407)	201.7681 (2.2122)	211.575 (1.9779)
Oklahoma	89.5371 (8.791)	93.3717 (2.6938)	94.9277 (11.9479)	95.9057 (6.9903)
	95.6417 (0.7946)	116.4465 (5.5005)	134.6299 (3.3225)	142.1835 (4.4474)
Oregon	22.6014 (2.0546)	23.5481 (0.9265)	23.9835 (2.8063)	24.2698 (1.5218)
	148.798 (2.9496)	165.8462 (0.6735)	187.7507 (5.082)	195.0992 (0.9917)
Pennsylvania	245.209 (14.0264)	262.0627 (8.3286)	266.0775 (11.9019)	269.1566 (30.8967)
	148.3641 (3.8809)	182.0904 (3.781)	202.8278 (3.641)	209.9695 (1.0181)
Rhode Island	525.3505 (19.582)	567.5595 (48.2044)	575.0087 (33.7958)	581.2616 (29.1788)
	14.1313 (14.9512)	40.058 (9.7145)	63.5159 (4.378)	72.9261 (6.2097)
South Carolina	53.923 (4.1185)	58.6347 (2.8089)	59.541 (7.608)	60.1552 (7.1674)
	106.388 (0.7893)	145.945 (0.4573)	164.819 (0.7008)	173.3599 (2.1321)
South Dakota	223.2095 (19.3942)	238.3093 (10.5149)	243.4993 (25.7527)	247.082 (20.2603)
	108.5187 (1.5359)	180.5164 (5.7085)	204.8778 (2.5351)	214.8058 (2.3189)
Tennessee	52.9573 (4.6225)	55.1586 (7.8362)	56.0279 (5.6532)	56.5847 (1.6501)
	134.7681 (0.5277)	165.2299 (0.6217)	185.2446 (1.3368)	193.0323 (1.3601)
Texas	4.1504 (0.0742)	5.0262 (0.096)	5.3109 (0.3997)	5.4723 (0.4304)
	124.1241 (0.7644)	162.2636 (1.572)	181.1574 (0.6365)	189.9649 (1.276)
Utah	0.4457 (0.0488)	0.8388 (0.0804)	0.9855 (0.0316)	1.0632 (0.0886)
	140.4688 (1.2429)	162.6954 (0.3185)	182.8507 (1.1373)	190.6428 (1.8942)
Vermont	208.0418 (14.602)	207.5862 (28.7397)	211.8239 (11.7211)	214.8205 (12.0706)
	201.4239 (1.2908)	201.8218 (9.7632)	228.3774 (7.9858)	238.7899 (10.4735)
Virginia	229.3687 (29.1747)	234.6789 (26.2501)	241.3835 (27.0661)	246.1942 (18.0281)
	136.7024 (10.6216)	150.7211 (1.7424)	175.6319 (12.4869)	184.376 (12.3504)
Washington	30.6461 (4.2305)	31.2016 (4.7612)	31.4536 (4.7841)	31.6307 (3.3364)
	192.9133 (1.8417)	210.6838 (0.799)	236.2365 (2.3052)	247.0236 (1.4173)
West Virginia	101.7369 (7.6218)	104.1273 (7.2661)	105.3228 (10.7347)	106.1582 (7.5983)
	80.3931 (2.4164)	94.6198 (2.5732)	110.4511 (3.1753)	116.898 (9.5415)
Wisconsin	15.2123 (0.7271)	16.305 (0.9739)	16.7813 (0.4781)	17.0618 (0.6374)
	174.8213 (2.5753)	194.8408 (2.8276)	218.807 (3.8575)	229.8226 (4.1193)
Wyoming	39.419 (3.6063)	40.3041 (4.3746)	40.7213 (5.4524)	41.0132 (2.1596)
	194.7722 (1.5526)	224.0127 (1.0131)	250.5465 (2.7424)	261.0091 (0.9649)

Table D.3 Results: total population

State	Current Policy	Potential intervention policy		
		P1	P2	P3
Alabama	0.059 (0.001)	0.089 (0.002)	0.095 (0.009)	0.097 (0.002)
	4.847 (0.055)	7.295 (0.047)	8.196 (0.069)	8.579 (0.055)
Alaska	0.27 (0.056)	0.286 (0.056)	0.293 (0.036)	0.298 (0.031)
	1.375 (0.025)	1.571 (0.008)	1.772 (0.015)	1.85 (0.036)
Arizona	0.153 (0.001)	0.458 (0.011)	0.515 (0.009)	0.553 (0.027)
	9.298 (0.083)	10.437 (0.103)	11.641 (0.095)	12.154 (0.101)
Arkansas	1.33 (0.093)	1.36 (0.196)	1.409 (0.143)	1.449 (0.026)
	3.692 (0.011)	4.205 (0.007)	4.706 (0.023)	4.927 (0.022)
California	32.172 (0.792)	31.881 (2.221)	32.687 (4.394)	33.205 (3.266)
	52.273 (2.319)	50.272 (3.816)	58.687 (0.865)	61.827 (2.734)
Colorado	2.508 (0.227)	2.809 (0.179)	2.873 (0.241)	2.91 (0.114)
	9.443 (0.135)	11.254 (0.07)	12.657 (0.184)	13.28 (0.192)
Connecticut	36.241 (2.473)	38.628 (0.448)	39.787 (1.344)	40.819 (2.605)
	0.898 (1.185)	1.09 (1.044)	2.003 (0.971)	2.247 (1.021)
Delaware	2.273 (0.037)	2.349 (0.174)	2.375 (0.023)	2.392 (0.135)
	0.688 (0.072)	0.781 (0.023)	0.998 (0.116)	1.093 (0.08)
District of Columbia	2.118 (0.042)	2.583 (0.198)	2.778 (0.094)	2.949 (0.175)
	0.979 (0.066)	1.116 (0.117)	1.331 (0.102)	1.386 (0.067)
Florida	6.291 (0.595)	6.743 (0.516)	6.837 (0.71)	6.9 (1.096)
	25.297 (0.192)	32.897 (0.258)	36.637 (0.184)	38.177 (0.332)
Georgia	12.152 (0.502)	13.3 (1.677)	13.629 (0.809)	13.845 (1.536)
	12.302 (0.321)	16.21 (0.274)	18.179 (0.143)	18.988 (0.146)
Hawaii	0.0033 (0.0001)	0.0039 (0.0001)	0.0039 (0.0001)	0.0039 (0.0002)
	2.856 (0.029)	3.052 (0.021)	3.422 (0.016)	3.572 (0.044)
Idaho	3.492 (0.281)	3.57 (0.417)	3.615 (0.176)	3.647 (0.122)
	2.291 (0.018)	2.609 (0.023)	2.917 (0.028)	3.038 (0.015)
Illinois	53.605 (5.329)	55.929 (3.526)	58.246 (2.647)	60.165 (6.25)
	19.871 (1.392)	21.163 (0.791)	24.029 (1.636)	25.111 (2.117)
Indiana	0.37 (0.013)	0.468 (0.032)	0.479 (0.029)	0.479 (0.026)
	9.551 (0.023)	10.829 (0.034)	12.221 (0.033)	12.799 (0.021)
Iowa	0.137 (0.004)	0.224 (0.005)	0.247 (0.005)	0.256 (0.015)
	6.4 (0.026)	6.588 (0.045)	7.357 (0.029)	7.691 (0.08)
Kansas	3.333 (0.152)	3.493 (0.365)	3.557 (0.173)	3.6 (0.551)
	4.925 (0.029)	5.96 (0.011)	6.663 (0.012)	6.954 (0.059)
Kentucky	7.291 (1.005)	7.278 (0.524)	7.537 (0.611)	7.734 (0.6)
	5.972 (0.188)	6.079 (0.15)	6.887 (0.245)	7.203 (0.099)
Louisiana	20.859 (1.443)	21.985 (1.758)	22.911 (1.566)	23.588 (1.571)
	4.203 (0.252)	4.642 (0.321)	5.33 (0.367)	5.591 (0.378)
Maine	0.1 (0.007)	0.152 (0.008)	0.159 (0.005)	0.164 (0.003)
	2.106 (0.023)	2.615 (0.02)	2.926 (0.023)	3.052 (0.029)
Maryland	5.709 (0.799)	6.255 (0.186)	6.391 (0.682)	6.48 (0.553)
	12.025 (0.204)	14.312 (0.198)	16.088 (0.158)	16.816 (0.231)
Massachusetts	56.92 (3.41)	59.813 (3.725)	61.555 (1.308)	62.936 (3.745)
	14.468 (0.399)	15.237 (0.113)	17.177 (0.317)	18.048 (0.433)
Michigan	46.949 (0.656)	50.21 (3.133)	51.383 (0.879)	52.248 (5.952)
	9.765 (0.187)	11.191 (0.438)	12.944 (0.379)	13.529 (1.51)
Minnesota	0.145 (0.01)	0.207 (0.011)	0.222 (0.005)	0.224 (0.011)
	11.744 (0.015)	13.262 (0.026)	14.876 (0.062)	15.51 (0.05)

For each state, the first and second rows indicate QALY gain (in 1,000 years) and extra cost ($billion), respectively.
See Table 3 for intervention policies P1/P2/P3.

Table D.3 Continued

State	**Current Policy**	**Potential intervention policy**		
		P1	**P2**	**P3**
Mississippi	2.645 (0.317)	2.904 (0.413)	2.991 (0.307)	3.047 (0.173)
	2.499 (0.012)	3.262 (0.059)	3.703 (0.095)	3.87 (0.053)
Missouri	2.605 (0.4)	2.928 (0.431)	3.009 (0.274)	3.062 (0.492)
	7.246 (0.137)	9.681 (0.152)	10.994 (0.06)	11.511 (0.04)
Montana	1.638 (0.072)	1.953 (0.11)	2.021 (0.178)	2.063 (0.166)
	1.434 (0.006)	2.014 (0.009)	2.26 (0.004)	2.358 (0.022)
Nebraska	0.593 (0.038)	0.828 (0.038)	0.866 (0.038)	0.891 (0.033)
	2.216 (0.008)	3.829 (0.04)	4.295 (0.018)	4.486 (0.045)
Nevada	3.222 (0.467)	3.424 (0.118)	3.469 (0.321)	3.498 (0.428)
	3.699 (0.024)	4.737 (0.051)	5.333 (0.126)	5.587 (0.089)
New Hampshire	2.879 (0.039)	2.989 (0.29)	3.022 (0.175)	3.046 (0.204)
	2.427 (0.141)	2.77 (0.106)	3.172 (0.038)	3.345 (0.138)
New Jersey	106.507 (0.87)	106.146 (3.813)	110.562 (7.344)	113.821 (4.555)
	-11.732 (1.557)	-11.976 (1.67)	-10.683 (1.331)	-10.594 (1.605)
New Mexico	2.127 (0.192)	2.299 (0.335)	2.347 (0.232)	2.383 (0.115)
	2.467 (0.086)	2.735 (0.07)	3.098 (0.094)	3.256 (0.023)
New York	175.279 (11.803)	187.79 (10.061)	192.459 (10.259)	196.282 (7.76)
	-4.002 (2.266)	-2.809 (5.053)	1.639 (7.242)	3.224 (1.975)
North Carolina	5.112 (0.438)	5.452 (0.578)	5.552 (0.329)	5.617 (0.526)
	13.136 (0.075)	16.197 (0.189)	18.123 (0.2)	18.947 (0.114)
North Dakota	0.0036 (0.0002)	0.0046 (0.0001)	0.0049 (0.0003)	0.0049 (0.0004)
	1.184 (0.01)	1.77 (0.007)	1.969 (0.006)	2.057 (0.022)
Ohio	11.098 (0.437)	11.412 (0.958)	11.623 (1.208)	11.767 (0.225)
	19.451 (0.191)	20.84 (0.209)	23.4 (0.087)	24.538 (0.144)
Oklahoma	3.936 (0.185)	4.147 (0.146)	4.221 (0.355)	4.268 (0.318)
	3.719 (0.267)	4.526 (0.289)	5.231 (0.21)	5.524 (0.255)
Oregon	1.017 (0.13)	1.07 (0.059)	1.092 (0.162)	1.107 (0.175)
	5.91 (0.086)	6.587 (0.135)	7.457 (0.218)	7.749 (0.219)
Pennsylvania	31.762 (1.538)	33.978 (1.507)	34.501 (0.722)	34.901 (3.677)
	18.987 (0.26)	23.3 (0.224)	25.952 (0.45)	26.865 (0.441)
Rhode Island	6.455 (0.156)	7.04 (0.116)	7.135 (0.376)	7.215 (0.349)
	0.198 (0.188)	0.474 (0.09)	0.722 (0.154)	0.822 (0.138)
South Carolina	2.647 (0.149)	2.879 (0.34)	2.924 (0.071)	2.954 (0.152)
	5.21 (0.013)	7.147 (0.044)	8.071 (0.029)	8.49 (0.015)
South Dakota	1.957 (0.245)	2.091 (0.274)	2.137 (0.113)	2.168 (0.139)
	0.934 (0.062)	1.552 (0.045)	1.762 (0.03)	1.847 (0.041)
Tennessee	3.47 (0.47)	3.614 (0.256)	3.671 (0.159)	3.708 (0.347)
	8.83 (0.012)	10.824 (0.038)	12.136 (0.035)	12.646 (0.023)
Texas	1.291 (0.025)	1.637 (0.122)	1.737 (0.137)	1.796 (0.193)
	33.502 (0.165)	43.783 (0.333)	48.884 (0.416)	51.263 (0.537)
Utah	0.013 (0.002)	0.025 (0.003)	0.029 (0.003)	0.032 (0.002)
	4.142 (0.026)	4.795 (0.04)	5.39 (0.036)	5.62 (0.042)
Vermont	1.358 (0.186)	1.357 (0.163)	1.384 (0.033)	1.404 (0.139)
	1.264 (0.043)	1.267 (0.011)	1.433 (0.063)	1.498 (0.049)
Virginia	20.448 (2.378)	20.992 (0.712)	21.597 (0.983)	22.031 (2.231)
	11.455 (0.731)	12.621 (1.005)	14.697 (0.383)	15.426 (0.715)
Washington	2.17 (0.208)	2.21 (0.35)	2.228 (0.116)	2.24 (0.204)
	13.633 (0.03)	14.887 (0.133)	16.693 (0.12)	17.456 (0.098)
West Virginia	2.039 (0.345)	2.094 (0.251)	2.12 (0.381)	2.137 (0.263)
	1.49 (0.119)	1.753 (0.179)	2.044 (0.119)	2.163 (0.166)
Wisconsin	0.973 (0.119)	1.057 (0.065)	1.09 (0.09)	1.109 (0.034)
	10.094 (0.045)	11.249 (0.102)	12.633 (0.216)	13.269 (0.249)
Wyoming	0.232 (0.007)	0.237 (0.01)	0.239 (0.017)	0.241 (0.025)
	1.138 (0.006)	1.309 (0.007)	1.464 (0.011)	1.525 (0.008)

Table D.4 Results: per 100k high-risk capita (age≥65 and Black/Hispanic race)

State	**Current Policy**	**Potential intervention policy**		
		P1	**P2**	**P3**
Alabama	1.3224 (0.0471)	1.992 (0.123)	2.1381 (0.0952)	2.1736 (0.1066)
	114.8275 (0.7544)	167.9324 (1.2372)	184.998 (0.2783)	192.2209 (1.3915)
Alaska	66.1428 (4.3828)	69.3788 (12.6861)	70.9597 (4.6726)	72.0942 (5.4774)
	204.5789 (3.9304)	237.0747 (2.8823)	263.8059 (0.981)	274.9506 (4.9843)
Arizona	2.9517 (0.1091)	8.451 (0.178)	9.4501 (0.4562)	10.0953 (0.3551)
	174.923 (0.1628)	192.9918 (0.8076)	211.5276 (1.6004)	219.6211 (1.9295)
Arkansas	59.5581 (1.7412)	60.7803 (7.7652)	62.8794 (5.7348)	64.6472 (8.289)
	144.7549 (1.3979)	169.0828 (0.5086)	186.5229 (0.7255)	192.9744 (2.1064)
California	123.2686 (6.4183)	121.8816 (9.2705)	124.6953 (5.756)	126.4703 (11.3193)
	154.7217 (10.3923)	153.7546 (10.505)	175.0187 (1.7072)	182.7191 (7.7841)
Colorado	66.3197 (1.5395)	71.3798 (5.8629)	72.7689 (6.5336)	73.5691 (6.4208)
	209.3216 (2.2019)	248.3994 (2.8654)	274.6811 (2.786)	284.7339 (3.541)
Connecticut	1128.4067 (34.7761)	1192.7411 (62.9244)	1229.8041 (70.1021)	1263.7643 (79.0609)
	39.9568 (19.3412)	52.6204 (22.628)	78.3942 (19.8173)	87.7327 (6.7843)
Delaware	256.6786 (11.0965)	263.7895 (9.3231)	266.7385 (15.0398)	268.5551 (21.616)
	128.1291 (1.4711)	145.1025 (9.6875)	166.948 (5.3813)	174.6446 (4.1059)
District of Columbia	446.8431 (23.1198)	545.1919 (10.9992)	591.1534 (26.9995)	632.8022 (20.0238)
	137.5698 (15.3392)	152.5712 (19.9094)	176.1823 (19.9318)	170.0514 (5.6377)
Florida	35.7616 (1.6426)	38.1537 (3.3856)	38.6695 (1.4654)	39.0174 (5.2672)
	142.7519 (0.3767)	185.2125 (0.7013)	204.2436 (1.6953)	211.5057 (1.5666)
Georgia	206.9485 (5.2309)	224.7448 (5.0124)	230.008 (9.6439)	233.4629 (30.0224)
	137.3245 (1.5532)	182.0301 (0.9354)	201.7155 (0.9092)	210.3962 (0.4857)
Hawaii	0.3229 (0.0067)	0.3602 (0.0044)	0.3713 (0.0142)	0.3813 (0.0219)
	240.5818 (1.6459)	261.4457 (1.4467)	287.5707 (1.1284)	298.4741 (1.7376)
Idaho	253.8436 (26.2806)	258.5431 (21.7488)	261.0977 (11.1854)	262.9506 (11.4115)
	156.5397 (0.4126)	179.5493 (0.4561)	198.1399 (0.598)	205.6591 (1.8739)
Illinois	551.0731 (41.0518)	571.9721 (31.1822)	593.4444 (55.9704)	610.9677 (18.9577)
	148.6277 (9.8588)	159.4495 (7.6198)	182.0387 (14.8237)	189.7237 (3.7355)
Indiana	6.5689 (0.1992)	7.6281 (0.306)	8.0084 (0.1234)	8.2106 (0.4434)
	177.3109 (0.4435)	203.512 (0.4868)	223.2777 (1.3873)	231.6106 (1.5355)
Iowa	4.9512 (0.3285)	7.545 (0.4694)	8.1766 (0.398)	8.3758 (0.4875)
	236.8371 (1.9533)	244.1527 (1.2843)	269.723 (0.5931)	278.9829 (0.3647)
Kansas	135.1659 (9.7898)	141.8361 (5.2661)	144.5896 (19.505)	146.5002 (20.9127)
	187.6923 (1.4615)	226.601 (0.4252)	251.1931 (2.0348)	260.4974 (0.9624)
Kentucky	248.921 (21.5632)	248.1346 (10.6577)	256.3749 (29.534)	262.5842 (40.3767)
	155.114 (1.7341)	159.1277 (1.9048)	178.0785 (1.0644)	186.5819 (2.2352)
Louisiana	536.7328 (20.6535)	562.8204 (8.0704)	585.6346 (10.38)	602.2924 (18.4582)
	110.6157 (6.3)	122.6743 (2.4242)	139.8089 (10.843)	147.1847 (15.5202)
Maine	12.7928 (0.3282)	18.9475 (0.508)	19.737 (1.1546)	20.2758 (1.4844)
	188.398 (1.658)	235.7656 (0.4128)	258.7349 (1.3307)	268.3102 (2.3597)
Maryland	193.3496 (25.7498)	209.8952 (5.4858)	214.2993 (25.0111)	217.1766 (14.8756)
	214.4641 (3.5062)	259.3624 (2.4809)	286.8802 (3.4664)	298.9598 (4.8521)
Massachusetts	1293.4625 (43.499)	1355.4327 (39.3931)	1397.1601 (64.0079)	1429.6607 (77.1051)
	242.3844 (2.7904)	255.8175 (2.4894)	284.2575 (3.6635)	295.7355 (5.5952)
Michigan	539.1213 (45.7097)	569.0494 (44.1684)	580.0697 (37.9035)	587.9722 (62.5811)
	130.2149 (1.8566)	151.9237 (2.8616)	170.163 (1.5545)	178.3167 (4.3537)
Minnesota	4.2674 (0.0804)	5.9872 (0.3609)	6.4263 (0.375)	6.5163 (0.306)
	235.968 (0.9231)	269.8412 (1.1981)	297.8497 (1.4142)	309.4169 (0.9595)

For each state, the first and second rows indicate QALY gain (years) and extra cost ($million), respectively.
See Table 3 for intervention policies P1/P2/P3.

Table D.4 Continued

State	Current Policy	Potential intervention policy		
		P1	P2	P3
Mississippi	119.4375 (7.9671)	128.6999 (18.6968)	132.5066 (2.8321)	134.9761 (3.3171)
	89.3765 (3.0903)	116.8371 (2.8207)	130.1864 (5.1484)	134.6158 (5.8038)
Missouri	64.7862 (7.099)	71.144 (4.5291)	73.0451 (4.2568)	74.2551 (4.2901)
	149.7758 (2.6672)	201.8418 (0.8648)	222.2484 (0.9892)	230.8272 (2.9707)
Montana	187.078 (5.7585)	223.4463 (13.9814)	232.2454 (14.938)	237.7086 (10.8005)
	147.5543 (0.5521)	204.9991 (2.6368)	226.8018 (1.2824)	234.5371 (3.4798)
Nebraska	40.9917 (3.1011)	55.8109 (4.0036)	58.1732 (1.8972)	59.6944 (5.8944)
	143.2755 (0.8085)	238.5268 (2.7482)	262.242 (1.4299)	271.5185 (1.2259)
Nevada	199.3373 (15.2856)	210.8821 (21.776)	213.7366 (21.5393)	215.5722 (10.2685)
	161.7937 (1.4274)	207.2035 (2.637)	227.8961 (2.0456)	236.4819 (0.7244)
New Hampshire	249.1513 (6.4476)	258.2507 (18.1697)	261.1701 (25.4137)	263.311 (21.1815)
	231.0975 (3.9057)	266.2511 (3.2116)	294.3878 (1.4044)	304.8176 (2.63)
New Jersey	1449.0184 (12.3346)	1428.7258 (54.6729)	1492.409 (64.2031)	1541.0264 (30.5778)
	-117.1089 (9.6256)	-113.7761 (11.5917)	-102.1925 (4.2511)	-103.4425 (31.4915)
New Mexico	149.9844 (15.2886)	160.8853 (8.8904)	164.0593 (6.3315)	166.3913 (13.4768)
	139.9593 (1.2412)	156.6455 (3.309)	173.4792 (0.4867)	180.0398 (4.5245)
New York	1192.724 (36.5261)	1271.4752 (39.4676)	1305.6163 (66.0462)	1333.8782 (45.6642)
	42.3791 (25.8136)	53.5562 (8.5143)	71.5324 (31.2474)	75.7359 (7.9878)
North Carolina	57.5882 (6.5294)	61.3229 (4.0536)	62.5053 (7.8972)	63.2818 (11.4538)
	162.0726 (0.4316)	199.0776 (0.9127)	218.4063 (1.6824)	225.4423 (2.3797)
North Dakota	0.5026 (0.018)	0.5925 (0.0365)	0.6577 (0.0263)	0.6696 (0.0208)
	233.4728 (1.51)	272.4623 (0.656)	303.053 (2.6185)	315.1125 (1.0613)
Ohio	95.3852 (5.7263)	98.1568 (9.2193)	99.9747 (2.2378)	101.2492 (1.6489)
	197.1788 (0.4106)	213.947 (1.5163)	235.6631 (1.6617)	244.0473 (2.7763)
Oklahoma	115.3151 (11.7243)	120.0487 (11.0339)	121.8271 (11.8753)	122.9168 (12.209)
	127.9159 (2.0361)	153.7339 (0.8963)	171.2285 (3.6333)	177.5473 (5.1359)
Oregon	28.5601 (1.5441)	29.7172 (4.2771)	30.2203 (3.8999)	30.5453 (4.0888)
	171.5001 (5.0482)	194.3729 (2.9922)	217.6283 (3.2375)	227.6405 (5.818)
Pennsylvania	294.3608 (8.8714)	316.1914 (7.8181)	321.5553 (31.471)	325.752 (20.8939)
	177.179 (1.6903)	219.9803 (5.3949)	242.1378 (3.6019)	250.8107 (4.4405)
Rhode Island	705.5617 (46.5141)	761.2243 (27.467)	771.2014 (8.175)	779.5369 (22.5017)
	36.6017 (21.6752)	70.0087 (13.7414)	91.6422 (24.306)	99.6921 (22.1316)
South Carolina	81.4449 (12.5604)	88.6635 (12.2922)	90.0415 (13.3939)	90.9705 (9.9992)
	116.9545 (0.9965)	159.3342 (0.358)	176.9393 (0.8076)	183.9471 (1.9143)
South Dakota	314.3999 (37.774)	337.3417 (12.5513)	345.4323 (34.6331)	351.1019 (20.326)
	146.7683 (0.9221)	229.6972 (5.626)	254.0452 (3.9422)	263.3605 (2.8125)
Tennessee	52.116 (8.4467)	54.4078 (7.197)	55.3076 (3.263)	55.8891 (9.0872)
	158.1713 (0.9369)	196.7924 (0.7603)	216.4754 (0.385)	225.0686 (1.2582)
Texas	6.0663 (0.3716)	6.9891 (0.5083)	7.1439 (0.4168)	7.2216 (0.3866)
	126.6188 (0.5392)	161.7524 (0.8203)	182.0206 (1.078)	189.3227 (1.4733)
Utah	0.5895 (0.0621)	1.0599 (0.124)	1.2884 (0.094)	1.4274 (0.1155)
	165.5807 (1.1184)	193.5472 (0.259)	212.7414 (2.0085)	220.2045 (2.3848)
Vermont	230.0873 (28.5374)	229.6422 (33.633)	234.1868 (15.417)	237.4564 (11.8162)
	253.1602 (1.2177)	258.4154 (7.8724)	285.1605 (2.451)	296.837 (2.5001)
Virginia	346.4866 (14.1999)	353.0317 (18.1267)	360.8032 (40.7357)	366.2462 (14.7545)
	172.0848 (10.1408)	193.5869 (7.0329)	218.6566 (6.4715)	228.7844 (4.0802)
Washington	43.7709 (4.7779)	44.5459 (4.0206)	44.8998 (7.8878)	45.1461 (7.2426)
	207.4593 (0.7993)	230.6977 (2.1228)	253.8344 (1.0608)	263.3477 (1.7083)
West Virginia	144.9818 (24.2007)	147.9763 (6.949)	149.4271 (18.4634)	150.4444 (16.8584)
	101.5696 (1.4379)	118.7848 (7.9043)	134.0472 (2.2608)	139.7665 (4.7196)
Wisconsin	24.1249 (3.5692)	25.7471 (1.7454)	26.5261 (3.57)	27.0107 (1.5625)
	203.3723 (1.7771)	227.9202 (1.2316)	253.1388 (1.6607)	263.7571 (0.5997)
Wyoming	36.9979 (4.9836)	37.6345 (1.7214)	37.8361 (1.6859)	37.9754 (1.7573)
	191.5266 (2.6604)	221.7177 (2.5299)	247.916 (0.8963)	258.9956 (2.8173)

Table D.5 Results: total high-risk population (age$\geq$65 and Black/Hispanic race)

State	Current Policy	Potential intervention policy		
		P1	P2	P3
Alabama	0.0034 (0)	0.0052 (0.0003)	0.0056 (0.0004)	0.0057 (0.0004)
	0.2924 (0.0007)	0.4276 (0.0017)	0.471 (0.0005)	0.4894 (0.0048)
Alaska	0.0065 (0.001)	0.0069 (0.0006)	0.007 (0.0008)	0.0071 (0.001)
	0.0196 (0.0002)	0.0227 (0.0003)	0.0253 (0.0004)	0.0264 (0.0001)
Arizona	0.0143 (0.0004)	0.042 (0.0009)	0.0472 (0.0007)	0.0507 (0.0006)
	0.7718 (0.0046)	0.8516 (0.0044)	0.9334 (0.0012)	0.9691 (0.0067)
Arkansas	0.0706 (0.0064)	0.0721 (0.0044)	0.0746 (0.0099)	0.0767 (0.0013)
	0.1709 (0.0003)	0.1996 (0.0003)	0.2202 (0.0005)	0.2278 (0.0009)
California	3.3405 (0.11)	3.3086 (0.2691)	3.3876 (0.2109)	3.4377 (0.2081)
	3.9418 (0.1722)	3.9163 (0.0451)	4.4579 (0.1361)	4.6541 (0.2677)
Colorado	0.1593 (0.0183)	0.1752 (0.0183)	0.1791 (0.0131)	0.1814 (0.0186)
	0.4318 (0.0021)	0.5124 (0.0035)	0.5666 (0.0061)	0.5873 (0.0057)
Connecticut	2.3568 (0.1248)	2.5095 (0.1056)	2.5868 (0.1542)	2.6566 (0.2043)
	0.0968 (0.0522)	0.1195 (0.0646)	0.164 (0.0316)	0.1802 (0.0718)
Delaware	0.155 (0.0157)	0.1602 (0.0156)	0.1621 (0.003)	0.1633 (0.0097)
	0.0711 (0.0021)	0.0805 (0.0054)	0.0926 (0.0068)	0.0969 (0.0041)
District of Columbia	0.2356 (0.0096)	0.2904 (0.0028)	0.3145 (0.0182)	0.3361 (0.0147)
	0.0677 (0.0083)	0.0755 (0.0018)	0.0868 (0.0057)	0.0841 (0.007)
Florida	0.6277 (0.0912)	0.6719 (0.0368)	0.6811 (0.0982)	0.6874 (0.125)
	2.457 (0.0231)	3.1877 (0.0197)	3.5153 (0.0116)	3.6403 (0.0073)
Georgia	1.2561 (0.124)	1.3662 (0.0486)	1.3983 (0.1991)	1.4193 (0.1517)
	0.8251 (0.009)	1.0935 (0.0111)	1.2118 (0.0086)	1.2639 (0.0148)
Hawaii	0.0001 (0)	0.0001 (0)	0.0001 (0)	0.0001 (0)
	0.0815 (0.0005)	0.0885 (0.0003)	0.0974 (0.0002)	0.1011 (0.0003)
Idaho	0.0954 (0.0086)	0.0972 (0.0095)	0.0982 (0.0061)	0.0989 (0.0027)
	0.0588 (0.0001)	0.0674 (0.0001)	0.0744 (0.0004)	0.0773 (0.0007)
Illinois	3.6262 (0.1261)	3.7678 (0.2419)	3.9093 (0.0589)	4.0246 (0.2016)
	0.9578 (0.0777)	1.0269 (0.045)	1.1711 (0.1322)	1.2202 (0.0372)
Indiana	0.0122 (0.0007)	0.0153 (0.0003)	0.0156 (0.0005)	0.0156 (0.0006)
	0.3015 (0.002)	0.346 (0.001)	0.3796 (0.0025)	0.3938 (0.0026)
Iowa	0.0031 (0.0001)	0.0049 (0.0002)	0.0054 (0.0001)	0.0056 (0.0003)
	0.1153 (0.0009)	0.1188 (0.0006)	0.1313 (0.0004)	0.1358 (0.0009)
Kansas	0.1096 (0.0172)	0.115 (0.011)	0.1172 (0.0114)	0.1187 (0.0027)
	0.1521 (0.0003)	0.1836 (0.0013)	0.2035 (0.0008)	0.211 (0.0003)
Kentucky	0.2285 (0.0153)	0.2279 (0.0195)	0.2355 (0.0214)	0.2412 (0.0058)
	0.1402 (0.0034)	0.1438 (0.0055)	0.161 (0.0025)	0.1686 (0.006)
Louisiana	1.5327 (0.1527)	1.6099 (0.0516)	1.6749 (0.1311)	1.7224 (0.132)
	0.307 (0.0345)	0.3403 (0.0149)	0.3875 (0.0421)	0.4078 (0.0086)
Maine	0.0011 (0.0001)	0.0017 (0.0001)	0.0018 (0.0001)	0.0018 (0)
	0.016 (0.0001)	0.02 (0)	0.022 (0.0001)	0.0228 (0)
Maryland	0.7352 (0.1057)	0.8 (0.0735)	0.817 (0.0639)	0.8281 (0.0278)
	0.8009 (0.0026)	0.9683 (0.0082)	1.071 (0.006)	1.1161 (0.0265)
Massachusetts	2.8912 (0.1389)	3.0325 (0.148)	3.1262 (0.0764)	3.1991 (0.0872)
	0.5353 (0.0098)	0.565 (0.0018)	0.6278 (0.0085)	0.6532 (0.0015)
Michigan	1.9233 (0.1665)	2.0377 (0.1121)	2.0777 (0.1222)	2.1065 (0.0411)
	0.4403 (0.033)	0.5128 (0.0278)	0.5736 (0.0358)	0.6008 (0.0449)
Minnesota	0.0043 (0.0002)	0.0061 (0.0001)	0.0065 (0.0002)	0.0066 (0.0002)
	0.231 (0.0014)	0.2641 (0.0016)	0.2916 (0.0009)	0.3029 (0.0031)

For each state, the first and second rows indicate QALY gain (in 1,000 years) and extra cost ($billion), respectively.
See Table 3 for intervention policies P1/P2/P3.

Table D.5 Continued

State	Current	Potential intervention policy		
	Policy	P1	P2	P3
Mississippi	0.2637 (0.0108)	0.288 (0.0112)	0.2969 (0.0202)	0.3027 (0.0273)
	0.1814 (0.0091)	0.2371 (0.004)	0.2641 (0.0059)	0.2731 (0.0053)
Missouri	0.1079 (0.0122)	0.12 (0.0033)	0.1233 (0.0124)	0.1255 (0.0141)
	0.2352 (0.005)	0.317 (0.0016)	0.349 (0.0072)	0.3625 (0.0024)
Montana	0.0178 (0.001)	0.0219 (0.0007)	0.0228 (0.0012)	0.0234 (0.0006)
	0.0119 (0.0002)	0.0165 (0.0004)	0.0182 (0.0003)	0.0188 (0.0001)
Nebraska	0.0201 (0.0015)	0.0279 (0.0011)	0.0291 (0.0019)	0.0299 (0.0012)
	0.0656 (0.0002)	0.1091 (0.0005)	0.12 (0.0011)	0.1243 (0.0014)
Nevada	0.3545 (0.0473)	0.3756 (0.0109)	0.3807 (0.0072)	0.384 (0.0093)
	0.2848 (0.005)	0.3646 (0.0072)	0.401 (0.0033)	0.4162 (0.0038)
New Hampshire	0.0314 (0.0025)	0.0326 (0.0037)	0.0329 (0.0006)	0.0332 (0.0028)
	0.0285 (0.0006)	0.0329 (0.0001)	0.0363 (0.0007)	0.0376 (0.0004)
New Jersey	8.5337 (0.3799)	8.47 (0.3805)	8.8489 (0.1965)	9.1372 (0.0621)
	-0.509 (0.0398)	-0.4919 (0.0218)	-0.4322 (0.0372)	-0.4375 (0.0375)
New Mexico	0.3019 (0.0245)	0.3248 (0.023)	0.3313 (0.0203)	0.3361 (0.0322)
	0.2727 (0.0063)	0.3051 (0.0065)	0.3379 (0.0058)	0.3507 (0.0094)
New York	14.2043 (0.6777)	15.2149 (0.9229)	15.6279 (0.7618)	15.9688 (0.4294)
	0.5415 (0.2522)	0.6686 (0.3384)	0.8676 (0.0805)	0.9146 (0.1686)
North Carolina	0.3081 (0.038)	0.3289 (0.0097)	0.3353 (0.0341)	0.3395 (0.0621)
	0.8532 (0.0051)	1.0478 (0.002)	1.1496 (0.0022)	1.1867 (0.0071)
North Dakota	0.00005 (0)	0.00006 (0)	0.00006 (0)	0.00006 (0)
	0.0151 (0.0002)	0.0225 (0.0001)	0.0251 (0.0001)	0.0261 (0.0003)
Ohio	0.3105 (0.0228)	0.3197 (0.0311)	0.3257 (0.0078)	0.3298 (0.0155)
	0.6366 (0.0007)	0.6907 (0.0052)	0.7609 (0.0046)	0.7879 (0.0059)
Oklahoma	0.1396 (0.0066)	0.1464 (0.0239)	0.1487 (0.0229)	0.1501 (0.0124)
	0.1431 (0.0059)	0.1719 (0.0037)	0.1915 (0.0043)	0.1985 (0.0043)
Oregon	0.0352 (0.0054)	0.037 (0.0009)	0.0377 (0.0032)	0.0381 (0.0031)
	0.187 (0.0031)	0.2119 (0.0055)	0.2373 (0.0014)	0.2482 (0.0026)
Pennsylvania	1.2793 (0.122)	1.3756 (0.0202)	1.3991 (0.0963)	1.4174 (0.0339)
	0.7632 (0.0112)	0.9475 (0.0172)	1.0428 (0.0272)	1.0802 (0.0097)
Rhode Island	0.3323 (0.0053)	0.3619 (0.0187)	0.3668 (0.0236)	0.3709 (0.0229)
	0.0175 (0.005)	0.0314 (0.0077)	0.0404 (0.0049)	0.0437 (0.0051)
South Carolina	0.2351 (0.0275)	0.256 (0.0283)	0.26 (0.0274)	0.2627 (0.0402)
	0.3372 (0.0019)	0.4594 (0.0034)	0.5102 (0.0047)	0.5304 (0.0027)
South Dakota	0.0285 (0.0011)	0.0306 (0.0021)	0.0314 (0.0038)	0.0319 (0.0009)
	0.0132 (0.0003)	0.0206 (0.0002)	0.0228 (0.0002)	0.0236 (0.0005)
Tennessee	0.1255 (0.0199)	0.131 (0.0163)	0.1332 (0.0192)	0.1346 (0.0107)
	0.3807 (0.0007)	0.4737 (0.0006)	0.521 (0.0031)	0.5417 (0.0022)
Texas	0.1257 (0.0049)	0.1504 (0.0082)	0.1541 (0.0121)	0.156 (0.0156)
	2.2925 (0.0229)	2.9277 (0.0095)	3.2948 (0.0132)	3.4271 (0.033)
Utah	0.0003 (0)	0.0006 (0.0001)	0.0007 (0.0001)	0.0007 (0.0001)
	0.0842 (0.0002)	0.0984 (0.0003)	0.1082 (0.0002)	0.112 (0.0003)
Vermont	0.009 (0.0004)	0.009 (0.0011)	0.0092 (0.0012)	0.0093 (0.0002)
	0.0097 (0.0001)	0.0099 (0.0001)	0.0109 (0.0002)	0.0114 (0.0003)
Virginia	1.4195 (0.1229)	1.4494 (0.0931)	1.4818 (0.1624)	1.5045 (0.1532)
	0.68 (0.0516)	0.7645 (0.012)	0.8633 (0.0426)	0.9032 (0.0405)
Washington	0.0845 (0.0039)	0.086 (0.0026)	0.0867 (0.0151)	0.0872 (0.0108)
	0.3988 (0.0036)	0.4434 (0.0026)	0.4879 (0.0037)	0.5062 (0.0017)
West Virginia	0.0287 (0.0046)	0.0294 (0.0017)	0.0297 (0.0029)	0.0299 (0.0017)
	0.0192 (0.0009)	0.0225 (0.0015)	0.0254 (0.0011)	0.0264 (0.0008)
Wisconsin	0.0337 (0.0032)	0.0363 (0.0044)	0.0374 (0.0009)	0.0381 (0.0022)
	0.2671 (0.0017)	0.2994 (0.0007)	0.3325 (0.0017)	0.3464 (0.0007)
Wyoming	0.0037 (0.0003)	0.0038 (0.0005)	0.0038 (0.0006)	0.0038 (0.0005)
	0.0193 (0.0002)	0.0223 (0.0001)	0.0249 (0.0001)	0.026 (0.0001)

D.4. Aversions in Health Outcomes (Results: Per 100k Capita)

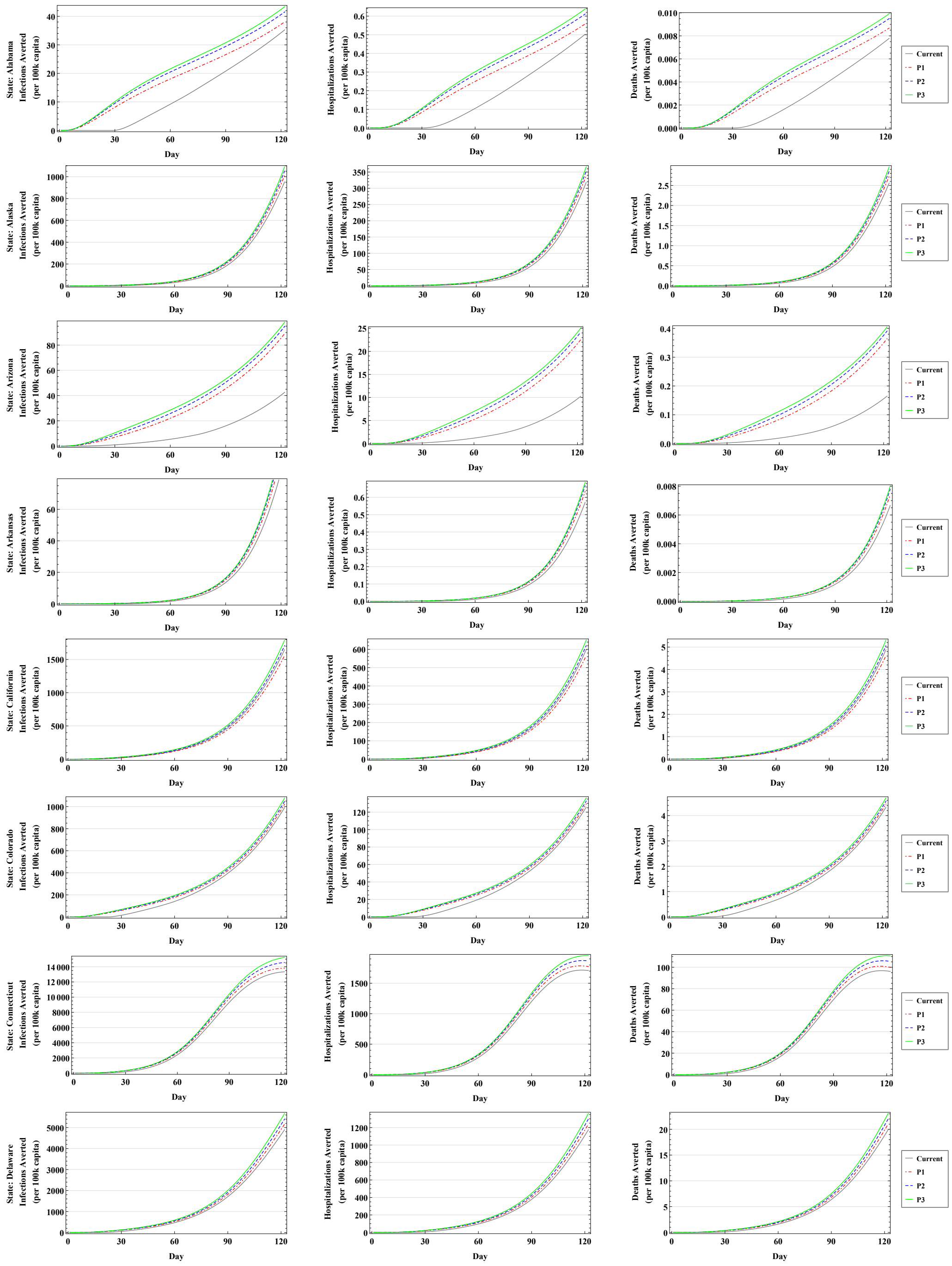

Figure D.1 (Color online) Average number of aversions under different intervention policies (compared to no intervention)

Notes. Intervention policies are compared with no intervention. Results are reported per 100k capita in each state. See Table 3 for intervention policies P1/P2/P3. Each row represents the results for a particular state.

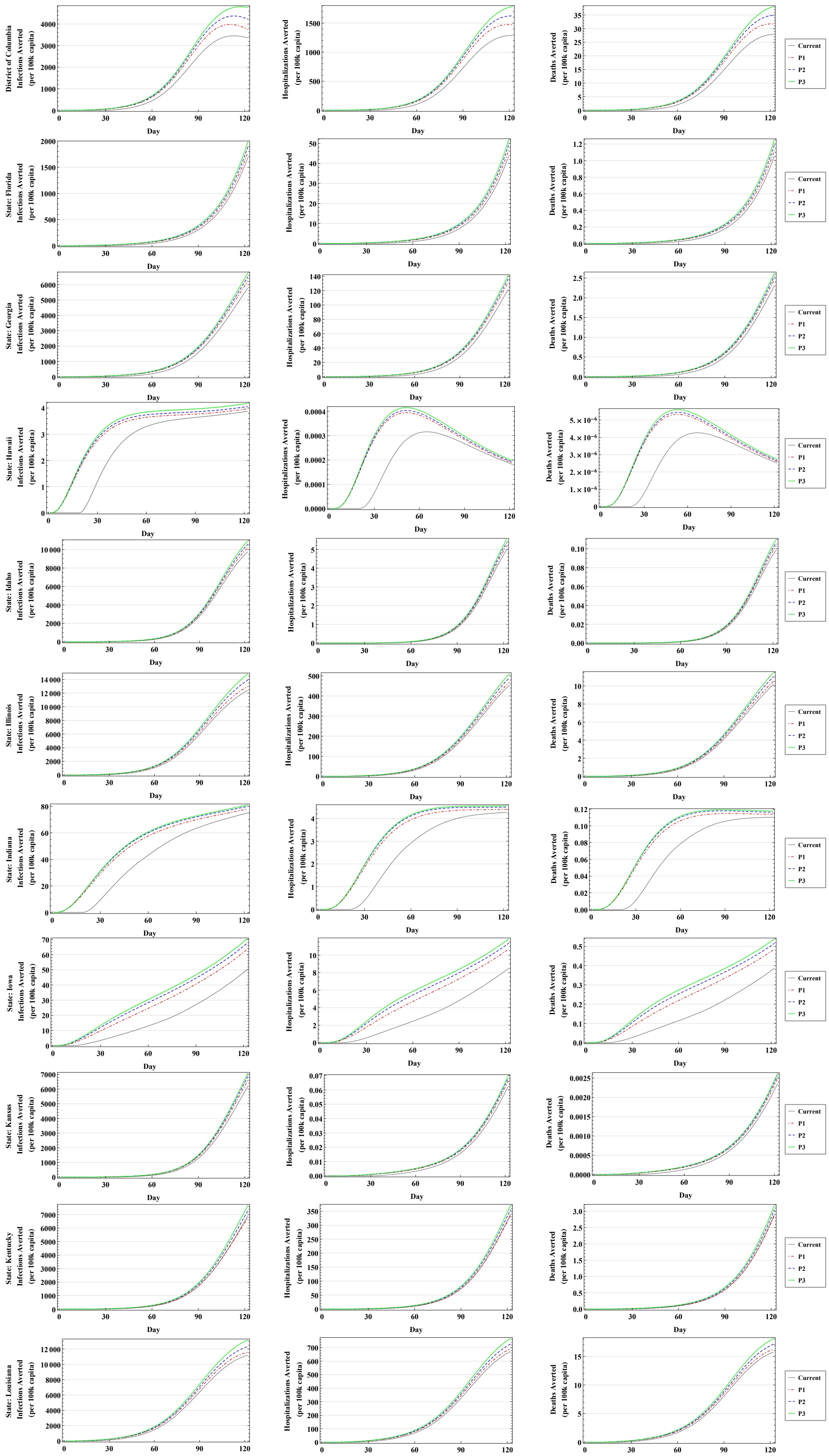

Figure D.1 Continued

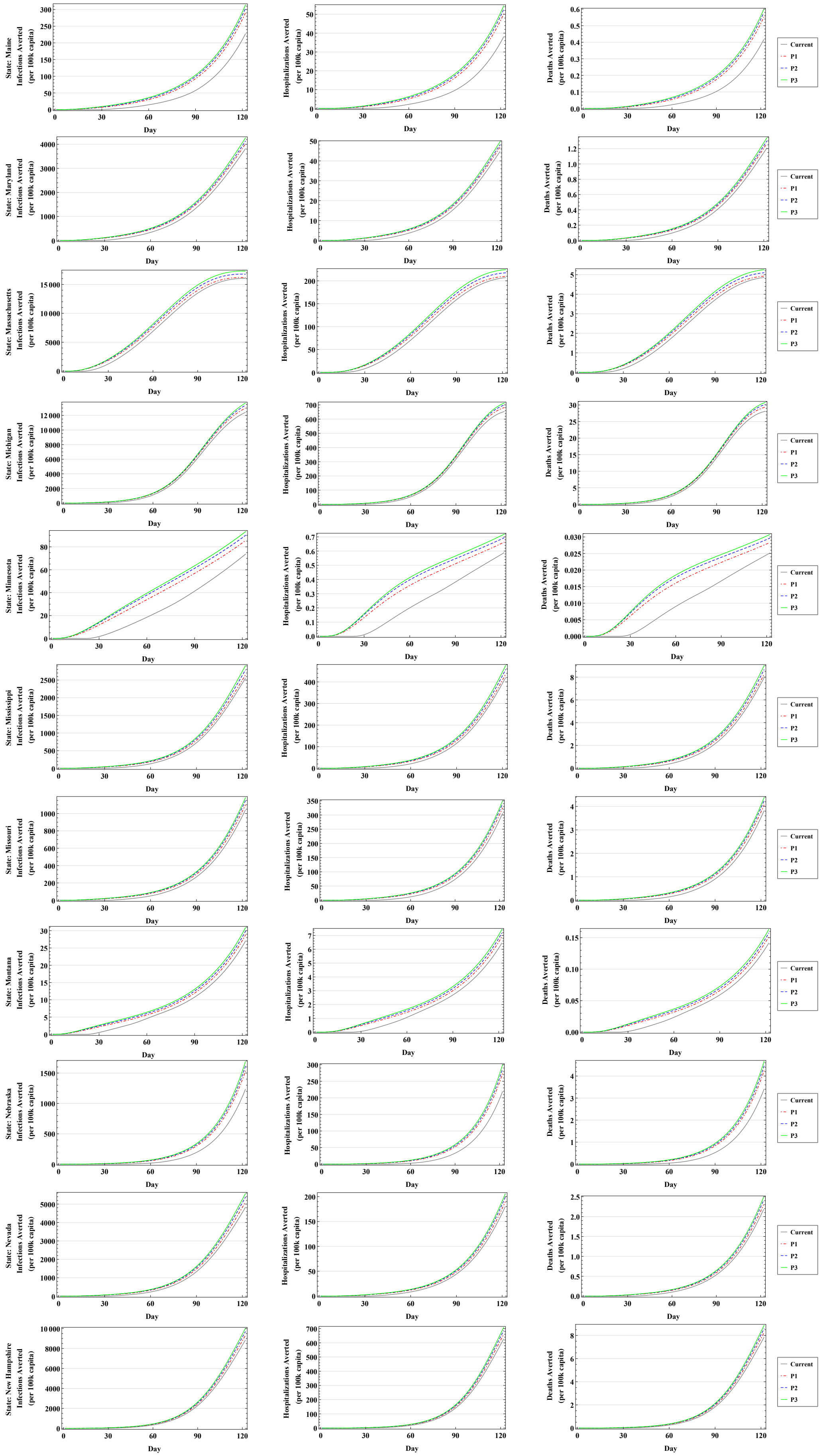

Figure D.1 Continued

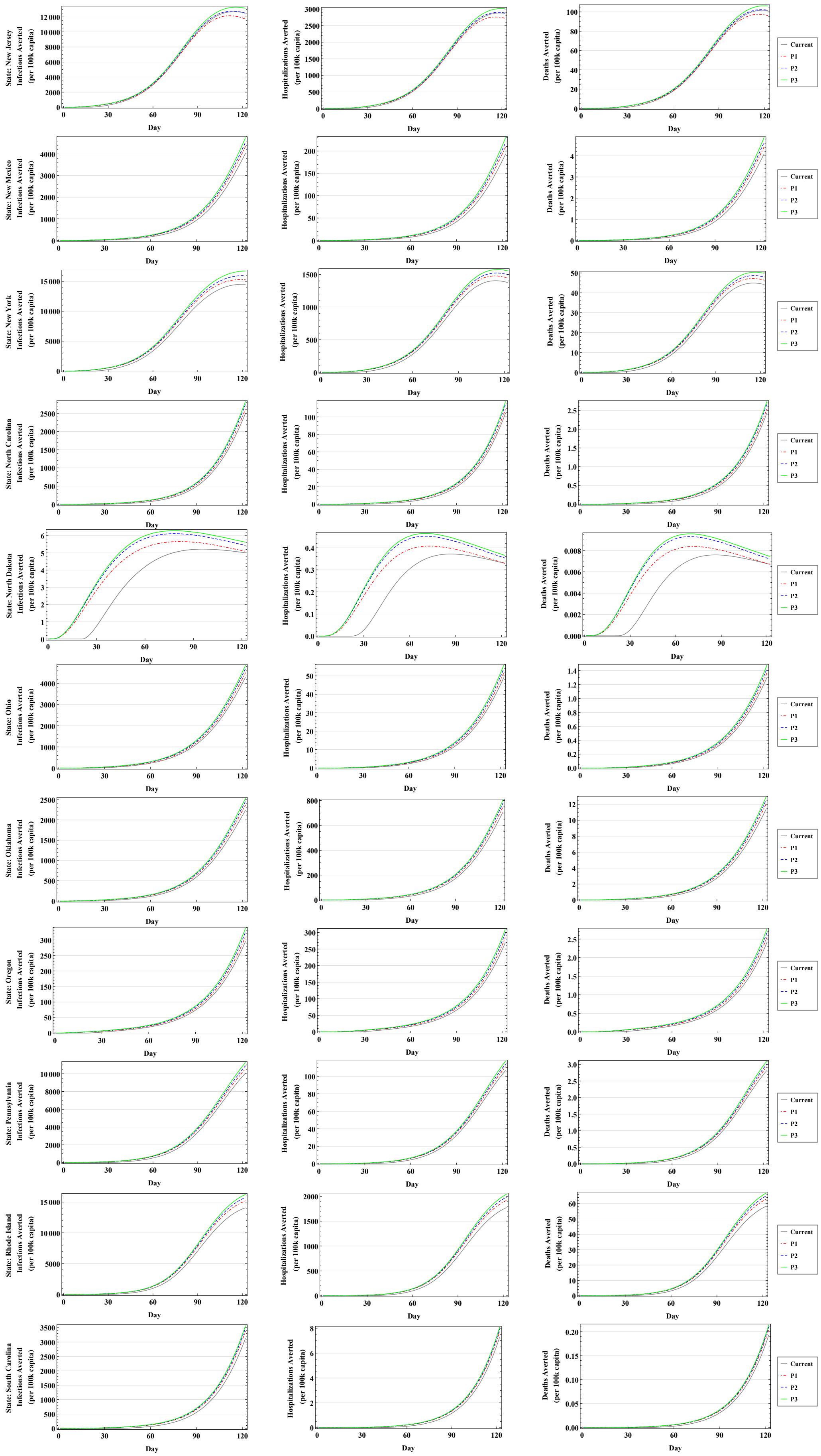

Figure D.1 Continued

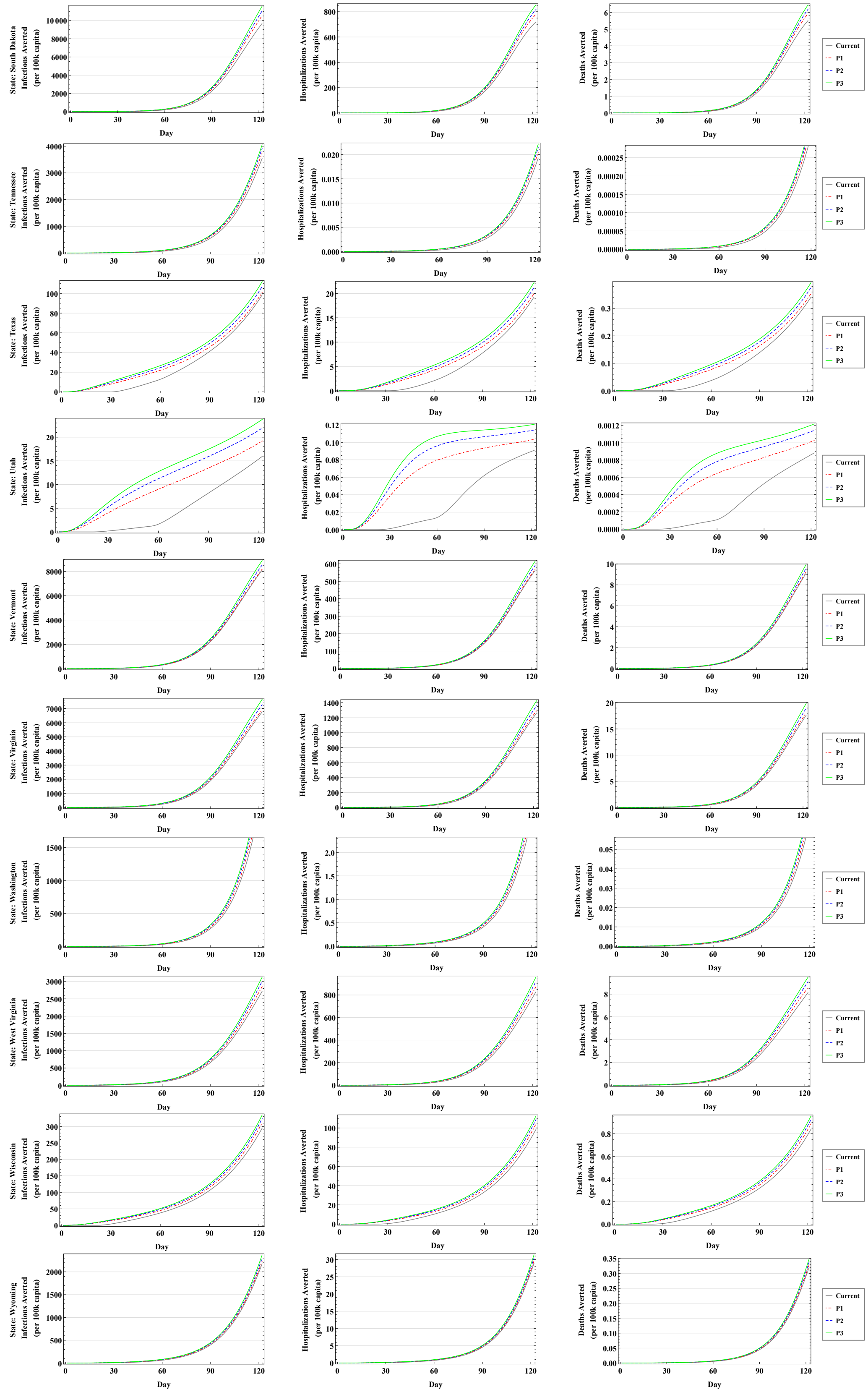

Figure D.1 **Continued**

D.5. Cost-Effectiveness Probability

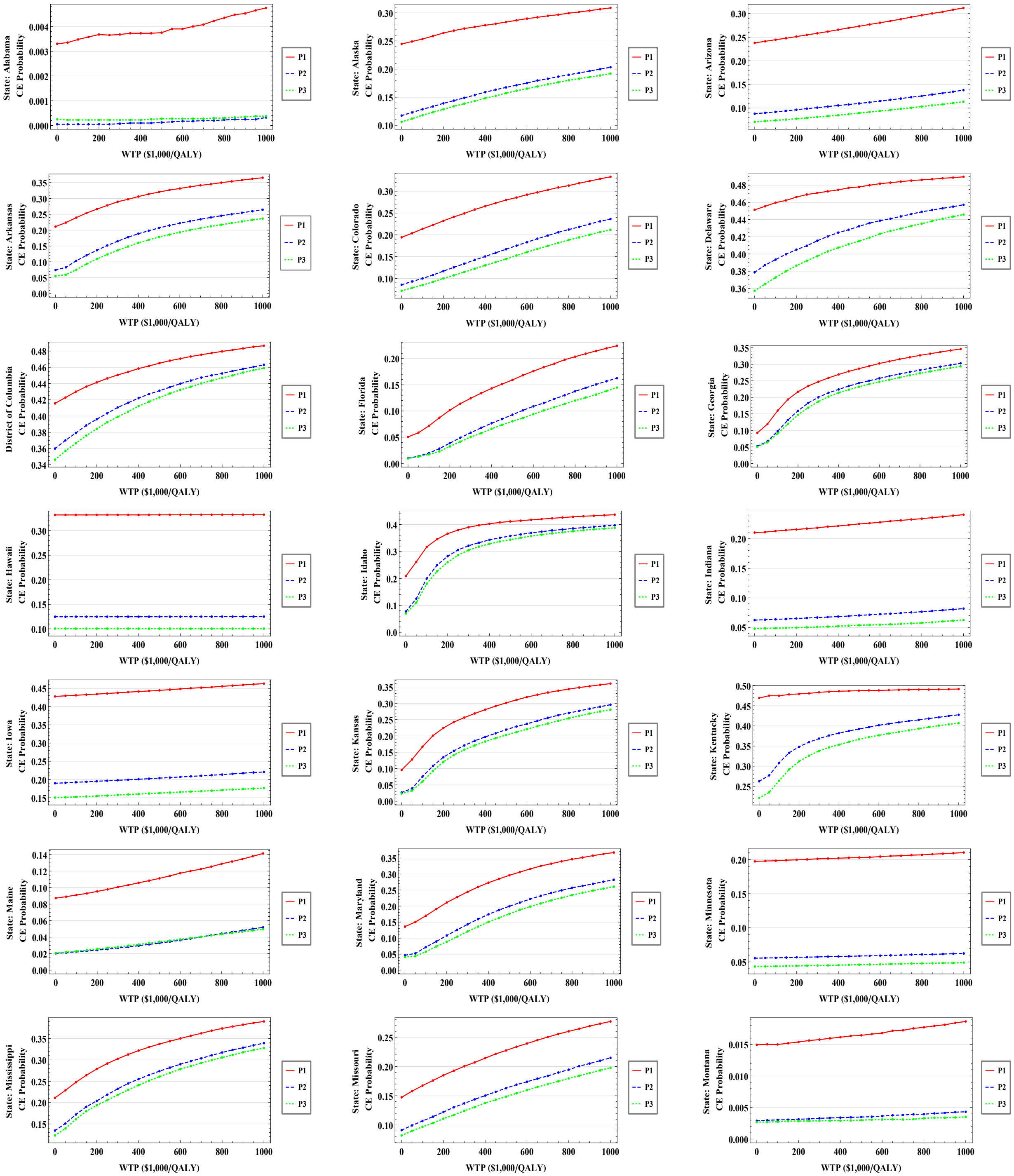

Figure D.2 (Color online) Cost-effectiveness probability of potential policies compared to the current policies

Notes. See Table 3 for intervention policies P1/P2/P3.

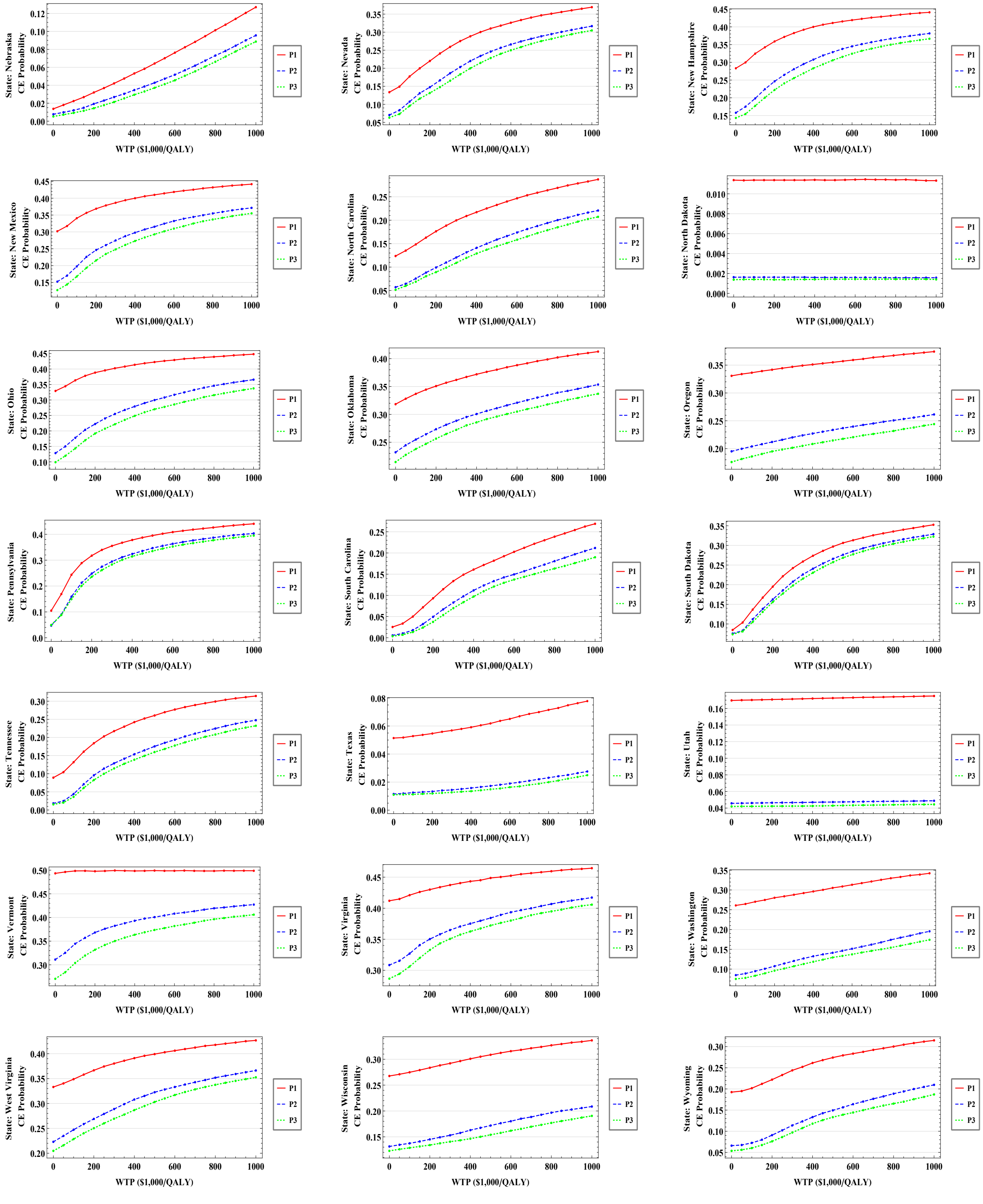

Figure D.2 Continued

APPENDIX E. Robustness Checks

E.1. qol Scores. For the case where qol scores are lower than those in Equation (EC.1), we have:

$$q_i = \begin{cases} 1.0, & \text{if } i \in \{1,11\} \text{ Compartment(s): susceptible, recovered,} \\ x \in [0.75, 0.85], & \text{if } i = 2 \quad \text{Compartment(s): exposed/presymptomatic,} \\ x \in [0.65, 0.75], & \text{if } i = 3 \quad \text{Compartment(s): infected asymptomatic,} \\ x \in [0.55, 0.65], & \text{if } i = 4 \quad \text{Compartment(s): infected symptomatic,} \\ x \in [0.45, 0.55], & \text{if } i = 5 \quad \text{Compartment(s): infected hospitalized (common bed),} \\ x \in [0.25, 0.35], & \text{if } i = 6 \quad \text{Compartment(s): infected hospitalized (ICU bed),} \\ x \in [0.05, 0.15], & \text{if } i = 7 \quad \text{Compartment(s): infected hospitalized (ICU bed \& ventilator),} \\ x \in [0.65, 0.75], & \text{if } i = 8 \quad \text{Compartment(s): carrier post discharge (was hospitalized common bed),} \\ x \in [0.55, 0.65], & \text{if } i = 9 \quad \text{Compartment(s): carrier post discharge (was hospitalized ICU bed),} \\ x \in [0.45, 0.55], & \text{if } i = 10 \quad \text{Compartment(s): carrier post discharge (was hospitalized ICU bed \& ventilator),} \\ 0.0, & \text{if } i = 12 \quad \text{Compartment(s): dead.} \end{cases} \tag{EC.3}$$

Furthermore, for the case where qol scores are higher than those in Equation (EC.1), we have:

$$q_i = \begin{cases} 1.0, & \text{if } i \in \{1,11\} \text{ Compartment(s): susceptible, recovered,} \\ x \in [0.95, 1.0], & \text{if } i = 2 \quad \text{Compartment(s): exposed/presymptomatic,} \\ x \in [0.85, 0.95], & \text{if } i = 3 \quad \text{Compartment(s): infected asymptomatic,} \\ x \in [0.75, 0.85], & \text{if } i = 4 \quad \text{Compartment(s): infected symptomatic,} \\ x \in [0.65, 0.75], & \text{if } i = 5 \quad \text{Compartment(s): infected hospitalized (common bed),} \\ x \in [0.45, 0.55], & \text{if } i = 6 \quad \text{Compartment(s): infected hospitalized (ICU bed),} \\ x \in [0.25, 0.35], & \text{if } i = 7 \quad \text{Compartment(s): infected hospitalized (ICU bed \& ventilator),} \\ x \in [0.85, 0.95], & \text{if } i = 8 \quad \text{Compartment(s): carrier post discharge (was hospitalized common bed),} \\ x \in [0.75, 0.85], & \text{if } i = 9 \quad \text{Compartment(s): carrier post discharge (was hospitalized ICU bed),} \\ x \in [0.65, 0.75], & \text{if } i = 10 \quad \text{Compartment(s): carrier post discharge (was hospitalized ICU bed \& ventilator),} \\ 0.0, & \text{if } i = 12 \quad \text{Compartment(s): dead.} \end{cases} \tag{EC.4}$$

Figure E.1 shows the results. As we lower qol scores (i.e., when health conditions across all compartments get deteriorated), the saving in the total QALY from current/potential policies compared to no intervention will increase. However, we observe no difference in the cost outcomes when chaning qol scores.

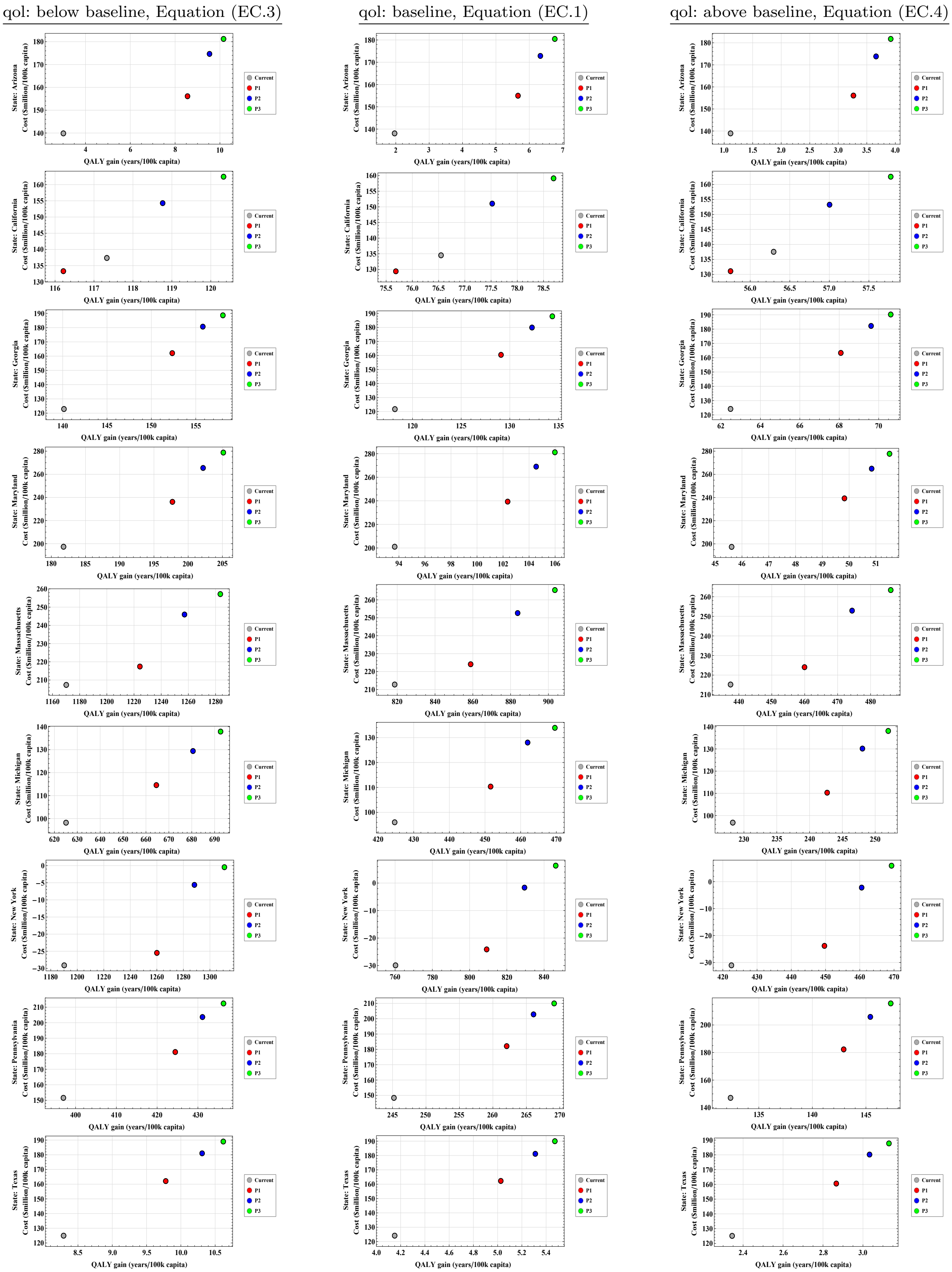

Figure E.1 **(Color online) Robustness checks under different qol scenarios**

Notes. See Table 3 for intervention policies P1/P2/P3.

E.2. Proportions of Population with Lost Income. In Equation (EC.2), we elaborated our baseline scenario for proportions of population with lost income. Now, in our robustness checks, we consider two alternative scenarios:

$$(p_1(t), p_2(t), p_3(t), p_4(t)) = \begin{cases} (50\%, 25\%, 15\%, 10\%), & \text{under Policy 1: if } 1 \le t \le 61, \\ (65\%, 20\%, 10\%, 5\%), & \text{under Policy 1: if } 62 \le t \le 92, \\ (80\%, 10\%, 4\%, 8\%), & \text{under Policy 1: if } 93 \le t \le 122, \\ (50\%, 25\%, 15\%, 10\%), & \text{under Policy 2: if } 1 \le t \le 92, \\ (65\%, 20\%, 10\%, 5\%), & \text{under Policy 2: if } 93 \le t \le 122, \\ (50\%, 25\%, 15\%, 10\%), & \text{under Policy 3: if } 1 \le t \le 122, \end{cases} \quad \text{(EC.5)}$$

$$(p_1(t), p_2(t), p_3(t), p_4(t)) = \begin{cases} (30\%, 30\%, 20\%, 20\%), & \text{under Policy 1: if } 1 \le t \le 61, \\ (45\%, 25\%, 15\%, 15\%), & \text{under Policy 1: if } 62 \le t \le 92, \\ (60\%, 20\%, 10\%, 10\%), & \text{under Policy 1: if } 93 \le t \le 122, \\ (30\%, 30\%, 20\%, 20\%), & \text{under Policy 2: if } 1 \le t \le 92, \\ (45\%, 25\%, 15\%, 15\%), & \text{under Policy 2: if } 93 \le t \le 122, \\ (30\%, 30\%, 20\%, 20\%), & \text{under Policy 3: if } 1 \le t \le 122, \end{cases} \quad \text{(EC.6)}$$

Compared to the baseline scenario, Equation (EC.5) increases (decreases) the ratio of population who lost less than 50% (more than 50%) of their income, while Equation (EC.6) does the reverse (see Table E.1).

Table E.1 **Summary of scenarios for proportion of population with lost income (when all three interventions are implemented)**

Scenario	**Ratio with lost income $\le 50\%$**	**Ratio with lost income $> 50\%$**
Equation (EC.5)	$p_1 + p_2$=75%	$p_3 + p_4$=25%
Baseline, Equation (EC.2)	$p_1 + p_2$=68%	$p_3 + p_4$=32%
Equation (EC.6)	$p_1 + p_2$=60%	$p_3 + p_4$=40%

Although we consider alternative scenarios for the robustness check, it should be noted that, in all of our simulations, we consider a ±10% variation based on the corresponding values for p_j's. Figure E.2 shows the results. As the ratio of population who lost more than 50% of their income increases, the extra total cost incurred by current/potential policies compared to no intervention will ramp up. However, we observe no difference in the QALY outcomes when chaning the ratio of population with lost income.

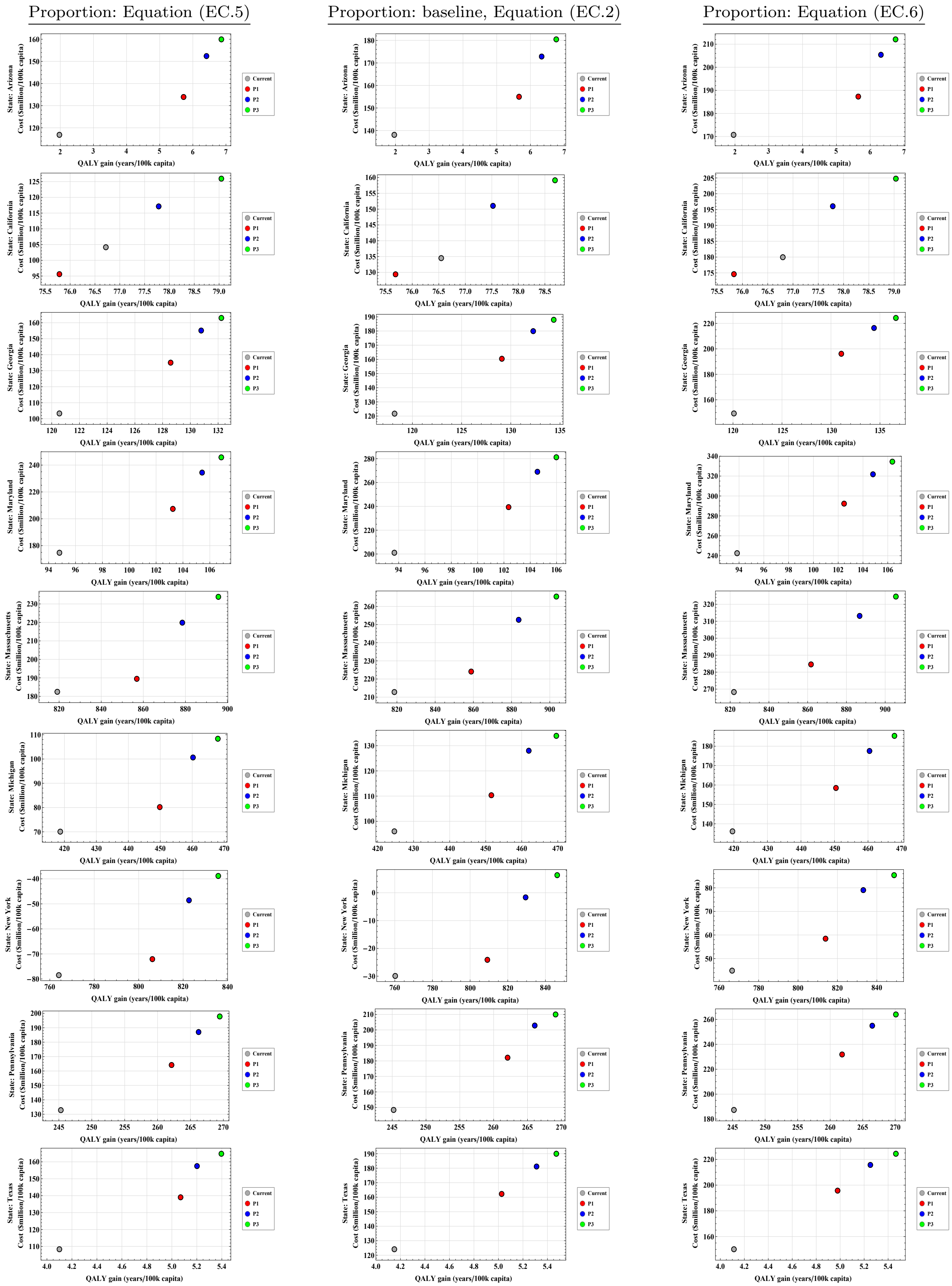

Figure E.2 (Color online) Robustness checks under different proportions of lost income

Notes. See Table 3 for intervention policies P1/P2/P3.