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

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Intervention policies, like stay-at-home orders, are shown to be effective in controlling the spread of the novel Coronavirus Disease 2019 (COVID-19). However, concerns over economic burdens of these policies have propelled U.S. states to move towards reopening. 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 51 U.S. states on various factors, including number of tests, positive and negative results, hospitalizations, ICU beds and ventilators used, residents' mobility, and deaths, and provide an analytical framework to measure per capita total costs versus quality-adjusted life years (QALY) under various intervention policies. Our results show that, compared to a hypothetical no intervention during March-June 2020, the policies undertaken across the U.S. on average saved each person up to 4.04 days worth of QALY while incurring $3,284.67 for him/her. Had the states undertaken more strict policies during the same time frame than those they adopted, the increase in the average QALY and cost per person would be up to 6 days and $4,953.81, respectively. We also find that stricter policies are not cost-effective at the typical willingness-to-pay rates. Imposing such strict policies, however, may be inevitable in the near future, especially if the risk of a second wave of COVID-19 increases. Finally, in addition to quantifying the health and economic impacts of intervention policies, 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.

Key words: COVID-19; societal intervention policies; health and economic impacts; QALY; total cost; 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 February 2020. In the United States, as of July 10, 2020, 3,106,931 total cases and 132,855 total deaths have been confirmed (CDC 2020). In response to the COVID-19 pandemic and 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 jobs, 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, we analyze the current policies 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 diesease progression over time. Utilizing data of 51 U.S. states 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 by intervention policies, their duration, sociodemographic/economic factors (e.g., age, race, and income), and residents' mobility in each state. 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). Finally, we compare the current policies with other potential policies that could have been imposed by each state. We do so by conducting an extensive simulation analysis for the period of March through June 2020. For each state, we report per capita total cost as well as quality-adjusted life years (QALY) obtained under such policies. 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 person's quality of life impacted by different stages of the disease (e.g., healthy, infected, hospitalized, dead, etc.).

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 show the following: (1) compared to a no-intervention scenario, the current policies imposed across the U.S. during March-June 2020 increased the per capita QALY and total cost up to 4.04 days and \$3,284.67, respectively. Moreover, under stricter policies, these changes would be up to 6 days and \$4,953.81, respectively. (2) At a typical willingness to pay (WTP) rate of \$25,000 per resident's QALY per year, stricter intervention policies than those currently imposed in the U.S. are typically not cost-effective. However, increasing WTP to \$100,000 could enhance the cost-effectiveness of such policies. (3) Regardless of the intervention policy, lowering residents' mobility should be viewed as an effective strategy in that it can tangibly improve per capita QALY gains without a significant impact on per capita total cost (max difference in the average per capita total cost = \$247.91).

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

2. Data and Methodology

2.1. Data

We utilize the *Star Schema* data tables (Foldi and Csefalvay 2020) with the following data attributes: 51 U.S. states, date, number of daily total COVID tests, positive and negative results, hospitalizations, ICU beds used, ventilators used, and deaths in each state. Of note, the beginning date for each state 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. In this study, we consider three main interventions: stay-at-home order and non-essential business closures, large-gathering ban, and school closures. For more details regarding the timelines of current intervention policies and the data we have collected, see Table EC.1 (all illustrations are provided in the electronic companion).

2.2. An Epidemiological Model

To analyze the spread of disease, we consider an epidemiological compartmental model known as SEIRS that considers *susceptible*, *exposed*, *infected*, and *recovered* populations.[1] 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)). Compared to conventional SEIRS, our framework has four notable differences: (1) Our model allows transitions between asymptomatic infected, symptomatic infected, and hospitalized populations. (2) Among hospitalizations, we account for demand for common beds, ICU beds alone, or ICU beds with mechanical ventilators. (3) For hospitalized patients who are discharged, we also consider the possibility of being infected (i.e., *carrier*) post-discharge (Modern Healthcare 2020). (4) For the current policies in each state, there exist time 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 EC.1). Due to the type/number of interventions undertaken in each 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. The outputs are the number of people in each compartment on any day; e.g., susceptible, exposed, infected symptomatic/asymptomatic, hospitalized with common bed, ICU bed, or ventilator, and death. For more details regarding our model, see the electronic companion.

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 EC.2). 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 (i.e., Policy 3 (1) in Table EC.2 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 EC.1).

[1] 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.

2.4. Projecting 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 to intervention policies. To address this, we will develop a longitudinal mixed-effect regression model to measure the impact of intervention policies on potential reductions in transmission rates (see §3.2 for results). For each state, we adjust our analysis by duration of interventions, median 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 EC.3 shows the summary of our data regarding the independent variables used in our longitudinal regression model.

2.5. Measuring Health and Economic Impacts

For each intervention policy, we measure health outcomes by the *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, with any other medical condition (e.g., infection) resulting in a value 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 the electronic companion for more details). Let $X(t) = \Big\{X_1(t), \ldots, X_{12}(t)\Big\}$ represent the state of the model at time t (i.e., $X_i(t)$ reveals the number of people projected to be in compartment i at time t). Also, let $q_i \in [0,1]$, $i \in \{1, 2, \ldots, 12\}$, 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 per capita QALY as the quality-adjusted life years that each person in the population can accrue over the time horizon T:

$$\text{QALY} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{12} q_i X_i(t)}{\sum_{i=1}^{12} X_i(t)} \quad \text{for} \quad t = 1, \ldots, T. \tag{1}$$

Furthermore, we measure economic impacts by the sum of direct and indirect costs, referred to as the total cost hereafter. The direct costs entail the costs of healthcare resources utilization (e.g., common beds, ICU beds, and ventilators). The indirect costs cover the costs associated with lost income and productivity as a result of undergoing societal intervention policies (for more discussion regarding the direct and indirect costs, see, e.g., Meltzer et al. (1999)). Following our foregoing notations, 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 costs for using one unit of these resources, respectively, PCI represent the per capita income, and θ be the ratio of lost income per person. Then, per capita total cost is measured as follows:

$$\text{Total cost} = \sum_{t=1}^{T} \left(\underbrace{\frac{C_1 * X_5(t) + C_2 * X_6(t) + C_3 * X_7(t)}{\sum_{i=1}^{12} X_i(t)}}_{\text{Direct cost}} + \underbrace{\text{PCI} * \theta}_{\text{Indirect cost}} \right) \quad \text{for} \quad t = 1, \ldots, T. \tag{2}$$

In addition to using Equations (1) and (2) to compare the total cost and QALY under each policy, we make use of *incremental cost-effectiveness ratio* (ICER) to compare the *cost-effectiveness* (see, e.g., Drummond et al. (2015)):

$$\text{ICER} = \frac{\text{Incremental total cost (\$ per capita)}}{\text{Incremental QALY (years per capita)}} = \frac{\text{Total cost (potential policy)} - \text{Total cost (current policy)}}{\text{QALY (potential policy)} - \text{QALY (current policy)}}. \tag{3}$$

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 our estimated QALY and costs parameters can be found in the electronic companion.

3. Numerical Results and Findings

3.1. Parameter Estimations and Model Validation

To estimate the parameters of the SEIRS model, we conduct a Markov chain Monte Carlo (MCMC) simulation (see, e.g., Bootsma and Ferguson (2007)) 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 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 EC.4 in the electronic companion shows the estimated parameters. Our various other model validation steps can also be found in the electronic companion.

REMARK 1 (UNOBSERVABLE INFECTED CASES). There is growing evidence that the majority of COVID-19 infected cases remain undiagnosed, mainly due to limited capacity of COVID-19 tests carried out across the U.S. As a result, the number of observed positive cases significantly differs from the total number of infected cases (Gao and Rosenlof 2020, Daily News 2020, Pharmaceutical Technology 2020, Science News 2020). To address this issue, for each state, we project the number of daily positive cases to the whole state's population as follows:

$$\text{Projected infections in a day} = \frac{\#\text{ observed positive cases in that day}}{\text{Total }\#\text{ tests in that day}} * \text{State's population.} \quad (4)$$

Compared to considering observed cases, using our measure in (4) results in a more pessimistic, yet more realistic, appraisal of the number of infections. Since, in the MCMC simulation, the number of hospitalizations should approximately match that in the data, the hospitalization rates that we have estimated are considerably lower than that reported in the literature (CDC 2020).

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, median 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). Thus, our first model is:

$$\begin{aligned}\text{Model 1: } \beta_0-\beta_i = {} & b_0 + b_1 * policy_i + b_2 * duration_i + b_3 * mobility_i^1 + b_4 * mobility_i^2 \\ & + b_5 * median\ age + b_6 * race\ ratio + b_7 * per\ capita\ income,\end{aligned} \tag{5}$$

where the notation is introduced in Table EC.5. 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 EC.6, we observe that performance measures are not unanimous in favoring one model. For example, Model 1 results in better Akaike information criterion (AIC) and Bayesian information criterion (BIC) values, whereas Model 3 yields better mean square error (MSE) and mean absolute error (MAE) values. Due to its simplicity and its quality that is fairly comparable with Model 3, we select Model 1 to carry forward in our simulation analyses (see §3.3). From our results in Table EC.7, we have observed that increasing the intensity and duration of interventions is associated with more reductions in transmission rates (statistically significant). Furthermore, elevating the median age and 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 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

We use our simulation model to compare the performance of intervention policies while accounting for variations in multiple parameters discussed thus far (further details are provided in the electronic companion). In Figure EC.1, we first present the cost-effectiveness (CE) probability of potential intervention policies against the current policy in each state. That is, we depict the ratio of simulation instances where a potential policy is more cost-effective than the current policy (ICER $\leq$WTP). In our baseline comparison, we consider WTP=\$25,000 (Echazu and Nocetti 2020). Our results reveal that, at this WTP value, current policies adopted by states are typically more cost-effective than the other potential policies we study. Of note, the potential policies we study are more strict than the current ones. Hence, they are able to better control the spread of the disease and yield improvements in QALY. These improvements in QALY, however, is offset by higher total costs (mainly impacted by the indirect cost of lost income). To further investigate this, we measure the CE probability by only considering the direct cost of healthcare resources utilization. Figure EC.1 shows that the potential policies we study become very cost-effective compared to current policies, if state authorities could mitigate concerns about indirect costs via other mechanisms (e.g., external funding sources for lost income or economic productivity of their residents). Finally, we observe that these potential policies become more attractive than the current policies if state authorities are willing to accept higher WTP values (e.g., WTP = $100,000 or $150,000).

Of note, states cannot sideline the indirect costs or immediately accept a higher WTP value, since the pandemic has contributed to an economic recession projected to be taken place in 2020-21 (World Bank 2020). These reasons have already influenced states not having (re)enacting strict policies as their top priority (Stat News 2020). Yet, alternative interventions with much less financial impacts, such as mandating wearing face masks, are shown to be as effective as a fraction of more strict policies (see, e.g., Lyu and Wehby (2020a)). Therefore, despite their economic implications, resuming more strict policies may be inevitable, especially as some states have already observed resurgence of COVID-19 cases (Associated Press 2020). Our analysis provides quantitative insights for authorities to evaluate/improve/reenact their previous policies. To further assist authorities, in Figure EC.2 we depict the average per capita QALY accrued and the total cost incurred under various intervention policies separately for each state. We observe that, compared to no intervention across the U.S. during March-June 2020, the average increase in QALY and total cost per person is between 0.09 and 4.04 days and $375.48 and $3,284.67 (under current policy), 0.19 and 4.32 days and $1,316.64 and $2,975.73 (under Policy 1), 0.42 and 5.64 days and $1,951.77 and $4,297.92 (under Policy 2), and 0.62 and 6.00 days and $2,194.83 and $4,953.81 (under Policy 3), respectively.

We make use of these results to also report the average extra total cost that can be incurred per person in each state for one extra day added to that person's QALY as a result of implementing a certain intervention policy. Our results in Figure EC.3 reveal that, in comparison with no intervention, other policies incur as low as \$217.87 (under current policy), \$488.63 (under Policy 1), \$489.81 (under Policy 2), and \$535.36 (under Policy 3) per extra day of QALY. It should be noted that a low value for this measure may not necessarily indicate a better performance in that state, as it may be pertained to very low costs of healthcare utilization or lost income. However, we also observe that lower values for this measure could be obtained in states where such costs are considerably high (e.g., California).

3.4. Robustness Checks

To test the robustness of our results, we perform various sensitivity analyses. In Figure EC.1, we re-run our analyses by altering the value of WTP from \$25,000 to \$50,000 and \$100,000. As we increase WTP (i.e., as states become willing to pay more for one extra year of QALY), the potential policies—advocating more strict interventions—could become more cost-effective. Despite this observation, our results are relatively robust to variations in WTP: the current policies across the U.S. are primarily more cost-effective than the potential policies we study. We also note that, had we ignored the indirect cost, the potential policies would have become more cost-effective than the current policies (consistent with our earlier finding). Of note, we observe that increasing WTP from \$25,000 to \$100,000 does not necessarily impact this type of cost-effectiveness, which is not surprising, given the assumption (for this particular sensitivity analysis) that indirect costs can be ignored.

Furthermore, we conduct sensitivity analyses on the impact of residents' mobility rates. For each potential intervention policy, in addition to the observed mobility rates in each state, we consider two hypothetical mobility scenarios where the rates of moving within 1 mile, between 1 and 10 miles, and beyond 10 miles from home are assumed as 50%, 30%, and 20% and 50%, 50%, and 0% (further details are discussed in the electronic companion). Our results in Figure EC.2 show that, under any potential intervention policy, lowering people's mobility could increase the average QALY per person in each state without significantly affecting the total cost. Specifically, we find that between the observed mobility and these hypothetical mobility scenarios, the maximum difference in the average per capita total cost across all states is \$247.91. Moreover, regarding the impact of mobility on the CE probability of potential policies, we observe mixed results. For example, for a same state, lowering mobility can improve the cost-effectiveness under one policy while worsening it under another policy (see, e.g., CA, FL, and IL in Figure EC.1).

Finally, there is a significant amount of heterogeneity in these results across states. Thus, we avoid providing a "one-size-fits-all" policy recommendation. Instead, we provide results separately for each state to further assist their authorities with imposing specific policies that can be effective in their specific state.

4. Discussion and Conclusion

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, jobs, 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 51 U.S. states 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 increasing the strictness of interventions, their duration, the median age, and per capita income, lowering the ratio of Black/Hispanic populations, and increasing the people's mobility rate within 10 miles from their homes (compared to the distance beyond that) are associated with more reductions in the disease 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 quality of life accrued versus the total cost incurred for both the current policy in place in each state and our counterfactual policies. Compared to no intervention during March-June 2020, we estimate that under the current intervention policies across the U.S., each individual has saved on average between 0.09 and 4.04 days worth of QALY, while the society has incurred an average total cost of $375.48 to $3,284.67 per person to achieve this. For our first counterfactual scenario, we assume that all interventions (stay-at-home order and non-essential business closure, large-gathering ban, and school closure) were imposed in March-April, the first was lifted in May, and then the first two were lifted in June. Under this scenario, our results show that each individual would have saved on average between 0.19 and 4.32 days worth of QALY, while the average extra total cost would be $1,316.64 and $2,975.73 per person. For the second scenario, we assume that all interventions were imposed in March-May, and the first was only lifted in June. Here, we find that the increase in the average QALY and total cost would be within 0.42 to 5.64 days and $1,951.77 to $4,297.92, respectively. The third scenario is the most strict one in which we assume all interventions were imposed through March-June. Our results reveal that the increase in the average QALY and total cost would be within 0.62 to 6.00 days and $2,194.83 to $4,953.81, respectively. Finally, we observe that, under any intervention policy, reducing residents' mobility rates can improve the average QALY per person without increasing the total cost drastically.

Our results show stricter intervention policies than the current policies imposed in the U.S. could also be cost-effective, although only at higher values of WTP (e.g., $100k). Imposing such restricter policies, however, may be inevitable in the near future depending on the severity of resurgence/second wave of COVID-19. Our findings provide quantitative evidence and important implications that can help public heatlh authorities to not only evaluate the existing policies retrospectively, but also enact more effective policies under such circumstances.

4.1. 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). That said, we did not consider the issue of capacity expansion for these resources. Also, such capacity expansions would require a parallel analysis on the number of providers (Keohane 2020). Since capacity expansions would bear extra direct costs, it 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. Furthermore, we have assumed lost income as a temporary factor, and hence, have not considered the financial ramifications of lost jobs that could go beyond a 4-month horizon. This can potentially make our estimates of indirect costs biased. Although we have analyzed a range of variations for the ratio of 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 as well as the methodology we employed. An alternative model and/or new data source may result in different outcomes. Nevertheless, our study provides a quantitative framework to streamline the process of analysis and enactment of societal intervention policies.

4.2. Future Research Directions and Conclusion

We now (a) identify three major ways in which future research can enhance our study, and (b) briefly conclude.

First, as data becomes available on states initiating alternative policies (e.g., mandating wearing face masks), the cost-effectiveness of such policies can also be examined. Of note, such policies can only be impactful in the presence of more strict intervention policies (Lyu and Wehby 2020a). Second, in our estimations, we have assumed the number of infections in the population to be proportional to the rate of confirmed positive tests. Compared to the case where this number is assumed to be equal to the number of confirmed positive tests, our notion is less optimistic, yet more realistic. As a result, we report hospitalization rates that are much smaller than that reported in the literature. Future research may examine more rigorous methods that could accurately estimate the number of partially observable infections. Third, in the absence of viable treatments, a recovery from COVID-19 does not necessitate permanent immunity. At the time of writing this paper, no fully studied treatment had become available, and the earliest time for delivery of such treatments is claimed to be in 2021 (McKinsey & Company 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 EC.4), 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.

This study sheds light on the trade-off between health and economic impacts of the COVID-19 pandemic. While financial ramifications of intervention policies instigate resistance against their long-term enactment, they may be inevitable depending on how this pandemic pans out. 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 policies that can be used to curb the infection rates.

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Online Appendices

EC.1. Main Illustrations

Table EC.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.

Table EC.2 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

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

Table EC.3 Summary of socio-demographics and mobility information

State	Avg. pci ($)[a]	Median Age	Race Ratio[b]	Mobility Ratio[d]			
				Time Frame 1[c]	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)	—

Avg. pci and median age are obtained from Mathematica, Wolfram Research, Inc. (see Table EC.10).
Race ratios are obtained from KFF (2018a). Mobility information is obtained from CUEBIQ (2020).
[a] Per capita income. [b] Ratio of Black or Hispanic population. [c] For characterization of time frames, see §2.1-2.2.
[d] 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 were not available. For these states, we take the average mobility rates from other states.

Table EC.4 Summary of estimated parameters 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	(0.49,1.78)*10^6	(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)	(0.00033,0.0009)	(47.63,87.33)	(10^{-6},0.93)	(0.03,0.36)	(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	(0.01,0.05)*10^6	(4.66,17.84)	(10^{-6},2.92)	(10^{-6},1.87)	—	(4.07,13.42)	(2.56,5.55)	(0.26,0.49)	(13.3,69.02)	(0.0019,0.0268)	(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	(0.39,1.16)*10^6	(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)	(0.0059,0.0197)	(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	(0.24,0.63)*10^6	(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},0.0042)	(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	(1.64,7.91)*10^6	(3.52,17.83)	(10^{-6},4.27)	—	—	(3.43,13.9)	(2.02,3.84)	(0.27,0.49)	(14.66,74.08)	(0.0022,0.0318)	(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	(1.04,2.06)*10^6	(0.86,5.4)	(3.28,10.1)	(0.99,4.85)	—	(5.68,17.59)	(2.25,5.48)	(0.27,0.49)	(13.92,67.9)	(10^{-6},0.028)	(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	(0.46,1.92)*10^6	(7.24,23.66)	(10^{-6},5.05)	(10^{-6},4.58)	—	(3.01,11.78)	(1.88,3.85)	(0.27,0.5)	(13.06,69.81)	(10^{-6},0.0323)	(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	(0.11,0.51)*10^6	(5.75,15.98)	(1.95,5.75)	(0.65,3.08)	—	(3.45,13.36)	(2.05,3.81)	(0.26,0.49)	(12.36,69.51)	(0.0018,0.0255)	(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	(0.07,0.27)*10^6	(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)	(0.0136,0.0413)	(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	(0.54,3.44)*10^6	(4,15.57)	(0.99,2.58)	(0.89,2.28)	—	(4.66,16.64)	(2.26,5.72)	(0.26,0.48)	(14.95,72.25)	(10^{-6},0.002)	(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	(1.98,4.91)*10^6	(3.73,17.02)	(10^{-6},2.93)	(10^{-6},1.96)	—	(4.94,16.35)	(2.43,5.83)	(0.26,0.49)	(12.96,53.69)	(10^{-6},0.0051)	(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	(0.16,0.52)*10^6	(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},0.0005)	(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	(0.13,0.31)*10^6	(8.29,23.84)	(10^{-6},2.98)	(10^{-6},5.1)	—	(6.92,17.66)	(3.7,6.87)	(0.27,0.49)	(13.09,71.65)	(10^{-6},0.0011)	(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	(1.36,4.52)*10^6	(5.57,21.37)	(0.11,3.5)	(0.11,2.96)	—	(3.67,11.33)	(2.02,3.67)	(0.27,0.5)	(11.48,57.86)	(10^{-6},0.0311)	(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	(1.36,3.52)*10^6	(2.86,10.49)	(0.9,8.81)	(0.57,7.3)	—	(3.98,14.54)	(2.41,5.79)	(0.26,0.49)	(14.45,74.94)	(10^{-6},0.0335)	(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	(0.56,1.32)*10^6	(4.3,17.94)	(10^{-6},1.79)	(10^{-6},6.59)	—	(3.7,13.43)	(2.01,4.78)	(0.26,0.49)	(15.71,76.67)	(10^{-6},0.0251)	(46.05,83.3)	(10^{-6},1.95)	(0.63,4.95)	(2.48,11.86)	(3.3,20.42)	(4.77,8.85)	(6.86,11.18)	(10.7,19.22)
Kansas	2,904,021	1.22	0.87	(0.21,0.65)*10^6	(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},0.0012)	(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	(0.11,0.75)*10^6	(3.84,19.44)	(1.85,4.58)	—	—	(2.84,12.45)	(2.06,3.48)	(0.27,0.5)	(13.0,63.8)	(10^{-6},0.0125)	(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	(0.81,2.72)*10^6	(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},0.0423)	(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	(0.03,0.12)*10^6	(1.81,10.03)	(0.89,10.96)	(10^{-6},7.01)	(10^{-6},8.35)	(3.51,13.68)	(1.99,4.6)	(0.27,0.5)	(14.99,71.1)	(0.0015,0.0107)	(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	(0.53,2.19)*10^6	(1.62,6.87)	(4.33,12.38)	(0.74,3.97)	—	(5.44,17.07)	(2.25,5.29)	(0.27,0.5)	(12.7,65.26)	(10^{-6},0.0311)	(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	(2.12,4.2)*10^6	(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},0.0598)	(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	(4.23,8.22)*10^6	(3.97,18.37)	(10^{-6},6.85)	(10^{-6},3.43)	—	(4.94,16.03)	(1.98,3.92)	(0.25,0.47)	(12.75,73.61)	(10^{-6},0.0275)	(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	(0.06,0.63)*10^6	(1.3,5.27)	(4.27,9.3)	(2.06,6.27)	—	(3.73,12.37)	(2.1,4.25)	(0.26,0.49)	(11.55,60.88)	(10^{-6},0.0274)	(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	(0.11,1.07)*10^6	(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},0.0607)	(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	(0.2,1.45)*10^6	(3.22,14.23)	(1.76,7.44)	(1.18,5.86)	—	(5.08,16.2)	(2.75,6.49)	(0.27,0.5)	(19.08,79.39)	(0.0161,0.015)	(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	(0.01,0.08)*10^6	(2.25,11.21)	(1.82,5.11)	(0.16,2.74)	(10^{-6},7.67)	(4.37,16.03)	(2.93,6.26)	(0.27,0.5)	(11.95,64.38)	(0.002,0.0086)	(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	(0.08,0.3)*10^6	(1.45,10.69)	(1.81,16.58)	(1.47,14.3)	(10^{-6},7.02)	(4.64,15.99)	(1.96,3.94)	(0.27,0.5)	(12.21,72.35)	(10^{-6},0.0169)	(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	(0.1,0.41)*10^6	(4.5,15.01)	(1.73,8.09)	(1.17,4.77)	—	(5.69,17.92)	(2.12,5.86)	(0.26,0.47)	(14.38,73.37)	(10^{-6},0.0317)	(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	(0.001,0.19)*10^6	(7.06,13.34)	(1.61,2.99)	(0.18,1.72)	—	(3.4,13.06)	(2,3.47)	(0.27,0.51)	(11.1,65.64)	(10^{-6},0.0225)	(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	(5.83,7.95)*10^6	(13.63,28.04)	(3.77,20.25)	—	—	(3.7,15.42)	(2.21,3)	(0.27,0.49)	(11.65,67.36)	(0.0042,0.0343)	(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	(0.06,0.19)*10^6	(2.2,6.83)	(1.93,5.58)	(0.05,1.86)	—	(4.06,10.12)	(2.08,4.74)	(0.27,0.5)	(14.01,69.86)	(10^{-6},0.0347)	(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	(4.33,16.14)*10^6	(10^{-6},14.55)	(10^{-6},8.14)	(10^{-6},6.65)	—	(4.15,14.71)	(2.28,4.71)	(0.26,0.49)	(16.2,67.48)	(10^{-6},0.0509)	(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	(0.26,2.14)*10^6	(0.42,5.44)	(2.94,7.42)	(0.6,5.68)	—	(4.59,16.17)	(2.1,5.51)	(0.27,0.48)	(13.35,69.05)	(10^{-6},0.015)	(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	(0.009,0.077)*10^6	(1.61,5.64)	(1.68,7.74)	(1.88,7.52)	—	(4.13,12.77)	(2.47,5.89)	(0.27,0.51)	(14.12,67.79)	(10^{-6},0.025)	(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	(0.91,2.26)*10^6	(2.77,7.96)	(2.79,7.36)	(0.08,2.99)	—	(4.02,14.64)	(2.2,5.6)	(0.26,0.49)	(13.82,57.8)	(10^{-6},0.015)	(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	(0.2,1.05)*10^6	(1.22,6.23)	(2.76,7.44)	(0.11,3.86)	—	(5.08,16.2)	(2.75,6.49)	(0.27,0.5)	(19.08,79.39)	(0.0161,0.003)	(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	(0.12,0.63)*10^6	(3.51,14.12)	(0.14,4.36)	(0.4,4.6)	—	(4.14,15.52)	(2.89,6.58)	(0.26,0.49)	(15,58.95)	(10^{-6},0.0224)	(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	(2.03,7.63)*10^6	(3.18,10.01)	(4.53,12.98)	(2.66,8.9)	—	(4.05,12.97)	(2.48,6.09)	(0.26,0.49)	(15.24,51.58)	(10^{-6},0.0227)	(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	(0.04,0.13)*10^6	(8.46,21.21)	(0.34,4.41)	(0.78,5.4)	—	(6.4,18)	(2.04,4.66)	(0.26,0.5)	(12.32,60.51)	(10^{-6},0.0683)	(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	(0.48,1.28)*10^6	(6.79,17.41)	(1.39,3.19)	(1.23,3.75)	—	(4.02,14.71)	(2.28,6.15)	(0.27,0.5)	(12.14,65.74)	(10^{-6},0.0051)	(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	(0.006,0.074)*10^6	(8.97,20.15)	(0.4,6.95)	(2.19,8.47)	—	(5.82,18.47)	(1.97,4.54)	(0.27,0.5)	(16.81,75.45)	(10^{-6},0.0212)	(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	(0.77,2.97)*10^6	(0.55,6.43)	(0.07,4.78)	(0.52,4.07)	—	(5.85,17.55)	(2.6,6.53)	(0.26,0.48)	(14.55,72.11)	(10^{-6},0.001)	(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	(2.33,6.17)*10^6	(0.66,5.13)	(2.72,7.66)	(2.74,7.05)	—	(5.23,15.7)	(2.39,6.45)	(0.27,0.49)	(14.44,55.98)	(0.0086,0.0117)	(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	(0.07,0.61)*10^6	(1.01,5.81)	(2.14,7.73)	(1.9,6.66)	—	(5.4,17.49)	(2.42,6.13)	(0.26,0.49)	(12.62,64.5)	(10^{-6},0.0188)	(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	(0.02,0.06)*10^6	(4.26,19.29)	(0.16,2.83)	—	—	(3.69,13.69)	(1.93,4.01)	(0.27,0.5)	(14.8,70.65)	(10^{-6},0.0223)	(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	(0.08,1.52)*10^6	(6.66,23.14)	(10^{-6},6.64)	—	—	(4.5,14.61)	(2.03,3.86)	(0.27,0.5)	(12.39,67.52)	(10^{-6},0.012)	(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	(1.36,3.52)*10^6	(1.96,8.9)	(3.85,8.12)	(0.17,3.45)	—	(5.01,17.72)	(2.06,4.11)	(0.27,0.5)	(14.38,59.54)	(10^{-6},0.0075)	(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	(0.02,0.11)*10^6	(5.34,19.78)	(1.25,6.85)	(1.13,6.45)	—	(5.13,15.74)	(3.32,6.85)	(0.27,0.5)	(13.51,70.88)	(10^{-6},0.0329)	(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	(0.21,1.24)*10^6	(10^{-6},10.45)	(10^{-6},5.61)	(0.02,5.54)	—	(3.6,13.51)	(2.09,4.76)	(0.26,0.47)	(13.37,66.74)	(10^{-6},0.0293)	(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	(0.033,0.246)*10^6	(10^{-6},4.15)	(0.09,4.8)	(0.03,4.62)	—	(5.96,18.53)	(4.16,7.23)	(0.26,0.48)	(15.12,63.78)	(10^{-6},0.0095)	(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 EC.9. 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}. For information about $N(0)$, μ, and ν, see Table EC.10.

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.

Table EC.5 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 EC.4). [b] Order of intervention policies is always set as: $0 \to 3 \to 2 \to 1$.
[c] Obtained from information in Table EC.1. [d] Information presented in Table EC.3. To avoid collinearity, we do not consider the average rate of mobility of more than 10 miles from homes. [e] Information presented in Table EC.3.

Table EC.6 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 EC.7 Results of mixed-effect model 1

Variable[a]	Estimate	Std. Error	df	t value	P value	Code[b]
Intercept	$-1.616*10^{-2}$	$9.772*10^{-2}$	$4.892*10^{1}$	-1.653	0.10467	.
$policy_i:\ 0 \to 3$	$4.431*10^{-2}$	$1.652*10^{-2}$	$1.059*10^{2}$	2.682	0.00849	**
$policy_i:\ 0 \to 3 \to 2$	$5.251*10^{-2}$	$7.077*10^{-3}$	$9.856*10^{1}$	7.419	$4.2*10^{-11}$	***
$policy_i:\ 0 \to 3 \to 2 \to 1$	$4.107*10^{-2}$	$1.256*10^{-2}$	$1.297*10^{2}$	3.269	0.00138	**
$duration_i$	$5.242*10^{-4}$	$2.150*10^{-4}$	$1.065*10^{2}$	2.438	0.01641	*
$mobility_i^1$	$1.571*10^{-2}$	$9.072*10^{-2}$	$9.348*10^{1}$	0.173	0.86303	
$mobility_i^2$	$1.084*10^{-1}$	$1.694*10^{-1}$	$5.900*10^{1}$	0.640	0.52471	
median age	$3.267*10^{-3}$	$2.308*10^{-3}$	$4.486*10^{1}$	1.416	0.16374	.
race ratio	$-2.546*10^{-3}$	$4.050*10^{-2}$	$4.639*10^{1}$	-0.063	0.95004	
per capita income	$7.012*10^{-8}$	$1.286*10^{-6}$	$4.803*10^{1}$	0.055	0.95637	

Results are obtained by the "lmer" function in the R computing package.
[a] For notations, see Table EC.5. [b] Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.2.

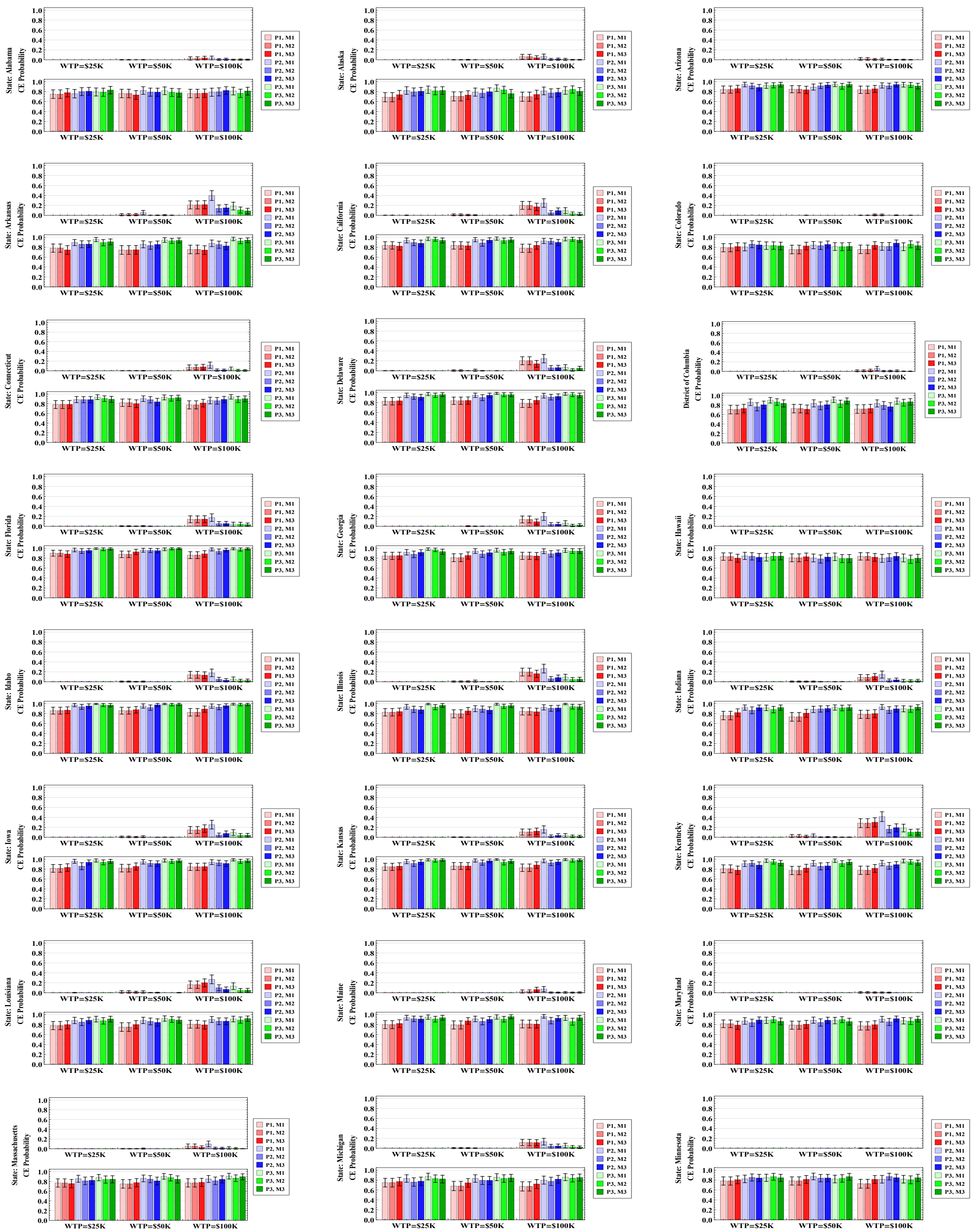


Figure EC.1 (Color online) Cost-effectiveness probability of potential intervention policies compared to the current policies in U.S. states

Notes. P1/2/3: potential intervention policies 1/2/3 (see Table EC.2). M1: mobility observed in each state. M2/3: mobility scenarios used for robustness check. For each state, for the upper (lower) plot, the CE probability is measured based on the total (direct) costs. Results are shown for WTP=$25,000, $50,000, and $100,000. Error bars represent 95% CIs.

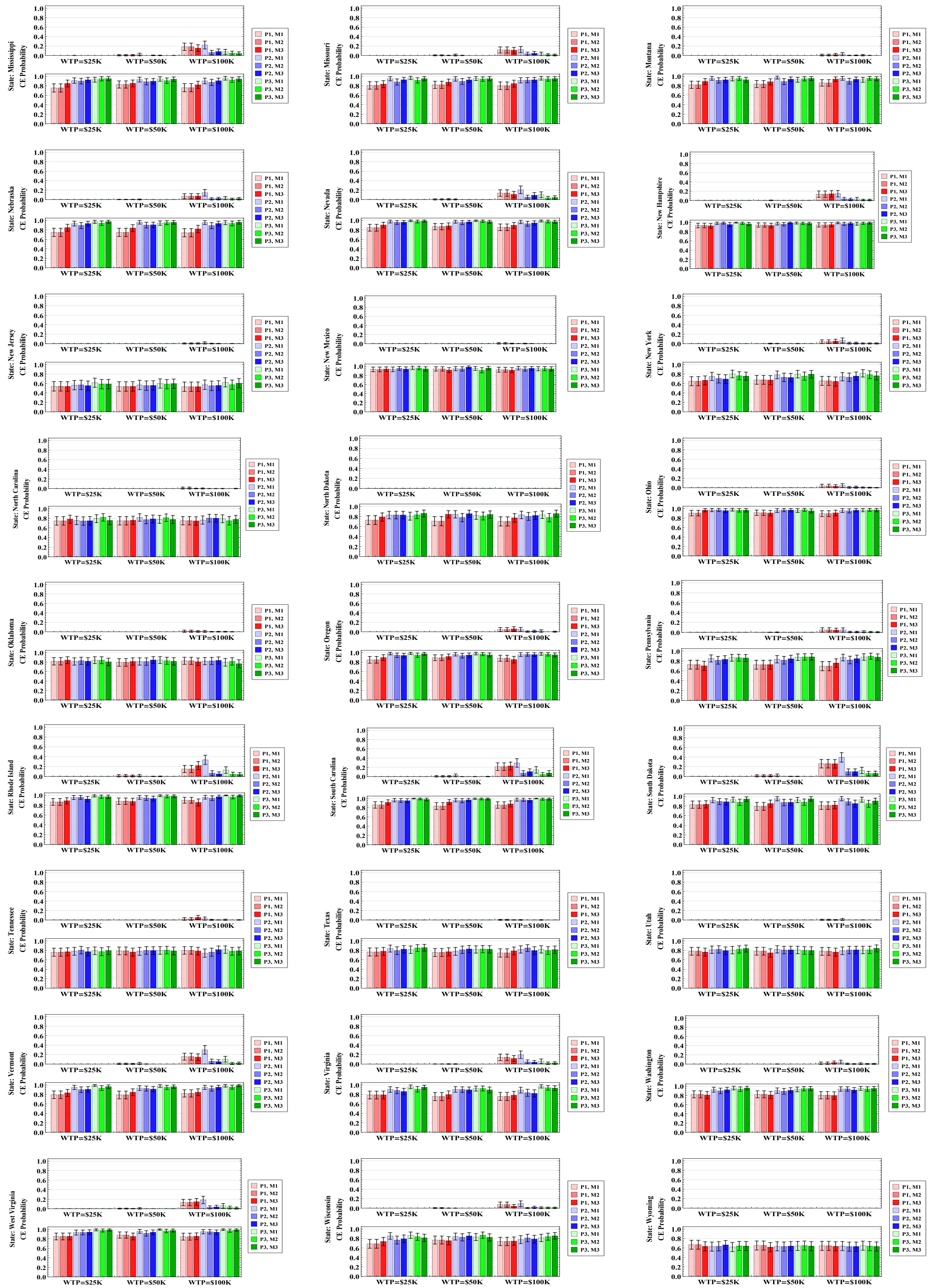


Figure EC.1 Continued.

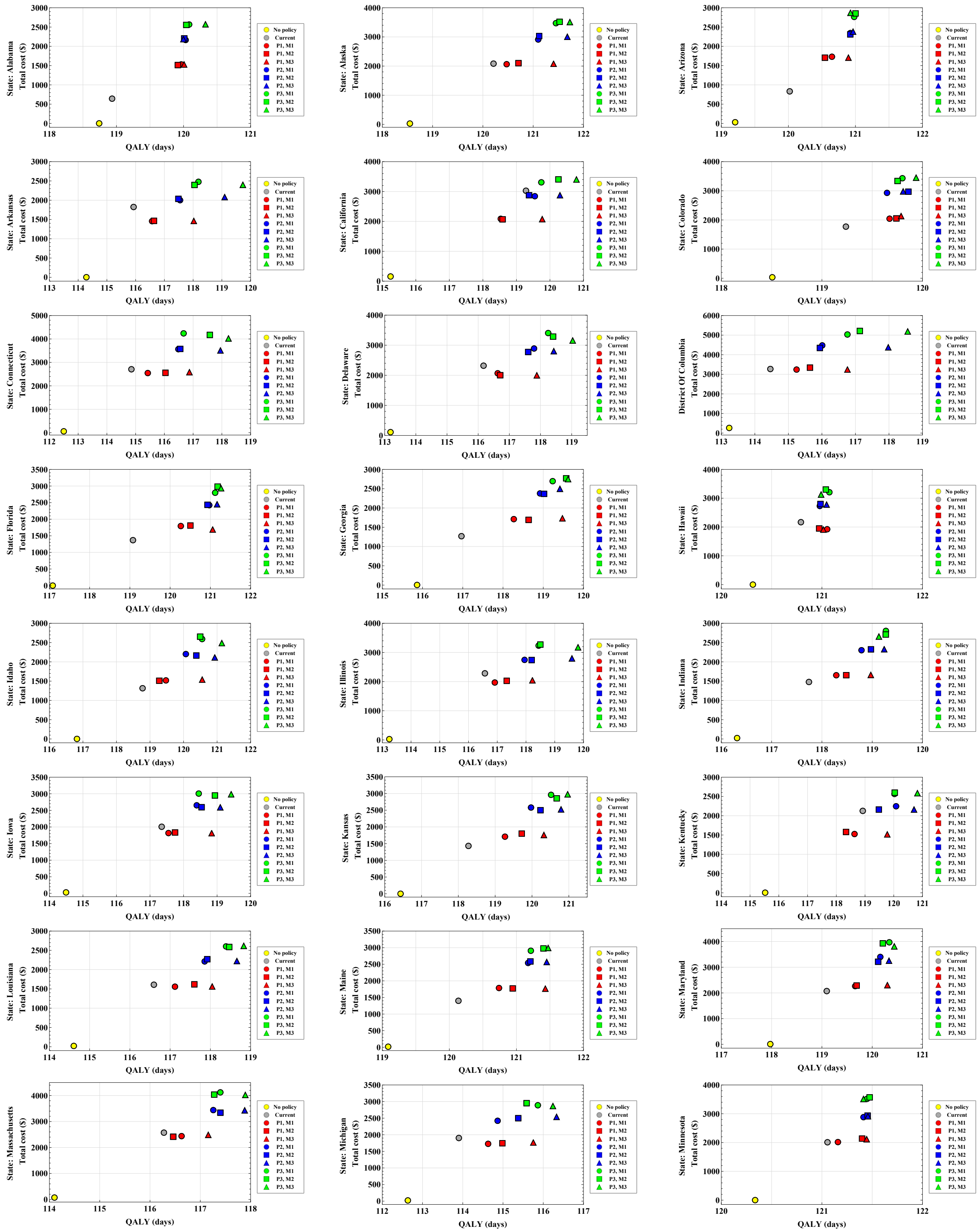


Figure EC.2 (Color online) Cost vs. QALY comparisons between intervention policies in U.S. states

Notes. x-/y-axis represents avg. per capita QALY accrued and avg. per capita total cost incurred, respectively. P1/2/3: potential intervention policies 1/2/3 (see Table EC.2). M1: mobility observed in each state ("No Policy" and "Current Policy" are evaluated under the observed mobility). M2/3: mobility scenarios used for robustness check. Complete results (including standard deviations) are provided in Table EC.8.

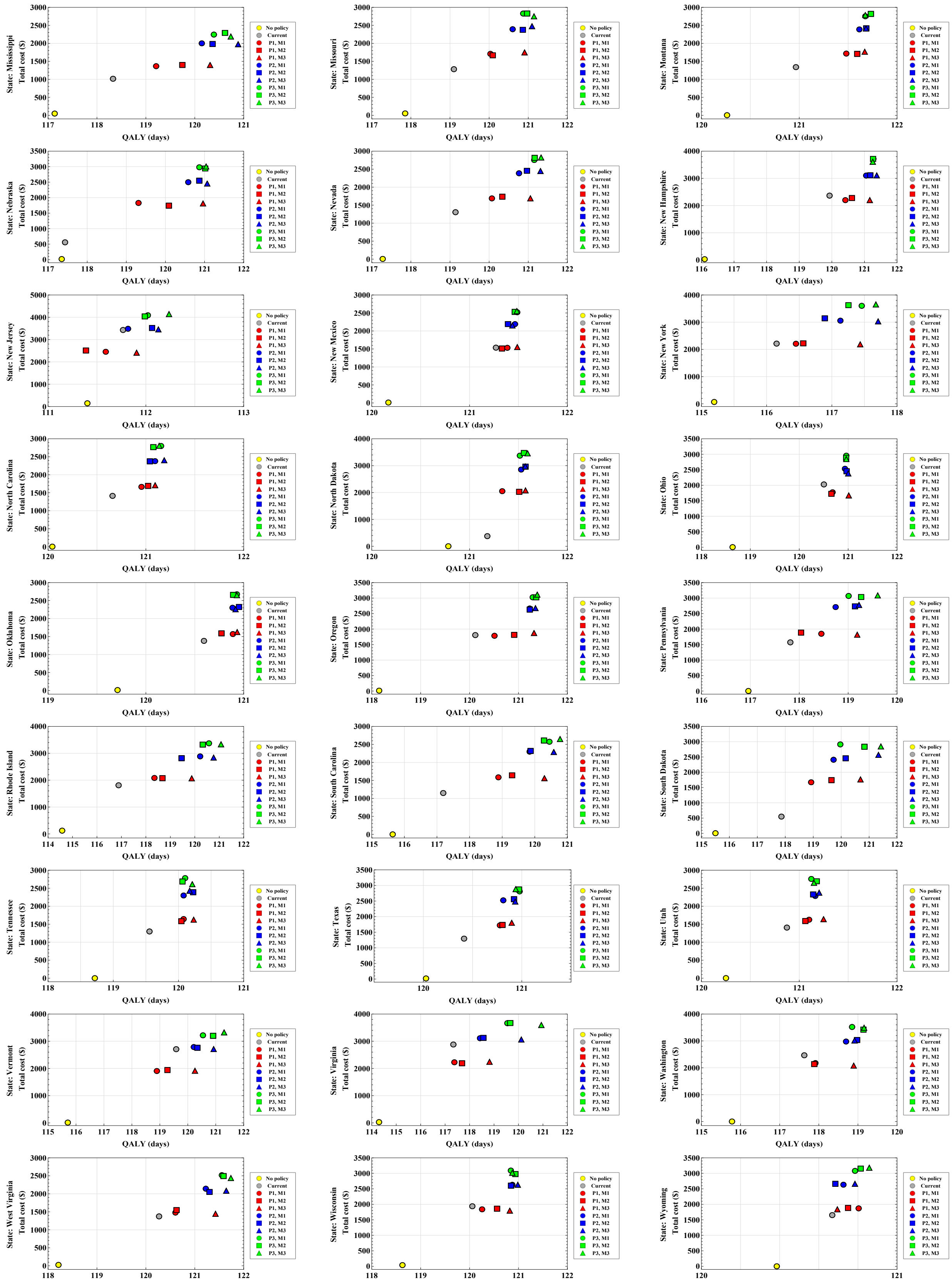
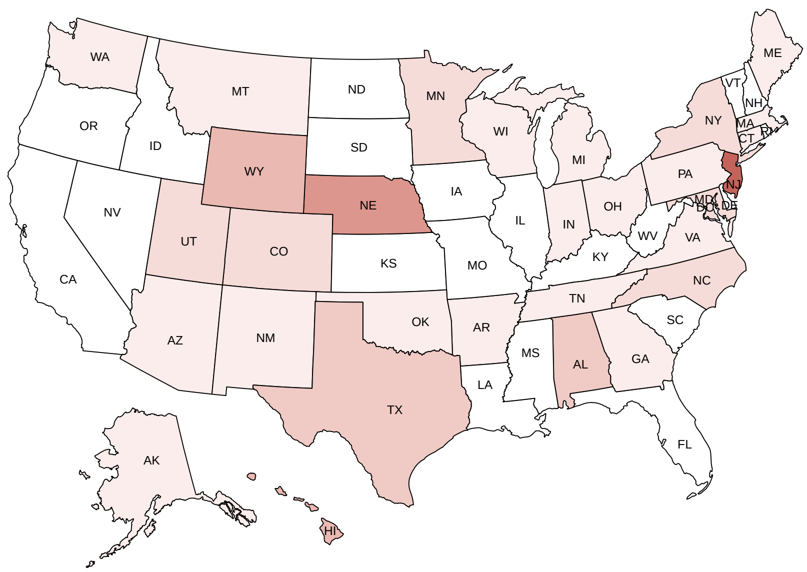


Figure EC.2 Continued.

Table EC.8 Complete results of cost vs. QALY comparisons (continued from Figure EC.2)

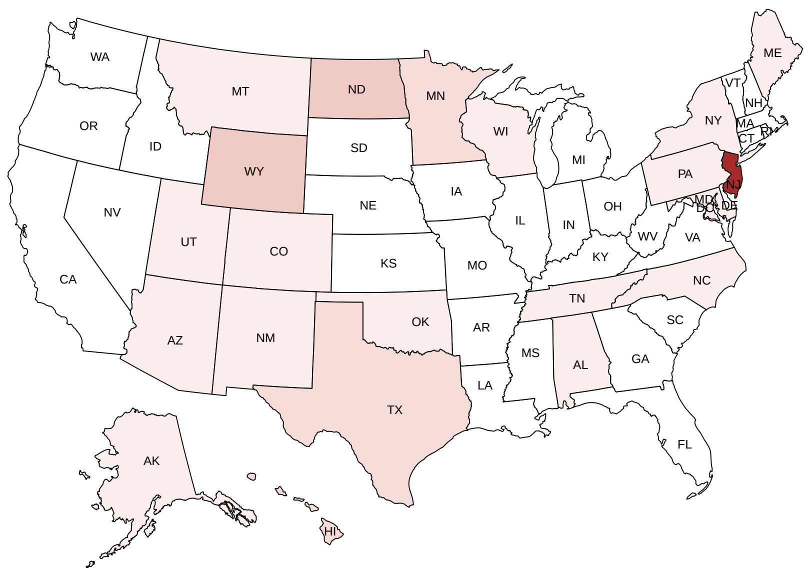
State	No policy	Current policy	Potential intervention policy 1			Potential intervention policy 2			Potential intervention policy 3		
			M1	M2	M3	M1	M2	M3	M1	M2	M3
Alabama	118.75 (1.61)	118.94 (1.51)	119.97 (0.91)	119.92 (0.89)	**120.01 (0.92)**	120.04 (0.79)	120.02 (0.87)	120 (0.87)	120.09 (0.85)	120.05 (0.84)	**120.33 (0.72)**
	0.97 (0.57)	642.12 (113.16)	1531.04 (266.88)	1513.4 (253.42)	1527.71 (267.03)	2164.07 (392.29)	2207.07 (419.61)	2184.2 (403.78)	2566.26 (540.88)	2555.93 (517.91)	2570.68 (517.04)
Alaska	119.24 (2.47)	120.59 (1.72)	120.82 (1.53)	**121 (1.35)**	**121.34 (0.83)**	121.26 (0.93)	121.24 (1.11)	**121.67 (0.37)**	121.5 (0.72)	**121.56 (0.57)**	**121.71 (0.29)**
	22.64 (31.47)	2113.98 (385.23)	2135.6 (377.24)	2087.61 (390.96)	2051.72 (359.79)	3053.41 (522.59)	2975.6 (617.35)	2998.99 (556.1)	3430.33 (722.97)	3622.14 (681.32)	3574.59 (691.63)
Arizona	119.25 (1.38)	120.02 (1.02)	120.63 (0.66)	120.56 (0.64)	**120.97 (0.41)**	121.01 (0.41)	120.95 (0.46)	120.93 (0.43)	120.91 (0.44)	**120.94 (0.41)**	**120.92 (0.41)**
	28.5 (21.06)	816.9 (166.77)	1713.97 (306.1)	1627.14 (300.19)	1691.29 (296.48)	2404.95 (401.32)	2341.46 (451.12)	2439.09 (442.75)	2835.64 (536.3)	2746.92 (562.34)	2714.22 (603.31)
Arkansas	114.29 (2.09)	115.93 (2.29)	116.58 (2.28)	**116.64 (2.74)**	**118.03 (2.33)**	117.55 (2.55)	117.49 (2.38)	**119.1 (1.81)**	118.19 (2.29)	118.05 (2.4)	**119.74 (1.54)**
	1.98 (5.5)	1824.07 (375.79)	1456.08 (265.93)	1465.11 (269.11)	1460.97 (269.72)	2000.41 (400.69)	2034.47 (408.87)	2080.1 (364.36)	2477.39 (488.79)	2395.31 (465.31)	2398.15 (499.86)
California	115.25 (2.39)	119.29 (1.55)	118.54 (2.17)	**118.59 (2.39)**	**119.77 (1.64)**	119.55 (2.08)	119.38 (2)	**120.3 (1.13)**	119.75 (1.59)	**120.26 (1.24)**	**120.8 (0.62)**
	156.13 (114.38)	3026.98 (620.52)	2087.1 (395.73)	2070.08 (341.55)	2075.15 (384.39)	2843.74 (480.93)	2877.83 (551.08)	2874.32 (498.83)	3307.71 (680.6)	3406.09 (702.91)	3402.35 (687.62)
Colorado	118.51 (1.36)	119.24 (0.99)	119.68 (0.81)	**119.75 (0.72)**	**119.79 (0.76)**	119.65 (0.78)	**119.86 (0.73)**	**119.81 (0.73)**	119.81 (0.72)	119.76 (0.83)	**119.94 (0.72)**
	32.4 (27.71)	1770.27 (374.03)	2043.22 (378.09)	2052.53 (337.19)	2132.35 (353.41)	2929.11 (515.44)	2969.11 (521.27)	2978.02 (534.95)	3430.57 (704.28)	3336.67 (722.06)	3449.59 (681.92)
Connecticut	112.2 (2.34)	114.43 (2.83)	115.05 (2.94)	**115.89 (2.91)**	**116.88 (2.59)**	117.04 (2.49)	116.76 (2.63)	**117.74 (2.25)**	117.51 (2.59)	117.04 (2.59)	**118.27 (1.82)**
	79.18 (88.22)	2669.61 (459.97)	2519.13 (448.58)	2444.48 (466.17)	2595.32 (427.43)	3534.54 (674.13)	3509 (617.14)	3583.77 (629.89)	4103.9 (808.37)	4193.18 (900.31)	4165.24 (835.84)
Delaware	113.19 (2.69)	116.18 (2.73)	116.63 (2.78)	**116.71 (2.39)**	**117.89 (1.8)**	117.8 (2.24)	117.61 (2.11)	**118.43 (1.58)**	118.25 (1.72)	**118.41 (1.57)**	**119.04 (1.42)**
	109.44 (80.03)	2319.27 (386.27)	2066.91 (365.83)	2002.43 (342.09)	1997.37 (366.04)	2890.35 (536.9)	2775.68 (526.25)	2801.44 (497.12)	3404 (690.6)	3286.47 (693.83)	3156.09 (650.25)
Dist. of Col.	113.6 (2.33)	114.73 (2.57)	115.44 (2.72)	**115.63 (2.94)**	**116.66 (2.78)**	115.78 (2.95)	**116.3 (2.78)**	**117.63 (2.5)**	116.92 (2.63)	116.79 (2.7)	**118.3 (1.7)**
	256.7 (114.67)	3278.23 (594.56)	3232.43 (575)	3244.06 (618.7)	3280.74 (553.34)	4554.63 (846.5)	4600.44 (811.25)	4572.06 (810.95)	5210.52 (960.49)	5235.68 (983.34)	5135.48 (1015.53)
Florida	116.55 (2.26)	118.81 (2.01)	120.07 (1.56)	**120.18 (1.56)**	**121.01 (0.67)**	120.86 (0.97)	120.85 (1)	**121.24 (0.45)**	121.19 (0.5)	121.18 (0.56)	121.17 (0.42)
	1.23 (2.7)	1329.44 (274.32)	1746.52 (306.16)	1770.52 (274.56)	1748.32 (299.17)	2422.44 (452.78)	2455.11 (444.51)	2457.66 (426.14)	2896.33 (578.14)	2937.45 (557.23)	2848.96 (602.69)
Georgia	116.03 (1.91)	117.2 (1.82)	118.58 (1.7)	**118.73 (1.77)**	**119.21 (1.36)**	118.92 (1.74)	**119.11 (1.31)**	**119.55 (0.82)**	119.4 (0.96)	**119.64 (1.03)**	**119.47 (0.99)**
	1.86 (5.06)	1270.6 (271.95)	1711.48 (304.64)	1664.9 (262.39)	1686.48 (327.06)	2382.27 (477.39)	2423.05 (431.75)	2453.72 (464.23)	2784.66 (584.91)	2815.02 (549.51)	2736.45 (568.77)
Hawaii	120.32 (0.7)	120.8 (0.47)	121.06 (0.37)	120.98 (0.36)	121.02 (0.37)	120.98 (0.35)	**120.99 (0.35)**	**121.05 (0.32)**	121.08 (0.32)	121.04 (0.33)	121 (0.37)
	0.06 (0.13)	2167.98 (372.14)	1923.12 (319.85)	1949.84 (339.75)	1909.86 (366.17)	2730.3 (518.47)	2799.25 (529.56)	2776.93 (512.17)	3207.34 (610.44)	3301.1 (687.63)	3126.7 (689.04)
Idaho	116.83 (1.56)	118.78 (1.76)	119.48 (1.77)	119.28 (1.81)	**120.56 (1.12)**	120.07 (1.43)	**120.39 (1.29)**	**120.94 (0.7)**	120.56 (1.09)	120.5 (1.17)	**121.15 (0.36)**
	1.31 (3.11)	1315.53 (284.83)	1518.7 (295.86)	1509.87 (268.86)	1538.36 (286.46)	2202.29 (374.84)	2163.67 (397.85)	2112.95 (373.27)	2592.12 (568.81)	2653.7 (540.79)	2486.11 (513.07)
Illinois	113.55 (2.09)	116.57 (2.56)	116.91 (2.68)	**117.59 (2.59)**	**118.79 (2.09)**	117.75 (2.62)	117.58 (2.52)	**119.48 (1.16)**	118.79 (2.06)	118.49 (1.86)	**119.84 (0.89)**
	16.95 (46.65)	2298.24 (412.63)	1969.62 (351.72)	1963.53 (360.05)	1945.15 (346.3)	2803.01 (488)	2834.1 (502.42)	2715.89 (530.96)	3265.21 (701.55)	3239.41 (628.42)	3158.64 (572.69)
Indiana	116.32 (2.19)	117.75 (1.95)	118.29 (1.83)	**118.49 (1.59)**	**118.98 (1.12)**	118.79 (1.3)	**118.98 (1.08)**	**119.24 (1.16)**	119.28 (1.22)	119.27 (1.02)	119.14 (1.14)
	23.3 (39.62)	1477.86 (273.47)	1652.52 (271.96)	1654.7 (297.19)	1659.78 (309.48)	2301.8 (435.76)	2324.98 (426.55)	2326.9 (402.46)	2803.32 (504.12)	2708.61 (565.8)	2655.61 (534.08)
Iowa	114.31 (2.47)	117.14 (2.24)	117.33 (2.29)	**117.53 (2.44)**	**118.85 (1.4)**	118.03 (2.48)	**118.56 (1.62)**	**119.26 (1.19)**	118.92 (1.64)	118.92 (1.31)	**119.2 (1.02)**
	26.82 (25.94)	1989.36 (349.35)	1815.32 (310.03)	1761.62 (319.07)	1784.28 (322.7)	2601.11 (526.83)	2579.24 (475.37)	2520.27 (456.85)	3014.23 (602.01)	3052.62 (565.58)	3028.94 (589.42)
Kansas	116.44 (2.07)	118.28 (2.04)	119.27 (1.95)	**119.73 (1.9)**	**120.33 (1.25)**	119.98 (1.55)	**120.24 (1.42)**	**120.79 (0.74)**	120.52 (1.07)	**120.68 (0.82)**	**120.97 (0.48)**
	0.83 (1.78)	1431.18 (277.45)	1708.5 (308.42)	1799.55 (314.49)	1757.61 (302.67)	2579.55 (456.29)	2500.73 (487.69)	2523.24 (449.15)	2959.06 (596.27)	2854.17 (563.37)	2974.87 (572.75)
Kentucky	115.53 (2.6)	118.93 (2.29)	118.64 (2.66)	118.34 (2.86)	**119.78 (1.9)**	120.09 (1.69)	119.49 (2.04)	**120.71 (0.91)**	120.03 (1.52)	**120.04 (1.57)**	**120.83 (0.69)**
	4.17 (11.55)	2126.2 (460.21)	1525.56 (293.2)	1579.62 (267.64)	1514.78 (284.64)	2245.89 (412.49)	2159.76 (417.27)	2159.97 (450.37)	2565.84 (502.41)	2598.94 (493.81)	2583.93 (549.17)
Louisiana	114.61 (2.37)	116.6 (2.4)	117.13 (2.39)	**117.61 (2.29)**	**118.05 (1.87)**	117.86 (2.16)	**117.93 (1.93)**	**118.66 (1.43)**	118.4 (1.8)	**118.47 (1.6)**	**118.83 (1.28)**
	20.12 (41.79)	1608.5 (292.16)	1558.01 (279.18)	1618.4 (283.53)	1561.29 (276.24)	2212.56 (433.46)	2269.3 (432.33)	2222.08 (415.62)	2602.22 (498.42)	2586.51 (552.14)	2615.49 (575.49)
Maine	119.09 (1.89)	120.14 (1.4)	120.75 (1.02)	**120.95 (0.82)**	**121.44 (0.33)**	121.18 (0.51)	**121.21 (0.55)**	**121.46 (0.26)**	121.22 (0.46)	**121.41 (0.3)**	**121.48 (0.25)**
	16.13 (16.19)	1399.34 (280.07)	1784.81 (307.56)	1772.32 (305.96)	1764.77 (314.1)	2539.74 (477.52)	2585.57 (473.71)	2567.39 (478.43)	2907.66 (678.93)	2977.35 (540.92)	2990.73 (637.23)
Maryland	118.16 (1.58)	119.22 (1.18)	119.77 (0.98)	**119.88 (1.23)**	**120.34 (0.77)**	120.26 (0.84)	120.21 (0.82)	**120.31 (0.76)**	120.3 (0.71)	120.12 (0.87)	120.3 (0.72)
	5.11 (17.27)	2140.06 (359.54)	2335.46 (364.45)	2373.38 (393.04)	2362.66 (395.39)	3194.02 (565.38)	3334.68 (615.55)	3368.03 (540.71)	3839.07 (764.91)	3952.53 (729.96)	3924.12 (813.6)
Massachusetts	114.11 (2.36)	116.28 (2.32)	116.63 (2.38)	116.47 (2.11)	**117.16 (1.98)**	117.26 (1.9)	**117.4 (1.87)**	**117.89 (1.74)**	117.4 (2)	117.28 (1.92)	**117.9 (1.48)**
	73 (134.63)	2571.26 (470.72)	2437.79 (414.98)	2414.36 (427.65)	2485.01 (462.77)	3439.35 (643.75)	3340.43 (577.44)	3429.04 (663.11)	4121.84 (879.88)	4035.34 (764.5)	4020.75 (787.58)
Michigan	112.64 (2.12)	113.91 (2.14)	114.64 (2.36)	**114.99 (2.17)**	**115.76 (2.11)**	114.87 (2.19)	**115.38 (2.24)**	**116.34 (1.79)**	115.87 (2.2)	115.59 (2.19)	**116.25 (1.83)**
	21.15 (36.57)	1902.15 (311.16)	1726.31 (308.89)	1744.68 (321.7)	1764.9 (321.61)	2420.3 (480.51)	2498.92 (472.37)	2537.39 (424.25)	2888.42 (557.35)	2951.21 (596.94)	2863.48 (562.45)
Minnesota	120.34 (1.03)	121.06 (0.57)	121.16 (0.51)	**121.4 (0.35)**	**121.45 (0.32)**	121.42 (0.31)	**121.46 (0.31)**	**121.46 (0.3)**	121.45 (0.29)	**121.48 (0.29)**	121.42 (0.28)
	0.87 (3.24)	2009.54 (336.83)	2016.26 (345.57)	2137.39 (374.95)	2115.16 (343.05)	2880.86 (558.31)	2934.02 (595.1)	2912.87 (551.1)	3517.79 (682.39)	3568.77 (686.66)	3510.37 (724.66)
Mississippi	117.14 (2.41)	118.33 (2.28)	119.21 (2.15)	**119.75 (1.4)**	**120.32 (1.17)**	120.15 (1.23)	**120.37 (1.13)**	**120.89 (0.72)**	120.4 (0.95)	**120.62 (0.86)**	**120.74 (0.7)**
	48.48 (53.86)	1015.35 (218.25)	1365.12 (232.35)	1399.06 (230.1)	1397.87 (247.01)	2000.26 (366.98)	1981.6 (314.15)	1974.96 (347.79)	2243.32 (418.04)	2289.53 (454.26)	2189.23 (470.18)
Missouri	117.86 (2.21)	119.1 (1.95)	120.04 (1.62)	**120.1 (1.3)**	**120.91 (0.71)**	120.61 (1.28)	**120.87 (0.76)**	**121.1 (0.45)**	120.88 (0.74)	**120.98 (0.69)**	**121.15 (0.44)**
	53.17 (33.04)	1281.44 (224.75)	1707.92 (253.17)	1667.34 (311.82)	1747.07 (317.75)	2392.32 (481.84)	2375.34 (446.97)	2475.21 (425.84)	2827.91 (580.68)	2828.45 (610.65)	2749.32 (578.22)
Montana	119.99 (1.63)	120.77 (1.15)	121.4 (0.58)	**121.57 (0.36)**	**121.69 (0.15)**	121.67 (0.18)	**121.69 (0.17)**	**121.7 (0.17)**	121.69 (0.17)	121.69 (0.17)	**121.72 (0.15)**
	3.34 (2.97)	1332.86 (282.64)	1721.21 (306.1)	1744.55 (297.87)	1753.89 (291.8)	2376.77 (458.12)	2435.53 (480.95)	2521.23 (464.88)	2938.63 (597.54)	2883.04 (588.81)	2979.03 (539.26)
Nebraska	117.35 (2.48)	117.44 (2.47)	119.32 (1.94)	**120.09 (1.25)**	**120.97 (0.53)**	120.59 (0.89)	**120.87 (0.69)**	**121.07 (0.34)**	120.87 (0.53)	**121.02 (0.4)**	**121.04 (0.39)**
	17.77 (19.34)	558.25 (104.58)	1828.55 (321.91)	1741.06 (287.46)	1810.89 (346.55)	2498.68 (485.92)	2546.91 (495.92)	2454.52 (412.45)	2980.09 (564.48)	2941.35 (602.35)	3004.46 (596.99)
Nevada	117.29 (2.31)	119.15 (2.04)	120.08 (1.68)	**120.34 (1.51)**	**121.06 (0.64)**	120.77 (1.04)	**120.97 (0.74)**	**121.32 (0.34)**	121.16 (0.48)	**121.17 (0.49)**	**121.33 (0.34)**
	5.42 (17.45)	1303.71 (253.88)	1687.75 (279.18)	1734.74 (286.66)	1688.67 (307.62)	2385.75 (460.49)	2454.51 (420.92)	2447.63 (468.6)	2754.25 (525.53)	2813.65 (570.66)	2823.91 (597.42)
New Hampshire	116.1 (2.31)	119.93 (1.46)	120.42 (1.23)	**120.62 (1.16)**	**121.17 (0.5)**	121.06 (0.67)	**121.18 (0.7)**	**121.38 (0.43)**	121.28 (0.46)	121.27 (0.45)	121.26 (0.42)
	28.9 (47.66)	2365.91 (416.32)	2200.11 (397.07)	2277.66 (369.56)	2200.47 (385.5)	3103.08 (570.01)	3112.92 (634.13)	3108.15 (529.18)	3716.78 (754.37)	3716.7 (780.87)	3608.6 (748.86)
New Jersey	111.41 (2)	111.77 (1.97)	111.59 (1.99)	111.39 (1.92)	**111.91 (2.12)**	111.82 (1.81)	**112.07 (2.47)**	**112.13 (2.16)**	112.03 (2.15)	111.99 (1.96)	**112.24 (2.14)**
	145.78 (80.57)	3430.45 (674.2)	2454 (451.92)	2510.82 (369.33)	2412.14 (448.21)	3484.85 (610.85)	3520.69 (592.23)	3454.98 (642.39)	4090.09 (772.61)	4039.28 (745.48)	4142.08 (770)
New Mexico	120.18 (0.99)	121.27 (0.32)	121.39 (0.28)	121.34 (0.29)	**121.49 (0.26)**	121.47 (0.23)	121.4 (0.27)	121.44 (0.24)	121.49 (0.22)	121.47 (0.25)	121.49 (0.22)
	11.75 (20.61)	1535.94 (276.35)	1531.76 (299.69)	1512.3 (260.27)	1551.26 (287.57)	2190.4 (406.95)	2191.69 (375.94)	2150.26 (397.31)	2520.12 (490.24)	2530.21 (514.13)	2551.85 (507.74)
New York	115.2 (2.56)	116.16 (2.47)	116.45 (2.48)	**116.57 (2.28)**	**117.44 (1.91)**	117.14 (1.89)	116.9 (2.1)	**117.71 (1.73)**	117.46 (1.8)	117.26 (2.11)	**117.68 (1.83)**
	67.46 (83.4)	2212.67 (411.59)	2207.72 (416.04)	2222.27 (413.82)	2184.38 (404.13)	3055.7 (577.94)	3142.29 (547.74)	3028.62 (570.85)	3601.1 (639.97)	3625.42 (692.96)	3650.63 (704.92)
North Carolina	120.09 (1.14)	120.68 (0.77)	120.98 (0.61)	120.96 (0.55)	**121.12 (0.52)**	121.07 (0.55)	121.1 (0.58)	121.03 (0.52)	121.05 (0.54)	**121.17 (0.44)**	**121.13 (0.5)**
	3.17 (7.23)	1482.28 (255.3)	1693.87 (284.65)	1715.32 (305.81)	1655.19 (288.62)	2426.49 (468.85)	2383.32 (456.36)	2398.18 (454.57)	2773.36 (546.45)	2784.11 (576.18)	2797.35 (538.95)
North Dakota	120.79 (0.88)	121.19 (0.57)	121.34 (0.46)	**121.51 (0.29)**	**121.58 (0.25)**	121.53 (0.26)	**121.58 (0.25)**	**121.57 (0.25)**	121.52 (0.26)	**121.56 (0.22)**	**121.6 (0.22)**
	2.68 (4.79)	378.15 (142.63)	2050.95 (378.62)	2026.71 (316.43)	2078.31 (384.63)	2854.62 (525.45)	2962.43 (503.48)	2972.47 (521.64)	3372.27 (676.36)	3472 (666.62)	3455.7 (714.57)
Ohio	118.64 (1.75)	120.51 (0.72)	120.69 (0.73)	120.66 (0.51)	**121.02 (0.36)**	120.94 (0.4)	**120.97 (0.44)**	**121.01 (0.36)**	120.97 (0.43)	120.96 (0.39)	120.97 (0.39)
	3.1 (8.65)	2027.35 (341.6)	1773.62 (308.49)	1724.03 (308.31)	1670.22 (292.04)	2532.89 (430.87)	2452.18 (425.18)	2379.57 (375.97)	2955.08 (555.46)	2885.62 (608.72)	2845.42 (570.09)
Oklahoma	119.72 (1.33)	120.6 (0.71)	120.89 (0.55)	120.78 (0.59)	**120.94 (0.54)**	120.89 (0.58)	**120.96 (0.51)**	**120.92 (0.52)**	120.94 (0.58)	120.9 (0.63)	120.94 (0.53)
	13.48 (10.81)	1380.3 (268.72)	1569.97 (275.92)	1589.46 (246.2)	1624.4 (271.51)	2300.99 (415.24)	2322.39 (408.51)	2257.02 (395.67)	2675.3 (545.63)	2658.49 (553.2)	2649.66 (552.01)
Oregon	118.16 (2.2)	120.12 (1.47)	120.51 (1.3)	**120.92 (0.93)**	**121.32 (0.43)**	121.23 (0.51)	**121.24 (0.52)**	**121.35 (0.33)**	121.3 (0.42)	**121.37 (0.35)**	**121.39 (0.31)**
	13.05 (28.6)	1805.9 (314.27)	1783.68 (307.5)	1813.39 (335.67)	1873.09 (311.23)	2664.46 (470.52)	2629.46 (471)	2674.36 (518.48)	3026.04 (662.19)	3023.96 (610.64)	3111.41 (599.43)
Pennsylvania	116.97 (1.93)	117.82 (1.82)	118.46 (1.74)	118.04 (1.96)	**119.19 (1.3)**	118.75 (1.48)	**119.15 (1.36)**	**119.23 (1.41)**	119.01 (1.4)	**119.27 (1.34)**	**119.61 (1.1)**
	2.49 (12.86)	1572.12 (292.85)	1848.76 (322.21)	1886.22 (341.86)	1816.62 (294.88)	2709.94 (468.82)	2733.14 (563.82)	2778.72 (486.55)	3068.78 (614.84)	3034.21 (583.73)	3084.09 (644.56)
Rhode Island	114.58 (2.1)	116.89 (2.57)	118.35 (2.51)	**118.68 (2.32)**	**119.88 (2.05)**	120.22 (1.68)	119.46 (2.24)	**120.78 (1.07)**	120.58 (1.45)	120.33 (1.64)	**121.08 (0.57)**
	121.76 (103.34)	1809.86 (326.18)	2081.93 (357.74)	2073.93 (376.36)	2066.12 (385.9)	2885.03 (545.87)	2817.26 (530.26)	2838.03 (569.73)	3371.33 (699.32)	3323.51 (625.29)	3333.36 (649.51)
South Carolina	115.65 (2.35)	117.2 (2.22)	118.89 (1.95)	**119.31 (1.57)**	**120.3 (1.17)**	119.85 (1.39)	**119.88 (1.44)**	**120.59 (0.59)**	120.45 (0.72)	120.29 (1.01)	**120.78 (0.47)**
	0.51 (1.11)	1148.58 (230.33)	1584.72 (301.06)	1640.39 (301.91)	1560.51 (280.77)	2298.39 (409.37)	2318.06 (368.22)	2288.76 (413.57)	2573.88 (493.53)	2608.14 (531.17)	2648.62 (583.17)
South Dakota	115.59 (2.61)	118.04 (2.71)	119.11 (2.44)	**119.83 (2.09)**	**120.73 (1.56)**	119.65 (2.13)	**120.38 (1.74)**	**121.23 (0.89)**	120.02 (1.96)	**121.02 (1.12)**	**121.47 (0.54)**
	7.28 (18.93)	539.56 (200.59)	1761.94 (314.24)	1719.7 (341.55)	1728.44 (287.87)	2459.48 (399.1)	2470.04 (480.94)	2536.17 (460.06)	2781.55 (580.77)	2879.31 (539.06)	2873.7 (542.52)
Tennessee	118.72 (1.65)	119.56 (1.24)	120.08 (1)	120.05 (0.95)	**120.24 (0.8)**	120.08 (0.9)	**120.23 (0.82)**	**120.18 (0.82)**	120.11 (0.88)	120.07 (0.82)	**120.22 (0.79)**
	0.17 (0.5)	1298.24 (297.62)	1642.39 (322.81)	1582.73 (300.94)	1624.5 (295.32)	2297.99 (404.04)	2388.38 (439.2)	2429.4 (407.06)	2780.98 (595.19)	2686.3 (547.79)	2610.48 (556.81)
Texas	120.03 (1)	120.42 (0.75)	120.78 (0.56)	**120.81 (0.56)**	**120.9 (0.41)**	120.82 (0.46)	**120.93 (0.4)**	**120.94 (0.42)**	120.98 (0.34)	120.98 (0.43)	120.94 (0.45)
	19.1 (10.61)	1294.93 (256.75)	1721.84 (291.38)	1733.51 (276.23)	1801.87 (318.6)	2522.98 (467.9)	2559.89 (445)	2480.64 (446.81)	2808.81 (606.14)	2871.32 (623.57)	2881.71 (605.2)
Utah	120.26 (1.05)	120.88 (0.63)	121.11 (0.5)	121.07 (0.6)	**121.25 (0.44)**	121.17 (0.43)	121.15 (0.51)	**121.21 (0.45)**	121.13 (0.43)	**121.18 (0.42)**	**121.16 (0.45)**
	2.02 (6.81)	1405.99 (278.37)	1624.76 (303.59)	1587.55 (302.05)	1639.27 (331.4)	2284.02 (427.26)	2326.85 (416.7)	2374.81 (390.78)	2757.37 (587.57)	2692.9 (510.46)	2649.2 (525.18)
Vermont	115.7 (2.83)	119.48 (2.22)	118.87 (2.71)	118.84 (2.5)	**120.43 (1.41)**	119.95 (1.92)	119.93 (1.97)	**121.06 (0.65)**	120.33 (1.67)	**120.55 (1.12)**	**121.26 (0.42)**
	21.97 (46.67)	2774.16 (546.01)	1965.6 (354.97)	1954.67 (358.74)	1921.73 (340.1)	2731.09 (431.78)	2679.15 (482.09)	2686.82 (505.27)	3161.96 (603.65)	3123.15 (632.63)	3165.17 (639.92)
Virginia	114.52 (1.99)	117.3 (2.55)	117.29 (2.65)	**117.49 (2.88)**	**119.26 (2.53)**	119.04 (2.72)	118.3 (2.71)	**120.32 (1.68)**	119.19 (2.42)	**119.9 (1.94)**	**120.44 (1.41)**
	32.96 (31.81)	2859.89 (561.68)	2136.05 (381.38)	2140.26 (336.57)	2137.56 (378.18)	3145.89 (600.77)	3110.44 (587.13)	3001.36 (589.23)	3595.81 (739.83)	3665.83 (689.45)	3579.7 (720.33)
Washington	115.48 (2.09)	117.55 (1.62)	117.88 (1.67)	117.56 (1.89)	**118.94 (1.07)**	118.54 (1.31)	**118.79 (1.15)**	**119.2 (0.84)**	119.01 (1.05)	118.97 (1.09)	118.87 (1.25)
	3.38 (8.85)	2357.39 (426.48)	2061.98 (361.41)	2005.44 (379.59)	2105.29 (394.18)	3034.39 (510.18)	2944.65 (521.96)	2992.76 (525.93)	3383.81 (690.45)	3402.66 (656.1)	3471.4 (655.89)
West Virginia	118.22 (2.01)	120.28 (1.58)	120.61 (1.44)	**120.63 (1.39)**	**121.43 (0.79)**	121.23 (0.89)	**121.31 (0.78)**	**121.65 (0.33)**	121.56 (0.52)	**121.59 (0.35)**	**121.74 (0.14)**
	25.16 (29.45)	1373.13 (269.56)	1478.57 (254.64)	1548.61 (269.14)	1444.45 (281.29)	2142.5 (424.47)	2051.8 (398.95)	2085.38 (370.38)	2517.96 (516.6)	2493.79 (509.7)	2437.54 (474.25)
Wisconsin	119.37 (2.22)	120.49 (1.22)	120.66 (1.14)	120.48 (1.06)	**120.84 (0.54)**	120.82 (0.73)	**120.83 (0.69)**	**120.97 (0.54)**	120.88 (0.54)	**120.95 (0.5)**	**121.01 (0.48)**
	28.22 (35.63)	2022.32 (353.97)	1905.51 (358.03)	1851.43 (312.88)	1846.28 (327.72)	2564.57 (473.86)	2635.34 (439.29)	2716.67 (444.42)	2991.43 (580.97)	3001.06 (616.29)	3092.43 (581.88)
Wyoming	120.06 (0.92)	120.42 (0.73)	120.6 (0.65)	**120.73 (0.68)**	**120.75 (0.67)**	120.76 (0.65)	120.72 (0.62)	120.73 (0.73)	120.77 (0.68)	120.77 (0.65)	120.68 (0.67)
	0.33 (1.48)	1640.34 (297.91)	1853.01 (325.67)	1842.62 (342.15)	1892.13 (350.6)	2604.43 (524.52)	2783.05 (486.7)	2639.63 (437.13)	3060.81 (676.26)	3163.46 (628.95)	3037.45 (575.26)

For each state, the first (second) row indicates avg. QALY (cost) obtained under various policies. Numbers represent the average (standard deviation) of QALY and cost obtained from simultions for each policy. P1/2/3: potential intervention policies 1/2/3 (see Table EC.2). M1: mobility observed in each state ("No Policy" and "Current Policy" are evaluated under the observed mobility). M2/3: mobility scenarios used for robustness check. Under any potential policy, when mobility rates are reduced in each state (scenarios M2/3 vs. M1), numbers in bold show improvements in avg. QALYs made by that policy.



Sorted results ($/day): SD: 217.87, FL: 588.04, NH: 609.92, KY: 624.84, WV: 655.37, ID: 671.62, IA: 692.96, NV: 697.88, CA: 710.94, VT: 728.05, RI: 731.44, DE: 740.27, SC: 740.50, IL: 755.34, KS: 775.77, LA: 798.16, MS: 810.42, OR: 912.03, ND: 942.19, MO: 986.21, AZ: 1,013.33, VA: 1,016.55, IN: 1,018.04, OH: 1,084.64, GA: 1,089.25, AR: 1,109.72, WA: 1,135.75, MA: 1,148.09, CT: 1,161.70, ME: 1,320.51, NM: 1,386.43, MI: 1,484.38, AK: 1,543.28, OK: 1,547.26, TN: 1,548.43, MT: 1,712.72, WI: 1,783.86, PA: 1,829.12, MD: 2,012.34, NY: 2,242.21, UT: 2,254.26, CO: 2,375.47, NC: 2,495.78, DC: 2,660.36, MN: 2,793.14, TX: 3,303.22, AL: 3,324.81, WY: 4,530.21, HI: 4,539.38, NE: 6,346.42, NJ: 9,009.26.

(a) Comparison: current policy vs. no intervention.

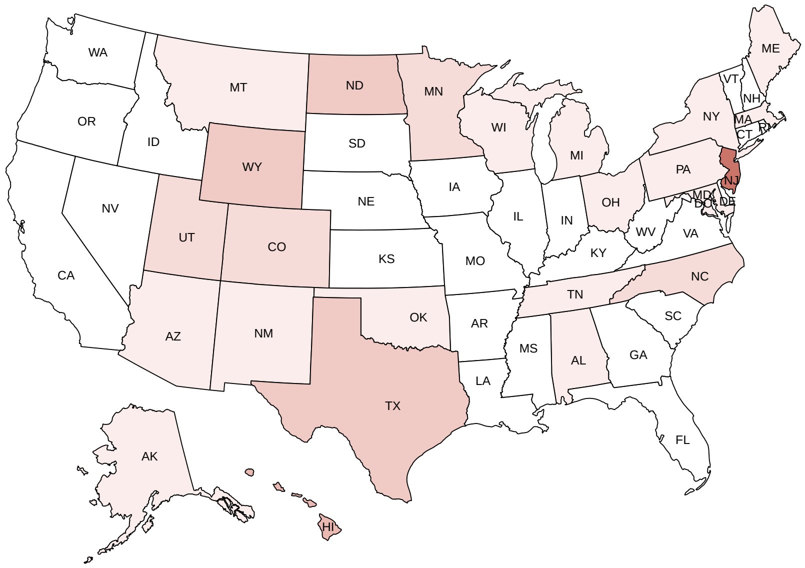


Sorted results ($/day): SC: 488.63, KY: 489.35, FL: 495.72, SD: 498.91, NH: 502.97, RI: 519.61, DE: 569.13, ID: 571.99, IL: 580.73, CA: 587.58, IA: 592.47, KS: 602.37, NV: 603.01, WV: 607.81, LA: 611.69, VT: 614.52, MS: 634.76, AR: 636.22, GA: 670.66, OR: 750.98, VA: 759.25, MO: 759.40, IN: 826.14, MI: 854.78, CT: 856.31, WA: 857.97, OH: 866.34, NE: 922.95, MA: 935.85, ME: 1,070.35, TN: 1,206.45, AZ: 1,219.39, MT: 1,223.46, PA: 1,237.60, NM: 1,250.00, AL: 1,250.13, OK: 1,320.16, AK: 1,334.81, MD: 1,446.08, WI: 1,457.71, DC: 1,609.62, NY:1,707.14, CO: 1,724.65, NC: 1,899.23, UT: 1,909.99, TX: 2,269.21, MN: 2,449.38, HI: 2,603.62, WY: 3,411.99, ND: 3,716.69, NJ: 12,284.28.

(b) Comparison: policy 1 vs. no intervention.

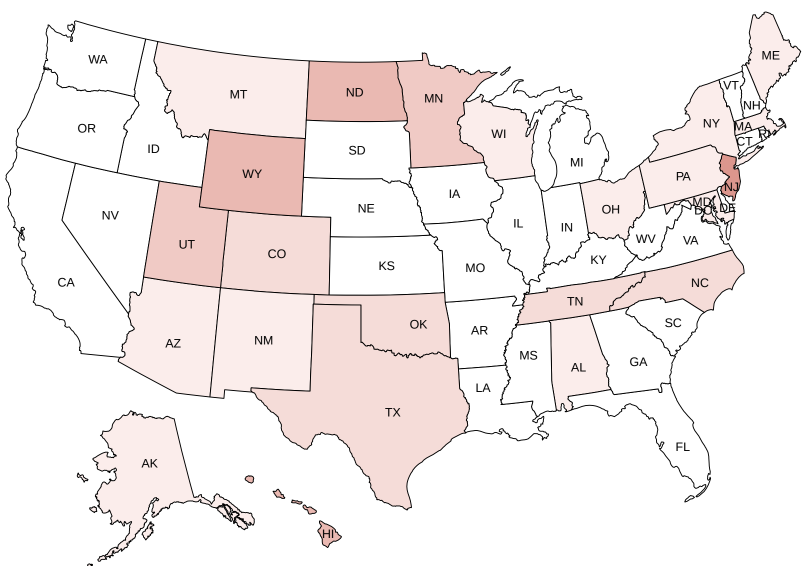
Figure EC.3 (Color online) U.S. map for comparison of policy interventions

Notes. Measure: increase in the average total cost ($) per one day increase in the average QALY per person.
For description of policies 1–3, see Table EC.2. All comparisons are made under the observed mobility in each state (mobility scenario 1).



Sorted results ($/day): RI: 489.82, KY: 492.12, SC: 547.16, FL: 561.43, DE: 603.71, SD: 604.91, AR: 613.14, NH: 620.38, CA: 624.6, VT: 637.45, MS: 648.88, IL: 664.34, LA: 674.23, ID: 677.82, NV: 683.3, VA: 688.44, IA: 692.59, WV: 702.96, CT: 713.96, KS: 727.92, NE: 767.19, GA: 825.04, MO: 851.63, OR: 861.58, IN: 921.06, WA: 988.76, MA: 1,066.2, MI: 1,075.59, OH: 1,101.42, ME: 1,209.55, AZ: 1,349.9, MT: 1,414.45, AK: 1,501.89, PA: 1,517.93, MD: 1,524.46, NY: 1,544.08, AL: 1,677.48, NM: 1,683.52, TN: 1,687.97, WI: 1,750.57, OK: 1,946, DC: 1,969.12, NC: 2,488.75, UT: 2,499.15, CO: 2,540.01, MN: 2,673.9, TX: 3,192.22, WY: 3,718.79, ND: 3,831.01, HI: 4,103.83, NJ: 8,036.52.

(c) Comparison: policy 2 vs. no intervention.



Sorted results ($/day): SC: 535.37, RI: 541.42, KY: 569.17, IL: 620.06, FL: 623.98, SD: 626.88, AR: 635, IA: 648.94, DE: 651.19, MS: 674.38, VT: 678.00, LA: 682.34, ID: 694.24, CA: 700.99, NV: 709.89, NH: 712.59, KS: 723.81, WV: 746.23, CT: 757.3, VA: 763.4, GA: 826.03, NE: 842.21, MI: 887.65, MO: 919.78, IN: 939.69, WA: 955.83, OR: 959.89, MA: 1,227.81, OH: 1,269.93, ME: 1,359.36, DC: 1,488.81, PA: 1,496.39, AK: 1,503.45, NY: 1,561.89, AZ: 1,682.43, MT: 1,734.02, MD: 1,795.91, NM: 1,904.86, AL: 1,912.39, WI: 1,967.9, TN: 2,008.34, OK: 2,182.23, CO: 2,627.58, NC: 2,901.27, TX: 2,936.19, UT: 3,157.81, MN: 3,161.63, HI: 4,216.72, WY: 4,336.09, ND: 4,605.87, NJ: 6,377.84.

(d) Comparison: policy 3 vs. no intervention.

Figure EC.3 **Continued.**

EC.2. Details of the SEIRS Model

Figure EC.4 shows the complete SEIRS compartmental model. We note that: (1) Following our discussion in the main body, recall that we consider piecewise oridnary differential equations (ODEs) to account for different transmission rates in each time frame. Therefore, the transmission rate depends on time t. It has been reported that implementing intervention policies could result in reductions in hospitalization/ mortality growth rates Lyu and Wehby (2020b). Although this may imply that hospitaliation/death rates also depend on time, such reductions were actually observed as a result of the reduction in transmission rate (i.e., in modelling the dynamics of the disease, transmission rate has an *upstream* impact). Therefore, we do not consider other rates in the SEIRS model to be dependent on time t. (2) Being exposed to the disease can be the beginning of the presymptomatic period WHO (2020). Therefore, we do not differentiate exposed and infected presymptomatic conditions. (3) All rates are between 0 and 1. Also, the sum of all rates emanating from a compartment must be less than or equal to 1. The only exception is for hospitalizations; i.e., $\sum_{i=1}^{3}\lambda_i=1$, which indicates that any hospitalization must be in one of three forms (combinations of common or ICU beds and using or not using ventilators). (4) A ventilator is only used with an ICU bed (not a common bed). This is consistent with the medical literature Gracey (1995), Wunsch et al. (2013).

Following notations introduced in **Table EC.9**, we solve the SEIRS model via the following ODEs:

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

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

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

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

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

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

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

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

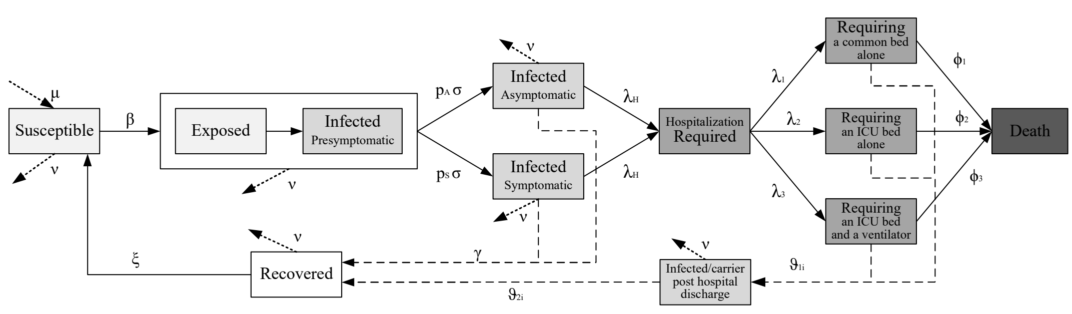


Figure EC.4 The SEIRS compartmental model

Notes. See Table EC.9 for notations. 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 EC.9 Summary of notations for ordinary differential equations

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: S, E, I_A, I_S, I_{HRi} and I_{PDi} for $i \in \{1,2,3\}$, R and D.

EC.3. Model Validation

To validate our model, we compare our predictions of number of infections, hospitalizations, and deaths with those observed in the data (see **Figure EC.5**). 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 EC.4**. From our results in **Figure EC.5**, we have observed that: (1) in the majority of cases, the numbers observed from the data are within the corresponding CIs from our predictions, and in most cases, the average of our predictions would mimic that of the data. (2) Our separate predictions for infections, hospitalizations, and deaths may not always have the exact same pattern as that observed in the data (see, e.g., District of Columbia in **Figure EC.5**). This could occur due to two reasons that are not mutually exclusive: (a) In our MCMC simulation, we consider 3 log-likelihood functions based on Poisson processes, one for each case of infections, hospitalizations, and deaths. (b) There is typically a time lag on the number of infections to emerge as hospitalized cases or the number of hospitalized cases to emerge as deaths (see, e.g., Lyu and Wehby (2020b)). Therefore, the number of patients in these three compartments do not always have a similar pattern over time. (3) In a few instances, there exist outliers for the number of infections obtained from the data. This is mainly because we use the measure discussed under Remark 1 in the main body, through which we project the number of observed cases to the whole population. Overall, our various tests give us confidence about the validity of our model and indicate that our predictions are fairly reliable.

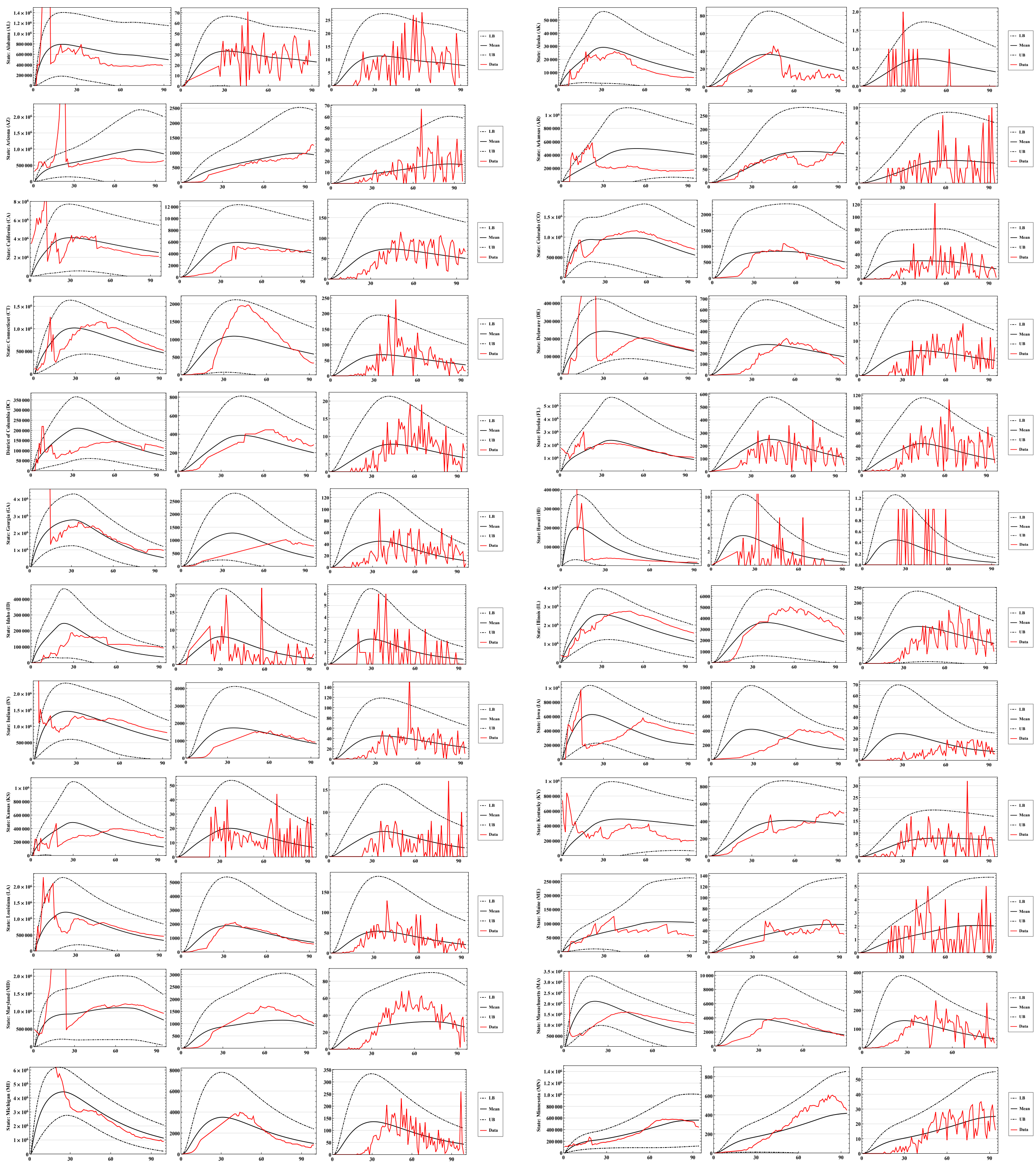


Figure EC.5 (Color online) SEIRS model validation: comparison of our predictions with the data

Notes. Each row represents the results for two states. For each state, columns 1/2/3 (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 EC.1, column "Data"). LB/UB: Lower/upper bounds represent 95% CIs for each outcome. Both lower/upper bounds are shown by dot-dashed lines. Not visible lower bounds imply negative values (replaced by 0).

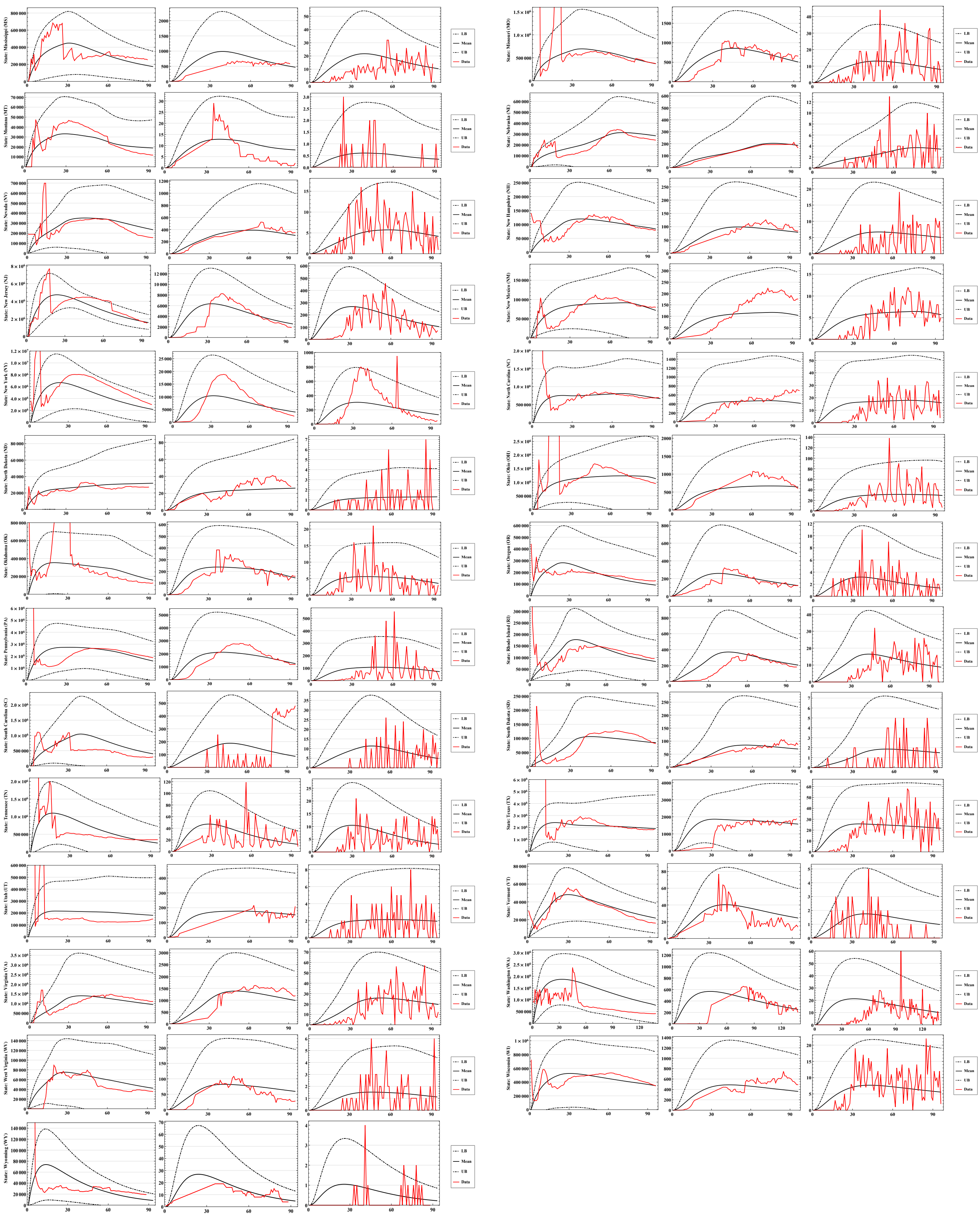


Figure EC.5 Continued.

EC.4. Parameter Estimations (related to QALY and Cost)

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

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

Regarding our notion in Equation (EC.2), the following points need to be taken into account: (1) Since we measure QALY per single day in our study, we divide the values in Equation (EC.2) by 365 to account for the daily counterparts. (2) 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 values. For example, for $i = 5$ (i.e., infected and hospitalized in a common bed), we select q_5 from the range [0.5,0.7]. (3) We set up these values such that the qol scores for different health states 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. Also, for cases that are still carriers of the disease post hospital discharge, we assume that patients who had been hospitalized (with an ICU bed and a ventilator) will have more improvement in their qol scores once discharged than patients who had been hospitalized (with just an ICU bed or a common bed). (4) The average qol score of 0.6 for infected hospitalized patients (with a common bed) is very close to that reported in the medical literature (Liu et al. 2020). Nevertheless, we will conduct an extensive simulation analysis where we allow variations for these qol scores based on their corresponding ranges.

Direct Cost. We take a back-of-the-envelope calculation to estimate the healthcare utilization costs, including the operating costs of a common bed, an ICU bed, and an ICU bed with a ventilator per day. (1) We first obtain the costs of using an ICU bed or an ICU bed with a ventilator per day Dasta et al. (2005). Since the values are reported for the year 2005, we then use the U.S. healthcare inflation rate YCHARTS (2020) to prorate the corresponding values for 2020. (2) To account for the operating cost of a common non-ICU bed, we note that the average ratio of cost of an ICU bed to that of a non-ICU bed is reported to be 5.85 Norris et al. (1995). (3) The state where resources are used/costs are incurred is not identified Dasta et al. (2005). To account for this, we use information on hospital adjusted expenses per inpatient day for each state KFF (2018b). Of note, the state of Washington is reported to have the highest inpatient expenses per day. Therefore, we consider the original costs that we have obtained under items 1–2 for this state, while we adjust costs for other states based on the ratio of inpatient expenses in those states compared to that in the state of Washington KFF (2018b). **Table EC.10** (the last 3 columns) shows the results of these estimations. In our simulation, we will consider a range for each of these costs by allowing a $\pm 10\%$ variation based on these reported values.

Indirect Cost. It should be noted that the indirect cost that we consider in the main body (Equation 2) is the result of the following calculations. For each state in each day, we have:

$$\begin{aligned} \text{Avg. lost income per person } &= \frac{\text{Total population} * \text{Employment rate} * \text{Income per employed person} * \text{Ratio lost income}}{\text{Total population}} \\ &= \text{Employment rate} * \text{Income per employed person} * \text{Ratio lost income} \\ &= \frac{\text{Number employment}}{\text{Total population}} * \text{Per capita income } * \frac{\text{Total population}}{\text{Number employment}} * \text{Ratio lost income} \\ &= \text{Per capita income} * \text{Ratio lost income.} \end{aligned}$$

Furthermore, **Table EC.10** shows the per capita income for each state. It is reported that job/income losses as a result of COVID-19 has less impacted people with higher socio-economic status New York Times (2020b). Therefore, we do not target top percentiles of income. Also, in our simulation, we will consider a range for the average per capita income by allowing a ±10% variation based on the reported values. Regarding the ratio of lost income, a survey was conducted in the U.S. showing that 5%-34% of people surveyed have lost between less than 10% to all of their income (Statista 2020). Applying a uniform distribution, we measure the mean and standard deviation of the ratio of lost income as 40.33% and 2.36%, respectively (i.e., on average 40% of people have lost all of their income). That said, this ratio is a function of number and intensity of intervention policies. However, there are no data reporting on this specific information. To accomodate this, we adopt this notion that, when all three intervention policies are undertaken, the ratio of lost income is in the range [0.3,0.5]. Whereas, when two policies are implemented (i.e., when stay-at-home orders and non-essential business closures are lifted), this range is lowered to [0.05,0.2]. Although this is a reasonable assumption (e.g, stay-at-home orders and non-essential business closures are much more strict than large-gathering ban), we acknowledge that the aforementioned ranges are only rough estimations. Nevertheless, considering these ranges in our simulation will allow us to account for potential variations in these measures.

EC.5. Comparison of Intervention Policies

Simulation and Setting. We compare the performance of current policies in each state against a no-intervention benchmark and the potential intervention policies. We make this comparison based on the QALY accrued and the total costs incurred per person throughout the time horizon of 01-March through 30-June (i.e., 122 days).[2] Furthermore, to account for variations in the SEIRS model, QALY, and cost parameters, we iterate our calculations of the QALY and the cost obtained from each policy 10,000 times for each state. In each iteration, a parameter takes a random value from its corresponding range.

Disease transmission rates. We select a random baseline transmission rate β_0 from our estimations in **Table EC.4**. Then, based on the model discussed in §3.2 (in the main body), we predict reductions in transmission rates for various time frames.[3] Of note, to simulate the no-intervention benchmark, we only use β_0 as our transmission rate.

Cost-effectiveness (CE) probability. Recall that a potential policy is said to be more cost-effective than the current policy if ICER≤WTP (see our discussion in the main body, §2.5). Since we run 10,000 iterations to measure QALY and cost values under each policy, there will be $10^4 \times 10^4 = 10^8$ comparisons of ICER with WTP. To this end, the 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. Indeed, the higher this probability, the higher the cost-effectiveness of the potential policy compared to the current policy.

Mobility rates. In our baseline comparison of policies, we utilize the current mobility rates observed for each state (referred to as the mobility scenario M1, hereafter).[4] In our robustness checks, we consider two other scenarios: **(M2)** The rates of moving within 1 mile, between 1 and 10 miles, and more than 10 miles from home are 0.5, 0.3, and 0.2 respectively. **(M3)** The rates of moving within 1 mile, between 1 and 10 miles, and more than 10 miles from home are 0.5, 0.5, and 0.0 respectively. As shown in **Table EC.3**, the average mobility rates over all states for these three categories are about 0.4, 0.3, and 0.3, respectively. Hence, compared to M1, in M2, we assume a 10% reduction in movements within 1 mile from home, and in M3, we assume no movement beyond 10 miles from home. We also note that mobility scenarios M2 and M3 are exercised for potential intervention policies. Indeed, both no-intervention and current policies are only evaluated under the observed mobility rates (scenario M1).

[2] For the calculation of QALY and cost, see Equations (1)-(2), respectively, in the main body.

[3] To predict these reductions, we use "predict()" function in the R computing package.

[4] The current mobility rates are demonstrated in **Table EC.3**.

Table EC.10 Summary of costs and demographics information

State	Population	Annual Birth	Annual Death	Healthcare Utilization Cost per day ($)		
				Common bed	ICU bed	ICU bed & ventilator
Alabama	4,849,377	57,313	53,879	470.29	2,751.20	3,892.49
Alaska	736,732	10,031	4,819	668.88	3,912.98	5,536.21
Arizona	6,731,484	81,942	60,523	818.44	4,787.87	6,774.04
Arkansas	2,966,369	36,640	31,322	572.63	3,349.91	4,739.56
California	38,802,500	462,617	282,520	1,075.82	6,293.55	8,904.33
Colorado	5,355,866	64,524	39,116	927.48	5,425.78	7,676.58
Connecticut	3,590,886	34,567	31,149	863.82	5,053.37	7,149.68
Delaware	935,614	10,683	9,454	925.35	5,413.31	7,658.93
Dist. of Col.	658,893	9,493	5,677	1,057.85	6,188.42	8,755.59
Florida	19,893,297	221,695	211,692	674.06	3,943.27	5,579.07
Georgia	10,097,343	127,873	86,319	561.97	3,287.54	4,651.32
Hawaii	1,431,603	16,878	12,748	805.34	4,711.25	6,665.64
Idaho	1,654,930	22,220	13,308	972.25	5,687.72	8,047.17
Illinois	12,859,995	144,299	110,004	802.90	4,697.00	6,645.47
Indiana	6,596,855	80,711	62,175	789.19	4,616.81	6,532.02
Iowa	3,107,126	37,672	28,809	487.04	2,849.20	4,031.15
Kansas	2,904,021	35,457	25,230	586.34	3,430.09	4,853.01
Kentucky	4,425,092	53,471	46,074	595.78	3,485.33	4,931.16
Louisiana	4,649,676	58,498	46,343	618.32	3,617.19	5,117.72
Maine	1,330,089	12,073	14,335	802.90	4,697.00	6,645.47
Maryland	5,976,407	70,091	51,453	857.42	5,015.95	7,096.74
Massachusetts	6,794,422	70,419	58,564	925.35	5,413.31	7,658.93
Michigan	9,909,877	109,472	95,983	731.02	4,276.48	6,050.50
Minnesota	5,489,594	67,642	43,200	724.62	4,239.06	5,997.56
Mississippi	2,994,079	35,978	31,536	417.59	2,442.94	3,456.35
Missouri	6,083,672	71,297	60,141	719.14	4,206.98	5,952.18
Montana	1,023,579	11,618	9,870	485.52	2,840.29	4,018.54
Nebraska	1,881,503	25,343	15,582	631.42	3,693.81	5,226.12
Nevada	2,839,099	35,932	25,610	606.44	3,547.69	5,019.40
New Hampshire	1,326,813	12,004	12,125	798.94	4,673.83	6,612.70
New Jersey	8,944,469	99,501	75,723	848.59	4,964.28	7,023.63
New Mexico	2,085,572	23,125	18,388	865.65	5,064.06	7,164.81
New York	19,746,227	222,924	164,817	876.31	5,126.43	7,253.04
North Carolina	10,042,802	119,203	94,312	680.46	3,980.69	5,632.01
North Dakota	756,927	10,536	6,250	560.14	3,276.85	4,636.20
Ohio	11,594,163	134,291	117,750	861.69	5,040.90	7,132.03
Oklahoma	3,878,051	48,759	40,266	600.35	3,512.06	4,968.98
Oregon	3,970,239	43,305	36,563	1,046.88	6,124.27	8,664.83
Pennsylvania	12,787,209	135,190	133,439	769.09	4,499.21	6,365.63
Rhode Island	1,056,298	10,481	9,802	855.60	5,005.26	7,081.61
South Carolina	4,896,146	56,353	50,744	626.85	3,667.08	5,188.31
South Dakota	858,469	11,911	7,337	469.98	2,749.42	3,889.97
Tennessee	6,549,352	80,239	67,977	653.96	3,825.66	5,412.68
Texas	26,956,958	378,664	202,786	793.15	4,639.98	6,564.80
Utah	2,942,902	48,642	17,443	893.97	5,229.78	7,399.26
Vermont	626,562	5,581	5,634	801.99	4,691.65	6,637.91
Virginia	8,326,289	98,403	69,729	633.85	3,708.06	5,246.29
Washington	7,061,530	87,950	58,587	1,081.91	6,329.19	8,954.75
West Virginia	1,844,128	17,888	22,567	552.22	3,230.52	4,570.65
Wisconsin	5,771,337	63,712	50,393	770.01	4,504.56	6,373.20
Wyoming	584,153	6,601	4,971	436.48	2,553.41	3,612.65

Information in columns 2–4 are obtained by Mathematica, Wolfram Research, Inc. (see below).
This information is used to measure $N(0)$, μ, and ν (see Table EC.4).

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"]`

References

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