

The Benefits of Coronavirus Suppression

A Cost-Benefit Analysis of the Response to the First
Wave of COVID-19

James Broughel and
Michael Kotrous

WORKING PAPER

COVID-19 RESPONSE



MERCATUS CENTER

George Mason University

Suggested Citation

James Broughel and Michael Kotrous. “The Benefits of Coronavirus Suppression: A Cost-Benefit Analysis of the Response to the First Wave of COVID-19.” Mercatus Working Paper, Mercatus Center at George Mason University, Arlington, VA, June 2020.

Author Affiliation and Contact Information

James Broughel
Senior Research Fellow
Mercatus Center at George Mason University
jrbroughel@mercatus.gmu.edu

Michael Kotrous
Program Manager, Innovation and Governance
Mercatus Center at George Mason University
mkotrous@mercatus.gmu.edu

Disclaimer

In response to the COVID-19 pandemic, the Mercatus Center has commissioned this series of working papers and policy briefs to promote effective ideas among key decisionmakers. To ensure a timely response to the global COVID-19 pandemic, this working paper has been exempted from the Mercatus Center’s normal standards and processes for working papers and is being published without peer review. Working papers present an author’s provisional findings and may be significantly revised before formal publication. The opinions expressed in Mercatus Working Papers are the authors’ and do not represent official positions of the Mercatus Center or George Mason University.

© 2020 by James Broughel, Michael Kotrous, and the Mercatus Center at George Mason University

Mercatus Center at George Mason University
3434 Washington Blvd., 4th Floor
Arlington, VA 22201
www.mercatus.org
703-993-4930

This paper can be accessed at <https://mercatus.org/publications/covid-19-economic-recovery/benefits-coronavirus-suppression-cost-benefit-analysis-response-first-wave-covid-19>

The Benefits of Coronavirus Suppression:
A Cost-Benefit Analysis of the Response to the First Wave of COVID-19

James Broughel and Michael Kotrous
Mercatus Center at George Mason University

Author Note

The authors thank Tracy Miller and Walter Valdivia for insightful comments, as well as Connor Haaland for helpful research assistance. We also acknowledge the Mercatus publications team for excellent copyediting, graphic design, and proofreading of the article.

Abstract

This paper estimates the benefits and costs of state suppression policies to “bend the curve” during the initial outbreak of COVID-19 in the United States. Relative to a baseline in which only the infected and at-risk populations mitigate the spread of coronavirus, we estimate that total benefits of suppression policies are between \$440 billion and \$1,049 billion up to August 4, 2020. We employ a value-of-production approach that values the benefits of each prevented COVID-19 death as avoided losses to total production. The production value of life differs significantly from the value of a statistical life (VSL) commonly employed in cost-benefit analysis, and we identify several problems with using the VSL. Relative to private mitigation, the costs of suppression policies are estimated to be between \$255 billion and \$464 billion. The cost estimate is based on suppression policies being enforced in the United States for between 50 and 91 days, which reflects that many states lifted stay-at-home orders and nonessential business closures in May 2020. Our results indicate that the net benefits of suppression policies to slow the spread of COVID-19 are likely positive and may be substantial, but given significant uncertainty, net benefits may be close to zero.

JEL codes: E32, H12, I18, I31, J17, K23

Keywords: COVID-19, social distancing, cost-benefit analysis, value of a statistical life

**The Benefits of Coronavirus Suppression:
A Cost-Benefit Analysis of the Response to the First Wave of COVID-19**

Between early April and mid-May of 2020, 38 states and the District of Columbia enforced statewide “stay-at-home” orders for their residents, meaning that 90 percent of the U.S. population was required to stay at home unless engaged in “essential” activities (IHME, 2020b). Many U.S. states also implemented legal orders that closed public schools and nonessential businesses, banned large public gatherings, and restricted private gatherings. These measures appear to have successfully slowed the spread of the coronavirus, at least when compared to projections of COVID-19 deaths in their absence, but the economic costs of the pandemic and social distancing have been staggering. As of the week ending May 2, 2020, the four-week moving average of new claims for unemployment benefits exceeded 4 million (DOL, 2020a), and initial unemployment benefits claims remained above 2 million in each of the next three weeks, through May 23, 2020 (DOL, 2020b). New business formation also contracted sharply, an indication that job creation and hiring would slow in the quarters ahead (Haltiwanger, 2020). For these reasons, over half of the U.S. states that had ordered all nonessential businesses to close had allowed at least some of those businesses to reopen by the end of May 2020.

The key challenge facing policymakers and public health officials during this period was how to save lives by “bending the curve” during the first wave of COVID-19, while also controlling the economic costs that accompany the pandemic and the policies aimed at slowing its spread. This is fundamentally a question of cost-benefit analysis (CBA).

In this paper, we offer a CBA for the legal orders implemented across the United States to address the first wave of the coronavirus. Relative to a baseline in which only private actions

are taken by people with symptoms of COVID-19, their households, and elderly people to mitigate the spread of coronavirus, we find that the enforcement of government orders to slow the initial outbreak of COVID-19 had substantial benefits—between \$440 billion and \$1,049 billion through August 4, 2020. The single most significant benefit of these directives is prevention of COVID-19 deaths. We estimate the net reduction in mortality from these measures to be valued in the range of \$299 billion to \$361 billion.

Our benefit estimate is considerably lower than other recent estimates in the literature (e.g. Greenstone & Nigam, 2020; Thunström et al., in press). This difference stems from the fact that we do not use the value of a statistical life (VSL) to measure the benefits of reduced mortality. We believe this measure is inappropriate in this case for several reasons. First, the VSL is intended for use when policies address small mortality risks and deaths occur among unidentifiable, “statistical” people. With COVID-19, millions of lives are potentially at stake, and at-risk populations are relatively easy to identify, making use of the VSL inappropriate. Moreover, we believe that a value of life that is tied to lifetime production is more consistent with the principle that benefits, including lives, should be valued according to society’s willingness to pay for them, not what any particular individual is willing to pay. We explain our approach to valuing lives in more detail in Appendix D. In addition to the prevention of COVID-19 deaths, we also consider the benefits that would result from reductions in lost wages due to illness, reductions in hospital and intensive care unit (ICU) stay costs, and prevention of permanent lung damage that has been observed in recovered COVID-19 patients.

To estimate the economic costs of suppression policies, we use an estimate from Scherbina (2020) that suppression policies have incremental costs of \$35.8 billion per week, or \$5.1 billion per day, on average. We multiply daily incremental cost by the number of days

during which suppression policies were enforced in the United States, which we weight by the distribution of state GDP relative to U.S. GDP. We estimate that the total economic costs of suppression policies up to August 4, 2020 are between \$255 billion and \$464 billion. We source the dates during which these policies were enforced by each state and the District of Columbia from IHME (2020b), which tracks suppression policies for the purposes of producing its COVID-19 forecasts.

We also consider how income losses will decrease private expenditures on health and risk reduction, thereby increasing mortality risks (Broughel & Viscusi, in press). We find that the countervailing mortality risks stemming from lost income may actually produce benefits (in the case that suppression policies are cost saving), initially up to \$7.8 billion; but this effect could also result in \$220 million in initial mortality costs. While this does not dramatically affect our estimate of the benefits that bending the curve has on mortality reduction, this countervailing risk effect does have significant implications for how mortality risks are valued more generally in cost-benefit analyses.

Our analysis hinges on several assumptions. First, our estimates rely on a model from the Institute for Health Metrics and Evaluation (IHME). Of importance to our analysis, the IHME forecasts the progression of COVID-19, including the number of hospitalizations, ICU admissions, and deaths, under the various government orders enacted across the U.S. states (Murray & IHME, 2020). However, the IHME model has been criticized for its underlying assumptions and has performed poorly in predicting daily COVID-19 deaths in the U.S. states (Marchant et al., 2020; Jewell, Lewnard, & Jewell, 2020). Our analysis relies on its forecast of cumulative hospitalizations, ICU admissions, and deaths in the United States only through August 4, 2020. Insofar as the IHME underestimates the total number of COVID-19 deaths in the United

States, especially in light of the fact that many states lifted stay-at-home orders and allowed many businesses and public spaces to reopen in May 2020, our estimate of total benefits of policies may overstate actual benefits. Further, the updates that the IHME made to its model as of its May 4 release may improve accuracy and address criticisms of its methodology (IHME, 2020a).

Second, despite considerable uncertainty about the COVID-19 disease and a lack of data about its trajectory and lethality in the United States, we assume that government interventions are highly effective at preventing COVID-19 infections, hospitalizations, and deaths. In other words, we assume that the baseline scenario would be relatively catastrophic, and that the relatively much lower numbers of infections, hospitalizations, and deaths that have actually occurred and are expected to occur going forward are largely attributable to government policy rather than private action. However, if the virus is less dangerous than some epidemiological models suggest, or if private behavioral responses to the virus are more intense than some models suggest, then the effect of government orders may be relatively minor (Luther, 2020). Our analysis is fundamentally about the question of what would have happened in the absence of those orders, which constitutes a counterfactual that is impossible to know with certainty.

Our results suggest that government orders implemented to respond to the initial outbreak of COVID-19 in the United States may be efficient. Despite the high daily costs of stay-at-home orders, nonessential business closures, and other restrictive policies, about one million COVID-19 deaths may have been prevented by bending the curve from March to early August of 2020.

As a cost-benefit analysis of a developing situation, the costs and benefits of state policies are subject to change according to evolving circumstances. Any second wave of coronavirus following the reopening of many U.S. businesses in May 2020 may require states to consider reimplementing suppression policies or pursuing alternative measures. While our

analysis cannot directly address the question of what might be the costs and benefits of policies to address a second wave, we nonetheless hope our estimates and the research surveyed in this article are helpful to future responses to the pandemic.

This paper proceeds as follows. First, we present our benefits analysis, including estimates of the benefits from reduced mortality and morbidity. Following that, we present a cost analysis, which includes the effects of suppression policies on economic output and the mortality risks associated with lost income. We then discuss the results and their limitations given considerable uncertainty surrounding a number of factors. The final section concludes. We then include a series of appendices that explore in detail the nature of the market failure that is associated with COVID-19; an assessment of regulatory alternatives that could be considered in place of suppression policies; an explanation of the reasoning underlying our value of reduced mortality estimates; and detailed information about state stay-at-home orders, including their duration.

BENEFITS ANALYSIS

Reduced Mortality

The likely most consequential benefit of government suppression orders is preventing deaths from COVID-19. A widely cited study from Imperial College London estimates that, absent government measures or behavioral change to respond to the virus's spread, coronavirus could result in approximately 2.2 million deaths in the United States, with almost all of those deaths occurring before August of 2020 (Ferguson et al., 2020).

In a more plausible scenario forecast by Ferguson et al. (2020), most of the sick isolate, other members of their households voluntarily quarantine, and elderly individuals and other high-risk populations practice social distancing behaviors. The authors assume that a significant

share (though not all) of the affected population will voluntarily comply with case isolation and household quarantines for three months, roughly from April through June, while elderly individuals will maintain social distancing for a fourth month (July) as well (Ferguson et al., 2020, pp. 6, 8). Under this mitigation scenario, Ferguson et al. (2020, p. 16) estimate that the United States would see 1.1 to 1.2 million deaths in “a single, relatively short epidemic.”¹ While the authors assume that social distancing of elderly individuals will be ordered by governments, we believe it is reasonable that elderly and other high-risk populations would engage in social distancing behaviors even without government enforcement.² We will use Ferguson et al.’s (2020) mitigation projection to produce estimates of deaths prevented by suppression policies, since this scenario reflects what may happen during outbreaks of the coronavirus if the federal and state governments across the United States allowed private businesses and individuals to adopt social distancing practices as they see fit.

The IHME projected, as of May 26, 2020, that between 116,000 and 174,000 people will die of COVID-19 in the United States by August 4 (the last date in its forecast), with its mean forecast predicting 132,000 total COVID-19 deaths. As of June 7, 2020, just over 109,000 COVID-19 deaths had been reported in the United States (World Health Organization, 2020). The IHME’s forecast of the first wave of COVID-19 attempts to account for variance in the number of COVID-19 cases and deaths across the 50 U.S. states and Washington, DC, and each jurisdiction’s policy response, such as stay-at-home orders, closure of public schools and

¹ “In the most effective mitigation strategy examined, which leads to a single, relatively short epidemic (case isolation, household quarantine and social distancing of the elderly), the surge limits for both general ward and ICU beds would be exceeded by at least 8-fold under the more optimistic scenario for critical care requirements that we examined. In addition, even if all patients were able to be treated, we predict there would still be in the order of 250,000 deaths in [Great Britain], and 1.1–1.2 million in the US” (Ferguson et al., 2020, p. 16).

² “Two of the interventions (case isolation and voluntary home quarantine) are triggered by the onset of symptoms and are implemented the next day. The other four [non-pharmaceutical interventions] (social distancing of those over 70 years, social distancing of the entire population, stopping mass gatherings and closure of schools and universities) are decisions made at the government level” (Ferguson et al., 2020, p. 6).

“nonessential” businesses, and travel restrictions (IHME, 2020b; Murray & IHME, 2020). Its May 26 model takes into account the possible effects of the easing of suppression policies in many states during May 2020 (IHME, 2020b). As of that date, 21 of 38 states that had enacted a stay-at-home order had lifted it, and 29 of 34 states that had required all nonessential businesses to close had allowed at least some of them to reopen (see Appendix E for a full list of policies and their dates of enforcement).

The May 26 IHME forecast assumes that government suppression measures that were lifted before May 26, 2020, will remain unenforced through August 4, 2020. If a state has announced a date at which it will ease a social distancing measure, the forecast assumes that it is lifted on that date and remains out of force through August 4. Finally, if a state has restrictions in place and has not announced a plan or date by which they may be lifted, it is assumed the measure stays in force through August 4.

Comparing the IHME estimate with the Ferguson et al. (2020) estimate allows for a rough approximation of the “treatment” (government shutdown orders designed to bend the curve of coronavirus infections) versus the “control” (the impacts of the first wave under private action to mitigate the pandemic), which we use to produce a range estimate of the number of lives saved by suppression policies through August 4. Using the May 26 estimate from the IHME, we estimate that the broad enforcement of suppression measures between early April and late May, with continuing enforcement from June through early August in some states such as New York and California, could prevent between 930,000 and 1.1 million COVID-19 deaths during the first wave in the United States.³

³ To estimate the upper bound of the reductions in COVID-19 deaths, we take the difference between the upper bound of the Ferguson et al. (2020) forecast (1.2 million) and the lower bound of the IHME (2020b) forecast (116,000), which is approximately 1.1 million. For the lower bound of reductions, the difference between the lower

This estimate assumes that there is significant compliance with government orders and that these orders have a significant causal effect on adherence to social distancing practices. On the one hand, the cost of infection is not fully internalized by prime-age workers, many of whom also face a high opportunity cost of forgone earnings and may engage in behavior that facilitates spread of the virus to high-risk populations. This point is discussed in greater detail in Appendix B, which discusses the market failures associated with the pandemic. On the other hand, Luther (2020) suggests that compliance with public health guidance to stay at home may be the result of voluntary action more than formal legal orders requiring people to do so. We acknowledge that if government orders are relatively ineffective, the benefit estimates here are overstated.

To put a monetary value on the social benefit of each life saved, we use the present value of workers' lifetime production.⁴ Our estimates of lifetime production come from Grosse, Krueger, and Mvundura (2009, p. S100) and are adjusted for inflation and productivity growth since that study's publication (see Table A-1 in Appendix A). The study calculated the present value of total worker production, including nonmarket production such as household production, for the American population, broken down by age group. Because the study includes nonmarket production, it is unlikely to discriminate against those who, for example, choose to stay at home to raise children rather than seek employment. Moreover, because the study includes a detailed breakdown of production value by age, it may provide a more precise estimate of the value of reduced mortality than other studies that have relied on values of life based only on population averages.

bound of the Ferguson et al. (2020) forecast (1.1 million) and the upper bound of the IHME (2020b) forecast (174,000) is approximately 930,000.

⁴ For a detailed explanation of the rationale for using this measure, see Appendix D.

Expected lifetime production varies substantially with age, with prime-working-age people having higher expected lifetime production remaining than elderly and very young individuals.⁵ Accordingly, we compute a weighted average of lifetime production according to the age distribution of COVID-19 deaths in the United States. The U.S. Centers for Disease Control and Prevention (CDC, 2020a) reports that, as of the week ending May 16, 2020, almost 80 percent of deaths from COVID-19 in the United States have been among people age 65 or older. We calculate an expected benefit of approximately \$321,000 in lifetime production per life saved from death by COVID-19. Table 1 shows our estimate of the expected lifetime production and share of COVID-19 fatalities by the age groups defined in CDC (2020a).

To calculate the estimated benefit value of suppression measures, we simply multiply our estimate of the expected social benefits from each prevented COVID-19 death by the projected number of prevented deaths. Multiplying \$321,000 by the range of estimates of lives saved—930,000 on the low end and approximately 1.1 million on the high end—yields a gross estimate of \$299 billion to \$353 billion in benefits from reductions in mortality alone. In the event that Ferguson et al.’s (2020) worst-case estimate of 2.2 million COVID-19 deaths without suppression measures is correct, the economic benefits of preventing 2.1 million deaths would total \$674 billion. However, that worst-case estimate assumes no behavioral response to mitigate against the pandemic, so it clearly overstates the potential benefits of government suppression. To be clear, our preferred benefit estimate range of \$299 to \$353 billion is a gross estimate of the benefits of prevented mortality. In the section on costs (countervailing risks), we will explain why a net estimate of the mortality reduction, which accounts for countervailing

⁵ The young have lower lifetime production in Grosse, Krueger, and Mvundura (2009, p. S100) because of discounting. Without discounting, their lifetime production is higher than that of older groups.

increases in mortality risk owing to the effects of depressing economic activity, is preferable to a gross estimate.

Table 1. Expected lifetime production lost to COVID-19 deaths.

| Age | Present value of lifetime production, 2020 USD | Number of COVID-19 deaths | Approx. share of COVID-19 deaths | Expected lifetime production lost |
|----------|--|---------------------------|----------------------------------|-----------------------------------|
| 0 to 4 | \$864,396 | 5 | >0.0% | \$63 |
| 5 to 14 | \$1,165,275 | 7 | >0.0% | \$118 |
| 15 to 24 | \$1,609,646 | 76 | 0.1% | \$1,773 |
| 25 to 34 | \$1,743,368 | 463 | 0.7% | \$11,699 |
| 35 to 44 | \$1,511,338 | 1,186 | 1.7% | \$25,978 |
| 45 to 54 | \$1,102,485 | 3,338 | 4.8% | \$53,336 |
| 55 to 64 | \$626,928 | 8,312 | 12.0% | \$75,524 |
| 65 to 74 | \$305,058 | 14,447 | 20.9% | \$63,874 |
| 75 to 84 | \$163,013 | 18,621 | 27.0% | \$43,994 |
| 85 plus | \$137,889 | 22,543 | 32.7% | \$45,051 |
| All | — | 68,998 | 100% | \$321,410 |

Sources: Grosse, Kruger, and Mvundura (2009, p. S100); Centers for Disease Control and Prevention (2020a); authors' calculations.

Note: Grosse, Kruger, and Mvundura (2009, p. S100) present lifetime production by five-year increments from ages 0 to 79, and then a single lifetime production estimate is given for those 80 or older. We calculate lifetime production for the age groups in CDC's data by taking the average of the lifetime production value for all ages in the range. See Table A-1 for adjustments of Grosse, Kruger, and Mvundura (2009) for inflation, productivity growth, and age group conversion. We use production values calculated at a 5 percent discount rate.

Reduced Health-Care Utilization, Hospitalizations, and ICU Stays

The coronavirus will not kill most people it infects, yet many of those infected will bear the cost of health-care services, which may be considerable in the aggregate if a significant

number are hospitalized, are admitted to an ICU, or, in the most extreme cases, require mechanical ventilation. The IHME projections as of May 26 estimate that the cumulative number of hospitalizations in the United States will be between 440,000 and 710,000, with the average forecast predicting 520,000 hospitalizations by August 4. Meanwhile, the cumulative number of admissions to an ICU in the United States is expected to total between 139,000 and 216,000, with an average forecast of 161,000, by August 4.⁶ Many people will also develop symptoms of COVID-19 that may not require hospitalization but that will require them to miss work.

In order to estimate the total expected number of symptomatic infections in the United States under suppression measures, we obtain estimates of the overall infection fatality rate (IFR)⁷ and the share of infections that are asymptomatic from studies of the *Diamond Princess* cruise liner.⁸ Russell et al. (2020) report an age-adjusted IFR of COVID-19 infections aboard the *Diamond Princess* cruise liner (1.3 percent) and also produce an adjusted IFR for COVID-19 in China (0.6 percent). Meanwhile, Mizumoto et al. (2020) estimate that about 18 percent of *Diamond Princess* passengers with confirmed COVID-19 infections were asymptomatic, though there is considerable uncertainty around the true proportion of asymptomatic infections. The CDC (2020d) estimates that 35 percent of people infected by coronavirus in the United States may never develop symptoms, which is closer to the 31 percent of asymptomatic cases among Japanese nationals evacuated from Wuhan (Nishiura et al., 2020). These estimates of the share of asymptomatic infections imply that between 65 percent and 82 percent of infections are

⁶ We estimate the cumulative number of hospital admissions and ICU admissions by calculating the sum of daily hospital admissions and daily new ICU admissions in the IHME projection.

⁷ For the purposes of this analysis, we use estimates of the overall IFR, though the IFR has been shown to vary significantly across counties in the United States (Basu, 2020) and by age (Russell et al., 2020; Verity et al., 2020).

⁸ Studying breakouts of coronavirus aboard cruise liners is informative because it offers an opportunity to observe the virus's spread within a well-defined and confined population that was, in the case of the *Diamond Princess*, comprehensively (though not universally) tested for infection.

symptomatic. Combining the estimates of the IFR and the proportion of symptomatic infections implies an infection fatality rate for symptomatic cases (IFR-S) between 0.7 percent and 2.0 percent.⁹ Our estimate, based on observational studies of COVID-19, is consistent with Basu's (2020) model-based estimate of the IFR-S for counties in the United States.

To estimate the range of possible symptomatic infections, we first divide the lower bound of deaths projected by the IHME (about 116,000) by the higher IFR-S (2.0 percent), and then we divide the upper bound of deaths projected by the IMHE (about 174,000) by the lower estimate of the IFR (0.7 percent). Using these bounds, we produce a range estimate of symptomatic infections of COVID-19 in the United States under government suppression measures of 5.8 million to 24.9 million.

To estimate the number of symptomatic infections, hospitalizations, and ICU stays under the baseline scenario of more limited mitigation strategies (i.e., no suppression orders), we begin with the projected number of deaths from Ferguson et al. (2020), approximately 1.1 million to 1.2 million in the United States. Dividing 1.1 million deaths by the high IFR-S estimate (2.0 percent) and 1.2 million by the low IFR-S estimate (0.7 percent), we estimate that between 55 million and 171 million people in the United States would need to have developed symptoms of COVID-19 in order for that number of deaths to occur.

To infer the number of hospitalizations and ICU admissions in the mitigation scenario, we first estimate the mean number of COVID-19 symptomatic infections in the suppression scenario. Using the mean forecast estimate of 132,000 deaths from the IHME (2020b) and the mean IFR-S of 1.4 percent, we estimate the mean number of expected symptomatic infections of

⁹ To estimate the lower bound of the IFR-S, we divide the lower IFR estimate (0.6 percent) from Russell et al. (2020) by the higher estimate of the share of symptomatic infections (82 percent), which gives a 0.7 percent IFR-S. For the upper bound, we divide the higher IFR estimate (1.3 percent) by the lower estimate of the share of symptomatic infections (65 percent), which is approximately 2.0 percent.

COVID-19 to be about 9.4 million. Assuming our mean estimate of 9.4 million symptomatic infections leads to the IHME's average forecast of 520,000 hospitalizations and 161,000 ICU admissions, this implies that 5.5 percent of infections with symptoms will result in hospitalizations, and 31.0 percent of hospital admissions will require intensive care. Under these assumptions, we estimate that between 3.0 million and 9.4 million hospitalizations will occur and between 930,000 and 2.9 million ICU stays will be demanded in the United States under the mitigation scenario.¹⁰

Of those admitted to the ICU, a sizable share will require mechanical ventilation. A study of hospitalized patients in Wuhan, China, who developed pneumonia after being infected by the coronavirus found that 47 percent of those in intensive care required mechanical ventilation (Wang et al., 2020). Not all COVID-19 patients in the ICU will develop pneumonia, so this percentage likely overstates the share of total ICU patients who will need mechanical ventilation. Accordingly, we use an estimate from Dasta et al. (2005) that 36 percent of ICU patients require mechanical ventilation. This estimate draws from a broader sample than patients with COVID-19 specifically or respiratory conditions generally, but it does appear to be a reasonable estimate of the need for mechanical ventilation to address COVID-19 in the United States when compared to Wang et al. (2020).

Assuming a 36 percent share, we estimate that between 335,000 and 1.0 million COVID-19 ICU patients will require mechanical ventilation under mitigation strategies, while suppression measures are projected to reduce the need for mechanical ventilation in the ICU to

¹⁰ We say "demanded" because the U.S. health-care system will be unable to serve peak daily demand under this scenario in many U.S. states. To keep our benefit analysis as an upper bound, we simply assume that everyone who demands a hospitalization or ICU stay will be accommodated.

between 50,000 and 78,000 people. This is 36 percent of the 139,000 to 216,000 people who the IHME is projecting will be admitted to the ICU.

To summarize, we compare figures presented under the suppression and mitigation scenarios. Taking the difference between these scenarios gives the estimated effects of suppression relative to the baseline scenario during the initial wave of the COVID-19 pandemic. We estimate the net effects of suppression policies to

- reduce the number of symptomatic infections by between 30 million and 165 million;
- reduce the number of hospitalizations in the United States by between 2.3 million and 9.0 million;
- reduce the number of total ICU admissions in the United States by between 710,000 and 2.8 million; and
- reduce the number of ICU patients requiring mechanical ventilation by between 260,000 and 950,000.

Table 2 shows our health-care utilization estimates under the private mitigation (Ferguson et al., 2020) scenario and the suppression (IHME, 2020b) scenario.

Table 2. Estimates of the net effects of COVID-19 suppression measures on health-care utilization.

| Category | Private mitigation scenario | Government suppression scenario | Net effect of suppression measures |
|---------------------------------|-----------------------------|---------------------------------|------------------------------------|
| COVID-19 symptomatic infections | 55–171 million | 5.8–24.9 million | 30–165 million |
| Hospitalizations | 3.0–9.4 million | 440,000–710,000 | 2.3–9.0 million |
| ICU admissions | 930,000–2.9 million | 139,000–216,000 | 710,000–2.8 million |
| No mechanical ventilation | 595,000–1.9 million | 89,000–138,000 | 460,000–1.8 million |
| Mechanical ventilation | 335,000–1.0 million | 50,000–78,000 | 260,000–950,000 |

Sources: CDC (2020d); Dasta et al. (2005); Ferguson et al. (2020); IHME (2020b); Mizumoto et al. (2020); Russell et al. (2020); authors’ calculations.

Note: Differences or sums may not be exact owing to rounding. We produce the lower bound of estimated net effects in each category by subtracting the upper bound of the “government suppression” estimates from the lower bound of the “private mitigation” estimates. To estimate the upper bound of net effects, we subtract the lower bound of the “government suppression” estimates from the upper bound of the “private mitigation” estimates.

Estimated Cost of Health-Care Utilization

Many of those who contract COVID-19 will not be hospitalized but will bear the cost of lost wages. The CDC (2020b) advises those with COVID-19 to isolate for at least 10 days, and to remain isolated until fever and other symptoms improve. We calculate the cost of a case of COVID-19 treated at home to be approximately equal to two weeks of lost earnings, which, on average, is just over \$1,900.¹¹

For those who develop more serious symptoms or develop complications, hospitalization may be necessary. To approximate the cost of a hospitalization from COVID-19, we use the

¹¹ We calculate this by multiplying the average hourly wage in January 2020, \$28.43, by the average number of hours worked by an “engaged person” in two weeks during 2017, which was about 68 hours.

estimate from Torio and Moore (2016) for the average cost of a hospitalization for pneumonia. Like COVID-19, pneumonia is a respiratory condition, and it is common for COVID-19 patients to develop pneumonia in mild and severe cases.¹² Adjusted to 2020 dollars, the average cost of a pneumonia hospitalization was just over \$11,000. This estimate likely overestimates the costs of non-ICU hospitalizations because it may include those patients who spend time in the ICU. That said, we will use this number since it is the best estimate available, with the understanding that it might overestimate the average cost of non-ICU hospitalizations, since ICU stays have substantially higher costs than a standard hospitalization, especially on the first day.

We break down ICU costs according to an estimate of how many ICU patients will require mechanical ventilation and how many will not. We use estimates from Dasta et al. (2005) on average costs and lengths of stay for ICU patients who require mechanical ventilation and those who do not. For the 36 percent of ICU patients we estimate will require mechanical ventilation, they are expected on average to have a 14-day ICU stay, 6 days of which will require mechanical ventilation. Using Dasta et al.'s (2005) estimates of daily ICU costs and mechanical ventilation, we estimate total ICU costs for patients requiring mechanical ventilation of approximately \$81,600, adjusted for inflation to 2020 dollars.¹³

For the remaining ICU patients who do not require mechanical ventilation (but who may require noninvasive ventilation), we again use Dasta et al.'s (2005) estimate of daily ICU costs and their estimate that the average ICU stay is eight days to calculate expected ICU costs of

¹² Detection of the novel coronavirus in mainland China was primarily among those suffering pneumonia. See Zhou, Yang, et al. (2020).

¹³ Dasta et al. (2005) estimate, all in 2002 dollars, that the first ICU day of mechanical ventilation costs about \$11,000, the second day about \$5,000, thereafter \$4,000 per day requiring mechanical ventilation. They also estimate an average ICU stay of 14 days, 6 of which require mechanical ventilation. For the other eight days, we assume daily costs of \$3,000, which is the daily cost of a standard ICU day with no mechanical ventilation after the first and second days in the ICU have passed. Altogether, we estimate average ICU costs of \$56,000 (in 2002 dollars) for patients, which is equivalent to \$81,600 in 2020 dollars.

\$41,000, also adjusted for inflation to 2020 dollars.¹⁴ This is comparable to Zhou, Yu, et al. (2020, p. 1058), which estimates a median ICU length of stay of eight days among a sample of 191 hospitalized COVID-19 patients in Wuhan.

Above, we presented estimates of the effects of suppression measures relative to the baseline scenario of more targeted mitigation practices (i.e., no suppression orders), in terms of the expected reductions in COVID-19 infections in which symptoms are present, hospitalizations, ICU admissions, and demand for mechanical ventilation. We calculate the financial value of these benefits by simply multiplying the number of people predicted to be relieved of each medical service by the economic cost of that service.

We find the following economic benefits of suppression policies to bend the curve during the first wave of the coronavirus in the United States:

- reduced symptomatic infections: \$57 billion to \$314 billion (30 million to 165 million people won't lose two weeks of wages owing to illness, which, on average, equals \$1,900 per person);
- reduced hospitalizations: \$25 billion to \$99 billion (2.3 million to 9.0 million people won't bear the cost of a hospitalization for COVID-19, which we approximate at \$11,000 per person hospitalized);
- reduced ICU stays without ventilation: \$19 billion to \$74 billion (460,000 to 1.8 million people won't require mechanical ventilation but will be admitted to the ICU for an average of eight days, which costs approximately \$41,000 per ICU patient); and

¹⁴ Dasta et al. (2005) estimate, all in 2002 dollars, that the first day in the ICU costs about \$6,700, the second day costs about \$3,500, and each ICU day thereafter costs about \$3,000. Taking their estimate of an average ICU stay of eight days for patients not requiring ventilation, average ICU costs are \$28,200 in 2002 dollars, or about \$41,000 in 2020 dollars. We assume the costs of noninvasive ventilation are reflected in the costs of ICU stays.

- reduced ICU stays that require mechanical ventilation: \$21 billion to \$78 billion (260,000 to 950,000 people won't bear the cost of 6 days of mechanical ventilation, on average, and 14 total days in the ICU on average, which costs approximately \$81,600).

We take the sum of the low-end estimates and then a sum of the high-end estimates to produce a range estimate of the benefits of suppression measures. We find that the range of benefits associated with reduced health-care utilization is between \$122 billion and \$565 billion.

Reduced Incidence of Permanent Lung Damage

Some patients who have recovered from COVID-19 develop acute respiratory distress syndrome (ARDS) and may have permanent lung damage and decreased lung capacity. Zhou, Yu, et al. (2020, p. 1058) find that 9 of 137 (6.6 percent) COVID-19 survivors in Wuhan who were ultimately discharged from the hospital developed ARDS.

To estimate the number of people who will be impacted by ARDS as a result of COVID-19, we assume that 6.6 percent of those who are hospitalized and recover will develop ARDS. We simply subtract the number of expected deaths from the range of estimates of expected total hospital admissions from above, and then multiply that number by 6.6 percent. Doing so, we estimate that between 119,000 and 548,000 ARDS cases would emerge under a targeted mitigation strategy, while only between 18,000 and 39,000 are expected to be seen under suppression policies.¹⁵ This means suppression measures may reduce ARDS cases resulting from COVID-19 by between 80,000 and 530,000 in the United States.

¹⁵ Above, we estimated that between 3.0 million and 9.4 million COVID-19 patients would be hospitalized in the scenario forecasted by Ferguson et al. (2020) in which 1.1 million to 1.2 million people die of COVID-19 in the United States. That means between 1.8 million and 8.3 million hospitalized COVID-19 patients would recover. Assuming 6.6 percent of those people develop ARDS, we estimate that between 119,000 and 548,000 COVID-19 patients develop ARDS in the United States under mitigation. Meanwhile, the IHME projects between 440,000 and 710,000 hospitalizations and between 116,000 and 174,000 deaths, meaning that between 266,000 and 594,000

A 2017 study of ARDS patients in the United States measured their use of inpatient and outpatient services within the first year of their diagnosis of ARDS. Ruhl et al. (2017, pp. 983, 986) find that 55 percent of their ARDS patient cohort sought inpatient services (e.g., hospitalization or skilled nursing facility) at a median cost of \$16,800, in 2014 dollars. Meanwhile, 88 percent of the cohort sought outpatient services from a primary care physician or specialists, such as a pulmonologist, at a median cost of \$6,761, also in 2014 dollars. In expected-value terms, an ARDS patient will bear approximately \$16,700 in inpatient and outpatient costs within the first year, after adjustment to 2020 dollars.

Considering only first-year health-care costs likely understates the expected total health-care costs for those who develop ARDS as a result of COVID-19. Further, permanent lung damage also likely has a significant effect on recovered patients' productivity for the remainder of their life. As such, we assume those who develop ARDS will see their lifetime total production decrease by 30 percent. Using the same Grosse, Krueger, and Mvundura (2009, p. S100) estimates on total lifetime production by age, we calculate the expected lifetime production lost for those hospitalized with COVID-19 who develop ARDS. We weight this average by the distribution of age among 22,060 patients hospitalized in the United States with coronavirus between the week ending March 7, 2020, and the week ending May 16, 2020, which skews younger than the distribution of deaths recorded in the United States (CDC, 2020c). Results are presented in Table 3.

hospitalized COVID-19 patients are expected to be discharged. Again assuming 6.6 percent of those people develop ARDS, we estimate between 18,000 and 39,000 cases of ARDS in the United States in the government suppression scenario.

Table 3. Expected lifetime production lost to lung damage resulting from COVID-19.

| Age | Lifetime production, 2020 USD | Number of COVID-19 hospitalizations | Approx. share of COVID-19 hospitalizations | Expected lifetime production lost (30% reduction) |
|----------|-------------------------------|-------------------------------------|--|---|
| 0 to 4 | \$864,396 | 68 | 0.3% | \$799 |
| 5 to 17 | \$1,283,053 | 91 | 0.4% | \$1,588 |
| 18 to 49 | \$1,571,597 | 5,356 | 24.3% | \$114,472 |
| 50 to 64 | \$746,446 | 6,561 | 29.7% | \$66,602 |
| 65 plus | \$234,035 | 9,984 | 45.3% | \$31,776 |
| Total | — | 22,060 | 100% | \$215,237 |

Sources: Grosse, Kruger, and Mvundura (2009, p. S100); Centers for Disease Control and Prevention (2020c); authors' calculations.

Note: Differences or sums may not be exact owing to rounding. Grosse, Kruger, and Mvundura (2009, p. S100) present lifetime production by five-year increments between ages 0 and 79, and then a single lifetime production estimate is given for those 80 or older. We calculate lifetime production for the age groups in CDC (2020c) by taking the average of lifetime production value for all ages in the range. See Table A-2 for adjustments of Grosse, Kruger, and Mvundura (2009) for inflation, productivity growth, and age group conversion.

Thus, we estimate that a patient who recovers from COVID-19 but develops ARDS will, on average, see a loss of just over \$215,000 to his or her lifetime production. Combined with the expected cost of care in the first 12 months (\$16,700), we estimate the present value of total costs of lung damage to be just under \$232,000. Multiplying that cost estimate by the 80,000 to 530,000 people who we expect won't develop ARDS as a result of suppression measures, we estimate the economic benefit of reduced permanent lung damage from suppression measures to be between \$19 billion and \$123 billion.

Aggregate Gross Benefits of COVID-19 Suppression Measures

To summarize, we expect that the primary benefits of policies that slow the spread of the novel coronavirus will be reduced mortality, reduced symptomatic infections leading to lost earnings, reduced health-care utilization in the form of hospitalizations and ICU stays, and reduced permanent lung damage among a subset of those who contract and recover from COVID-19. Compared with the outcomes projected under Ferguson et al.'s (2020) model of only limited voluntary mitigation practices (the no-suppression scenario), including case isolation, household quarantine, and social distancing among elderly individuals and high-risk populations, we estimate total gross benefits in the range of \$440 billion to \$1,041 billion.

For the lower bound, we estimate

- \$299 billion in benefits from 930,000 prevented COVID-19 deaths;
- \$57 billion in benefits from 30 million fewer COVID-19 symptomatic infections;
- \$25 billion in benefits from 2.3 million fewer hospitalizations;
- \$19 billion in benefits from 460,000 fewer ICU stays (without mechanical ventilation);
- \$21 billion in benefits from 260,000 fewer ICU stays requiring mechanical ventilation;
- and
- \$19 billion in benefits from reductions in the cost and lost productivity resulting from 80,000 cases of lung damage.

For the upper bound, we estimate

- \$353 billion in benefits from 1.1 million prevented COVID-19 deaths;
- \$314 billion in benefits from 165 million fewer COVID-19 symptomatic infections;

- \$99 billion in benefits from 9.0 million fewer hospitalizations;
- \$74 billion in benefits from 1.8 million fewer ICU stays (without mechanical ventilation);
- \$78 billion in benefits from 950,000 fewer ICU stays requiring mechanical ventilation;
- and
- \$123 billion in benefits from reductions in the cost and lost productivity resulting from 530,000 cases of lung damage.

Note that the mortality reduction benefits associated with suppression measures are gross estimates and do not yet account for any increases in mortality risk that accompany economic dislocations. We return to this issue shortly.

THE COSTS OF SUPPRESSION AND SOCIAL DISTANCING

Forgone Output

A shock to economic output is to be expected regardless of what policies the government enacts in response to the outbreak of COVID-19. Relative to a baseline of continued pre-pandemic economic activity, Mulligan (2020, p. 7) estimates that the impacts of shutting down nonessential activities during the pandemic have total welfare costs of \$1,768 billion on a quarterly basis. An even more pessimistic forecast from Makridis and Hartley (2020) estimates total losses in GDP of just over \$2 trillion during the first two months of the COVID-19 outbreak in the United States (April and May). However, both estimates are of the total economic costs of private and public measures to slow the spread of COVID-19. The key challenge in calculating the costs of suppression measures is isolating the costs of policy from the costs of private action undertaken to mitigate risks during the pandemic.

Scherbina (2020) estimates that the incremental cost of suppression policies relative to mitigation of COVID-19 is approximately \$35.8 billion per week, or about \$5.1 billion per day, on average.¹⁶ According to this estimate, suppression policies alone may impose economic costs of \$143 billion every four weeks and \$465 billion every quarter, which are equivalent to 8.7 percent of GDP on an annual basis.

To estimate the aggregate costs of state-level suppression policies, we calculate the number of days during which the U.S. states enforced stay-at-home orders and nonessential business closures. Requiring residents to stay at home and requiring nonessential businesses to close are not the only suppression policies, but they likely imposed the most costs on economic output among the public policy interventions that were widely enforced during the initial outbreak of COVID-19. The start and end dates of these orders for each state are sourced from IHME (2020b) and listed in Table E-1 in Appendix E. If a policy remained in force as of May 26, 2020, we assume, like the IHME, that the policy will remain in force through the end of the forecast on August 4.

We weight the number of days that each state enforced stay-at-home orders and nonessential business closures by each state's GDP relative to U.S. GDP (Bureau of Economic Analysis, 2020). Weighting the number of suppression days by GDP reflects the fact that a day of suppression in larger states, such as California, causes more lost output than a day of suppression

¹⁶ Scherbina (2020) considers mitigation policies as described by Ferguson et al. (2020), as we do. "Suppression can be achieved by restricting travel, closing schools and nonessential businesses, banning social gatherings, and asking citizens to shelter in place. These measures, often referred to as a 'lockdown,' are highly restrictive on social freedoms and damaging to the economy. In contrast, a mitigation policy 'focuses on slowing but not necessarily stopping epidemic spread.' Mitigation measures may involve discouraging air travel while encouraging telecommuting, requiring companies to provide physical separation between workers, banning large gatherings, isolating the vulnerable, and identifying and quarantining contagious individuals and their recent contacts" (Scherbina, 2020, p. 1).

in smaller states, such as Maine. We then sum across states to calculate a weighted average of the number of days nonessential business closures and stay-at-home orders were in place.

Distinguishing the incremental costs specific to a stay-at-home order from the incremental costs of a nonessential business closure order (as well as distinguishing the incremental costs of when these policies are enforced jointly) is a difficult task. Accordingly, we calculate two weighted averages to produce lower- and upper-bound estimates of the number of days in which suppression policies were enforced in the United States, shown in Tables E-2 and E-3 in Appendix E.

First, we calculate the number of days that both a stay-at-home order and a nonessential business closure order were enforced at the same time. For the 21 states that did not enforce both types of legal orders jointly, we set the number of days of suppression equal to zero. In this lower-bound scenario, we estimate that U.S. states will enforce suppression, on average, for 50 days, or about 7 weeks.

Second, we calculate the number of days that *either* a stay-at-home order or a nonessential business closure order was enforced by states. For the six states that did not enforce either measure, we set the number of days of suppression policies equal to zero. In this upper-bound case, we estimate that suppression policies were enforced for an average of 91 days, which is equal to 13 weeks, or one economic quarter.

Multiplying the range of the estimated number of days in which the U.S. states enforced suppression policies (50–91 days) by the estimated incremental costs of suppression policies (\$5.1 billion), we estimate that state policies resulted in losses to economic output between \$255 billion and \$464 billion. Importantly, these cost estimates may overstate the incremental costs of policies if states that enforced them as of May 26, 2020, lift them before August 4, 2020. On the

other hand, our estimate may understate the incremental costs of these policies if states that lifted their orders before May 26, 2020, reenact those policies to slow an increase in COVID-19 cases or deaths.

Countervailing Risks from Lost Income

By early May of 2020, the United States faced the prospect of a prolonged economic recession. In the week ending May 2, 2020, the four-week moving average of weekly unemployment claims was almost 4.2 million (DOL, 2020a), and initial unemployment benefits claims remained above 2 million for each of the next three weeks, through May 23, 2020 (DOL, 2020b). Economic dislocation can impose costs not just on household finances but also on health and safety. While the effects of the business cycle on mortality can be positive or negative, depending on the risk being considered, the effects of lost income over the long term have more unambiguous detrimental effects on health. When incomes fall enough, deaths can be expected. Recent estimates suggest that for every \$111 million (in 2020 dollars) in reduced income, one expected death will occur (Broughel & Viscusi, in press). The mechanism driving this effect is that economic costs reduce expenditures made by households to reduce risks privately.

However, countervailing changes in mortality risks owing to income shocks can be positive or negative, depending on whether policies on balance impose costs or are cost saving. The total cost estimate of suppression policies above ranges from about \$255 billion to \$464 billion. Costs of \$255 billion to \$464 billion would correspond to about 2,300 to 4,200 additional expected deaths. However, total gross benefits are estimated be in the range of \$440 billion to \$1,041 billion. Because these benefits come in the form of cost savings or prevention of lost production (and by extension prevention of lost income), they result in offsetting countervailing

risk *reductions*, an estimated 4,000 to 9,400 expected lives saved. The net effect, therefore, of these countervailing risks ranges from 7,100 additional expected lives saved to 200 additional expected deaths.

Assuming these changes in risk are spread equally across the population, the age distribution of which is different from the age distribution of COVID-19 deaths, the lost production associated with 200 expected deaths would be approximately \$220 million, assuming a production value of the average American to be approximately \$1.1 million (see Table A-3 in Appendix A). The benefit associated with 7,100 fewer expected deaths is \$7.8 billion.

Taken together, the countervailing mortality risks associated with lost income may actually produce benefits up to \$7.8 billion, but this effect could also result in up to \$220 million in production costs. Whether the countervailing mortality risks are, on balance, beneficial will depend on whether suppression policies are cost saving. Combining these estimates with the gross mortality benefits estimated in the section on reduced mortality (\$299 billion to \$353 billion), we estimate net mortality benefits between \$299 billion and \$361 billion.

There are several factors to consider about these estimates. First, these expected deaths or lives saved could play out over a longer time horizon than the time period reviewed in our benefits analysis. The main channels by which income is likely to influence mortality are mental health and childhood socioeconomic status, which are long-acting channels (Broughel & Viscusi, in press). Similarly, the change in countervailing mortality risks is not static. Because some fraction of the net benefits associated with suppression measures will be reinvested and earn interest, countervailing changes in risk will grow as income grows with returns to capital. In this sense, the countervailing-risk changes calculated here are different from the changes in risk described in the benefits analysis, which can be thought of as occurring in a one-time fashion.

While the calculation of the net change in countervailing mortality risks does not significantly change our conclusion, we believe it is an important exercise in cost-benefit analysis to calculate these effects. Most estimates of the value of mortality risk reductions in cost-benefit analysis are gross estimates of the direct benefits of policies. As such, they often miss significant increases or decreases in countervailing risks, which, in some cases, can exceed the direct benefits of regulation. The implications of this distinction are made clearer in the next section, when we discuss other cost-benefit analyses of COVID-19 suppression measures.

DISCUSSION AND UNCERTAINTY

The most significant factor in our estimate of benefits is reduced mortality, estimated to be valued at \$299 billion to \$361 billion. After accounting for reduced health-care utilization and reduced development of permanent lung damage among a sizable subset of hospitalized patients who recover from COVID-19, we estimate that the total benefits of first-wave suppression policies are between \$440 billion and \$1,049 billion. Table 4 shows estimates of net effects, per person prevented costs, and aggregate benefits presented in the benefits section of the paper. It also shows our estimate of the total incremental cost of state suppression policies, between \$255 billion and \$464 billion, as well as our calculation of net benefits.

Our benefits estimate differs significantly from some other results from the recent literature. For example, Thunström et al. (in press) estimate that the United States should reasonably be willing to spend or forgo over \$12 trillion, or more than half of 2019 GDP, to reduce the negative health outcomes resulting from the pandemic. The study estimates net benefits of \$5.2 trillion, or 24 percent of 2019 U.S. GDP, after accounting for the costs of social distancing, which include the estimated effects of both private action and public health

interventions. Greenstone and Nigam (2020), using age-adjusted values of a statistical life, estimate that the mortality benefits of social distancing are more than \$8 trillion, or roughly \$60,000 per U.S. household. According to a back-of-the-envelope cost-benefit estimate by Zingales (2020), the United States should be willing to spend or forgo up to \$65 trillion, just over three years' worth of 2019 GDP, to address the pandemic.

Table 4. Net benefit estimates of COVID-19 suppression measures for mortality, health-care utilization, and lung damage (ARDS).

| Category | Effect relative to baseline | Value per person, 2020 USD | Value, 2020 USD |
|---------------------------------|------------------------------------|-----------------------------------|-------------------------------|
| Net reductions in mortality | 930,000–1.1 million | — | \$299–\$361 billion |
| Prevented COVID-19 deaths | 930,000–1.1 million | \$321,000 | \$299–\$353 billion |
| Initial deaths from lost income | (7,100)–200 | \$1.1 million | (\$7.8 billion)–\$220 million |
| COVID-19 symptomatic infections | 30–165 million | \$1,900 | \$57–\$314 billion |
| Hospitalizations | 2.3–9.0 million | \$11,000 | \$25–\$99 billion |
| ICU admissions | 710,000–2.8 million | — | — |
| No mechanical ventilation | 460,000–1.8 million | \$41,000 | \$19–\$74 billion |
| Mechanical ventilation | 260,000–950,000 | \$81,600 | \$21–\$78 billion |
| ARDS cases | 80,000–530,000 | \$232,000 | \$19–\$123 billion |
| Total benefits | — | — | \$440–\$1,049 billion |
| Total Costs | — | — | \$255–\$464 billion |
| Net Benefits | — | — | (\$24)–\$794 billion |

Source: Authors' calculations. Some sums may not be exact, owing to rounding.

We have several concerns about these estimates. One is that these estimates are best thought of as describing the costs or benefits of social distancing generally, not the costs and benefits of government suppression measures. This is not a criticism of these studies, just a clarification that a considerable amount of social distancing would occur even absent government shutdown orders. Our estimate, like that of Scherbina (2020), is of the costs and benefits of suppression policies, not the combined effect of suppression policies and private mitigation, the latter of which may be less useful to policymakers.

Second, the studies above consider only direct mortality reductions and fail to account for countervailing mortality risks associated with economic dislocations of social distancing generally and suppression policies specifically. While this countervailing effect may be positive or negative and did not have a significant effect on our general conclusion, it does have serious implications for other analyses, most notably that of Zingales (2020). Forgoing \$65 trillion in output could lead to 590,000 expected deaths based on a value of one induced death per \$111 million from Broughel and Viscusi (in press). The importance of countervailing risks becomes much more apparent once economic costs reach such large magnitudes.¹⁷

Another concern relates to the value of life chosen in these analyses. The studies above utilize the VSL to monetize mortality risk reductions, which is based on the willingness to pay to reduce death risks among the population and is, on average, about \$10 million for Americans (Department of Transportation, 2016). While we acknowledge considerable support for the VSL among economists, the VSL also has several problems that we believe make it unsuitable for use

¹⁷ The value of a statistical life (VSL) goes into the calculation of the \$111 million cost per statistical death figure, because the estimate is inferred from individual behavior using a structural model that incorporates the VSL. Just as COVID-19 represents a health risk shock that is likely too large for the VSL to be appropriate in benefits analysis, so too the income shock associated with three years' worth of forgone GDP may be too large for a VSL-based estimate of the mortality risk cutoff to be reliable.

in a COVID-19 CBA and possibly unsuitable for CBA more generally. The Office of Management and Budget (2003), Cameron (2010), and Pindyck (2020) note that the VSL is appropriate for valuing small risk reductions among unidentifiable individuals.¹⁸ It would therefore be inappropriate to use the VSL to value changes in very large, out-of-sample risks like those associated with COVID-19, which also affects known at-risk populations.

Moreover, the analyses above fail to fully account for the social opportunity cost of capital. The benefits to the individual of policy interventions that extend life are, by definition, temporary. While it may be reasonable for individuals or groups of individuals to value the benefits of extending life at around \$10 million, society faces a high opportunity cost for expending that same amount to extend life on behalf of those individuals. In particular, some of the resources spent saving lives would be invested instead, which produces benefits in the future (similarly, some of the benefits from extended life come in the form of investment). The above-mentioned studies make no distinction between benefits and costs that come in the form of consumption and benefits and costs that come in the form of investment. This is a problem because much of GDP is invested, while the benefits of extending life to individuals age 65 and older largely constitute consumption. This creates an imbalance between benefits and costs, because benefits and costs will grow at different rates depending on whether they are consumed or invested (Williams & Broughel, 2019).

¹⁸ Referencing the value of a statistical life, OMB *Circular A-4* states in regulatory analysis instructions to agencies, “You should make clear that these terms refer to the measurement of willingness to pay for reductions in only small risks of premature death. They have no application to an identifiable individual or to very large reductions in individual risks” (OMB, 2003). Also, “Noneconomists think we are valuing one whole, distinct, individual, and identifiable ‘life,’ when we are actually seeking to value tiny risk reductions for many different people” (Cameron, 2010, p. 5). According to Pindyck (2020, p. 19), the VSL “is a local measure that tells us how much wealth or consumption an individual would sacrifice in return for a small increase in the probability of survival. It does *not* tell us how much an individual would sacrifice to avoid a significant probability of death, which might be very different from the VSL” (emphasis in original).

Notably, our upper-bound estimate of \$1,049 billion in potential benefits of suppression policies is more consistent with a cost-effectiveness approach taken by van den Broek-Altenburg and Atherly (2020a; 2020b) that utilized the quality-adjusted life year metric (QALY).¹⁹ The QALY metric is well accepted among health-care experts, and a key advantage it has over the VSL is that it more concretely ties the value of life to the amount of life expectancy remaining for an individual, as well as the quality of remaining years of life. The justification for using QALYs in CBA is, however, somewhat hard to make. A QALY is a value assessed based on surveys with little connection to economic efficiency. Moreover, the threshold for a QALY, usually in the range of \$50,000 to \$150,000 per QALY, is essentially a rule of thumb that researchers have converged around (Neumann, Cohen, & Weinstein, 2014; Neumann & Cohen, 2018).

An important source of uncertainty in our benefit and cost estimates, particularly regarding reductions in COVID-19 deaths, is our choice of baseline against which to evaluate the impact of state public health policies. The Ferguson et al. (2020) projection of targeted mitigation assumes that only infected people, their households, and elderly individuals take action to mitigate against the spread of COVID-19. However, in an analysis of aggregated smartphone location data, Luther (2020) observes that almost all the increases in large numbers of people staying at their residences occurred before states formally enforced stay-at-home policies. If the private response to COVID-19 more closely resembles population-wide social distancing than targeted private mitigation, then the incremental costs and benefits of suppression policies reported in this article are likely both overstated.

¹⁹ Specifically, van den Broek-Altenburg and Atherly (2020a) estimate that total costs spent addressing COVID-19 that exceed about \$1 trillion would fail to be cost effective in terms of life-years gained. Their estimate uses a standard cost-effectiveness benchmark of spending no more than \$100,000 per life-year gained. In a more recent cost-effectiveness analysis using QALYs, van den Broek-Altenburg and Atherly (2020b) find cost per QALY gained of between \$500,000 and \$6.7 million.

Our benefits estimate is also limited by our use of the model from the IHME to forecast the pandemic's progression under government suppression orders. The underlying methods and assumptions in the IHME model have been criticized (Jewell, Lewnard, & Jewell, 2020), and, to date, the IHME model has performed poorly in predicting daily deaths (Marchant et al., 2020). Major updates incorporated into the model as of May 4 may address these concerns of methodology and accuracy (IHME, 2020a). But if the IHME model underestimates the number of deaths or the amount of health-care utilization during the first wave, then our estimates overstate benefits.

There are also limitations to the cost measures presented here. First, the cost estimates focus on lost output, which may not precisely reflect the total production costs of the pandemic. Declines in some forms of market production, such as childcare or restaurant dining, could be made up for by nonmarket production in the household, such as homeschooling or making dinner at home. In this sense, estimates of changes in output could overestimate the costs of suppression policies. On the other hand, the value of some market production, such as research and development (R&D) expenditures or investments in human capital, can have external benefits that are greater than their contributions to short-run output. In this sense, it's conceivable that some declines in market production will underestimate the total cost to output. Another limitation of the cost analysis is uncertainty regarding the incremental costs specific to stay-at-home orders, nonessential business closures, and other suppression policies, as well as their incremental costs when these policies are enforced separately versus jointly.

Importantly, this is a CBA produced during a developing and rapidly changing public health emergency. Many U.S. states lifted their stay-at-home and nonessential business closure orders in May 2020. The total benefits and costs of government policies to address the initial

outbreak of COVID-19 and mitigate against its continued spread are subject to change based on how effectively states deploy techniques and technologies that facilitate more targeted public health interventions, such as testing or contact tracing, or if states revert to suppression policies to address any spikes in cases or deaths.

Public health interventions clearly have a role to play in reducing the impacts of COVID-19. Cities with earlier and more aggressive public-health interventions in response to the 1918 Spanish flu may have recovered more quickly (Correia, Luck, & Verner, 2020). Effective interventions may also reduce the economic costs associated with uncertainty, which affects investments in capital and R&D. Baker et al. (2020) project that year-over-year GDP may decline 11 percent (and possibly up to 20 percent) in 2020, estimating that about half of that contraction can be attributed to uncertainty caused by the COVID-19 pandemic.

However, the COVID-19 pandemic is distinct from the 1918 Spanish flu in a way that has significant implications for the efficiency of various policy responses.²⁰ As shown in Tables 1 and 3, the age distribution of COVID-19 deaths and hospitalizations skews heavily toward elderly individuals, while the 1918 Spanish flu pandemic caused deaths in much greater concentrations among people age 15 to 44 (Erkoreka, 2010). Those who contribute the most to economic production are not those most at risk during the current pandemic, which suggests that tailored policies can optimize both suppression of coronavirus spread and the economic impacts of COVID-19.

Indeed, Acemoglu et al. (2020) find that targeted interventions that protect elderly people and other at-risk groups from infection significantly reduce COVID-19 deaths and losses to output by allowing working-age people to live under less strict suppression measures. Such

²⁰ Additionally, the effectiveness of 1918 Spanish flu interventions is disputed. See Lilley, Lilley, and Rinaldi (2020).

targeted interventions could include widespread random testing, contact tracing, variolation, and accelerating the testing, approval, and use of drug therapies and vaccines. These policy alternatives are discussed in more detail in Appendix C. They deserve separate cost-benefit analysis and may address the economic and health impacts of the COVID-19 pandemic more effectively than the widespread suppression measures in place in the second quarter of 2020.

CONCLUSION

Suppression policies imposed in the U.S. states have likely brought (and will continue to bring) substantial benefits. Relative to targeted private mitigation against the risk of infection, we estimate that the benefits of suppression policies that bent the curve of COVID-19 are between \$440 billion and \$1,049 billion through August 4, 2020. However, we find that suppression policies had substantial costs, too, between \$255 billion and \$464 billion. Our results suggest that the net benefits of suppression policies are likely substantial, possibly as high as \$800 billion, but net benefits may also be close to zero. Moreover, this estimate assumes that the bending of the curve in the United States is largely attributable to suppression policies that were implemented in most U.S. states for between 50 and 91 days on average and that, in the absence of such policies, about one million people in the United States would have died of COVID-19.

Going forward, the costs and benefits of suppression policies will largely depend on the deployment and efficacy of more targeted interventions to contain the coronavirus after the reopening of nonessential businesses and the easing of stay-at-home requirements. We discuss several such interventions in Appendix C, including widespread random testing, stratified periodic testing, contact tracing, variolation, and accelerating the testing, approval, and use of

drug therapies and vaccines. Such measures may offer a path to a rebound in economic activity without risking another outbreak.

It may well be that there are no good options available to policymakers during a pandemic. Choosing the least bad option from a set of many bad alternatives may be the only choice. CBA that properly considers the relevant tradeoffs both now and in the future can assist in identifying the best available option and offer guidance toward a better path forward.

REFERENCES

- Acemoglu, D., Chernozhukov, V., Werning, I., & Whinston, M.D. (2020). A multi-risk SIR model with optimally targeted lockdown. NBER Working Paper No. 27102. Cambridge, MA: National Bureau of Economic Research.
- Allen, D., Block, S., Cohen, J., Eckersley, P., Eifler, M., Gostin, L., ... Weyl, E.G. (2020). Roadmap to pandemic resilience: Massive scale testing, tracing, and supported isolation (TTSI) as the path to pandemic resilience for a free society. Cambridge, MA: Edmond J. Safra Center for Ethics at Harvard University. Retrieved from <https://ethics.harvard.edu/Covid-Roadmap>.
- Baker, S.R., Bloom, N., Davis, S.J., & Terry, S.J. (2020). COVID-induced economic uncertainty. NBER Working Paper No. 26983. Cambridge, MA: National Bureau of Economic Research.
- Basu, A. (2020). Estimating the infection fatality rate among symptomatic COVID-19 cases in the United States. *Health Affairs*, 39, 1–6.
- Bradford, D.F. (1975). Constraints on government investment opportunities and the choice of discount rate. *The American Economic Review*, 65, 887–899.
- Broughel, J., & Viscusi, W.K. (in press). The mortality cost of expenditures. *Contemporary Economic Policy*.

Cameron, T. (2010, summer). Euthanizing the value of a statistical life. *Review of Environmental Economics and Policy*, 4, 161–178.

Chu, C., Cheng, V., Hung, I., Chan, K., Tang, B., Tsang, T., ... Yuen, K. (2005). Viral load distribution in SARS outbreak. *Emerging Infectious Diseases*, 11, 1882–1886.

Chu, C., Poon, L., Cheng, V., Chan, K., Hung, I., Wong, W., ... Yuen, K. (2004, November). Initial viral load and the outcomes of SARS. *CMAJ*, 171, 1349–1352.

Cleevly, M., Susskind, D., Vines, D., Vines, L., & Wills, S. (2020, April). A workable strategy for Covid-19 testing: Stratified periodic testing rather than universal random testing. *Centre for Economic Policy Research, Covid Economics*, 8, 44–70.

Correia, S., Luck, S., & Verner, E. (2020). Pandemics depress the economy, public health interventions do not: Evidence from the 1918 flu. Unpublished manuscript.

Cropper, M., & Sussman, F. (1990). Valuing future risks to life. *Journal of Environmental Economics and Management*, 19, 160–174.

Dasta, J.F., McLaughlin, T.P., Mody, S.H., & Piech, C.T. (2005). Daily cost of an intensive care unit day: The contribution of mechanical ventilation. *Critical Care Medicine*, 33, 1266–1271.

Dudley, S., & Brito, J. (2012). *Regulation: A primer*. Arlington, VA: Mercatus Center at George Mason University.

Erkoreka, A. (2010). The Spanish influenza pandemic in occidental Europe (1918–1920) and victim age. *Influenza and Other Respiratory Viruses*, 4, 81–89.

Ferguson, N., Laydon, D., Nedjati Gilani, G., Imai, N., Ainslie, K., Baguelin, M., ... Ghani, A. (2020). Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. COVID Response Team. Imperial College London.

Greenstone, M., & Nigam, V. (2020). Does social distancing matter? Becker Friedman Institute for Economics Working Paper No. 2020-26. Chicago: University of Chicago.

Grosse, S.D., Krueger, K.V., & Mvundura, M. (2009). Economic productivity by age and sex: 2007 estimates for the United States. *Medical Care*, 47, S94–S103.

Haltiwanger, J. (2020, April). Applications for new businesses contract sharply in recent weeks: A first look at the weekly business formation statistics. Unpublished manuscript, Department of Economics, University of Maryland, College Park, MD. Retrieved April 8, 2020, from http://econweb.umd.edu/~haltiwan/first_look.pdf.

Hanson, R. (2020, March 14). Expose the young [Web log post]. Retrieved March 14, 2020, from <http://www.overcomingbias.com/2020/03/expose-the-young.html>.

Institute for Health Metrics and Evaluation (IHME). (2020a, May 4). COVID-19: What's New for May 4, 2020. Retrieved June 6, 2020, from http://www.healthdata.org/sites/default/files/files/Projects/COVID/Estimation_update_050420.pdf.

Institute for Health Metrics and Evaluation (IHME). (2020b, May 26). COVID-19 hospital needs and death projections. Retrieved May 27, 2020, from <http://www.healthdata.org/covid/data-downloads>.

Jewell, N., Lewnard, J., & Jewell, B. (2020, April). Caution warranted: Using the Institute for Health Metrics and evaluation model for predicting the course of the COVID-19 pandemic. *Annals of Internal Medicine*.

Kirzner, I. (2012). The pure time preference theory of interest: An attempt at clarification. In P.J. Boettke & F. Sautet (Eds.), *Essays on capital and interest: An Austrian perspective*. Indianapolis, IN: Liberty Fund.

Lilley, A., Lilley, M., & Rinaldi, G. (2020, May). Public health interventions and economic growth: Revisiting the Spanish flu evidence. Unpublished manuscript.

Lind, R. (1982). A primer on the major issues relating to the discount rate for evaluating national energy options. *Discounting for Time and Risk in Energy Policy*, 3, 21–94.

Liu, Y., Yan, L., Wan, L., Xiang, T., Le, A., Liu, J., ... Zhang, W. (2020, March). Viral dynamics in mild and severe cases of COVID-19. *The Lancet Infectious Diseases*, 20, 656–657.

Luther, W. (2020, May 28). Estimating the effect of state-level stay-at-home orders. Unpublished manuscript.

Makridis, C., & Hartley, J. (2020). The cost of COVID-19: A rough estimate of the 2020 U.S. GDP impact. Arlington, VA: Mercatus Center at George Mason University. Retrieved from <https://www.mercatus.org/publications/covid-19-policy-brief-series/cost-covid-19-rough-estimate-2020-us-gdp-impact>.

Marchant, R., Samia, N., Rosen, O., Tanner, M.A., & Cripps, S. (2020). Learning as we go: An examination of the statistical accuracy of COVID19 daily death count predictions. Manuscript in preparation, e-print on arXiv. Retrieved from <https://arxiv.org/abs/2004.04734>.

Marglin, S.A. (1963). The opportunity costs of public investment. *The Quarterly Journal of Economics*, 77, 274–289.

Mizumoto, K., Kagaya, K., Zarebski, A., & Chowell, G. (2020). Estimating the asymptomatic proportion of coronavirus disease 2019 (COVID-19) cases on board the Diamond Princess cruise ship, Yokohama, Japan, 2020. *Eurosurveillance* 25, 2–6.

Mulligan, C.B. (2020, April). Economic activity and the value of medical innovation during a pandemic. BFI Working Paper No. 2020-48. Chicago: Becker Friedman Institute for Economics at the University of Chicago.

Murray, C. & IHME COVID-19 Health Service Utilization Forecasting Team. (2020, April). Forecasting the impact of the first wave of the COVID-19 pandemic on hospital demand and deaths for the USA and European Economic Area countries. Unpublished manuscript, medRxiv preprint 2020.04.21.20074732.

Neumann, P.J., Cohen, J.T., & Weinstein, M.C. (2014). Updating cost-effectiveness: The curious resilience of the \$50,000-per-QALY threshold. *The New England Journal of Medicine*, 371, 796–797.

Neumann, P.J., & Cohen, J.T. (2018). QALYs in 2018: Advantages and concerns. *JAMA*, 319, 2473–2474.

Nishiura, H., Kobayashi, T., Miyama, T., Suzuki, A., Jung, S., Hayashi, K., ... Linton, N.M. (2020). *International Journal of Infectious Diseases*, 94, 154–155.

Pindyck, R. (2020). COVID-19 and the welfare effects of reducing contagion. NBER Working Paper No. 27121. Cambridge, MA: National Bureau of Economic Research.

Romer, P. (2020, March 24). Simulating COVID-19: Part 2 [Web log post]. Retrieved May 7, 2020, from <https://paulromer.net/covid-sim-part2/>.

Ruhl, A.P., Huang, M., Colantuoni, E., Karmarkar, T., Dinglas, V.D., Hopkins, R.O., & Needham, D.M. (2017). Healthcare utilization and costs in ARDS survivors: A 1-year longitudinal national U.S. multicenter study. *Intensive Care Medicine*, 43, 980–991.

Russell, T.W., Hellewell, J., Jarvis, C., van-Zandvoort, K., Abbott, S., & Ratnayake, R. (2020). Estimating the infection and case fatality ratio for coronavirus disease (COVID-19) using age-adjusted data from the outbreak on the Diamond Princess cruise ship, February 2020. *Eurosurveillance* 25, 10–14.

Scherbina, A. (2020, March). Determining the optimal duration of the COVID-19 suppression policy: A cost-benefit analysis. AEI Economic Policy Working Paper Series. Washington, DC: American Enterprise Institute. Retrieved March 27, 2020, from <https://www.aei.org/research-products/working-paper/determining-the-optimal-duration-of-the-covid-19-suppression-policy-a-cost-benefit-analysis/>.

Skorup, B., & Mitchell, T. (2020). Aggregated smartphone location data to assist in response to pandemic. Arlington, VA: Mercatus Center at George Mason University. Retrieved from <https://www.mercatus.org/publications/covid-19-policy-brief-series/aggregated-smartphone-location-data-assist-response>.

Thunström, L., Newbold, S., Finnoff, D., Ashworth, M., & Shogren, J.F. (in press). The benefits and costs of flattening the curve for COVID-19. *Journal of Benefit-Cost Analysis*.

Torio, C., & Moore, B. (2016). National inpatient hospital costs: The most expensive conditions by payer, 2013. HCUP Statistical Brief #204. Rockville, MD: Agency for Healthcare Research and Quality.

U.S. Bureau of Economic Analysis (BEA). (2020, April). Gross domestic product by state, 4th quarter and annual 2019. Suitland, MD: Bureau of Economic Analysis. Retrieved June 1, 2020, from <https://www.bea.gov/system/files/2020-04/qgdpstate0420.pdf>.

U.S. Census Bureau. (2019). 2018 American Community Survey 5-Year Estimates: Table S0101, Age and Sex. Suitland, MD: U.S. Census Bureau. Retrieved May 27, 2020, from <https://data.census.gov/cedsci/table?q=Age%20and%20Sex&t=Age%20and%20Sex&hidePreview=false&tid=ACST5Y2018.S0101&vintage=2018>.

U.S. Centers for Disease Control and Prevention (CDC). (2020a, April 29). Provisional death counts for coronavirus disease (COVID-19). Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved May 27, 2020, from https://www.cdc.gov/nchs/nvss/vsrr/covid_weekly/index.htm.

U.S. Centers for Disease Control and Prevention. (2020b, May 6). What to do if you are sick. Atlanta, GA: U.S. Centers for Disease Control and Prevention. Retrieved May 7, 2020, from <https://www.cdc.gov/coronavirus/2019-ncov/if-you-are-sick/steps-when-sick.html>.

U.S. Centers for Disease Control and Prevention. (2020c, May 16). COVID-NET: COVID-19-associated hospitalization surveillance network. Retrieved May 27, 2020, from https://gis.cdc.gov/grasp/COVIDNet/COVID19_5.html.

U.S. Centers for Disease Control and Prevention. (2020d, May 20). COVID-19 pandemic planning scenarios. Retrieved May 31, 2020, from <https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html>.

U.S. Department of Labor (DOL). (2020a, May 7). Unemployment insurance weekly claims. Washington, DC: U.S. Department of Labor. Retrieved May 7, 2020, from <https://oui.doleta.gov/press/2020/050720.pdf>.

U.S. Department of Labor. (2020b, May 28). Unemployment insurance weekly claims. Washington, DC: U.S. Department of Labor. Retrieved June 1, 2020, from <https://oui.doleta.gov/press/2020/052320.pdf>.

U.S. Department of Transportation (DOT). (2016). Guidance on treatment of the economic value of a statistical life (VSL) in U.S. Department of Transportation analyses – 2016 adjustment. Official memorandum. Washington, DC: U.S. Department of Transportation. Retrieved May 8,

2020, from <https://cms8.dot.gov/sites/dot.gov/files/docs/2016%20Revised%20Value%20of%20a%20Statistical%20Life%20Guidance.pdf>.

U.S. Office of Management and Budget (OMB). (2003, September 17). Circular A-4: Regulatory analysis. Washington, DC: U.S. Office of Management and Budget. Retrieved from https://obamawhitehouse.archives.gov/omb/circulars_a004_a-4/.

van den Broek-Altenburg, E., & Atherly, A. (2020a, March 24). Economic cost of flattening the curve [Web log post]. Retrieved March 24, 2020, from <https://theincidentaleconomist.com/wordpress/economic-cost-of-flattening-the-curve/>.

van den Broek-Altenburg, E., & Atherly, A. (2020b, May 7). Revisiting the economic cost of flattening the curve [Web log post]. Retrieved May 7, 2020, from <https://theincidentaleconomist.com/wordpress/revisiting-the-economic-cost-of-flattening-the-curve/>.

Verity, R., Okell, L.C., Dorigatti, I., Winskill, P., Whittaker, C., Imai, N., ... Ferguson, N.M. (2020). Estimates of the severity of coronavirus disease 2019: a model-based analysis. *The Lancet Infectious Diseases*, 20, 669–677.

Viscusi, W.K. (2018). *Pricing lives: Guideposts for a safer society*. Princeton, NJ: Princeton University Press.

Wang, D., Hu, B., Hu, C., Zhu, F., Liu, X., Zhang, J., ... Peng, Z. (2020). Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus: Infected pneumonia in Wuhan, China. *JAMA*, 323, 1061–1069.

Williams, R., & Broughel, J. (2019, winter). Toward an improved OMB annual report on federal regulations. Regulation 42. Retrieved from <https://www.cato.org/sites/cato.org/files/2019-12/v42n4-5.pdf>.

World Health Organization (WHO). (2020, June 7). Coronavirus disease (COVID-19) situation report – 139. Geneva, Switzerland: World Health Organization. Retrieved June 8, 2020, from https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200607-covid-19-sitrep-139.pdf?sfvrsn=79dc6d08_2.

Yeoh, B. (2020). Regulators could allow early use of COVID-19 vaccine or treatment. Arlington, VA: Mercatus Center at George Mason University. Retrieved from <https://www.mercatus.org/publications/covid-19-policy-brief-series/regulators-could-allow-early-use-covid-19-vaccine-or>.

Yu, X., Sun, S., Shi, Y., Wang, H., Zhao, R., & Sheng, J. (2020). SARS-CoV-2 viral load in sputum correlates with risk of COVID-19 progression. *Critical Care*, 24, 170.

Zhou, F., Yu, T., Du, R., Fan, G., Liu, Y., Liu, Z., ... Xiang, J. (2020). Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: A retrospective cohort study. *The Lancet*, 395, 1054–1062.

Zhou, P., Yang, X., Wang, X., Hu, B., Zhang, L., Zhang, W., ... Shi, Z. (2020). A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature*, 579, 270–273.

Zingales, L. (2020, March 13). Captured western governments are failing the coronavirus test [Web log post]. Retrieved March 25, 2020, from <https://promarket.org/captured-western-governments-are-failing-the-coronavirus-test/>.

Zou, L., Ruan, F., Huang, M., Liang, L., Huang, H., Hong, Z., ... Wu, J. (2020). SARS-CoV-2 viral load in upper respiratory specimens of infected patients. *New England Journal of Medicine*, 382, 1177–1179.

Appendix A. Production-Value-of-Life Tables

Table A-1. Author calculations of the present value of lifetime production by age, adjusted to age groups in CDC COVID-19 deaths counts.

| Age | Lifetime total production, 2007 USD | Lifetime total production, 2020 USD | CDC COVID-19 deaths age groups | Lifetime total production, 2020 USD |
|----------|-------------------------------------|-------------------------------------|--------------------------------|-------------------------------------|
| 0 to 4 | \$568,817 | \$864,396 | 0 to 4 | \$864,396 |
| 5 to 9 | \$692,331 | \$1,052,093 | 5 to 14 | \$1,165,275 |
| 10 to 14 | \$841,290 | \$1,278,457 | | |
| 15 to 19 | \$999,322 | \$1,518,608 | 15 to 24 | \$1,609,646 |
| 20 to 24 | \$1,119,137 | \$1,700,684 | | |
| 25 to 29 | \$1,164,022 | \$1,768,893 | | |
| 30 to 34 | \$1,130,428 | \$1,717,842 | 25 to 34 | \$1,743,368 |
| 35 to 39 | \$1,051,137 | \$1,597,348 | 35 to 44 | \$1,511,338 |
| 40 to 44 | \$937,939 | \$1,425,328 | | |
| 45 to 49 | \$802,484 | \$1,219,486 | 45 to 54 | \$1,102,485 |
| 50 to 54 | \$648,498 | \$985,483 | | |
| 55 to 59 | \$486,469 | \$739,257 | | |
| 60 to 64 | \$338,632 | \$514,598 | 55 to 64 | \$626,928 |
| 65 to 69 | \$230,954 | \$350,967 | 65 to 74 | \$305,058 |
| 70 to 74 | \$170,533 | \$259,149 | | |
| 75 to 79 | \$123,803 | \$188,136 | 75 to 84 | \$163,013 |

| | | | | |
|---------|----------|-----------|---------|-----------|
| 80 plus | \$90,738 | \$137,889 | | |
| | | | 85 plus | \$137,889 |

Sources: Grosse, Kruger, and Mvundura (2009, p. S100); CDC (2020a).

Note: We use the Grosse, Kruger, and Mvundura (2020, p. S100) estimates that apply a 5 percent discount rate, and then we adjust for inflation using the CPI from January 2007 to January 2020. We also adjust for average annual labor productivity growth, measured in terms of real output per hour, from 2007 to the end of 2019, which was approximately 1.39 percent per year on an annualized basis. Lifetime total production values represent an average of the production values for the age groups from Grosse, Kruger, and Mvundura (2009) that the CDC age groups span.

Table A-2. Author calculations of the present value of lifetime production by age, adjusted to age groups in CDC hospitalized patient counts.

| Age | Lifetime total production, 2007 USD | Lifetime total production, 2020 USD | CDC hospitalization age groups | Lifetime total production, 2020 USD |
|----------|-------------------------------------|-------------------------------------|--------------------------------|-------------------------------------|
| 0 to 4 | \$568,817 | \$864,396 | 0 to 4 | \$864,396 |
| 5 to 9 | \$692,331 | \$1,052,093 | 5 to 17 | \$1,283,053 |
| 10 to 14 | \$841,290 | \$1,278,457 | | |
| 15 to 19 | \$999,322 | \$1,518,608 | | |
| 20 to 24 | \$1,119,137 | \$1,700,684 | | |
| 25 to 29 | \$1,164,022 | \$1,768,893 | 18 to 49 | \$1,571,597 |
| 30 to 34 | \$1,130,428 | \$1,717,842 | | |
| 35 to 39 | \$1,051,137 | \$1,597,348 | | |
| 40 to 44 | \$937,939 | \$1,425,328 | | |
| 45 to 49 | \$802,484 | \$1,219,486 | | |
| 50 to 54 | \$648,498 | \$985,483 | 50 to 64 | \$746,446 |
| 55 to 59 | \$486,469 | \$739,257 | | |

| | | | | |
|----------|-----------|-----------|---------|-----------|
| 60 to 64 | \$338,632 | \$514,598 | | |
| 65 to 69 | \$230,954 | \$350,967 | 65 plus | \$234,035 |
| 70 to 74 | \$170,533 | \$259,149 | | |
| 75 to 79 | \$123,803 | \$188,136 | | |
| 80 plus | \$90,738 | \$137,889 | | |

Sources: Grosse, Kruger, and Mvundura (2009, p. S100); CDC (2020c).

Note: We use the Grosse, Kruger, and Mvundura (2020, p. S100) estimates that apply a 5 percent discount rate, and then we adjust for inflation using the CPI from January 2007 to January 2020. We also adjust for average annual labor productivity growth, measured in terms of real output per hour, from 2007 to the end of 2019, which was approximately 1.39 percent per year on an annualized basis. Lifetime total production values represent an average of the production values for the age groups from Grosse, Kruger, and Mvundura (2009) that the CDC (2020c) age groups span.

Table A-3. Expected lifetime production lost to increased mortality from lost national income.

| Age | Lifetime total production, 2020 USD | U.S. population (2018) | Approx. percentage of U.S. population (2018) | Expected lifetime production, 2020 USD |
|----------|-------------------------------------|------------------------|--|--|
| 0 to 4 | \$864,396 | 19,836,850 | 6.1% | \$53,102 |
| 5 to 9 | \$1,052,093 | 20,311,494 | 6.3% | \$66,180 |
| 10 to 14 | \$1,278,457 | 20,817,419 | 6.4% | \$82,422 |
| 15 to 19 | \$1,518,608 | 21,204,226 | 6.6% | \$99,723 |
| 20 to 24 | \$1,700,684 | 22,286,970 | 6.9% | \$117,382 |
| 25 to 29 | \$1,768,893 | 22,779,537 | 7.1% | \$124,788 |
| 30 to 34 | \$1,717,842 | 21,788,439 | 6.7% | \$115,914 |
| 35 to 39 | \$1,597,348 | 20,730,622 | 6.4% | \$102,551 |
| 40 to 44 | \$1,425,328 | 20,032,588 | 6.2% | \$88,426 |
| 45 to 49 | \$1,219,486 | 20,827,879 | 6.5% | \$78,659 |
| 50 to 54 | \$985,483 | 21,761,694 | 6.7% | \$66,416 |

| | | | | |
|----------|-----------|-------------|------|--------------------|
| 55 to 59 | \$739,257 | 21,611,374 | 6.7% | \$49,477 |
| 60 to 64 | \$514,598 | 19,675,357 | 6.1% | \$31,356 |
| 65 to 69 | \$350,967 | 16,409,942 | 5.1% | \$17,836 |
| 70 to 74 | \$259,149 | 12,125,477 | 3.8% | \$9,731 |
| 75 to 79 | \$188,136 | 8,549,216 | 2.6% | \$4,981 |
| 80 plus | \$137,889 | 12,153,946 | 3.8% | \$5,190 |
| Total | — | 322,903,030 | 100% | \$1,114,134 |

Sources: Grosse, Kruger, and Mvundura (2009, p. S100); U.S. Census Bureau (2019).

Note: Differences or sums may not be exact owing to rounding. Grosse, Kruger, and Mvundura (2009, p. S100) present lifetime production by five-year increments between ages 0 and 80+. The U.S. Census Bureau (2019) reports population by age in the same five-year increments, except that it separates those who are 80–84 years old from those 85 or older, so we take the sum of those two groups to align them with the Grosse, Kruger, and Mvundura (2009, p. S100) production estimates. Refer to Table A-1 and Table A-2 for adjustments of Grosse, Kruger, and Mvundura (2009) for inflation and productivity growth.

Appendix B. Market Failure Analysis

Market failures provide the economic justification for government intervention in private markets (Dudley & Brito, 2012). An economic analysis should therefore include an analysis of the market failure at hand to ensure there is even the potential that government intervention could increase social welfare. Without a market failure, no net social benefits are possible.

A fatal, contagious disease like COVID-19 has several attributes of a market failure worthy of consideration. First, public health itself is a public good. Fewer contagious diseases mean a more productive workforce, which provides benefits to all citizens. Moreover, the benefit to one citizen from living in a healthy society doesn't necessarily mean fewer benefits fall on other citizens (and inversely, the costs of living in an unhealthy society can fall on everyone and be nonrivalrous). Because public goods are often associated with free-rider problems (i.e., it is hard to get people to pay for public goods voluntarily since they will receive them or not, irrespective of whether they individually pay), there could be underinvestment in public health and therefore a rationale for government intervention to address pandemics on the grounds of public goods.

Of course, public health covers a broad range of issues, not just pandemics such as COVID-19. The market failure argument often made specifically with a pandemic relates to negative externalities. When a pandemic is spreading across a region, the probability that any particular individual will get sick usually remains small. For people focused solely on their own self-interest, it might make sense to continue life as usual. This is especially true for younger, working-age people who so far have experienced relatively fewer adverse health outcomes, even after contracting the virus. When any individual maintains normal activities, however, the marginal risk to others is increased, even if only by a small amount. When everyone behaves in

this way, risk can increase substantially, and this could negatively impact welfare relative to what is socially optimal.

However, there is another market failure to consider. It might be true that staying home and engaging in social distancing reduce a negative externality of increased risk on one's fellow citizens right now. However, risk reduction can't be invested in an account, and there is a negative externality imposed on people in the future when production is stalled by staying home. Forgoing production means less investment in the economy and less growth, and these costs fall primarily on future generations. The external benefits of production are not fully captured by market prices because the productive returns to capital are not fully reflected in the price of a capital asset owing to time preference (Kirzner, 2012).

Therefore, staying at home to avoid illness imposes a negative externality on the future, while maintaining business as usual imposes a negative externality to high-risk populations in the present. Government CBAs often take a static approach that emphasizes short-run concerns. For example, the approach often taken is for outcomes affecting future citizens to enter the utility function of current citizens, or for current citizens to value leaving a bequest to future citizens, without the utility of future generations entering the social welfare function directly. This is true, for example, in the models underlying mortality risk valuations (Cropper & Sussman, 1990). Our view is that CBA ought to account for the relative importance of these countervailing market failures, and we employ a method of valuing benefits and costs that attempts to do so.

Appendix C. Consideration of Regulatory Alternatives

The policy approach of the U.S. states has been to enforce suppression measures that attempt to slow the spread of coronavirus. Cities, counties, and states have, in isolation or some combination, forced the closure of schools and nonessential businesses, restricted travel, banned large public events, restricted the size of private gatherings, and ordered residents to stay home. The enactment of these measures has varied considerably across states (probably because the impact of the disease varies considerably across the states), but the broad goal of these measures is to prevent scenarios under which demand for hospital and ICU beds, as well as mechanical ventilators, outstrips the capacity of the health-care system.

These suppression measures, which are applied in a broad and uniform manner, contrast with more targeted interventions that attempt to slow the spread of the virus without subjecting almost the entire population of a city, county, or state to restrictions. Targeted measures, whether done voluntarily or under government mandate, might include isolation of the sick, two-week quarantines for households with symptoms, contact tracing of those identified as infected, and voluntary social distancing for elderly individuals and other high-risk populations.

The primary concern raised about these more targeted measures is that these measures alone do not account for carriers of the virus who may spread the disease without showing symptoms. In the absence of widespread testing to confirm who does and does not carry the virus, the virus may continue to spread at a high rate by asymptomatic carriers of the virus,²¹ potentially resulting in a much higher number of morbidities and deaths than under the suppression approach.

²¹ An analysis of passengers who were comprehensively tested for COVID-19 aboard the *Diamond Princess*, a cruise liner quarantined off the coast of Japan in early February of 2020, revealed that about 18 percent of cases were without symptoms (Mizumoto et al., 2020). Meanwhile, the CDC (2020d) estimates that 35 percent of people who are infected by coronavirus in the United States may never develop symptoms.

Widespread random testing is one means of achieving targeted isolation of the sick, both the symptomatic and asymptomatic. Romer (2020) proposes that 7 percent of the U.S. population (about 23 million people) be randomly selected each day so that, on average, each person in the United States would be tested for COVID-19 once every two weeks. However, technological, regulatory, and simple supply challenges have stood in the way of the millions of weekly tests that would likely be required to successfully isolate the infected and allow most others to return to the normal course of their lives. Cleevly et al. (2020) propose “stratified periodic testing” of certain subgroups, such as health-care workers in hospitals and nursing home facilities, who are likely to spread coronavirus at a greater rate than the general population, particularly to high-risk patients. Another means of targeted isolation in the near term is the use of smartphone applications that allow for notification of those who have come in close contact with the sick. The use of aggregated location data could allow for the easing of suppression measures in regions at a lower risk of a coronavirus outbreak (Skorup & Mitchell, 2020). A report from Harvard's Edmond J. Safra Center for Ethics proposes that a combination of at least 5 million daily tests, contact tracing, and case isolation be employed in order to address COVID-19 in a more targeted manner (Allen et al., 2020).

Other alternatives could include facilitating treatment of the sick or the development of herd immunity. The FDA could enact reforms that accelerate the development and availability of drug therapies and vaccines, but even the most optimistic outlooks place the final approval, manufacture, and distribution of a coronavirus vaccine in early 2021 (Yeoh, 2020). Variolation may also facilitate immunity and allow people to safely engage in work and economic activity in the near term. By purposefully exposing themselves to a small, controlled dose of the coronavirus, relatively young and healthy people may reduce their own risk of an adverse health

outcome that may result from an accidental high-dose exposure, while also promoting herd immunity among the general population and reducing risk of exposure for the elderly and high-risk populations (Hanson, 2020). However, the safety and effectiveness of variolation depends on two assumptions being satisfied, both of which would need to be studied further and considered before implementation. First, variolation requires that the degree of exposure to coronavirus determines the severity of the resulting illness, which was shown for the coronavirus strain that caused the SARS epidemic in 2002–2003 (Chu et al., 2004; Chu et al., 2005). For the 2019 novel coronavirus, some studies have found a significant positive relationship between viral loads and the severity of symptoms (Liu et al., 2020; Yu et al., 2020), while Zou et al. (2020) find similar viral loads among asymptomatic and symptomatic cases of COVID-19. Second, exposure to the novel coronavirus must result in immunity for a meaningful period of time for variolation to be successful, and the reinfection rates of COVID-19 are not conclusive.

We believe these alternatives that allow for more targeted interventions merit serious consideration and separate CBAs. However, our analysis is focused on suppression measures and their costs and benefits relative to the absence of these measures, which is the question that seems most pertinent to debates in mid-2020 about whether to “reopen” the economy.

Appendix D. The Production Value of Life vs. the Value of a Statistical Life

A potential criticism of our analysis is that we use a value of life that does not count benefits of life aside from contributions to production.²² For example, Greenstone and Nigam (2020) claim that an advantage of the value of a statistical life (VSL) is that “the VSL captures the *full* benefits an individual expects to derive from her own life, including from leisure, time with friends and family, and consumption of goods and services” (emphasis in original). One could argue that our value-of-production approach undervalues life because it fails to account for the nonpecuniary benefits that an individual derives from life. Foreseeing this criticism, the purpose of this appendix is to address this concern and to provide further clarity about the distinction between the VSL approach and our own.

While there is some truth to the claim that the value-of-production method misses aspects of life, counterintuitively, it is actually the VSL method that undervalues life because it ignores significant benefits of extended life that accrue in the future. Figure D-1 below illustrates the value of extended life using both approaches.²³ On the x-axis is time, and on the y-axis is the value of extended life. Time t_0 is the time ascribed to death. A policy intervention extends life to time t_1 .

²² Some economists express concern about using terms such as “value of life” in CBA and prefer terminology such as “value of changes in mortality risk.” If mortality risk falls owing to a policy, this implies someone’s life has been extended. Implicitly, therefore, assigning a dollar value to changes in mortality risk assigns a dollar value to the person or persons whose life has been extended. This is true even if analysts cannot identify the exact person or persons saved, or even if analysts cannot identify the precise number of lives saved by a policy because of data limitations. In other words, explicitly or implicitly, economists are putting a dollar value on someone’s life when they monetize changes in mortality risk in CBA.

²³ Figure D-1 could be viewed as representing the “implicit value of life” from the perspective of an individual whose life is extended (i.e., the value of life to the individual implicit in what the individual is willing to pay to reduce a small death risk), or it could be viewed as describing the sum of what a group is willing to pay collectively to prevent the death of one member of the group. In general, the sum of what the group is collectively willing to pay to save a life must equal the average implicit value of life for the individuals whose lives are actually extended for the aggregation approach not to be biased.

What is the value of this marginal extension of life? When life is extended, the benefit comes in two forms: nonpecuniary consumption A and consumption out of the accrual of pecuniary income B. The value of a statistical life therefore is represented by the areas A and B in Figure D-1. In other words, part of what people are willing to pay for to reduce mortality risk is expected nonpecuniary benefits like those described in Greenstone and Nagam (2020), and part of what people are willing to pay for is expected benefits deriving from financial income in the future. Empirically, A is usually thought to be much larger than B, perhaps an order of magnitude larger (Viscusi, 2018).

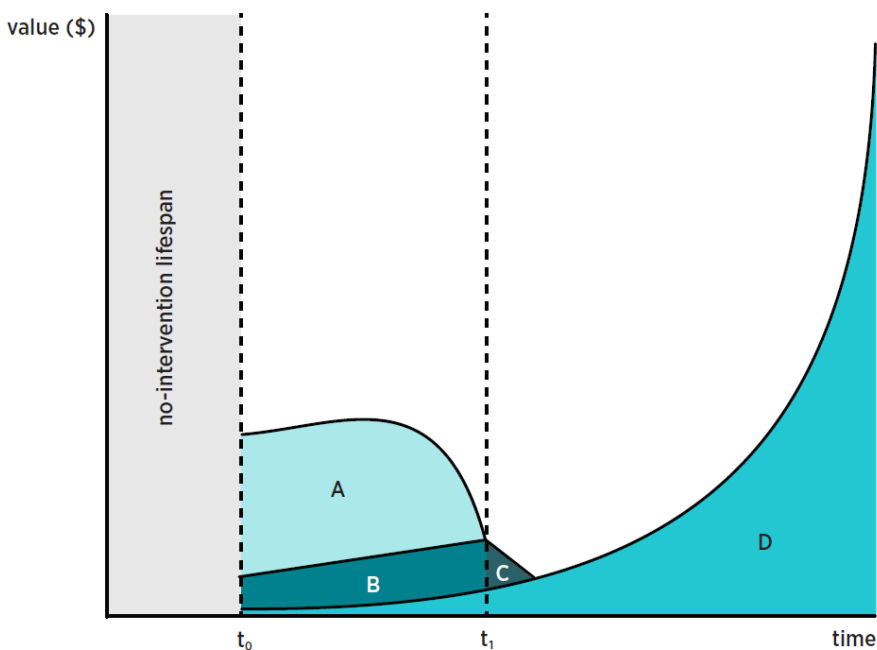


Figure D-1. The Value of Extended Life.

Source: Author's illustration.

The VSL may also include an area like C, which represents additional consumption as a result of a moderately larger bequest left to one's heirs. In the figure, heirs consume their marginal inheritance beginning at the new time of death, t_1 , until the bequest is either exhausted

or is far enough in the future that it is no longer of importance to the individual(s) whose valuation process is portrayed in the figure.

Critically, the VSL ignores D—the value of returns to invested capital that are not reflected in the individual’s willingness to pay for the capital asset.²⁴ These are social returns not accounted for in individual decision-making owing to time preference.²⁵ In other words, the VSL is premised upon individual preferences, but individual preferences do not fully account for the long-run social opportunity cost of capital.²⁶ Further, the divergence between private benefits and social benefits increases with time,²⁷ owing to compounding. This is the market failure that was identified in Appendix B; there are external benefits to production accruing primarily in the future, which private individuals do not incorporate into decision-making.

The VSL may represent the implicit value an individual places on his or her own life, or the value a group of individuals places on extending the life of one member of the group. But from a comprehensive social perspective, what matters is A, B, C, *and* D. The cumulative area of all four regions is what society should be willing to pay for the risk reduction, not the value of a statistical life. Moreover, though the present value of the value-of-production value of life is generally lower than the VSL value, when combined with the practice of discounting, the value-of-production approach projects how returns to invested capital can be expected to grow without

²⁴ As discussed in Appendix B, the discrepancy between the price of a capital asset and its social opportunity cost is owing to the universal phenomenon of time preference. This is what gives rise to interest and is a main reason why a shadow price is required for the valuation of capital goods in CBA. See Kirzner (2012) on the pure time preference theory of interest. See generally Marglin (1963), Bradford (1975), and Lind (1982) on the “shadow price of capital” approach to CBA.

²⁵ Observed marginal willingness-to-pay values in the marketplace will generally deviate from society’s willingness to pay whenever individuals’ discount rates deviate from the social discount rate.

²⁶ Pindyck (2020, p. 19) notes, “The VSL has a number of well-recognized problems, but the biggest one is that it reflects individual preferences, not the preferences of society.”

²⁷ One might argue that capital assets will eventually depreciate in value to zero. This is no doubt true of some specific assets. However, the returns from specific capital assets can be reinvested into other capital assets through financial markets. For the economy as a whole, the rate of return to capital, net of depreciation, is generally positive.

bound in the future. In that sense, the value of life is infinite under the value-of-production approach. The VSL value, by contrast, represents a fixed, finite bundle of consumption. This bundle will not grow at the rate of return to capital in the future. Hence it is inappropriate to discount the VSL at the rate of return to capital because what the VSL represents is not growing at this rate and may not be growing at all.²⁸

Critics of our approach might complain that A is not explicitly accounted for, and we concede that it isn't explicit. But one doesn't need to know A in order to determine society's willingness to pay for the reduction in mortality risk, because A isn't what matters *in the limit*.²⁹ The VSL may be a good reflection of the short-run benefits associated with extending life.³⁰ However, the value-of-production approach is a superior measure of long-run social benefits. Those who prefer a fuller accounting of social benefits should therefore prefer the value-of-production approach.

Moreover, regulatory costs also generally displace some capital investment, and the full social costs of displaced investment will not be amortized into the market price of capital investments on the cost side of the ledger, either. Assuming rates of return are equivalent on both sides of the ledger (i.e., capital investment on both the cost and benefit sides of the ledger earns the marginal social rate of return to capital), what matters from a cost-benefit standpoint is whether the present value of capital investment is increased on balance.³¹

²⁸ Despite being inappropriate, discounting in this way is often done. See Williams and Broughel (2019).

²⁹ When taking a mathematical limit of a polynomial, all that matters is the term of the highest degree in the polynomial.

³⁰ Even this may be an overstatement. If a policy prevents a death, this constitutes an extremely significant event for the individual whose death has been delayed. CBA should capture the value to citizens who are affected by policy, and it is unlikely that someone's marginal spending on risk reduction bears any relation to the value the individual places on inframarginal changes in risk, such as a change from having no life to having extended life. Thus it is unclear whether the VSL is ever appropriate for valuing changes in mortality risk in CBA.

³¹ This assumes capital investment has the highest recurring annual rate of return among all benefits and costs, which seems reasonable in most cases.

Appendix E. U.S. State Suppression Policies to Slow the First Wave of COVID-19

The COVID-19 forecast produced by the Institute for Health Metrics and Evaluation (IHME) considers several state-level policies in its model (2020b). While the details of each policy vary among the U.S. states, the IHME broadly groups public health interventions into five categories:

- *Stay-at-Home Orders:* 38 states and the District of Columbia enacted a stay-at-home order, 21 of which were lifted between the last week of April and the middle of May. Meanwhile, 18 orders remained in force as of May 26.
- *Public School and University Closures:* All 50 states and the District of Columbia ordered educational facilities to be closed by April 4, and all these measures remained in force as of May 26, effectively meaning U.S. primary, secondary, and higher education facilities were shuttered and operated in a remote capacity from April through the end of the 2020-2021 academic year.
- *Any Restriction on Size of Gatherings:* 49 states and the District of Columbia placed some legal restriction on public or private gatherings, with the exception being North Dakota, and only four states had lifted their restrictions entirely as of May 26. In total, 45 states and the District of Columbia enforced some restriction on gathering size as of May 26.
- *Legally Ordered Closure of Any Business:* 49 states and the District of Columbia required at least one type of business (like bars, restaurants, or hair salons) to close starting in late March or early April. As of May 26, only South Dakota and Arizona were not actively legally enforcing the closure of some businesses in their state.
- *Legally Ordered Closure of All Nonessential Businesses:* More restrictive than the category above, 34 states and the District of Columbia ordered all businesses not deemed

“essential” to be shut down starting in March or April. As of May 26, only 5 states and the District of Columbia actively required that all nonessential businesses remain closed.

- *Severe Travel Restrictions:* As of May 26, only Alaska had issued a legal order significantly restricting the travel of its residents within the state, which took effect on March 28 and remained in effect as of May 26.

State public health policies requiring the closure of all nonessential businesses were significantly eased in May of 2020, and over half of the stay-at-home orders issued in March and April had been lifted or allowed to expire by May 26. However, the residents of 17 U.S. states and the District of Columbia remained subject to stay-at-home orders as of May 26. In addition, almost all states still required some businesses to be closed, while other businesses resumed operations under significant sanitation and social distancing restrictions. Finally, restrictions on public or private gatherings remained almost universally enforced in the United States as of May 26, with educational facilities expected to remain closed during the summer break.

The start and end dates of legal orders in each category (except “severe travel restrictions”) are listed by state in Table E-1. If an order had not been lifted or if an end date had not been formally announced for an active order, then the end date is “to be determined,” or TBD. The IHME forecast assumes that measures that were in force as of May 26 and had no announced end date would remain in force through the last date of its projections, August 4.

Table E-1. Start and end dates of most common policies to enforce social distancing, by state

| State | Stay-at-home order | | School closures | | Gathering size limits | | Any business closure | | Nonessential business closures | |
|-------|--------------------|------|-----------------|-----|-----------------------|------|----------------------|------|--------------------------------|------|
| | Start | End | Start | End | Start | End | Start | End | Start | End |
| AL | 4/4 | 4/30 | 3/19 | TBD | 3/19 | TBD | 3/19 | TBD | 3/28 | 4/30 |
| AK | 3/28 | 4/24 | 3/16 | TBD | 3/24 | TBD | 3/17 | TBD | 3/28 | 4/24 |
| AZ | 3/30 | 5/16 | 3/16 | TBD | 3/30 | 5/16 | 3/30 | 5/16 | — | — |
| AR | — | — | 3/17 | TBD | 3/27 | TBD | 3/19 | TBD | — | — |
| CA | 3/19 | TBD | 3/19 | TBD | 3/11 | TBD | 3/19 | TBD | 3/19 | TBD |
| CO | 3/26 | 5/9 | 3/23 | TBD | 3/19 | TBD | 3/17 | TBD | 3/26 | 5/9 |
| CT | — | — | 3/17 | TBD | 3/12 | TBD | 3/16 | TBD | 3/23 | 5/20 |
| DE | 3/24 | TBD | 3/16 | TBD | 3/16 | TBD | 3/16 | TBD | 3/24 | 5/8 |
| DC | 3/30 | TBD | 3/16 | TBD | 3/13 | TBD | 3/16 | TBD | 3/25 | TBD |
| FL | 4/3 | 5/18 | 3/17 | TBD | 4/3 | TBD | 3/17 | TBD | — | — |
| GA | 4/3 | TBD | 3/18 | TBD | 3/24 | TBD | 3/24 | TBD | — | — |
| HI | 3/25 | TBD | 3/19 | TBD | 3/17 | TBD | 3/17 | TBD | 3/25 | 5/1 |
| ID | 3/25 | 5/1 | 3/23 | TBD | 3/25 | 5/1 | 3/25 | TBD | 3/25 | 5/1 |
| IL | 3/21 | TBD | 3/17 | TBD | 3/13 | TBD | 3/16 | TBD | 3/21 | 5/1 |
| IN | 3/25 | 5/18 | 3/19 | TBD | 3/12 | TBD | 3/16 | TBD | 3/24 | TBD |
| IA | — | — | 4/4 | TBD | 3/17 | TBD | 3/17 | TBD | 3/17 | 5/8 |
| KS | 3/30 | 5/4 | 3/17 | TBD | 3/17 | TBD | 3/30 | TBD | — | — |
| KY | — | — | 3/20 | TBD | 3/19 | TBD | 3/16 | TBD | 3/26 | 5/11 |
| LA | 3/23 | 5/15 | 3/16 | TBD | 3/13 | 5/15 | 3/17 | TBD | 3/22 | 5/1 |
| ME | 4/2 | TBD | 3/16 | TBD | 3/18 | TBD | 3/18 | TBD | 3/25 | 5/1 |
| MD | 3/30 | TBD | 3/16 | TBD | 3/16 | TBD | 3/16 | TBD | 3/23 | 5/15 |
| MA | — | — | 3/17 | TBD | 3/13 | TBD | 3/17 | TBD | 3/24 | 5/18 |

| | | | | | | | | | | |
|----|------|------|------|-----|------|------|------|-----|------|------|
| MI | 3/24 | TBD | 3/16 | TBD | 3/13 | TBD | 3/16 | TBD | 3/23 | 5/7 |
| MN | 3/28 | 5/18 | 3/18 | TBD | 3/28 | TBD | 3/17 | TBD | — | — |
| MS | 4/3 | 4/27 | 3/19 | TBD | 3/24 | TBD | 3/24 | TBD | 4/3 | 4/27 |
| MO | 4/6 | 5/15 | 3/23 | TBD | 3/23 | TBD | 3/23 | TBD | — | — |
| MT | 3/26 | 4/26 | 3/15 | TBD | 3/24 | TBD | 3/20 | TBD | 3/26 | 5/1 |
| NE | — | — | 4/2 | TBD | 3/16 | TBD | 3/19 | TBD | — | — |
| NV | 3/31 | 5/9 | 3/16 | TBD | 3/24 | TBD | 3/18 | TBD | 3/21 | 5/1 |
| NH | 3/27 | TBD | 3/16 | TBD | 3/16 | TBD | 3/16 | TBD | 3/28 | 5/11 |
| NJ | 3/21 | TBD | 3/18 | TBD | 3/16 | TBD | 3/16 | TBD | 3/21 | 5/2 |
| NM | — | — | 3/13 | TBD | 3/12 | TBD | 3/16 | TBD | 3/24 | 5/15 |
| NY | 3/22 | TBD | 3/18 | TBD | 3/12 | TBD | 3/16 | TBD | 3/22 | TBD |
| NC | 3/30 | 5/8 | 3/14 | TBD | 3/14 | TBD | 3/17 | TBD | 3/30 | 5/8 |
| ND | — | — | 3/16 | TBD | — | — | 3/20 | TBD | — | — |
| OH | 3/23 | TBD | 3/16 | TBD | 3/12 | TBD | 3/15 | TBD | 3/23 | 5/4 |
| OK | — | — | 3/17 | TBD | 3/24 | TBD | 4/1 | TBD | 4/1 | 4/24 |
| OR | 3/23 | TBD | 3/16 | TBD | 3/12 | TBD | 3/17 | TBD | — | — |
| PA | 4/1 | TBD | 3/17 | TBD | 4/1 | TBD | 3/18 | TBD | 3/23 | 5/8 |
| RI | 3/28 | 5/9 | 3/16 | TBD | 3/17 | TBD | 3/17 | TBD | — | — |
| SC | 4/7 | 5/4 | 3/16 | TBD | 3/18 | TBD | 3/18 | TBD | — | — |
| SD | — | — | 3/16 | TBD | 4/6 | 4/28 | — | — | — | — |
| TN | 4/2 | TBD | 3/20 | TBD | 3/23 | TBD | 3/23 | TBD | 4/1 | TBD |
| TX | 4/2 | 5/1 | 3/19 | TBD | 3/21 | TBD | 3/21 | TBD | — | — |
| UT | — | — | 3/16 | TBD | 3/19 | TBD | 3/19 | TBD | — | — |
| VT | 3/24 | 5/15 | 3/18 | TBD | 3/13 | TBD | 3/17 | TBD | 3/25 | 5/4 |
| VA | 3/30 | TBD | 3/16 | TBD | 3/15 | TBD | 3/17 | TBD | 3/24 | 5/15 |
| WA | 3/23 | TBD | 3/13 | TBD | 3/11 | TBD | 3/16 | TBD | 3/25 | TBD |

| | | | | | | | | | | |
|----|------|------|------|-----|------|-----|------|-----|------|------|
| WV | 3/25 | 5/4 | 3/14 | TBD | 3/24 | TBD | 3/18 | TBD | 3/24 | 5/4 |
| WI | 3/25 | 5/13 | 3/18 | TBD | 3/17 | TBD | 3/17 | TBD | 3/25 | 5/11 |
| WY | — | — | 3/19 | TBD | 3/20 | TBD | 3/19 | TBD | — | — |

Source: IHME (2020b)

Note: State policy information as of May 26, 2020.

Table E-2. Number of days during which both stay-at-home and nonessential business closures were enforced.

| State | GDP, 2019Q4 (in millions of dollars) | Percent of GDP | First day both orders enforced | Last day both orders enforced | Number of Days | Expected Number of Days |
|-------|--------------------------------------|----------------|--------------------------------|-------------------------------|----------------|-------------------------|
| AL | \$234,054 | 1.1% | 4/4 | 4/30 | 26 | 0 |
| AK | \$55,759 | 0.3% | 3/28 | 4/24 | 27 | 0 |
| AZ | \$372,522 | 1.7% | — | — | 0 | 0 |
| AR | \$135,225 | 0.6% | — | — | 0 | 0 |
| CA | \$3,183,251 | 14.7% | 3/19 | 8/4 | 138 | 20 |
| CO | \$396,367 | 1.8% | 3/26 | 5/9 | 44 | 1 |
| CT | \$288,985 | 1.3% | — | — | 0 | 0 |
| DE | \$76,410 | 0.4% | 3/24 | 5/8 | 45 | 0 |
| DC | \$148,231 | 0.7% | 3/30 | 8/4 | 127 | 1 |
| FL | \$1,111,378 | 5.1% | — | — | 0 | 0 |
| GA | \$625,329 | 2.9% | — | — | 0 | 0 |
| HI | \$98,536 | 0.5% | 3/25 | 5/1 | 37 | 0 |
| ID | \$82,265 | 0.4% | 3/25 | 5/1 | 37 | 0 |
| IL | \$908,913 | 4.2% | 3/21 | 5/1 | 41 | 2 |
| IN | \$381,733 | 1.8% | 3/25 | 5/18 | 54 | 1 |
| IA | \$197,172 | 0.9% | — | — | 0 | 0 |

| | | | | | | |
|----|-------------|------|------|------|-----|----|
| KS | \$175,703 | 0.8% | — | — | 0 | 0 |
| KY | \$217,564 | 1.0% | — | — | 0 | 0 |
| LA | \$267,051 | 1.2% | 3/23 | 5/1 | 39 | 0 |
| ME | \$68,441 | 0.3% | 4/2 | 5/1 | 29 | 0 |
| MD | \$434,312 | 2.0% | 3/30 | 5/15 | 46 | 1 |
| MA | \$604,208 | 2.8% | — | — | 0 | 0 |
| MI | \$548,567 | 2.5% | 3/24 | 5/7 | 44 | 1 |
| MN | \$385,907 | 1.8% | — | — | 0 | 0 |
| MS | \$120,429 | 0.6% | 4/3 | 4/27 | 24 | 0 |
| MO | \$336,816 | 1.6% | — | — | 0 | 0 |
| MT | \$52,948 | 0.2% | 3/26 | 4/26 | 31 | 0 |
| NE | \$129,098 | 0.6% | — | — | 0 | 0 |
| NV | \$180,406 | 0.8% | 3/31 | 5/1 | 31 | 0 |
| NH | \$89,836 | 0.4% | 3/28 | 5/11 | 44 | 0 |
| NJ | \$652,412 | 3.0% | 3/21 | 5/2 | 42 | 1 |
| NM | \$105,263 | 0.5% | 3/24 | 5/15 | 52 | 0 |
| NY | \$1,751,674 | 8.1% | 3/22 | 8/4 | 135 | 11 |
| NC | \$596,383 | 2.8% | 3/30 | 5/8 | 39 | 1 |
| ND | \$57,400 | 0.3% | — | — | 0 | 0 |
| OH | \$706,764 | 3.3% | 3/23 | 5/4 | 42 | 1 |
| OK | \$207,381 | 1.0% | — | — | 0 | 0 |
| OR | \$255,418 | 1.2% | — | — | 0 | 0 |
| PA | \$824,603 | 3.8% | 4/1 | 5/8 | 37 | 1 |
| RI | \$64,441 | 0.3% | — | — | 0 | 0 |
| SC | \$249,958 | 1.2% | — | — | 0 | 0 |
| SD | \$54,057 | 0.3% | — | — | 0 | 0 |

| | | | | | | |
|--------------|---------------------|---------------|------|------|-----|-----------|
| TN | \$385,741 | 1.8% | 4/2 | 8/4 | 124 | 2 |
| TX | \$1,918,065 | 8.9% | — | — | 0 | 0 |
| UT | \$192,013 | 0.9% | — | — | 0 | 0 |
| VT | \$35,271 | 0.2% | 3/25 | 5/4 | 40 | 0 |
| VA | \$561,846 | 2.6% | 3/30 | 5/15 | 46 | 1 |
| WA | \$610,488 | 2.8% | 3/25 | 8/4 | 132 | 4 |
| WV | \$78,507 | 0.4% | 3/25 | 5/4 | 40 | 0 |
| WI | \$351,922 | 1.6% | 3/25 | 5/11 | 47 | 1 |
| WY | \$39,794 | 0.2% | — | — | 0 | 0 |
| Total | \$21,606,817 | 100.0% | — | — | — | 50 |

Sources: Bureau of Economic Analysis (2020); IHME (2020b); authors' calculations.

Note: We set the number of days of suppression policies equal to zero for the 21 states that did not enforce both a nonessential business closure and stay-at-home order. Refer to Table E-1 for the dates on which suppression policies were enacted and lifted in the U.S. states and the District of Columbia.

Table E-3. Number of days during which either a stay-at-home order or nonessential business closure order (inclusive) was enforced.

| State | GDP, 2019Q4 (in millions of dollars) | Percent of GDP | First day either order enforced | Last day either order enforced | Number of Days | Expected Number of Days |
|-------|--------------------------------------|----------------|---------------------------------|--------------------------------|----------------|-------------------------|
| AL | \$234,054 | 1.1% | 3/28 | 4/30 | 33 | 0 |
| AK | \$55,759 | 0.3% | 3/28 | 4/24 | 27 | 0 |
| AZ | \$372,522 | 1.7% | 3/30 | 5/16 | 47 | 1 |
| AR | \$135,225 | 0.6% | — | — | 0 | 0 |
| CA | \$3,183,251 | 14.7% | 3/19 | 8/4 | 138 | 20 |
| CO | \$396,367 | 1.8% | 3/26 | 5/9 | 44 | 1 |
| CT | \$288,985 | 1.3% | 3/23 | 5/20 | 58 | 1 |
| DE | \$76,410 | 0.4% | 3/24 | 8/4 | 133 | 0 |
| DC | \$148,231 | 0.7% | 3/25 | 8/4 | 132 | 1 |

| | | | | | | |
|----|-------------|------|------|------|-----|----|
| FL | \$1,111,378 | 5.1% | 4/3 | 5/18 | 45 | 2 |
| GA | \$625,329 | 2.9% | 4/3 | 8/4 | 123 | 4 |
| HI | \$98,536 | 0.5% | 3/25 | 8/4 | 132 | 1 |
| ID | \$82,265 | 0.4% | 3/25 | 5/1 | 37 | 0 |
| IL | \$908,913 | 4.2% | 3/21 | 8/4 | 136 | 6 |
| IN | \$381,733 | 1.8% | 3/24 | 8/4 | 133 | 2 |
| IA | \$197,172 | 0.9% | 3/17 | 5/8 | 52 | 0 |
| KS | \$175,703 | 0.8% | 3/30 | 5/4 | 35 | 0 |
| KY | \$217,564 | 1.0% | 3/26 | 5/11 | 46 | 0 |
| LA | \$267,051 | 1.2% | 3/22 | 5/15 | 54 | 1 |
| ME | \$68,441 | 0.3% | 3/25 | 8/4 | 132 | 0 |
| MD | \$434,312 | 2.0% | 3/23 | 8/4 | 134 | 3 |
| MA | \$604,208 | 2.8% | 3/24 | 5/18 | 55 | 2 |
| MI | \$548,567 | 2.5% | 3/23 | 8/4 | 134 | 3 |
| MN | \$385,907 | 1.8% | 3/28 | 5/18 | 51 | 1 |
| MS | \$120,429 | 0.6% | 4/3 | 4/27 | 24 | 0 |
| MO | \$336,816 | 1.6% | 4/6 | 5/15 | 39 | 1 |
| MT | \$52,948 | 0.2% | 3/26 | 5/1 | 36 | 0 |
| NE | \$129,098 | 0.6% | — | — | 0 | 0 |
| NV | \$180,406 | 0.8% | 3/21 | 5/9 | 49 | 0 |
| NH | \$89,836 | 0.4% | 3/27 | 8/4 | 130 | 1 |
| NJ | \$652,412 | 3.0% | 3/21 | 8/4 | 136 | 4 |
| NM | \$105,263 | 0.5% | 3/24 | 5/15 | 52 | 0 |
| NY | \$1,751,674 | 8.1% | 3/22 | 8/4 | 135 | 11 |
| NC | \$596,383 | 2.8% | 3/30 | 5/8 | 39 | 1 |
| ND | \$57,400 | 0.3% | — | — | 0 | 0 |

| | | | | | | |
|--------------|---------------------|---------------|------|------|-----|-----------|
| OH | \$706,764 | 3.3% | 3/23 | 8/4 | 134 | 4 |
| OK | \$207,381 | 1.0% | 4/1 | 4/24 | 23 | 0 |
| OR | \$255,418 | 1.2% | 3/23 | 8/4 | 134 | 2 |
| PA | \$824,603 | 3.8% | 3/23 | 8/4 | 134 | 5 |
| RI | \$64,441 | 0.3% | 3/28 | 5/9 | 42 | 0 |
| SC | \$249,958 | 1.2% | 4/7 | 5/4 | 27 | 0 |
| SD | \$54,057 | 0.3% | — | — | 0 | 0 |
| TN | \$385,741 | 1.8% | 4/1 | 8/4 | 125 | 2 |
| TX | \$1,918,065 | 8.9% | 4/2 | 5/1 | 29 | 3 |
| UT | \$192,013 | 0.9% | — | — | 0 | 0 |
| VT | \$35,271 | 0.2% | 3/24 | 5/15 | 52 | 0 |
| VA | \$561,846 | 2.6% | 3/24 | 8/4 | 133 | 3 |
| WA | \$610,488 | 2.8% | 3/23 | 8/4 | 134 | 4 |
| WV | \$78,507 | 0.4% | 3/24 | 5/4 | 41 | 0 |
| WI | \$351,922 | 1.6% | 3/25 | 5/13 | 49 | 1 |
| WY | \$39,794 | 0.2% | — | — | 0 | 0 |
| Total | \$21,606,817 | 100.0% | — | — | — | 91 |

Sources: Bureau of Economic Analysis (2020); IHME (2020b); authors' calculations.

Note: We set the number of days of suppression policies equal to zero for the 6 states that did not enforce either nonessential business closures or a stay-at-home order. Refer to Table E-1 for the dates on which suppression policies were enacted and lifted in the U.S. states and the District of Columbia.