Tool

The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19

A Decision Support Tool for State and Local Policymakers

Raffaele Vardavas, Aaron Strong, Jennifer Bouey, Jonathan William Welburn, Pedro Nascimento de Lima, Lawrence Baker, Keren Zhu, Michelle Priest, Lynn Hu, Jeanne S. Ringel

RAND Social and Economic Well-Being
RAND Health Care

TL-A173-1
May 2020

RAND
CORPORATION

For more information on this publication, visit www.rand.org/t/tla173-1

Published by the RAND Corporation, Santa Monica, Calif.

Preface

With the rapid spread of coronavirus disease 2019 (COVID-19) and in the absence of evidence-informed guidance, state and local policymakers have put policies in place quickly and with little evidence to support their choices or little consideration of the potentially serious trade-offs. There is an urgent need for a comprehensive and systematic assessment of potential public health interventions to address COVID-19. In this document, we describe the interdisciplinary and multisectoral approach used to develop a tool to fill that need. The tool provides the information and context that policymakers need now to understand the effects of interventions, weigh the trade-offs between them, and decide when and how these interventions can be relaxed.

The tool should be of interest to policymakers and others who wish to use it to understand the potential impacts of various nonpharmaceutical interventions (e.g., school closures, stay-at-home orders) on health and economic outcomes in their communities. This document detailing the methods that underly the tool will be of interest to policymakers or staff members and researchers who wish to better understand and assess the structure and assumptions of the models and analyses that make up the tool.

This research was jointly conducted by the Community Health Environmental Policy Program in RAND Social and Economic Well-Being and the Access and Delivery Program in RAND Health Care.

RAND Social and Economic Well-Being

RAND Social and Economic Well-Being is a division of the RAND Corporation that seeks to actively improve the health and social and economic well-being of populations and communities throughout the world. The Community Health and Environmental Policy Program focuses on such topics as infrastructure, science and technology, community design, community health promotion, migration and population dynamics, transportation, energy, and climate and the environment, as well as other policy concerns that are influenced by the natural and built environment, technology, and community organizations and institutions that affect well-being. For more information, email chep@rand.org.

RAND Health Care

RAND Health Care, a division of the RAND Corporation, promotes healthier societies by improving health care systems in the United States and other countries. We do this by providing health care decisionmakers, practitioners, and consumers with actionable, rigorous, objective evidence to support their most complex decisions. For more information, see www.rand.org/health-care, or contact RAND_Health-Care@rand.org.

Funding for this research was provided by gifts from RAND supporters and income from operations.

Contents

Figures

Tables

Acknowledgments

This project would not have been possible without the support and assistance of many people. First, this project was inspired in part by work led by our RAND colleague, Melinda Moore, during the Ebola crisis in 2014 and 2015 to develop an assessment tool for policymakers to systematically consider different interventions to address an infectious disease outbreak. Moore passed away in 2019, but her influence on her colleagues and this work is substantial. We hope that she would be proud of how we have built on her work to help address the current pandemic. We also are grateful to our many RAND colleagues who have informed this work through information-sharing and discussions of key issues. In particular, we thank David Groves for his input on decisionmaking under uncertainty and ideas on visualizing the data. We also thank Alyson Youngblood and Heather McCracken for their outstanding work designing and producing the web tool. Finally, we thank the quality assurance reviewers for this project: Courtney Gidengil, a senior physician policy researcher at RAND; Carter Price, a senior mathematician at RAND; Marco Hafner, a senior economist at RAND Europe; Chris Bauch, a professor in applied mathematics at the University of Waterloo; and Adam Rose, a research professor in public policy at the University of Southern California. Their thoughtful and constructive comments significantly improved this document. Any remaining errors are the sole responsibility of the authors.

Abbreviations

ABM	agent-based model
AHA	American Hospital Association
ARDS	acute respiratory distress syndrome
BEA	Bureau of Economic Analysis
CDC	Centers for Disease Control and Prevention
CFR	case fatality rate
CGE	computable general equilibrium
COVID-19	coronavirus disease 2019
CT	computed tomography
GAMS	General Algebraic Modeling System
GSI	gross state income
ICU	intensive care unit
IHME	Institute for Health Metrics and Evaluation
IMPLAN	Economic Impact Analysis for Planning
ODE	ordinary differential equation
NCES	nested, constant elasticity of substitution
NDSSL	Network Dynamics and Simulation Science Laboratory
NPI	nonpharmaceutical intervention
MEPS	Medical Expenditure Panel Survey
MPSGE	Mathematical Programming System for General Equilibrium
PERT	Program Evaluation and Review Technique
SEIR	susceptible-exposed-infected-recovered
SIR	susceptible-infected-removed

1. Introduction

Facing the rapid spread of the coronavirus disease 2019 (COVID-19) pandemic, national, state, and local leaders have taken unprecedented measures to protect their communities. To mitigate the spread of the virus and prevent critical health care systems from being overwhelmed, policymakers have implemented a variety of public health interventions, including closing schools and nonessential businesses, prohibiting large gatherings, quarantining the most vulnerable, and placing all residents under stay-at-home orders.

These interventions will have wide-ranging effects on the health, economy, and social well-being of populations. But, by necessity, decisions are being made quickly and often with limited evidence-based guidance on their likely effects.

In the coming weeks and months, decisionmakers will again face tough decisions: how and when to relax mitigation measures and whether to reinstate those measures to combat a resurgence of the virus.

Objective of the COVID-19 Decision Support Tool

The objective of this tool is to provide a decision support framework for state and local policymakers to inform decisions regarding COVID-19 interventions. The framework draws on evidence from past disease outbreaks, peer-reviewed literature, and data from the current pandemic. We have modeled and assessed the impact of a variety of nonpharmaceutical interventions (NPIs) on health and economic outcomes, along with other important policy considerations, such as the cost and ease of implementing interventions. This tool can inform decisions about which NPIs to implement, when to implement them, and when they can be relaxed.

Focus on Nonpharmaceutical Interventions

The tool focuses on the use of NPIs because they are the primary interventions available in the early phase of a pandemic. Because the virus is novel, no established immunity exists to prevent it from spreading rapidly. A vaccine could provide immunity to the virus but is expected to take at least a year to develop. At the same time, medical treatment of the disease is limited by both a lack of information on the effectiveness of available treatments and the need for newly developed drugs to go through clinical trials. The goal of NPIs is therefore to delay and reduce the peak number of cases per day or, in other words, “flatten the curve” to reduce pressure on health services and allow time for clinical trial completion and vaccine distribution (Aledort et al., 2007).

Best Uses of the Tool

The tool combines information from an epidemiological model, an economic model, and a qualitative policy analysis to assess the effects of NPIs. The epidemiological model is a population model, also known as a *compartmental model* or *stock-and-flow model*. This type of model divides the population into compartments that represent people at different clinical stages: susceptible (pre-infection), exposed, infected, and recovered. Data from prior disease outbreaks are combined with emerging data on COVID-19 to generate parameters that capture the flow of disease transmission. Because of its speed and flexibility, this type of model is well suited for quickly providing an understanding of the dynamics of disease spread (Manheim et al., 2016). It is also particularly useful for comparing the relative efficacy of different social-distancing interventions in reducing contagion (Manheim et al., 2016).

The economic model is a simplified model of each state's economy that incorporates the relationships across industries, households, and government. We modified an existing model to quickly estimate NPI effects by adjusting industry definitions to match those most likely to be influenced by social distancing. Our approach has been to restrict output in certain sectors consistent with industry estimates or previous literature regarding NPI impacts. We then allow these restrictions to flow through the economy and affect other sectors and households to produce an estimate of the total economic impact in terms of lost income to households. The model is calibrated using readily accessible data and is intended to provide order-of-magnitude estimates of the economic consequences associated with various social-distancing interventions.

The qualitative assessment of NPIs is based on a standard policy analysis approach that compares policy alternatives across a set of decision criteria. The assessments are based on a review of the scientific and popular literature from past pandemics and the current pandemic. This type of analysis provides a systematic way to compare the costs, benefits, and trade-offs of different interventions.

Drawing from the quantitative and qualitative analyses, the tool provides practical information for policymakers who are deciding how best to combat COVID-19 and on how and when to relax social-distancing NPIs once the disease is under control. This model is not intended to accurately forecast case counts, deaths, or economic losses, but is intended to illustrate the relative benefits and costs of pursuing different strategies as one part of a multidimensional decisionmaking process.

Unique Contribution of This Tool

Our interdisciplinary and mixed-methods approach combining quantitative modeling and qualitative assessment provides a more-comprehensive package of information than any individual model regarding what policymakers need to know now to understand the various effects of NPIs, weigh the trade-offs between them, and decide when and how they can be relaxed. We are not aware of any other tool that compiles this type of information to support a systematic assessment. The data inputs are updated daily to ensure that the model results provide policymakers with the most-recent and relevant information. In addition, we model the impact of social-distancing interventions in a more-sophisticated way than the other COVID-specific models we have seen. In the epidemiological model, our method accounts for differences in the patterns of interaction in different contexts (e.g., home, work, commercial), and in the economic model, our method accounts for differences in impact across different sectors of the economy (e.g., restaurants, hospitality, air travel).

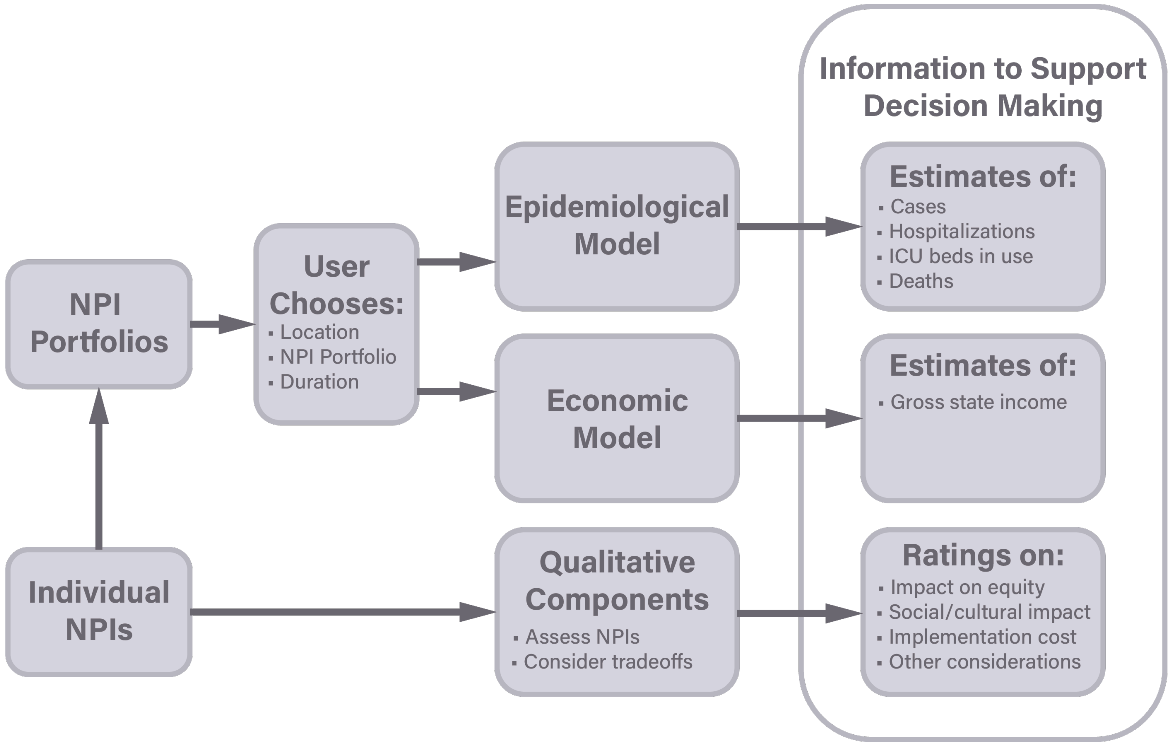
2. Methods Used to Build the Tool

We used a mixed-methods approach to develop the decision support tool to inform the selection and use of a variety of NPIs. We combined quantitative modeling of the health and economic impacts with qualitative assessments of other important considerations, such as cost and ease of implementation, equity, and social well-being. In this section, we outline the components of the tool and how they are connected. We also describe how the NPIs that are considered in the tool were selected. In the subsequent sections, we provide detailed descriptions of how each component of the tool was developed.

Components of the Tool

The tool is intended to provide a systematic assessment of NPIs to inform decisionmaking at the state and local levels. To do this, we built an epidemiological model to project the health impacts (e.g., cases, hospitalizations, intensive care unit [ICU] utilization, and deaths) and an economic model to project the impact on the economy (e.g., loss in gross state income [GSI]). The models are connected through a common set of NPI portfolios, representing different combinations of NPIs (e.g., schools, bars, and restaurants closed and large events banned). In addition, a qualitative assessment of a broader variety of individual NPIs (e.g., travel bans, wearing masks), including those in the portfolios, is provided in the tool, and the NPIs are evaluated on an expanded set of criteria (see the Qualitative Assessment section). Figure 2.1 illustrates the components of the tool and how they fit together.

Figure 2.1. Components of the Decision Support Tool



Selection of Nonpharmaceutical Interventions for Inclusion in the Modeling Component of the Tool

The first step in developing the decision support tool was to identify a set of NPIs to be included and assessed in the modeling component of the tool. The NPIs serve as the primary connection between the epidemiological and economic models.

NPIs documented in the pandemic preparedness literature include interventions for disease isolation (e.g., screening, testing, case tracing, travel restrictions), individual and public hygiene behavioral changes (e.g., wearing masks, disinfections), and various social-distancing policies (e.g., school closure, large gathering bans, mandatory quarantine). For the modeling component, we chose to focus first on the mandatory social-distancing interventions because they do not require additional technology or labor support and can quickly reduce the level of contact and disease transmission. These interventions were used widely in the first wave of the COVID-19 pandemic in the United States when widespread community transmission was discovered and the United States' testing capability was catching up. All of these NPIs are included in the Centers for Disease Control and Prevention's (CDC's) guidance for community mitigation efforts and are recommended when the spread of disease within the community is substantial (CDC, 2020a). The definitions for the selected social-distancing NPIs are presented in Table 2.1.

Table 2.1. Social-Distancing Nonpharmaceutical Interventions

NPIs	Definition
School closures	Closure of schools—public and private colleges; public, charter, and private K–12 schools
Bars and restaurants closures	Closure of bars, nightclubs, and wineries; closure of dine-in services, only allowing online ordering and take-away services
Large event bans	Banning social gatherings that involve close contacts among people; in the United States, the implementation of bans on large gatherings can be divided into the following categories: all gatherings prohibited, more than ten people gathering prohibited, 50 or more people prohibited, other, no action.
Nonessential business closures	Temporarily cease all nonessential business activities
Shelter-in-place order for high-risk population	High-risk populations advised to stay home unless it is absolutely necessary to go out; during the 2020 COVID-19 pandemic, the vulnerable populations are defined as • people aged 65 years and older • people who live in nursing homes or long-term care facilities • people with chronic lung disease or moderate to severe asthma • people who have serious heart conditions, are immunocompromised, or who have severe obesity, diabetes, chronic kidney disease undergoing dialysis, and liver disease
Shelter-in-place order for all people	Remain at home and away from other people unless it is absolutely necessary to go out.

The literature generally indicates that NPIs are most effective when they are initiated early, conducted comprehensively, sustained for a longer period, and are implemented in combination with other interventions (Markel et al., 2007). Their efficacy also is influenced by the contagiousness (typically captured by R_0) and the virulence (case fatality) of the pathogen, the principal mode of transmissions, attack rate in different groups, proportion of asymptomatic infections, and compliance among the targeted populations (Flaxman et al., 2020). NPIs do not provide long-lasting immunity and many are labor intensive, politically controversial, and can cause social and economic disruptions and ethical concerns (Institute of Medicine Forum on Microbial Threats, 2007). Therefore, a timely and comprehensive assessment of the positive and negative impacts of different combinations of NPIs on the pandemic and the economy is critical for policymakers to make appropriate decisions.

Using data on the policy response to COVID-19 in the United States (Kaiser Family Foundation, 2020), we identified five common combinations of interventions, which we call *NPI portfolios*. Many states have already implemented all of the social-distancing NPIs identified in Table 2.1. To provide information about the potential impacts of removing some of the social-distancing requirements, we create a portfolio (Level 5 in Table 2.2) that includes all of the NPIs and four portfolios that sequentially remove NPIs, assuming that the most-restrictive policies will be lifted first. The five NPI portfolios, ordered based on their level of control and expected impact on the economy, are presented in Table 2.2.

Table 2.2. Nonpharmaceutical Intervention Portfolios

Portfolio	Description
Level 1: Close schools	All schools are closed.
Level 2: Close schools, bars, and restaurants; and ban large events	In addition to school closures, all bars' and restaurants' dine-in services are closed, only allowing for take-out options. Also, large gatherings are banned.
Level 3: Close schools, bars, and restaurants; ban large events; and close nonessential businesses	In addition to school, bar, and restaurant closures, all nonessential businesses are closed.
Level 4: Close schools, bars, and restaurants; ban large events; close nonessential businesses; and issue a shelter-in-place order for the most vulnerable	In addition to the closure of all nonessential businesses, a shelter-in-place order is recommended for the vulnerable population, including the elderly, children, and other at-risk populations.
Level 5: Close schools, bars, and restaurants; ban large events; close nonessential businesses; and issue a shelter-in-place order for everyone but essential workers	In addition to the interventions above, a shelter-in-place order is issued for the everyone but essential workers.

Location and Duration of Nonpharmaceutical Interventions

When a user opens the tool, they will be asked to select which state they are interested in. The tool then indicates the NPI portfolio that is the closest match for what is currently implemented in that state. Users can then select an alternative NPI portfolio for comparison. The user also can choose from a set of prespecified dates (e.g., May 15, June 1, June 15, July 1) when the selected NPI portfolio is implemented. The details of how each of the intervention portfolios are modeled are provided in the sections on the epidemiological model and the economic model.

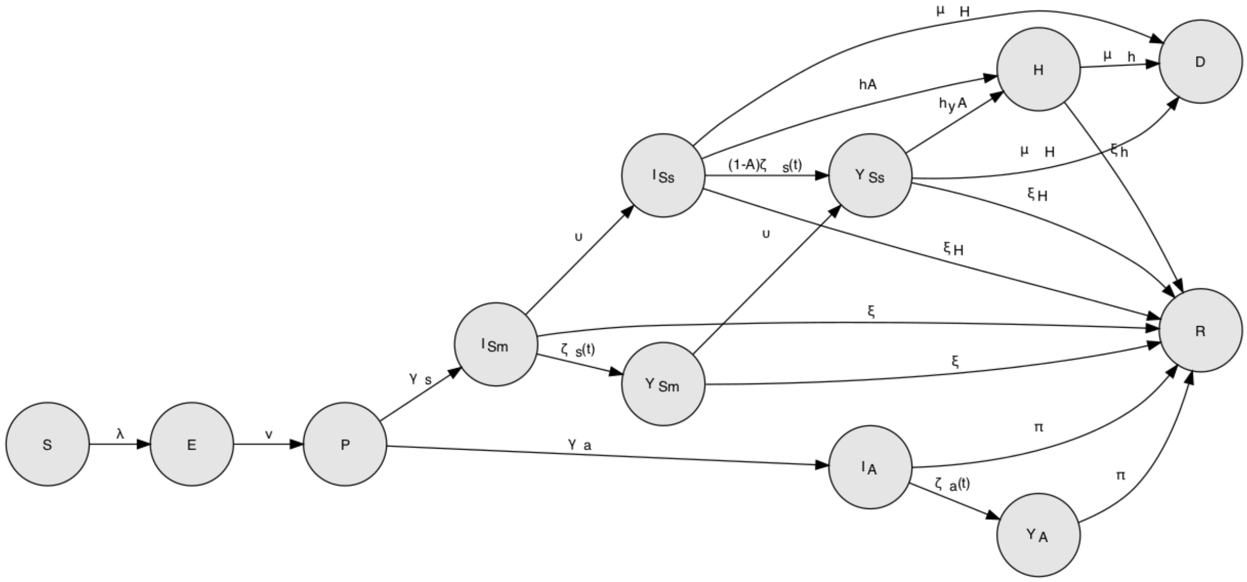
3. Epidemiological Model

The epidemiological model takes into account the impact of the various public health interventions on the pandemic over time in U.S. states. The selected NPI portfolios feed into this task, providing information about COVID-19, the interventions to be modeled, and estimates of their effectiveness. The model provides output that, along with a qualitative assessment of interventions, will help policymakers select interventions, choose when to implement them, and decide when they can be relaxed.

Model Approach

Our model employs system dynamics, which is an approach to understanding the nonlinear behavior of complex systems over time using stocks, flows, internal feedback loops, and time delays. In models of health systems, such models often are referred to as *compartmental models* because they consider various compartments to represent the population size of different demographic, socioeconomic, and health states and consider flows to represent transitions and progression between different states. These models provide a framework in which numbers of people in different compartments (each one homogeneous with respect to some specified characteristic) and the relationships between such compartments, which model the dynamics of the population, can be described in mathematical terms. Modeling a diverse population requires that the population be subdivided into groups with common characteristics that are relevant to the infection under consideration. These subdivisions of the population are called *compartments*. Compartmental models are commonly used to describe the progress of an epidemic in a large population comprising many individuals. One common example is the deterministic population-level Susceptible-Exposed-Infected-Recovered (SEIR) model of disease transmission. Our approach builds on a SEIR model but also considers additional infectious states to better describe COVID-19. Figure 3.1 displays a detailed view of our compartmental model, whereby individuals in our population progress over the different stages of the infection.

Figure 3.1. Disease Model Diagram



State Variables

Individuals in our population are divided into 12 key compartments: The noninfected and susceptible (S), the exposed and infected but not yet infectious (E), the presymptomatic or primary infectious stage (P), the infected with mild symptoms (I_{Sm}), the infected with severe symptoms (I_{Ss}), the diagnosed infected with mild symptoms (Y_{Sm}), the diagnosed infected with severe symptoms (Y_{Ss}), the hospitalized (H), the infected asymptomatic (I_A), the diagnosed infected asymptomatic (Y_A), the recovered (R), and those that died (D). We assume that individuals in the P and I_A compartments are completely asymptomatic and thus are unaware of being infectious. The arrows connecting the disease states describe the progression rates between the different compartments. We assume that mild symptoms are a dry cough and a fever, while severe symptoms also include shortness of breath. The sum of the population in all of the states gives the total population N. However, we assume that $N = 1$, and thus each state variable gives the proportion of the population belonging to that state.

We also model different population strata within each compartment. There are ten total strata, composed of five age groups split by chronic conditions or healthy status. For each age group, we consider differences in population size, social mixing, asymptomatic rate, and case fatality rate (CFR).

Hospitalization and Intensive Care Unit

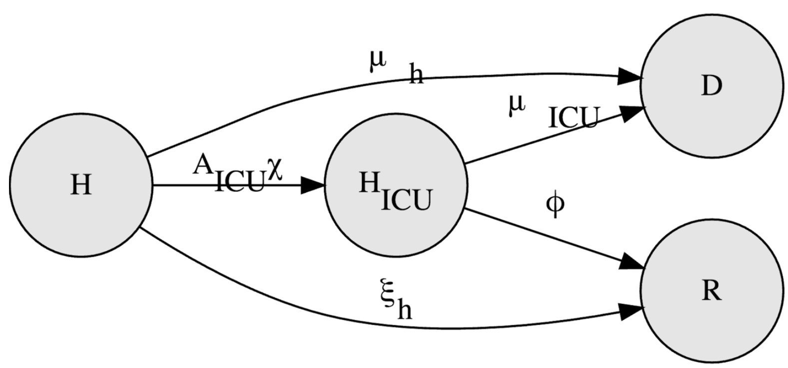
In response to feedback, we are modeling the hospital at a more-granular level and have split the hospital compartment (H) into two subcompartments. One compartment, H_{ICU}, represents the ICU; the other, H, represents the rest of the hospital. In the model, the ICU and the hospital can reach capacity, at which point they take no more patients until they have free beds. Accessibility to the hospital and ICU are denoted by the indicator variables A and A_{ICU}. However, because of the unreliability of current hospitalization data, we do not yet use these variables. These indicator variables are always set to one and the hospital and ICU always remain accessible. In the future, we hope that more-reliable data will enable us to introduce these parameters.

In our model, most of those who develop severe symptoms get hospitalized. The percentage of severe cases hospitalized remains constant as long as the hospital has not reached its capacity in terms of available beds. Those that are hospitalized can transition into the ICU. This transition is not shown in Figure 3.1; instead, we show it separately in Figure 3.2. We assume that, provided there is ICU accessibility, all patients who develop critical symptoms (and therefore require a ventilator) will transition to the ICU. Those in the H compartment are currently hospitalized but are not in the ICU. Patients that are currently in the ICU belong to the H_{ICU} compartment.

We assume that patients who recover in the ICU move immediately to the recovered compartment rather than back to the hospital. This is to ensure that individuals do not make multiple trips to the ICU. The time spent in the H_{ICU} compartment therefore represents both the ICU and the time spent recovering after intensive care in the hospital.

When the ICU is closed, we assume that all those who required ICU access will die until the ICU is reopened. When the hospital is closed, we assume that a higher proportion of severe cases become critical and that all critical cases will die.

Figure 3.2. Hospital and Intensive Care Unit Model Diagram



A summary of state variables is given in Table 3.1.

Table 3.1. Model State Variables

State Variable Name	Symbol	Description
Susceptible	S	No immunity (not recovered) and no exposure
Exposed	E	Exposed to infection and in incubation phase, noninfectious and no symptoms
Primary infectious	P	Infectious with no symptoms, exposed to infection and in incubation phase
Secondary infectious: mild symptoms, no positive test	I_{Sm}	Infectious and mildly symptomatic (dry cough and fever), untested or false negative test
Secondary infectious: severe symptoms, no positive test	I_{Ss}	Infectious and severely symptomatic (trouble breathing), untested or false negative test
Secondary infectious: mild symptoms, positive test	Y_{Sm}	Infectious and mildly symptomatic (dry cough and fever), tested positive
Secondary infectious: severe symptoms, positive test	Y_{Ss}	Infectious and severely symptomatic (trouble breathing), tested positive
Secondary infectious: hospitalized	H	Infectious and severely symptomatic, hospitalized and not in the ICU
Secondary infectious: hospitalized in the ICU	H_{ICU}	Infectious and critically symptomatic, hospitalized and in the ICU
Secondary infectious: asymptomatic, no positive test	I_A	Infectious but with no symptoms, untested or false negative test
Secondary infectious: asymptomatic, positive test	Y_A	Infectious but with no symptoms, tested positive
Recovered	R	Assumed immune
Expired	D	Died in hospital or disease advanced to critical before hospitalization

Data Inputs

Table 3.2 provides an overview of the key data inputs and their sources. We then describe each data input in greater detail.

Table 3.2. Data Inputs

Data	Details	Source
State population, by age	Five-year age groups were combined to create model strata	U.S. Census Bureau, 2020
State chronic population, by age	Chronic condition tables were combined with state population census age groups to calculate the size of the chronic population for each age group	Heron, 2019; Agency for Healthcare Research and Quality, undated.
State hospital capacity	State-level availability of beds and projected possible beds	Harvard Global Health Institute, 2020
State testing, deaths, and hospitalization time series	Daily flows and stocks of positive tests, negative tests, hospitalizations, and deaths for each state	COIVD Tracking Project, undated
Nonpharmaceutical intervention time series	Daily time series inferred from dates on sheet. Daily NPI bundle calculated based on active interventions.	Raifman et al., 2020; Kaiser Family Foundation, 2020
Mixing matrices	Matrices are averaged from the two sources.	Prem, Cook, and Jit, 2017; Marathe, 2014
Effect of NPIs on mixing	Estimated by the RAND Corporation team and informed by Google mobility data	Google, undated

State Population, by Age and Chronic Status

For state populations, we use the 2018 figures from the U.S. Census Bureau, which give the population in five-year age bands by state and sex. To calculate the proportion of each age band with chronic conditions, we use chronic condition life tables, which give the probability of having a chronic condition by age and sex. These chronic life tables were created by using mortality statistics to split Medical Expenditure Panel Survey (MEPS) data on health status into chronic and acute conditions by age and gender (Agency for Healthcare Research and Quality, undated).

We assume that each five-year age group is represented by a midpoint rounded down to the nearest integer (e.g., the 55–59 age group is assumed to be 57). The chronic and healthy populations are then calculated for each age group by gender and state. These quantities are summed so that they match our population strata. For instance, the "age 55–64, chronic conditions" strata is the sum of

- women with chronic conditions ages 55–59
- women with chronic conditions ages 60–64
- men with chronic conditions ages 55–59
- men with chronic conditions ages 60–64.

This information provides the populations of the ten population strata for each state.

State Hospital Capacity

Hospital capacity estimates are taken directly from the Harvard Global Health Institute, 2020, estimates.

Case Counts, Testing, Hospitalizations, and Deaths

State-level data for case counts, positive tests, negative tests, hospitalizations, and deaths come from the COVID Tracking Project, an effort led by journalists and staffed by volunteers that publishes high-quality U.S. COVID data (COVID Tracking Project, undated). This information comes from state and district public health authorities, news reporting, and press conferences. (For a full list of their sources, see COVID Tracking Project, 2020.)

We use the COVID Tracking Project API to pull flows (the number of new daily occurrences) for positive tests, negative tests, deaths, and hospitalizations. We also pull estimates for stocks (the number of people with a status) for those currently hospitalized in each state to estimate how much bed capacity is used.

Because the data are aggregated from many sources and because some states are inconsistent in their reporting methods, there are likely to be some errors and inaccuracies. However, this data set is widely used by reputable institutions, including Johns Hopkins University, *The Atlantic*, *New York Times*, and CNN.

Nonpharmaceutical Intervention Time Series

The dates on which different NPIs were implemented are tracked by a group at Boston University (Raifman et al., 2020). We extract the dates for the interventions we are interested in and transform from a wide to a long format. We check these data against information from the Kaiser Family Foundation and update them if states have begun to reopen (Kaiser Family Foundation, 2020). To decide which NPI bundle applies, we look at the combination of policies applied, usually using the most stringent policy applied as the current level. This shows one of the limitations of our method: Because we track only five different NPI bundles, we do not have a way to accurately classify all combinations. Fortunately, most states have proceeded to implement NPIs in an order that is consistent with our chosen bundles.

Mixing Matrices

We model mixing in the population using mixing matrices. A *mixing matrix* describes the amount of contact that occurs between each of the population strata. We assume that mixing behaviors vary by context. For instance, in school, there is a great deal of mixing between children, whereas in the home, there is more mixing across generations. We consider six different mixing locations: household, work, school, commercial, recreational, and other. The mixing matrix that describes all mixing is a weighted sum of the mixing matrices for these different contexts. We use two sources for mixing matrices in the baseline scenario.

First, we use available data provided by the Network Dynamics and Simulation Science Laboratory (NDSSL) at Virginia Polytechnic Institute and State University that represent a synthetic population of the city of Portland, Oregon (Marathe, 2014). The NDSSL data for Portland, Oregon, provide an instance of a time-varying social contact network for a normative workday, derived from daily activities. The data were created from an urban transportation agent-based model, which simulated the daily movements of individuals across locations in Portland, Oregon. From these data, an edge list connecting nodes or vertices representing individuals was constructed (Blum, 2015). The edge weights represent the duration of a typical day where individuals interact with each other. The original data set contains 1.6 million individuals, 630,000 households, and an edge list that represents almost 20 million face-to-face daily contacts across various types of activities and locations. This synthetic data set also contains information on age, gender, and health status.

The second data source is based on self-reported survey data. Over the course of one day in eight European countries, 7,290 participants reported 97,074 unique contacts. These self-reports listed the age, sex, and location of the contact (Mossong et al., 2008). Mixing matrices were created by age group across household, work, school, and other contexts. Another paper extrapolated these results to create mixing matrices for 152 countries, including the United States (Prem, Cook, and Jit, 2017). We use the U.S. matrix as our second data source.

These sources represent two very different methodologies for quantifying social mixing matrices, and both have drawbacks. The NDSSL data define a *contact* as two simulated individuals inhabiting the same sublocation at the same time. This method likely over-weights locations where there are many individuals in low mixing environments, such as workplaces. Furthermore, the data are synthetic and represent only Portland on a usual workday, and so might not be indicative of the entire United States averaged across all days.

The Prem mixing matrices define a *contact* as physical contact, or a two-way, in-person conversation with at least three words exchanged (Prem, Cook, and Jit, 2017). Because these contacts are self-tracked, they are likely underreported and might over-weight contacts in close environments that are more easily remembered, such as the home. Although they are ostensibly representative of the United States, the original data were for European countries.

The mixing matrices produced by these methods are quite different. As a compromise, we averaged the two mixing matrices for each mode. Averaging required the following additional assumptions:

- The Prem, Cook, and Jit, 2017, data did not contain separate mixing matrices for commercial, recreational, and other mixing; all were captured by a single matrix. To define these matrices, we assumed that the mixing matrices were the same and that the weights between the matrices were split in the same ratio as in the NDSSL data.
- The Prem, Cook, and Jit, 2017, data did not contain separate data for those with chronic conditions. We assumed that, within an age group, those with chronic conditions had the same mixing behavior as those who were healthy. To determine

weights of the chronic relative to the healthy contacts, we used the same proportions as in the NDSSL data.

- We averaged both the mixing matrices and the relative weights for the mixing matrices.

The resultant averaged mixing matrices for each location allow us to calculate the level of social mixing for each state between every population strata.

Effect of Nonpharmaceutical Interventions on Mixing

We model the effect of different social-distancing interventions as changes in the weights of mixing matrices. For instance, school closures would reduce the weight on the school mixing matrix to zero. More detail is given on mixing matrix weights in "Mixing Matrices and Interventions" later in this section. We could not find peer-reviewed sources for how interventions would change the weights of the mixing matrices. To estimate these values, we sought the opinions of the team, especially within the epidemiological modeling and assessment group subteams. After several iterations, we reached a consensus on a set of weights for each of the NPI bundles chosen. This involved rotating estimates between teams for revision until no further changes were suggested. To inform these estimates, we used Google Mobility Reports, which show how the amount of time spent in different contexts has changed over time. At the time of writing, Google has begun to release more-detailed mobility time series, so these could be used to improve our estimates in future iterations (Google, undated).

Parameter Sources

Parameters indicate how people move between states in the model. Our parameters are discussed as disease progression rates and proportional flows. *Proportional flows* indicate the proportion of people that move into states where there are more than one next step; for example, from the incubation phase to the symptomatic or asymptomatic phase.

Parameter estimates were selected from a review of the literature and with the input of RAND experts. To carry out sensitivity analyses of the parameters and to calibrate the model, we constructed a large set of independent case runs, each with a different and unique combination of model parameter values. Parameter values for the case runs are sampled using a Latin-Hypercube approach (Helton and Iman, 1983; Hoare, Regan, and Wilson, 2008). We use either a uniform or a beta-PERT (Program Evaluation and Review Technique) distribution to sample the model parameter value, as specified within a sensitivity analysis range (Cottrell, 1999). In the latter case, the reference value is used to specify the mode of the beta distribution used for our parameter value sampling. Summaries of parameter estimates, sources, and sensitivity are shown in Table 3.3 and Table 3.4.

Table 3.3. Disease Progression Rate Parameter Estimates

Parameter	Sample Distribution	Reference Value	Sensitivity Range	Sources
Noninfectious incubation phase length	PERT	3	2.2–8.4	Backer, Klinkenberg, and Wallinga, 2020; Li, Guan, et al., 2020
Infectious incubation phase length	PERT	2	1.6–5.6	Backer, Klinkenberg, and Wallinga, 2020; Li, Guan, et al., 2020
Severe symptom onset to hospitalization	Uniform	2.5	1.5–3.5	Wang, Hu, et al., 2020
Hospital stay length (includes patients who are admitted to the ICU)	Uniform	8	3–16	Wang, Tang, and Wei, 2020; Pan et al., 2020
ICU stay length	Uniform	4	2.5–9	Moghadas et al., 2020
Severe symptom onset to death for those not hospitalized	Uniform	6	4–10	Expert judgment
Mild symptomatic phase length (might lead to severe disease or recovery)	PERT	6	4–10	Wang, Hu, et al., 2020; Wang, Tang, and Wei, 2020
Asymptomatic phase length	PERT	9	7–12	Expert judgment

NOTE: All values are in days.

Disease Progression Rates

Incubation Phase

The incubation phase is the time from exposure to the virus to the appearance of the first symptoms. We assumed that the duration of the noninfectious incubation period accounts for 60 percent of the incubation period (i.e., stage E), and 40 percent accounts for the infectious primary stage P. We estimate that the noninfectious incubation phase length is three days (range: 2.2–8.4 days) and that the infectious incubation phase length is two days (range: 1.6–5.6 days). The mean incubation phase length was estimated to be five days. The upper limit might be conservative (Backer, Klinkenberg, and Wallinga, 2020). Another study found that the mean incubation period was 5.2 days (95-percent confidence interval of 4.1, 7.0), with the 95th percentile of the distribution at 12.5 days (Li, Guan, et al., 2020). Backer, Klinkenberg, and Wallinga, 2020, found that the median incubation period for COVID-19 is just more than five days and that 97.5 percent of people who develop symptoms will do so within 11.5 days of infection.

Symptomatic Phases

The first symptoms commonly observed are likely to be a dry cough and a fever, although other initial symptoms are possible. Wang, Hu, et al., 2020, found that the median time from first symptoms to dyspnea (difficulty breathing) was 5.0 days. Wang, Tang, and Wei, 2020, found that the median time from first symptom to death was 14 days (range: 6–41 days) and tended to be shorter among people aged 70 years or older with a median of 11.5 days (range: 6–19 days).

Those younger than 70 had a median of 20 days (range: 10–41 days) from first symptom to death. We assume a mean mild symptomatic phase length of six days. This phase length is a weighted mean of the time to develop severe symptoms and the time to recovery for those with a mild disease, which we assume is similar to time to recovery for asymptomatic disease. In our model, we did not consider age heterogeneity here because we considered it in the probability of developing severe symptoms, and we want to avoid the potential issue of double counting an effect.

Critical Phase and Hospitalization

Pan et al., 2020, found that patients recovering from COVID-19 pneumonia (without severe respiratory distress during the disease course) and lung abnormalities on chest computed tomography (CT) scans showed the greatest severity approximately ten days after the initial onset of symptoms. Wang, Hu, et al., 2020, found that the median time from first symptoms to hospital admission was 7.0 days, and the time to acute respiratory distress syndrome (ARDS) was 8.0 days. This means that time from severe symptoms to ARDS and/or hospitalization is between two and three days. Some of this time is spent with mild symptoms, and we assumed that those who are severely symptomatic will take 2.5 days (range: 1.5–3.5 days) to become critically ill. If the hospital is not at capacity (i.e., $A = 1$), then this is also the time to be hospitalized. Experts on our team estimated that if patients needed to be hospitalized but hospitals were unable to accept more patients, then those that died would do so within three to five days of when they would have been admitted. We therefore assume that death would occur, on average, six days after severe symptom onset.

Duration in the Hospital

Wang, Tang, and Wei, 2020, found that the median hospital stay among those discharged alive was ten days. Because this quantity is highly uncertain, we assumed a mean of eight days in the hospital and a broad range (3–16 days), including ICU stays. We assume no age heterogeneity here.[1]

Duration in the Intensive Care Unit

Those who have critical illnesses and survive until discharge are assumed to take longer to recover than those who have severe illness (Moghadas et al., 2020). We assume that the total time spent in the hospital is longer for those who enter the ICU. In one study, only 10 percent of patients who entered the ICU had been discharged 12 days after entering the hospital (Arentz et al., 2020). We assumed that entering the ICU adds four days (range: 2.5–9 days) of hospital stay

[1] To model age heterogeneity, we could use results from Arentz et al., 2020, who found that 87 percent of hospitalized patients were aged 30 to 79 years (38,680 cases). This age group was the most affected by a wide margin, followed by ages 20 to 29 (3,619 cases, or 8 percent), those 80 and older (1,408 cases, or 3 percent), and 1 percent each in those younger than ten and those ages ten to 19 years.

and, therefore, we assumed that those who enter the ICU are in the hospital for an average of 20.7 days.

Duration Asymptomatic

We assumed that the duration of all infected stages via the asymptomatic branch has a mean of 14 days. Because we assume a mean of five days to either develop symptoms or proceed with the asymptomatic stage, we assumed that the duration of the asymptomatic stage is nine days (range: 7–12 days).

Table 3.4. Proportional Parameter Estimates

Proportion	Sample Distribution	Reference Value	Sensitivity Range	Sources
Asymptomatic proportion	PERT	31%	18%–45%	Day, 2020; Government of Iceland, 2020; Whitehead and Feibel, 2020
Ages 0–19, healthy and chronic conditions		48%		
Ages 20–24, healthy and chronic conditions		44%		
Ages 25–54, healthy and chronic conditions		28%		
Ages 55–64, healthy and chronic conditions		20%		
Ages 65–100, healthy and chronic conditions		19%		
Proportion of symptomatic cases that are severe	Uniform	20%	15%–25%	Yang et al., 2020; China Centers for Disease Control and Prevention, 2020
Proportion of severe cases that are critical	Uniform	25%	20%–30%	CDC, 2020b
Proportion of severe cases that are hospitalized (when the hospital has remaining capacity)	PERT	93%	80%–100%	Expert judgment
Proportion of hospitalized severe or critical cases that result in death	PERT	12%	3%–24%	Wu and McGoogan, 2020; CDC 2020b
Ages 0–19, healthy		0.9%		
Ages 20–24, healthy		2.6%		
Ages 25–54, healthy		7.2%		
Ages 55–64, healthy		12.6%		
Ages 65–100, healthy		17.4%		
Ages 0–19, chronic conditions		7.7%		
Ages 20–24, chronic conditions		10.2%		
Ages 25–54, chronic conditions		16.6%		
Ages 55–64, chronic conditions		24.2%		
Ages 65–100, chronic conditions		30.9%		
Proportion of severe cases that result in death when the ICU has no remaining capacity.	Uniform	90%	80%–100%	Expert judgment

Proportion	Sample Distribution	Reference Value	Sensitivity Range	Sources
Proportion of severe and critical cases not hospitalized that result in death	Uniform	40%	25%–55%	Wu and McGoogan, 2020; CDC 2020b
Ages 0–19, healthy		2.9%		
Ages 20–24, healthy		8.7%		
Ages 25–54, healthy		24.1%		
Ages 55–64, healthy		42.1%		
Ages 65–100, healthy		58.0%		
Ages 0–19, chronic conditions		25.8%		
Ages 20–24, chronic conditions		33.9%		
Ages 25–54, chronic conditions		55.5%		
Ages 55–64, chronic conditions		80.6%		
Ages 65–100, chronic conditions		100%		
Proportion of nonhospitalized deaths without positive tests, which are not counted in reported deaths	Uniform	50%	40%–60%	Expert judgment

NOTE: Age and chronic condition distributions are based on expert judgment.

Symptomatic Versus Asymptomatic Split

Day, 2020, found that, in an isolated Italian village where everyone was tested, 50 to 75 percent of individuals were asymptomatic. A report from Iceland noted that blanket testing revealed that 50 percent of the people who tested positive had no symptoms (Government of Iceland, 2020). Per person, the transmission rate of undocumented infections was 55 percent (range: 46–62 percent) of documented infections, yet, because of their greater numbers, undocumented infections were the infection source for 79 percent of documented cases. More recently, Robert Redfield, director of the CDC, told NPR that as many as 25 percent of people infected remain asymptomatic (Whitehead and Feibel, 2020). Experts on our team agree that the proportion of asymptomatic individuals varies. We assume a wide range of possible values, from 18 percent to 45 percent of all cases. We assumed that this changes as a function of age: 48 percent of children and 19 percent of people older than 65 asymptomatic in the reference case. We consider age heterogeneity in Table 3.4.

Mild Versus Severe Split

Yang et al., 2020, concluded that a total of 81 percent of cases are mild, meaning that they did not result in pneumonia or resulted in only mild pneumonia; 14 percent of cases were severe (marked by difficulty breathing); and 5 percent were critical (marked by respiratory failure, septic shock, and/or multiple organ dysfunction or failure). A report by the China CDC, 2020, suggested that about 80 percent of COVID-19 cases are mild. About 15 percent of patients have gotten severe cases, and 5 percent have become critically ill. We therefore assumed that 20 percent of symptomatic cases progress to severe status.

Nonhospital Mortality

If the hospital has remaining capacity, most patients with severe disease will be hospitalized. But some percentage of patients might not be hospitalized and instead might die at home. A significant number COVID-19 deaths have been documented in New York nursing homes (New York Department of Health, 2020). To account for these deaths, we assume that, on average, 93 percent (range: 80–100 percent) of severe cases are admitted to the hospital, with the remainder dying at home. Some of these deaths might not be counted in official death tolls. We assume that all hospitalized deaths and all deaths that occur in individuals who had a positive test are counted. We assume that 50 percent (range: 40–60 percent) of those who die outside the hospital and without a positive test are not counted.

Mortality

We assumed that only those who are severely symptomatic can develop critical conditions and that only those who are in critical condition can die. In China, all deaths were reported among those with critical disease (Arentz et al., 2020). Among severe and critical cases, there are three mortality rates to consider: the mortality rates for those not hospitalized, those hospitalized but not in the ICU, and those hospitalized in the ICU. We assumed that most severe cases (98 percent) are hospitalized if the hospital is accessible. This accounts for a small proportion of people who die at home, usually without being tested for the disease.

The China CDC found that 49 percent of those in the ICU died. This is consistent with CDC estimates that the proportion in the ICU who die is 39 percent to 72 percent. The China CDC also reports that 67 percent to 85 percent of ICU patients go on to develop ARDS. In our model, we assume that all patients entering the ICU are critical and will develop ARDS (CDC, 2020b).

According to CDC, 2020b, a range of 26 percent to 32 percent of patients were admitted to the ICU. This is similar to the proportion of severely symptomatic people that develop critical conditions, which we assume to be 25 percent. We assume that 50 percent of those in the ICU die (Russell et al., 2020). We assume that all hospital deaths occur in the ICU if the ICU is accessible and, therefore, that the CFR in the hospital is 12 percent on average (range: 3–24 percent) and is sampled from a beta-PERT distribution. This CFR is scaled based on the population strata, with older groups and those with chronic conditions more likely to die. This is based on evidence that CFR were shown to be higher in the elderly and in those with high body mass indexes and comorbidities (Wu and McGoogan, 2020). The China CDC found that, among those with preexisting conditions, the CFR was 10.5 percent for cardiovascular disease, 7.3 percent for diabetes, 6.3 percent for chronic respiratory disease, 6.0 percent for hypertension, and 5.6 percent for cancer (Wu and McGoogan, 2020). For those with no preexisting conditions, the CFR was 0.9 percent.

As explained in the "Hospitalization and Intensive Care Unit" section, the model does not currently consider the case where hospitals and ICUs are at capacity. However, we hope to add this feature in the future. In this section, we discuss how we will model this eventuality. When the ICU is at capacity, we assume that 90 percent of those who are unable to be admitted and would require mechanical ventilation in the ICU will die. This percentage is based on expert judgment from physicians. Therefore, 90 percent (range: 80–100 percent) of those who would go on to develop a critical condition die in the hospital. When both the ICU and hospital are closed, we assume that 40 percent (range: 25–55 percent) of those who have severe disease die because of lack of sufficient oxygen. This percentage is based on expert judgment and includes those who would have entered the ICU, so the proportion of severe but not critical patients who die when the hospital cannot be accessed is closer to 20 percent.

Model Parameters

Key parameters for this study include the rate at which those in the noninfectious incubation phase progress to the primary infectious stage, denoted by ν; the rate at which those in the primary infectious stage progress to the asymptomatic and symptomatic disease states, denoted by γ_A and γ_S, respectively; and the rate at which those with mild symptoms develop severe symptoms, denoted by υ. Rates of recovery and returning to a noninfected state are denoted by π, ξ, and ξ_H. The parameters and their formulas are shown in Table 3.5.

The rate at which those with severe symptoms get hospitalized is denoted by h. Hospitalization is contingent on whether the hospital has reached capacity. We have an indicator variable A that can be either one or zero to model accessibility to the hospital. Those who are hospitalized but not yet diagnosed are assumed to be diagnosed upon entry to the hospital. We assume that those who have been diagnosed and have developed severe symptoms access the hospital at a faster rate h_y compared with those not yet diagnosed with severe symptoms. Those who are hospitalized either recover at a rate ξ_h or die at a rate μ_h.

Those with severe symptoms who have not been hospitalized yet are assumed to die at a rate μ_H. This rate is very small when the hospitals are accessible (i.e., $A = 1$). However, this rate is assumed to increase rapidly when hospitals have reached capacity and are no longer accessible (i.e., $A = 0$). The rates at which symptomatic and asymptomatic infected individuals are diagnosed is ζ_A and ζ_S, respectively. These rates are assumed to change over time depending on the availability of testing kits.

Our model considers a population that is split into different demographic strata based on five age groups and health statuses. Health status strata describe whether an individual has one or more underlying chronic diseases. The relationship between the rates γ_S and γ_A depends on each population strata. This allows us to model different probabilities of being asymptomatic depending on age and health status. Likewise, the relationship between the mortality rates and the recovery rates also depends on population strata.

Table 3.5. Model Parameter Formulas

Parameter	Formula
Noninfectious incubation phase length	$1/\nu$
Infectious incubation phase length	$1/(\gamma_A + \gamma_S)$
Severe symptom onset to hospitalization	$1/h$
Hospital stay length (includes patients who are admitted to the ICU)	$1/(\mu_h + \xi_h + \chi)$
ICU stay length	$1/(\mu_{ICU} + \phi)$
Severe symptom onset to death for those not hospitalized	$1/\mu_H$
Mild symptomatic phase length (might lead to severe disease or recovery)	$1/(\upsilon + \xi)$
Asymptomatic phase length	$1/\pi$
Asymptomatic proportion	$\gamma_A/(\gamma_A + \gamma_S)$
Proportion of symptomatic cases that are severe	$\upsilon/(\upsilon + \xi)$
Proportion of severe cases that are critical	$\chi/(\mu_h + \xi_h + \chi)$
Proportion of severe cases that are hospitalized (when the hospital has remaining capacity)	$h/(h + \mu_H + \xi_H)$
Proportion of hospitalized severe or critical cases that result in death	$\chi\mu_{ICU}/(\mu_h + \xi_h + \chi)(\mu_{ICU} + \phi)$
Proportion of hospitalized severe cases that result in death when the ICU has no remaining capacity	$\mu_h/(\mu_h + \xi_h)$
Proportion of severe or critical cases not hospitalized that result in death	$\mu_H/(\mu_H + \xi_H)$

Force of Infection

The *force of infection* (λ) describes the rate at which those who are susceptible become directly or indirectly infected by an infectious person. The force of infection is characterized by how infectious people are in each state. Two parameters describe this; specifically, the contact mixing, c, which describes the rate at which infectious people mix with others, and the biological transmissibility, β,which defines the probability of transmission between an infectious and a susceptible person given a contact or other indirect interaction (e.g., touching the same elevator button within a given period). Each disease state would have a different content mixing rate and transmissibility. The unsimplified force of infection is given by Equation 3.1, where the coefficient c represents the social mixing contact rate and β represents the transmissibility for each disease state.

$$\lambda = [c_P\beta_P P + c_{I_{Sm}}\beta_{I_{Sm}}I_{Sm} + c_{I_{Ss}}\beta_{I_{Ss}}I_{Ss} + c_{Y_{Sm}}\beta_{I_{Sm}}Y_{Sm} \\ + c_{Y_{Ss}}\beta_{I_{Ss}}Y_{Ss} + c_h\beta_{I_{Ss}}H + c_{I_A}\beta_{I_A}I_A + c_A\beta_A Y_A] \tag{3.1}$$

Those who are in the primary infectious stage or are asymptomatic are unaware of their positive status and thus act as if they are not infected. However, those who have symptoms will reduce their contacts as their conditions become more severe or if they receive a positive test result. Likewise, tested asymptomatic people also will begin to practice increased social distancing to protect their social contacts. Thus, we can assume that social and physical contacts follow the inequalities in Equation 3.2.

$$c_P = c_{I_A} > c_h > c_{I_{Sm}} > c_{Y_A} \sim c_{I_{Ss}} > c_{Y_{Sm}} > c_{Y_{Ss}} \tag{3.2}$$

Under ideal conditions, the physical contact rate that leads to disease transmission between health care workers and COVID-19 patients (c_h) would be close to zero. However, contact precautions in health care settings cannot always be perfectly adhered to, given shortage of personal protective equipment and emergent situations. Hospitalized patients might have contact with many more individuals than those who are experiencing symptoms at home, so despite better proportions, we assume that transmission rates in the hospital are similar compared with those who are symptomatic but not being professionally cared for.

The transmissibility of each of the disease states was at first assumed to increase with symptoms. However, recent studies have shown that viral loads peak in the primary infectious stage and decrease monotonically after the onset of symptoms (He et al., 2020; Zou et al., 2020; Kelvin Kai-Wang To et al., 2020). Thus, we assumed the relationship in Equation 3.3.

$$\beta_h \sim \beta_{I_{Ss}} \sim \beta_{I_{Sm}} < \beta_{I_A} \sim \beta_P \tag{3.3}$$

To simplify the force of infection, we define an effective contact rate c_{eff} and an effective transmissibility β_{eff}. The product of these two $c_{eff}\beta_{eff}$ is assumed to characterize the rate of infections caused by an undiagnosed asymptomatic infected person in either state P or I_A. Rates of infections in the other disease states are characterized using m coefficients that give the multiplicative effect on infectivity with respect to the primary infectious state or asymptomatic state. For example, m_{Ss} gives the overall average multiplicative infectivity of a symptomatic severe individual relative to an asymptomatic individual. This multiplicative factor combines the effect of decreased social mixing with increased biological transmissibility. We choose the asymptomatic untested individual as our reference because they do not change their social mixing behavior. The infectivity of each state relative to the primary infectious stage is shown in Table 3.6.

The expression for the force of infection is described in Equation 3.4.

$$\lambda = c_{eff}\beta_{eff}[P + m_{Sm}I_{Sm} + m_{Ss}I_{Ss} + m_{tSm}Y_{Sm} + m_{tSs}Y_{Ss} + m_h H + I_A + m_{tA}Y_A] \tag{3.4}$$

Table 3.6. Infectivity Multiplier Estimates

Disease State	Symbol	Sample Distribution	Infectivity Relative to Primary Infectious Phase	Sensitivity Range
Primary infectious	N/A	N/A	100%	N/A
Secondary infectious: mild symptoms, no positive test	m_{Sm}	PERT	80%	50–160%
Secondary infectious: severe symptoms, no positive test	m_{Ss}	PERT	60%	40%–120%
Secondary infectious: mild symptoms, positive test	m_{tSm}	PERT	50%	20%–100%
Secondary infectious: severe symptoms, positive test	m_{tSs}	PERT	25%	20%–100%
Secondary infectious: hospitalized	m_h	PERT	20%	10%–80%
Secondary infectious: asymptomatic, no positive test	N/A	N/A	100%	N/A
Secondary infectious: asymptomatic, positive test	m_{tA}	PERT	70%	40%–140%

NOTE: N/A = Not applicable.

Testing Rates

The last set of parameters represents testing. Under the assumption of unconstrained testing rates, the parameters ζ_A and ζ_S describe the per-person testing rates of those who are asymptomatic and symptomatic, respectively. The latter includes only those who are symptomatic and are not yet hospitalized. Those who are symptomatic and hospitalized are considered tested if they did not previously test positive. The final per-person testing rate ζ is associated with all the tests on the susceptible, the exposed, and those in the primary infection stage. This rate includes the true negatives and the false negatives. The assumption of unconstrained testing rates means that anyone who seeks a test is tested and, therefore, testing capacity can accommodate the growth of the epidemic, including the exponential phase. The model diagram shown in Figure 3.1 considers unconstrained testing rates. However, the implementation of the model considers constraints in the daily number of testing kits that are available. This number is assumed to start low and grow linearly to a predefined maximum daily testing rate capacity. Thus, the actual rates describing the testing rates from each disease state could be reduced based on the capacity constraint. We assume that people who are hospitalized take priority and are tested first. The remaining number of testing kits is then assumed to be used to test those with severe symptoms. After that, the remaining number of testing kits is used to test to test those with mild symptoms, followed by the asymptomatic. In a model which included health care workers as a separate strata, these would be assumed to be treated first. This approach requires specifying a constant proportion of testing kits used to successfully identify those who are COVID-19–positive compared with those that are COVID-19–negative. This constant proportion, along with the initial testing capacity and the growth rate in testing, are found from analyzing testing rate data for each state. Testing rates depend on the testing policy. In our model, a *testing policy* is specified by the initial daily testing capacity, a continuous differentiable function describing how the capacity grows over time, and the maximum daily capacity.

Differential Equations and Model Outputs

Our deterministic model is formulated by a set of coupled ordinary differential equations (ODEs). The ODEs describing the dynamics of those who have been infected are:

$$\begin{aligned}
\frac{dE}{dt} &= \lambda S - \nu E, \\
\frac{dP}{dt} &= \nu E - (\gamma_S + \gamma_A)P, \\
\frac{dI_{Sm}}{dt} &= \gamma_S P - [\upsilon + \xi + \zeta_S]I_{Sm} \\
\frac{dI_{Ss}}{dt} &= \upsilon I_{Sm} - [\xi_H + \mu_H + hA + (1-A)\zeta_S]I_{Ss} \\
\frac{dY_{Sm}}{dt} &= \zeta_S(t)I_{Sm} - (\upsilon + \xi)Y_{Sm} \\
\frac{dY_{Ss}}{dt} &= \upsilon Y_{Sm} + (1-A)\zeta_S I_{Ss} - [\xi_H + h_y A + \mu_H]Y_{Ss} \\
\frac{dH}{dt} &= A(hI_{Ss} + h_y Y_{Ss}) - (\mu_h + \xi_h)H \\
\frac{dI_A}{dt} &= \gamma_A P - [\pi + \zeta_A]I_A \\
\frac{dY_A}{dt} &= \zeta_A(t)I_A - \pi Y_A
\end{aligned}$$

$$\frac{dH_{ICU}}{dt} = A_{ICU}\chi H - (\mu_{ICU} + \phi)H_{ICU}$$

The ODEs describing the dynamics of the susceptible and the noninfected removed states are:

$$\begin{aligned}
\frac{dS}{dt} &= -\lambda S \\
\frac{dD}{dt} &= \mu_H(I_{Ss} + Y_{Ss}) + \mu_h H, \\
\frac{dR}{dt} &= \xi(I_{Sm} + Y_{Sm}) + \xi_H(I_{Ss} + Y_{Ss}) + \xi Y_{Sm} + \xi_h H + \pi(I_A + Y_A)
\end{aligned}$$

These ODEs are integrated numerically to track the dynamics of the population in each compartment as they change over time. The model is implemented in “R” using the deSolve package (Soetaert, Petzoldt, and Setzer, 2010), using the lsoda and the fourth-order Runge Kutta

Method (Hindmarsh and Petzold, 1995). Thus, the model can track the point prevalence of people in each of the compartments and for each population strata.

Additional Outputs

We also can extract and combine incidence rates that flow into different compartments to track the cumulative quantities by population strata. Our model focuses on the following six additional outputs that are based on tracking incidence rates:

1. true cumulative case counts: $\frac{dC_T}{dt} = \lambda S$
2. reported cumulative case counts $\frac{dC_R}{dt} = \zeta_S I_{Sm} + \zeta_S(1-A)I_{Ss} + hAI_{Ss} + \zeta_A I_A$
3. cumulative number of people tested $\frac{dT}{dt} = \dot{C}_R + \zeta_G(S + E + P)$
4. reported recovered $\frac{dR_R}{dt} = \pi Y_A + \xi_h H + \xi Y_{Sm} + \xi_H I_{Ss}$
5. reported deaths: $\frac{dD_R}{dt} = \mu_H Y_{Ss} + \mu_h H$
6. reported CFR: $\text{CFR}_R(t) = D_R(t)/C_R(t)$.

Estimating R_0 and the Force of Infection

Model parameters describing disease progression can be estimated directly. Disease transmissibility and contact rates in each disease state are harder to estimate. This requires estimating the m coefficients and the $c_{eff}\beta_{eff}$. The values of the multiplicative coefficients and their ranges are estimated using expert opinion. The value of the effective infectivity $c_{eff}\beta_{eff}$ and its range is instead estimated from the value of R_0. The basic reproductive number R_0 represents the average number of secondary infections caused by an infectious person during the time they are infectious and at disease invasion. This represents the early stage of the epidemic, when each infectious person is surrounded by susceptible individuals. To extract an estimate for R_0, we use the number of reported cases during the early stages of the epidemic. In the region where the growth is exponential, the log of the case counts and the log of the deaths increase linearly with time. A linear regression of the log of the case counts time series and a regression of the log of the deaths provide estimates for the growth rate r. The estimated value of R_0 from r can be found using Equation 3.5 (Heffernan, Smith, and Wahl, 2005).

$$R_0 = 1 + r(\tau_E + \tau_I) \tag{3.5}$$

The time scale $\tau_E + \tau_I$ represents the typical duration for which a person is infected and is the sum of the durations of the noninfectious incubation phase and the infectious phase. The value of τ depends on the disease progression times and, more specifically, on the dwelling or sojourn times of those in each of the infected disease states. These sojourn times are model inputs. Roughly, $\tau_E + \tau_I$ is between 14 and 21 days.

The estimation of the value of the growth rate r and hence of R_0 using a linear regression approach has limitations. In the exponential phase, case reports are not very reliable because of backlogs and limited testing capacity. By the time testing rates and capacity stabilize, many jurisdictions are already in a stage where they have implemented social distancing. We have taken the approach of prioritizing the use of state-specific death data during the disease invasion exponential growth phase for each U.S. state to obtain their respective growth rates. However, some states produce a linear regression with an unacceptably bad fit to the data. For these cases, we assumed that the value of R_0 is between two and four based on the population density of the state. In this case, the value of R_0 is assumed to range from two for the state with the lowest population density to four for the state with the highest population density.

We use the value of R_0 to estimate $c_{eff}\beta_{eff}$. To do this, we need an algebraic expression for R_0 that is specific to our model structure. In simple mathematical models of infectious diseases, such as Susceptible-Infected-Removed (SIR) or SEIR models, R_0 can be expressed as the product of three terms, as shown in Equation 3.6.

$$R_0 = c\beta\tau_I \tag{3.6}$$

Compared with an SEIR model, our COVID-19 model considers more-infectious compartments with different contact mixing and transmissibly values and compartments that branch off from each other. R_0 can be expressed as the product of three terms in a similar way $R_0 = c_{eff}\beta_{eff}\tau_{eff}$. By analyzing our coupled ODEs using the next-generation matrix approach, we get the expression for τ_{eff} shown in Equation 3.7.

$$\tau_{eff} = \frac{(\mu_h+\xi_h)[\gamma_A(Ah+\mu+\xi)+\pi(Ah+\mu+m\gamma_S+\xi)]+\pi Ahm_h\gamma_S}{\pi(\gamma_A+\gamma_S)(\mu_h+\xi_h)(Ah+\mu+\xi)} \tag{3.7}$$

This expression has been simplified by considering the case where testing rates ζ_A and ζ_S are zero. R_0 is estimated during the disease invasion stage, when cases grow exponentially and testing rates are very small. We note that although τ_{eff} expresses a time scale, it includes the multiplicative coefficients m. Thus, τ_{eff} gives the time scale of the whole infectious state's τ_I when all multiplicative coefficients m are set equal to one. Using a more-direct approach instead of the next-generation matrix approach, we verified that the expression for τ_{eff} does indeed give τ_I when all multiplicative coefficients m are set equal to one. Because

$$R_0 = c_{eff}\beta_{eff}\tau_{eff} \Rightarrow c_{eff}\beta_{eff} = \frac{R_0}{\tau_{eff}}, \tag{3.8}$$

we can use the values for the multiplicative coefficients and the progression rates used in the model to find the value from τ_{eff} and, together with our estimate for R_0, we can obtain the value for $c_{eff}\beta_{eff}$. This, in turn, can be used to obtain λ, the force of infection.

Mixing Matrices and Interventions

Our model considers different population groups or strata, such as age group, health status, and whether individuals are health care workers. The simplest stratification considers five age groups. Moreover, we consider different activity levels or modes of social mixing between these population strata. When considering different population strata and mixing modes, we describe how the contact rate c_{eff} that enters the equation for R_0 depends on the mixing across population strata and over the different mixing modes (household, work, school, commercial, recreational, and other).

For this first version of the model, we consider ten population strata in five age groups with and without underlying conditions; our analysis produces the following outputs:

1. a set of ten-by-ten matrices M_m denoting the proportion of contacts of individuals in population strata (row) i that mixes with those in population strata (column) j over mixing mode m. Thus, each row sums to one.
2. a set of vectors k_m with five elements each, giving the normalized number of contacts (or duration of contacts) that individuals in age group i have over mixing mode m. Normalization implies that the sum over the elements i of k_m is one.
3. a set of scalars w_m giving the proportion of contacts (or duration of contacts) describing the status-quo distribution of weights based on how people mix over the different mixing modes.

Thus, under status-quo conditions, the number of contacts can be expressed using Equation 3.9 with a proportionality.

$$c_{eff}(\mathrm{sq}) \propto \mathbf{v}^T \cdot \{\textstyle\sum_m w_m\,(\mathrm{sq})[\mathrm{diag}(k_m) \cdot M_m]\} \cdot \mathbf{v} \tag{3.9}$$

Here, sq denotes the status-quo mixing conditions and $\mathrm{diag}(k_m) \cdot M_m$ gives the contact matrix, where the sum across each row for mixing mode m is proportional to the true number of daily contacts (or duration of contacts). The vector $\mathbf{v}$ is the distribution of the population of the state across the population strata. The actual mixing matrix is given mathematically by Equation 3.10.

$$\textstyle\sum_m w_m\,(\mathrm{sq})[\mathrm{diag}(k_m) \cdot M_m] \tag{3.10}$$

Therefore, having computed $c_{eff}\beta_{eff}$ from R_0, we find the proportionality constant κ as shown in Equation 3.11.

$$c_{eff}(g_{po})\beta_{eff} = \frac{R_0}{\tau_{eff}} = \kappa\mathbf{v}^T \cdot \{\textstyle\sum_m w_m\,(\mathrm{sq})[\mathrm{diag}(k_m) \cdot M_m]\} \cdot \mathbf{v} \tag{3.11}$$

We assume that the proportionality constant κ remains the same value as we explore different social-distancing NPIs.

Interventions

Social-distancing NPIs can be thought of as changing the locations in which people spend their time and mix socially. We follow an approach outlined by Prem, Cook, and Jit, where the effect of NPIs is modeled as a set of scalar weights on different mixing modes, $w_m(I)$, where I is the intervention (Prem, Cook, and Jit, 2017). For example, if schools were closed (represented as $school$), we could define the value of $w_{school}(school) = 0$, $w_{household}(school) > w_{household}(sq)$ to represent greater time spent at home and $w_{work}(school) < w_{work}(sq)$ because some parents are likely to stay home to take care of their children. In our model, w_m is proportional to the number of daily unique contacts that occur in location m. At baseline, the weights sum to one, $\sum_m w_m\,(sq) = 1$. However, the sum of the weights under different interventions need not sum to one. This is because weights represent unique contacts, and the goal of NPIs is to shift time and mixing to locations where there are few unique contacts. Consider a stringent intervention that confined people to their home. Although weights would decrease to zero for all locations except the home, the home weight might not increase significantly because spending more time at home does not increase unique contacts if all of the members of the household were contacts at the baseline scenario. Thus, NPIs can decrease the value of c_{eff} through reducing social mixing, although some interventions might simply displace mixing from one location to another.

Contacts within the home are a special case because they reliably occur between the same people each day. This is in contrast with other settings where contacts vary daily. This means that, on average, a contact within the home contributes less to disease transmission than a contact outside the home. To model this, we assume that transmission within the home is proportional to the mixing that is occurring in other locations, so as these weights decrease, the weight on $w_{household}$ also decreases. The values of $w_{household}$ for each intervention are the product of the household mixing estimated by our team and the weighted change of mixing in other contexts relative to baseline.

Table 3.7 shows the weights used at baseline and for each intervention. The baseline weights were determined by the relative number of contacts that occur in each matrix. The matrices are normalized so that the row sums are equal to one and the weights are proportional to the population-weighted normalization factor. For instance, at baseline there is relatively more mixing at work than in recreational settings, so this has a higher baseline weight. Using our combined matrices, 32.8 percent of unique contacts occur at work. The normalized matrices describe the groups between which mixing occurs, and the weights for each matrix quantify how much mixing occurs. Within the model, we allow the strength of NPIs to vary across states based on calibrating case counts and deaths to the data. The difference in the sum of the weights between each NPI and baseline is allowed to vary in the range of 90 percent to 110 percent of the reference values given in Table 3.7. A lower weight indicates that NPIs are less effective, perhaps because of lower compliance or environmental factors, whereas a higher weight indicates that they reduce social mixing to a greater extent.

To model the impact of an intervention, we need to make an assumption about what replaces the intervention after it is removed. We term this the *new normal*. This new normal is highly uncertain. If the effective R_0 in the new normal is above one, then there will be rebound and a second wave of cases. If it is below one, then there will be no such second wave. Like in other models, we assume that the new normal would be less intense than social distancing, but that mixing would be about half normal levels (Biocomplexity Institute, 2020). We also assume that new normal mixing will be lower if prior interventions were more stringent. To simulate the new normal, we assume that mixing in the new normal is the average of mixing in the last implemented intervention and mixing at baseline.

Table 3.7. Intervention Mixing Matrix Weights

NPI Portfolio	$w_{household}$	w_{work}	w_{school}	$w_{commercial}$	$w_{recreational}$	w_{other}
Baseline	18.4%	32.8%	16.1%	9.0%	4.2%	19.5%
Level 1: Close schools	14.7%	23.0%	0.0%	9.0%	5.1%	17.5%
Level 2: Close schools, bars, and restaurants; and ban large events	12.1%	23.0%	0.0%	6.3%	3.8%	11.7%
Level 3: Close schools, bars, and restaurants; ban large events; and close nonessential businesses	4.3%	6.6%	0.0%	3.6%	3.0%	5.8%
Level 4: Close schools, bars, and restaurants; ban large events; close nonessential businesses; and quarantine the most vulnerable (shelter-in-place)	3.9%	6.6%	0.0%	3.4%	2.5%	5.0%
Level 5: Close schools, bars, and restaurants; ban large events; close nonessential businesses; and quarantine everyone but essential workers (shelter-in-place)	2.7%	6.6%	0.0%	2.7%	0.8%	1.9%

Other Models

A growing number of models have been developed by health care systems, academic institutions, consulting firms, and others to help forecast COVID-19 cases and deaths; medical supply needs, including ventilators, hospital beds, and ICU beds; and timing of patient surges. The American Hospital Association (AHA) has compiled a summary report that compares existing efforts (AHA, 2020).

Two notable COVID-19 models that use a system dynamics approach are the CHIME model, developed by Penn Medicine, and the PatchSim model, developed by the University of Virginia.

Both are geographically specific, assume an R_0 of approximately 2.5, and model social distancing as reducing rates of infection by 25 to 30 percent. The CHIME model uses a SEIR compartmental model and aims to assist hospitals and public health officials with hospital capacity planning. The hospital bed and ICU bed utilization numbers are based on fixed ratios.

The University of Virginia uses a meta-population compartmental model and considers the spread between geographic areas using travel data. It uses detailed country data for different geographical regions, and each region is calibrated. The model is calibrated using a past model and data on influenza spread to refine model of spread.

An alternative to system dynamics is to use a statistical-based approach. The most notable statistically based model was developed by the Institute for Health Metrics and Evaluation (IHME). The IHME model was designed as a planning tool for hospital administrators and government officials who need to know when the demand on health system resources will be greatest. The IHME uses a variety of statistical models based on curve-fitting algorithms to generate forecasts of deaths and hospital resource needs. Some infectious disease epidemiologists have criticized the IHME model because they believe that it is not well suited to describe the COVID-19 transmission dynamics. Fundamentally, this is because it uses a statistical curve-fitting model approach that replaces an underlying causal model for transmission and disease progression (Begley, 2020).

Limitations

In this section, we discuss some of the limitations of our model. These are split into limitations of the modeling techniques chosen, data limitations, and features that are currently missing but could be added in the future.

Modeling Limitations

As discussed earlier, population-level models are more useful for comparing the relative impact of different interventions than as forecasting tools. They make strong assumptions about functional forms and about how the outbreak will progress. These assumptions allow them to be built and deployed quickly with relatively little data, but such assumptions also limit the extent to which models can be tuned to observed outbreak statistics (Manheim et al., 2016).

All population models are based on the law of mass action, which assumes that individuals within a given strata and compartment mix homogenously.[2] Humans generally do not mix homogeneously, but this approximation often is close enough to be useful. This assumption limits the interventions that can be investigated because it does not allow some individuals within a compartment to act differently to others. Agent-based models (ABMs) and

[2] In chemistry, the law of mass action is the proposition that the rate of a chemical reaction is directly proportional to the product of the activities or concentrations of the reactants.

microsimulations are better suited to depart from mass-action homogeneity in mixing but are much harder to inform, develop, and deploy. ABMs are thus less agile and adaptable to new information or circumstances.

ODEs make assumptions about the smoothness of functions. However, reactions during an outbreak can be discontinuous, either because of reporting errors or because the real world does not operate smoothly. For instance, COVID-19 testing up until March 16, 2020, in New York state showed that more than 70 percent of tests were coming back positive. On March 17, 2020, an additional 2,687 negative tests were reported, almost 30 times the sum of all negative tests reported before that date, and the positive proportion fell to below 15 percent. ODEs are not designed to accommodate such discontinuities and therefore might have problems fitting data accurately.

ODEs do not distinguish between individuals in each compartment; individuals are selected at random. Thus, the last to enter the compartment can be the first out. Although average parameters can be matched, this leads to an exponential dwelling time distribution for each compartment. This is unlikely to be a good model for the process. One way to correct for this limitation is to create a series of compartments for each disease state. The dwelling time across all these compartments can be made to correspond to an Erlang or Weibull distribution (Oguntunde, Odetunmibi, and Adejumo, 2014). However, this correction is not currently implemented within the model, and we therefore assume exponential dwelling time distributions.

Population-level models belong to a theory-based class of models. In contrast to statistical models, which are based on regression or machine-learning techniques, theory-based models specify a conceptualization of the disease progressions and causal links in the dynamics. Other theory-based models include microsimulation models and ABMs. Population-level models are relatively simple to conceptualize and implement. They have less challenging data requirements, less challenging computation and execution time requirements, and less complexity than other types of models, including other theory-based models. The speed and ability to represent changes in the disease dynamics make population models particularly useful for exploring different features of disease dynamics. However, this simplicity comes with a set of limitations. Population-level models are based on the assumption of the law of mass action and, thus, they assume homogenous mixing in the population. This limitation is alleviated by specifying different population strata and a contact matrix but the degree to which heterogeneous mixing occurs is limited by the number of population strata. Because population-level models are formulated by ODEs that are integrated numerically by solvers, careful attention needs to be taken in terms of making sure that the integration is accurate, stable, and converges (Press et al., 1992). These solvers are not very well suited in modeling parameter values that change abruptly or according to a prespecified time series. This presented some challenges in modeling the variable testing rates and accessibilities to the hospital.

Population-level models usually are formulated as deterministic differential equations and do not capture uncertainty resulting from chance variation well. They do not track the trajectories of single individuals but rather capture the dynamics of population densities in each disease state. Thus, they can consider a fractional number of people in each disease state. This can be a problem because a fractional number of people can still lead to new cases of infections when, in reality, the disease prevalence might be low enough that the probabilistic expectation of new infections is unlikely. Although these models do not track individual trajectories, the last person into any disease compartment has the same chance of progressing out of the compartment as anyone else. This naturally leads to a memory-less process and to an exponential dwelling time distribution of individuals in each compartment. This can cause issues if the subsequent infectious compartment is characterized by a very different contact rate and transmissibility. This is a known issue that can be corrected by concatenating multiple compartments that each describe the same disease state. This leads to a convolution of exponential dwelling time distributions and thus an Erlang distribution (Oguntunde, Odetunmibi, and Adejumo, 2014; Greenhalgh and Rozins, 2020).

More generally, population-level models are a good modeling choice for comparing potential interventions but are less useful than statistical models for forecasting disease incidence. They provide a good approach when used for qualitative understanding of disease outbreaks. In particular, they are excellent for comparing potential future interventions. They also run rapidly, require less input data, and their results and structure are communicated easily. However, they are harder to tune to match observed outbreak statistics or to give accurate quantitative predictions.

Data Limitations

Unobservable True Cases

Ideally, any epidemic model would be built using time series of the true case count. However, because many cases of COVID-19 are asymptomatic and because cases are verified only through testing, the true case count cannot be observed. Instead, we observe two imperfect proxies: confirmed cases and deaths.

Confirmed cases are confounded by testing rates. In locations where there are few tests conducted, it appears as if there are few cases. Changes in the testing rate confound attempts to estimate the R_0 by fitting curves to case counts. Initial testing shortages, followed by a sharp increase in availability, causes a surge in the number of confirmed cases, which causes overestimation of R_0. This pattern is common across the United States, particularly in New York.

Deaths are an imperfect proxy of true cases for several reasons. The time between contracting the disease and death (assuming admission to the hospital) is approximately three weeks. Therefore, estimations of the true case count or the effectiveness of NPIs based on deaths are almost one month out of date. Furthermore, COVID-19 has a relatively low CFR. This means that there are many true cases for each death. In small communities, the number of deaths might be so low that there is too much noise to accurately judge the true case count. These effects mean that it is difficult to use deaths to show the prevalence of COVID-19 outside population centers, and such estimates will always be out of date.

Additionally, deaths might be confounded by testing. Deaths might be attributed to COVID-19 only if individuals die in hospital and have a positive COVID-19 test. This number is an underreport because it does not count those who were not tested or those who died at home.

Measurement Error

COVID-19 tests are conducted at testing centers and medical clinics around the country. Testing results are reported by lab services companies and are aggregated at the state level. There might be errors or delays in this process, which means that testing time series are not reported correctly. Similarly, it might be difficult to attribute some deaths to COVID-19. These factors introduce errors into the data, which limits the ability of any model to accurately predict true cases and, therefore, future outcomes.

Parameter Estimates

Parameter estimates are discussed in detail earlier and are summarized in Table 3.3. For many of these parameters, such as the proportion asymptomatic, mixing matrices across age groups, and CFRs, there are widely agreed-upon estimates. The model is highly sensitive to many of these parameters, and these sensitivities are explored through Latin-Hypercube sampling. Interpretations of point estimates from the model must take into account these significant uncertainties and the corresponding confidence intervals.

Future Features for Consideration

Hospital and ICU Capacity

This report details how we would modify CFRs if the hospital and ICU were to reach capacity and were therefore unable to accept more patients. However, these modifications are not currently implemented because of the difficulty of reproducing current hospitalization data (which may be unreliable). Because we do not model the impact of the health care system being overwhelmed, we likely understate the number of deaths in states where hospital admissions exceed capacity. In the future, we hope to better fit hospitalizations and therefore implement these CFR modifications.

Better Estimates for the Basic Reproductive Number

Our approach in estimating the growth rate—and thus the value for each state—is simplistic and has limitations. A better approach is to scale the reported case counts based on a vulnerability factor that takes into account the differences in population demographics and the proportions of the vulnerable or at-risk population (Lachmann et al., 2020).

Seasonality

Influenza exhibits seasonality in temperate climates, with outbreaks typically occurring during the winter months. Seasonality is thought to be because of a combination of cyclic immunity; lower immune activity during periods of low light; greater crowding in cold months; indoor heating; and improved virus survival in cold, dry conditions (Lofgren et al., 2007). It is unknown whether COIVD-19 will exhibit seasonality and whether transmission might be greater in certain environmental conditions. Given the wide variation in climate across the United States, it is possible that the virus might spread more rapidly in cool, dry locations (which would manifest as a larger R_0). We would like to explore this by changing transmissibility in states that have climates that are more favorable to flu transmission to see whether this explains some of the variation in R_0.

State Mixing

Currently, the model assumes that no mixing occurs across state lines. This assumption might be of little consequence now because the virus has already spread to almost every county in the United States. This makes new seeding events relatively unimportant. However, as the virus becomes more controlled in some areas of the country, preventing travel to other states could prove crucial to controlling cases. Many countries, such as China, have banned travel from noncitizens and introduced mandatory quarantines for returning nationals. U.S. states might take similar actions in the future. We hypothesize that state mixing is a function of the number of flights between two states, state populations, and state adjacency. Future iterations of this research could try to model the effect of state mixing and understand the impact of NPIs that are designed to decrease it.

Behavioral Feedback

NPIs rely on compliance to be effective. Compliance might change as a function of perceived risk and perceived cost of complying. Compliance is likely to be especially important as social-distancing measures are relaxed and the perceived risk decreases. We would like to model how compliance changes with perceived risk. One avenue currently being explored relates mobility data and social media activity to case counts.

Nonpharmaceutical Intervention Combinations

The NPIs considered within the model are limited to five prespecified NPI combinations and a baseline scenario. In the future, it would be useful to consider more combinations of NPIs. One could model how NPIs interact such that any NPI combination could be modeled. This might be useful for states thinking about the order and timing of relaxing social-distancing measures.

Mixing Matrix Changes

The effect of NPIs is modeled through changing the weights of mixing matrices. This assumes that NPIs change how much mixing occurs in each location, but not *how* people mix in that location. One example is that commercial mixing, which usually would include bars and restaurants, is now limited to grocery stores. This means not only that less mixing is occurring, but also that a smaller proportion of that mixing is between young adults and other young adults. We could introduce more flexibility into how changes in NPIs are modeled by premultiplying by nondiagonal matrices rather than by scalars or diagonal matrices.

Removing Interventions: A New Normal

We assume that, after interventions are removed, mixing reverts to a new normal with approximately half of baseline mixing. In reality, there is likely to be a slow reversion to normal, which would occur at different rates in different contexts. For instance, many businesses might be quick to reopen to maintain their cashflows, but many schools have already announced that they plan to remain remote for the fall 2020 term. In future versions, we could model these reversions as a decay from the last intervention applied to a new normal with different time scales for different contexts.

Additional Population Stratifications

We have stratified our population into five age groups. The first is made up of individuals ages zero to 19. In a future version, we will further stratify this age group. This would allow us to explore additional interventions, such as comparing school closure for students in high school only or reopening schools in phases based on grade.

4. Economic Model

We developed a model of each state's economy that incorporates the relationships across industries, households, and government. We modified an existing model to quickly estimate the effects of the selected NPI portfolios (see Table 2.2 in Section 2) by changing the definitions of industries to reflect how the NPIs are likely to interact with the economy. Our approach is to restrict output in certain sectors consistent with industry estimates or with previous literature regarding NPI impacts. We then allow these restrictions to flow through the economy and affect other sectors and households to produce an estimate of the total economic impact in terms of lost income to households. The model is calibrated using readily accessible data and is intended to provide rough order-of-magnitude estimates of the economic consequences associated with various social-distancing interventions.

Model Details

Our approach to the development of a computable general equilibrium (CGE) model is based on the work of Sue Wing, 2007; Rausch and Rutherford, 2008; and Nadreau, 2015. The Economic Impact Analysis for Planning (IMPLAN) Social Accounting Matrix for each state is used to calibrate the initial values of parameters within the model. We use 2016 data because they reflect the most-recent information to which we have ready access for the entire United States. The IMPLAN data provide calibration values for 536 different sectors. IMPLAN data are based on the national-level input-output tables developed by the Bureau of Economic Analysis (BEA) and then downscaled to the local levels using a proprietary algorithm. IMPLAN has been a staple of regional economics for the past 40 years.[3] To deliver a manageable modeling process and ensure a clear interpretation of results, we aggregated the 536 sectors to 15 sectors (as recommended in the methodology implemented by Nadreau, 2015), but we also develop specific sectors that are likely to be affected by state and local social-distancing policies. Each sector is viewed as having a representative firm that is assumed to maximize profit, implying that it uses the least-cost combination of inputs needed to produce its output. It is further assumed that the firm is a price-taker in a competitive market and the sector is in equilibrium—i.e., the quantity supplied equals the quantity demanded. In addition to data on consumption and earnings for nine representative households by income level, IMPLAN also offers relevant data for both state and local governments and federal governments. Households are assumed to maximize utility, taking

[3] Recently, Thomas Rutherford and Andrew Schreiber developed an open-source method for downscaling the BEA tables, but the authors have not sufficiently vetted the algorithm to see whether it provides advantages over the IMPLAN data. For more information on this approach, see Rutherford and Schreiber, undated.

good and factor prices as given.[4] Finally, markets clear as prices adjust, with global prices assumed to be constant for imports and exports. Thus, we assume that each state or metropolitan area is a small, open economy that does not affect global prices. Our approach is to build a static general equilibrium model of the economy of each state and then limit sector output by the impact of social-distancing policies. Our model is a standard general equilibrium model that has been used to estimate regional and national impacts of policy changes across a wide variety of settings. We provide a brief overview of the model and advise the reader to consult Sue Wing, 2007; Rausch and Rutherford, 2008; and Nadreau, 2015, for more details. We have provided our choices regarding key parameters in the text.

Firm's Problem

In the development of our calculation, we modeled the production in each sector *i* as a representative firm that has chosen its output to maximize profit at a given price. In our model, firms are assumed to be perfectly competitive, meaning that they do not set prices but respond to prices in their decisionmaking. The production process follows a nested, constant elasticity of substitution (NCES) function as described in Equation 4.1:

$$Y_{it} = \phi \left(\alpha \left(\beta K_i^\rho + (1-\beta) L_i^\rho \right)^{\frac{\eta}{\rho}} + (1-\alpha) \right) \left(\sum_j \left(\theta_j X_{ij} \right)^\gamma \right)^{\frac{\eta}{\gamma}} \Bigg)^{1/\eta} \tag{4.1}$$

where K_i is capital used in sector *i*, L_i is labor used in sector *i*, and X_{ij} are intermediate inputs produced by sector *j* that are used by sector *i*. We choose an NCES production function because of its flexibility and because Perroni and Rutherford, 1995, have proven that calibration of the NCES is possible for an arbitrary dimension as long as the given Slutsky matrix is negative semidefinite, the function will have the appropriate convexity conditions to ensure an equilibrium. Other functional forms could be used.

We rewrote these production functions in the calibrated share form to allow for an easy calibration using the existing IMPLAN data. We assume that η is set so that the implied elasticity of substitution is zero (i.e., perfect complements); ρ is set so that the implied elasticity is one and results in a Cobb-Douglas production function; and γ is set to imply an elasticity of four.[5] Thus, the intermediate goods that are inputs in production are more substitutable than capital and labor. Additionally, the aggregate capital-labor input and the aggregate intermediate

---

[4] Income in the IMPLAN data is total income from earnings from labor, land, capital, and from government transfers.

[5] Rather than discuss the parameter values of $\eta, \rho,$ and γ, we opt to report the *implied* elasticities because these have more readily accessible meaning for economists. Our assumption of perfect complements in the uppermost nest implies that the functional form degenerates to a minimum operator of the inputs. These parameter choices are consistent with Nadreau, 2015.

input are assumed to be perfect complements. Finally, α, β, and θ_j are expenditure share parameters, and ϕ is a technological adjustment parameter.

Consumer's Problem

The consumer's problem is quite similar to the producer's problem. We assumed that a representative household maximizes utility, receiving income from the factors of production (capital and labor), net sales of exports, transfer payments from either the federal or state government, and investments in inventory. Households must balance their budgets and supply all factors inelastically. We discuss how households are affected by social-distancing policies in a later section. We assumed that the utility function is simply a Cobb-Douglas utility function, calibrated to the consumption data in the IMPLAN data. We normalize the amount of labor and capital to the 2016 levels using Equation 4.2:

$$U_i = \sum_i \alpha_i \ln(D_i) \qquad (4.2)$$

where α_i is the budget share of good i in the benchmark data and D_i is household demand of good i.

Equilibrium

We calibrate the model to the initial conditions defined by the social accounting matrices produced from the IMPLAN data. The static model was written in the General Algebraic Modeling System (GAMS) using the Mathematical Programming System for General Equilibrium (MPSGE) subsystem and uses the Path solver. An equilibrium is characterized by a set of goods and factor prices together with market-clearing levels of production and consumption.

Regions

We replicate the analysis for all 50 states as well as a national-level model. In future iterations, we will add metropolitan areas.

Sectoring

For the CGE model, we divide the economy into 13 sectors. For a social-distancing analysis, the key sectors with direct impacts are restaurants and bars; hospitality (generally); education; nonessential retail; and air transportation. These sectors correspond to IMPLAN sectors as shown in Table 4.1.

Table 4.1. IMPLAN Sectors in Social-Distancing Sectors

Sector	Sector Stub	IMPLAN Sectors
Restaurants and bars	REST	501–503
Hospitality	HOSP	488–500
Education	EDU	472–474, 532, 534
Air transport	AIRT	408
Nonessential retail	NERT	396–399, 403–407

In addition to the five sectors identified, there are sectors that correspond to agriculture, construction, utilities, fossil fuels, wholesale and retail trade, mining, food processing, manufacturing, services, and the rest of the economy. These divisions follow Nadreau, 2015.

Implementing the Nonpharmaceutical Intervention Portfolios

To implement the five NPI portfolios described in Table 2.2 in Section 2, we map each intervention in each portfolio to five sectors within the economy: (1) education; (2) restaurants and bars; (3) hospitality, including hotels, museums, and amusement parks; (4) air transport; and (5) nonessential retail. We normalize the analysis to consider weekly durations. We assume that the impacts do not vary with time so that these results can be scaled to match the duration of the policy.

Our assumptions for the impact of the NPI portfolios on each of the five sectors are summarized in Table 4.2, and the sources behind them are described in detail below. Our baseline levels of the impact of an NPI are based on estimates derived from industry associations or lobbying groups, transfers from related sectors where little information is available, or related literature on previous social-distancing interventions that we use to calibrate a national model. In particular, for school closures, we calibrate the output reduction in the education sector to match the gross domestic product declines in Smith et al., 2011. In addition to these baseline levels, we vary the level of impact around the baseline level to produce low-impact and high-impact scenarios for each of the policy scenarios in addition to the baseline.

Using Smith et al., 2011, and the calibration of the national model, the baseline reduction in education output is set to 0.75. We vary this between 0.50 and 0.90 to analyze sensitivity. In addition, school closures induce a labor supply reduction for those parents who must now stay home to care for their children. According to an analysis by Edwards, Evans, and Schwam, 2020, approximately 5.9 percent of households are single parent families with that parent working, 2.7 percent of which have no in-home options for day care and 1.8 percent of which have a nonworking adult who might provide care but also might be part of the vulnerable population. Additionally, approximately 17.6 percent of households are two parent families with both parents working, 8.5 percent of which are without in-home care options. Thus, we estimate that approximately 10 percent of working adults could have long-term absenteeism, resulting in a 10-

percent reduction of the labor supply. As discussed in Smith et al., 2011, there could be large absenteeism stemming from those infected with the disease for those sectors not directly affected by social-distancing policies. Additionally, there will be labor supply reduction directly and indirectly from COVID-19 resulting from both sickness and caregiving for those who are sick. As long as the infection rate remains low, social-distancing policies will likely have a dominant effect on the labor supply. In future iterations of this work, we will incorporate feedback between an epidemiological model and our model.

For the restaurants and bars sector, the National Restaurant Association has estimated that industry sales are likely to decline by 25 percent (Gangitano, 2020). The New York State Restaurant Association has estimated that sales likely declined by 58 percent in the first three weeks of March (Romeo, 2020). Using these two estimates, we set the upper bound on output to 60 percent (a rough average of the two associations) and use 40 percent and 75 percent as our low and high impacts. In addition, as we move to stay-at-home orders, we further reduce the baseline level to 25 percent and set 10 percent and 50 percent as our lower and upper bounds. We map the cancellation of large events to the hospitality industry, which includes hotels, amusement parks, casinos, and similar businesses. The American Hotel and Lodging Association (AHLA) estimates that roughly 70 percent of its workers will be laid off as a result of COVID-19 (AHLA, undated). We follow the estimates of the restaurants and bars for the larger hospitality sector because the most-extreme estimates match those of the AHLA.

In a recent survey of the retail sector, NuOrder estimated that retail sales are likely to decline by 50 percent as a result of COVID-19. Groceries are part of retail, so our baseline level of output for nonessential retail is set to 40 percent with low and high values of 25 percent and 75 percent, respectively. Again, in the most severe policy, we further decrease this in line with the restaurants and hospitality industries (Binlot, 2020).

For the air transportation sector, we mimic the hospitality assumptions with one exception. Air transportation consists of both cargo and passenger traffic. According to Rodrigue, 2020, cargo revenue is roughly 25 percent of air transportation revenue. Therefore, we modify the hospitality numbers to reflect this by reducing the decrease by 25 percent. Thus, the baseline scenario for air transportation is 70 percent with low and high values of 50 percent and 80 percent, respectively. Additionally, we place a lower bound for air transportation of 30 percent in the most extreme case of social distancing.

Because of the general equilibrium nature of the model, there will be considerable reallocation of displaced labor to sectors that are not directly affected by social-distancing policies. As we reduce the output of a sector, its labor demand will fall and workers will reallocate to sectors that are not constrained by policy. Because factors are supplied inelastically, there is no unemployment implied by the model but wages fall—and they fall to a considerable extent in the more-extreme scenarios of social distancing, which can be thought of as unemployment, to a degree. Given the presumably short-term nature of social-distancing policies (most of which likely will be repealed in a matter of months), we would not expect a fundamental restructuring of the economy. Therefore, we limit the increase in output to 50 percent of the baseline level.

Table 4.2. Impact of Nonpharmaceutical Intervention Portfolios on Industry Sectors

Portfolio ID	Scenario	EDUC	REST	HOSP	AIRT	NERT
0	No action	1.00	1.00	1.00	1.00	1.00
1L	Close schools.	0.90	1.00	1.00	1.00	1.00
1B		0.75	1.00	1.00	1.00	1.00
1H		0.50	1.00	1.00	1.00	1.00
2L	Close schools, bars, and restaurants; and ban large events.	0.90	0.75	0.95	1.00	1.00
2B		0.75	0.60	0.75	0.80	1.00
2H		0.50	0.40	0.60	0.70	1.00
3L	Close schools, bars, and restaurants; ban large events; and close nonessential businesses.	0.90	0.75	0.75	0.80	0.75
3B		0.75	0.60	0.60	0.70	0.40
3H		0.50	0.40	0.40	0.50	0.25
4L	Close schools, bars, and restaurants; ban large events; close nonessential businesses; and quarantine vulnerable populations (shelter-in-place).	0.90	0.50	0.50	0.65	0.75
4B		0.75	0.25	0.25	0.50	0.40
4H		0.50	0.10	0.10	0.40	0.25
5L	Close schools, bars, and restaurants; ban large events; close nonessential businesses; and quarantine everyone but essential workers (shelter-in-place).	0.90	0.50	0.50	0.50	0.50
5B		0.75	0.25	0.25	0.35	0.25
5H		0.50	0.10	0.10	0.30	0.10

Results

We first present the national-level results to provide a baseline. Table 4.3 presents the income declines separated by household for all the NPI portfolios. To put these raw income losses into perspective, we normalize by the baseline income in Table 4.3. Although much of the discussion within the popular media has focused on lower-income households, our analysis suggests that higher-earning households are affected with a larger proportion of income decline from social-distancing policies. Although it might seem counterintuitive, this is because of the incorporation of labor income and also all sources of income. As we have seen in recent weeks, the Small Business Association program to provide forgivable loans has been overprescribed. This suggests that the impact of social distancing is affecting not only labor income but also capital income, along with those who receive other nonlabor income. Because those who receive nonlabor sources of income are directly and indirectly affected by social distancing, their incomes are likely to decline substantially. The general equilibrium approach incorporates changes in labor income and also nonlabor income that might be substantial portions of value added in different sectors. This is also consistent with a *Financial Times*-Peterson poll that found that roughly the same proportion of households reported that 73 percent would experience some income decline because of COVID-19 with between 19 percent and 29 percent experiencing significant declines (Fedor and Zhang, 2020). Importantly, none of the effects of the 2020 Coronavirus Aid, Relief, and Economic Security Act has been incorporated into this analysis. The focus is solely on the effects that social distancing could have on the economy without federal policy.

Table 4.3. Income Declines per Week, by Household Income ($ millions)

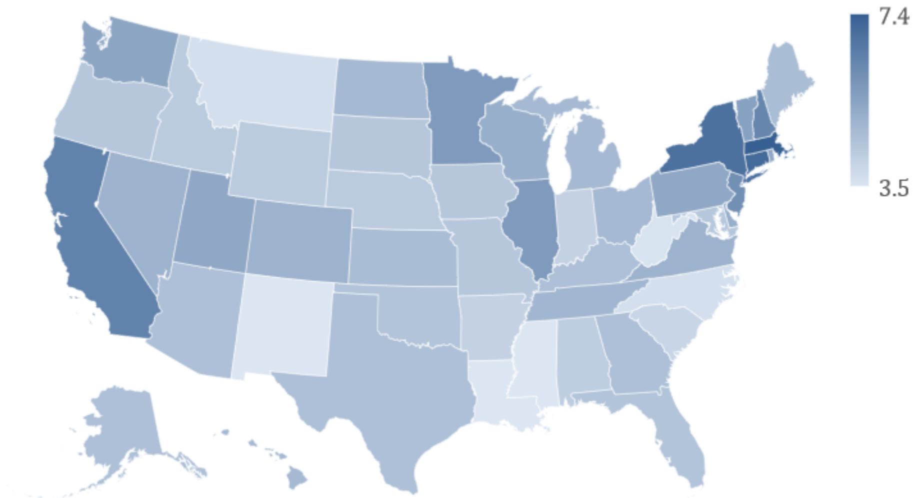
Portfolio ID	< 15K	15K–30K	30K–40K	40K–50K	50K–70K	70K–100K	100K–150K	150K–200K	> 200K	Total
1L	100	300	400	500	1,300	2,000	2,500	1,500	3,100	11,600
1B	100	400	500	700	1,700	2,600	3,300	1,900	3,900	15,100
1H	100	500	700	900	2,200	3,400	4,400	2,500	5,000	19,700
2L	100	400	500	700	1,800	2,700	3,500	2,000	4,200	16,000
2B	100	600	800	1,100	2,700	4,200	5,300	3,100	6,300	24,200
2H	200	800	1,100	1,500	3,700	5,700	7,300	4,200	8,500	32,900
3L	100	600	800	1,000	2,500	3,900	5,000	2,900	6,000	22,600
3B	200	900	1,200	1,600	3,900	6,000	7,700	4,400	9,100	34,800
3H	200	1,100	1,500	2,000	5,000	7,700	9,900	5,700	11,700	44,900
4L	200	700	1,000	1,300	3,200	5,000	6,400	3,700	7,700	29,100
4B	200	1,100	1,400	1,900	4,800	7,300	9,500	5,500	11,400	43,100
4H	300	1,300	1,700	2,300	5,800	8,800	11,400	6,600	13,900	52,100
5L	200	900	1,200	1,500	3,800	5,900	7,600	4,400	9,100	34,600
5B	300	1,200	1,600	2,200	5,500	8,400	10,900	6,300	13,100	49,500
5H	300	1,600	2,100	2,800	7,100	10,900	14,000	8,100	17,200	64,200

Table 4.4. Percentage Income Declines, by Household Income

Portfolio ID	< 15K	15K–30K	30K–40K	40K–50K	50K–70K	70K–100K	100K–150K	150K–200K	> 200K	Average
1L	0.4	1.2	2.2	3.2	4	4.5	5.3	6	9.8	4.6
1B	0.6	1.6	2.9	4.3	5.3	5.9	6.9	7.9	12.5	6
1H	0.7	2.1	3.9	5.6	6.9	7.8	9.2	10.4	16	7.9
2L	0.6	1.7	3.1	4.5	5.6	6.2	7.3	8.3	13.5	6.4
2B	0.9	2.6	4.7	6.8	8.4	9.4	11.1	12.6	20.1	9.7
2H	1.2	3.5	6.4	9.3	11.5	12.8	15.2	17.2	27.1	13.1
3L	0.8	2.4	4.4	6.3	7.9	8.7	10.4	11.8	19	9
3B	1.3	3.7	6.7	9.8	12.1	13.5	16	18.2	29	13.9
3H	1.7	4.7	8.7	12.7	15.6	17.4	20.7	23.5	37.4	17.9
4L	1.1	3.1	5.6	8.2	10.1	11.2	13.3	15.1	24.5	11.6
4B	1.6	4.5	8.3	12.1	14.9	16.6	19.7	22.5	36.4	17.2
4H	1.9	5.5	10	14.5	18	20	23.7	27.1	44.4	20.8
5L	1.3	3.6	6.7	9.7	12	13.3	15.8	18	29.1	13.8
5B	1.8	5.2	9.6	13.9	17.2	19.1	22.7	25.8	41.8	19.8
5H	2.4	6.7	12.4	17.9	22.2	24.6	29.3	33.4	54.7	25.6

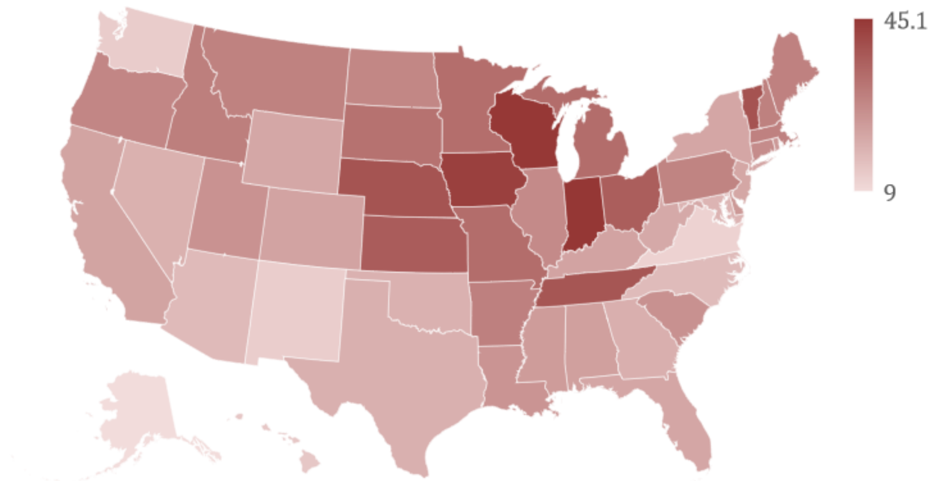
Our second set of results focuses on the distribution of impacts across states. Figure 4.1 shows the distribution of aggregate percentage losses across all states for the optimistic school-closure scenario (1L). This scenario incorporates low levels of impacts in the education sector but decreases the labor supply by 10 percent. These losses are largest for New York, Connecticut, Massachusetts, and California with most states between 4 percent and 5 percent. This could be a reflection of higher per capita incomes stemming through the labor supply reductions.

Figure 4.1. Aggregate Income Loss as a Percentage of Baseline Income, by State for the Optimistic School-Closure Scenario (1L)



At the opposite end of the spectrum, Figure 4.2 provides the distribution for the pessimistic stay-at-home order for the entire population. Most of the larger income losses are concentrated in the Midwest: Iowa, Wisconsin, Indiana, Nebraska, and Ohio. The effects of stay-at-home orders are in final-demand sectors, which suggests that these states produce relatively high amounts of final-demand goods and that states like Virginia produce more intermediate goods and services that are not as affected by stay-at-home orders. By *final demand*, we mean not only personal consumption but also consumption by all institutions within the model, including federal, state, and local governments. We show the full set of results by each state in Table A.1 in the appendix.

Figure 4.2. Aggregate Income Loss as a Percentage of Baseline Income, by State for the Pessimistic Stay-at-Home Order for the Full Population (5H)



Discussion

This analysis provides an initial assessment of the possible short-term economy-wide effects of social distancing. We recalibrate and modify an existing model to quickly implement economy-wide models on short time horizons. These results should be taken as rough order-of-magnitude estimates meant to help inform decisionmakers in accordance with the timeline of the crisis. Considerable effort would be required to further modify the model to better incorporate nuances of the economy. This presents an important trade-off, and we believe that the current model provides important information now, when it is needed. Additional modifications and nuances can be added over time.

Limitations

The model is subject to a few limitations. One key challenge is that resilience strategies and coping mechanisms might be available to some households but not others. For example, households with more-flexible work schedules and the availability of telework would mean smaller labor supply impacts. Thus, we might be overestimating the impacts of these social-distancing measures, but we think that the choice of sectors affected by these policies might be understated. For example, we have considered only nonessential retail being affected by these policies. The difficulty with expanding the definition of nonessential businesses is twofold. First, there is no clear baseline definition of what is nonessential. Some governors have identified specific retail sectors as nonessential, but, to our knowledge, no one has specified which manufacturing or service industries are nonessential. Second, this lack of specificity creates a problem of compliance and enforcement. Retail has a public-facing front; other industries are not nearly as public and might continue operations even in the face of a nonessential business closure.

Another key challenges is that we have not factored in the larger macroeconomic environment in which the models are operating. For example, we do not consider the decline in oil prices. Importantly, we have not included the demand-side shocks that are likely to occur as a result of people staying home. These shocks are different than the reduction in output that we have modeled and are associated with household behavior as a result of social-distancing policies.

There have been considerable federal efforts to mitigate the economic impacts of social distancing that need to be examined. The longer-term economic outcomes have not been considered but deserve attention. For example, we are assuming that the previous baseline would be achieved once these policies are removed. There might be substantial change in the economy because of this event that we have not considered. Additionally, there are dynamic effects of longer-term social distancing that might not be linear, as we have assumed. For example, business closures resulting from bankruptcy have not been considered, and these are likely to increase with the duration of these policies. Similarly, households might be able to rebound quickly from short disruptions but are likely to take much longer to recover if these policies are in effect for longer durations. These nonlinear impacts will be different depending on the resilience mechanisms available to households, and those mechanisms might vary by household income because of savings and paid time off.

Despite these limitations, we believe that the model provides important and timely information. Our aim was to provide estimates of how the economic costs are distributed across states and across alternative policies so that decisionmakers charged with imposing and removing social-distancing policies have better information about the economic costs and benefits of these policies.

5. Qualitative Assessment of Nonpharmaceutical Interventions

The epidemiological model and the economic model focus on a set of social-distancing NPI portfolios. In this qualitative assessment, we explore a broader variety of NPIs and an expanded set of policy considerations. The qualitative assessment of NPIs will be useful for understanding the strengths and weaknesses of different interventions and the trade-offs between them.

The three primary steps in this analysis were to (1) identify a relevant set of NPIs to include, (2) select a set of criteria on which to assess each NPI, and (3) synthesize available information to develop an assessment for each NPI-criterion combination.

To carry out this process, we first conducted a review of the literature on NPIs to capture the variety of health policies associated with disease outbreaks characterized by a novel virus, high contagiousness, and person-to-person direct transmitted respiratory diseases. We gathered data from the following five sources:

1. peer-reviewed scientific articles on NPIs
2. historical data on NPIs applied in the United States during past epidemics
3. multilateral, national, and local pandemic preparedness planning technical reports and white papers
4. international government announcements and records on COVID-19
5. global media reports on COVID-19.

Given the short time frame and the evolving nature of information available on COVID-19, we designed the review so that about half of the data would come from scientific and historical review papers and half would come from current reports and technical guides.

The review was guided by Thomas and Harden's 2008 framework for thematic synthesis of qualitative research evidence. We undertook the literature search using various databases, including PubMed, JSTOR, and Google Scholar. In addition, we conducted broad-based searches using Google. We used Boolean connectors, AND/OR, to combine search terms; for example, (NPI common name1)* OR (NPI common name 2)*AND H1N1. We chose to exclude opinion pieces, editorials, conference proceedings, theses, and any documents not published in English. The peer-reviewed studies we identified could be categorized into four types: modeling studies, systematic reviews, qualitative studies, and mixed-method studies.

NPIs focus on changing the physical and social environments where disease transmission happens. Using the literature, we categorized NPIs into the following three broad types:

1. individual and public behavioral changes; for example, the type of behaviors promoted by the social group or government agencies to help reduce disease transmission, including frequent hand-washing, wearing face masks, and the disinfection of public spaces

2. policies to aid disease isolation by identifying and isolating the suspected cases during an epidemic, including symptomatic surveillance, temperature screening, testing, and case tracing
3. policies on social distancing to reduce contact mixing, including school closures, large gathering bans, nonessential business closures, and shelter-at-home quarantine.

We adapted a set of criteria for assessing the extent to which an NPI meets its intended goal. The assessment tool was adapted from a RAND assessment framework that was developed in response to the Ebola crisis in 2014–2015 (Chamberlin, Efron, and Moore, 2015). The tool includes criteria that were critical for policy decisionmaking and was designed to answer many of the questions raised in public debates. In Table 5.1, we present the criteria, their definitions, and the questions considered in their evaluation.

Table 5.1. Evaluation Criteria and How They Are Applied

Criteria	Definition	Questions Considered in Evaluation	Color Coding
Barriers to implementation	The ease with which the proposed intervention can be implemented in terms of technical complexity, logistics, and resources	• Does the agency responsible for implementation have the needed authority to do so? • Are there mechanisms for coordination and partnership between agencies and across different levels of government? • Does the agency have the resources to implement the proposed policy in terms of staff, skills, financial resources, training, expertise, and so on? • Are the facilities, equipment, personnel, and other supports available for the proposed intervention? • Is the intervention legal under current law, or will statutes have to be amended or enacted? • Has the intervention been implemented frequently?	Green: low barrier Yellow: moderate barrier Red: high barrier
Efficacy	Whether an intervention achieves its intended goal under the best possible operational conditions	• How well does this intervention achieve its goals? • How much evidence do we have for the positive outcome(s) generated by this intervention? • If a specific technology is required to implement this intervention, does it exist and is it readily available? • Is it effective in reducing contact mix? • Does it help infected patients get health care? • Does it help reduce new cases?	
Cost to implement	Cost to the government and stakeholders to implement the interventions	• What are the direct and indirect costs to implement the intervention? Are there any intangible costs—for example, damage to reputation, loss of credibility and trust? • What are the one-time fixed costs—new capital expenditures, equipment, training, and so on—that are required for executing the intervention? • What are the operations and maintenance costs (ongoing costs)? • What are the opportunity costs (other things that could have been done instead with the same resources)?	Green: inexpensive Yellow: moderately expensive Red: very expensive
Impact on equity	The degree to which the implementation or effect of the	• Is an intervention likely to be discriminatory? • Which groups are likely to be burdened by the intervention? • Which groups are likely to benefit most and least from	Green: little impact Yellow: moderate impact Red: severe impact

Criteria	Definition	Questions Considered in Evaluation	Color Coding
	intervention is distributed fairly across the population, the impact on the low-income population	the intervention? • How might the intervention change the distribution of burden and benefits in society?	
Political barriers	The extent to which the intervention will be acceptable to relevant powerful groups, decisionmakers, legislators, and administrators	• Is the proposed intervention acceptable to policymakers, government decisionmakers, legislators, and other relevant stakeholders?	Green: low barrier Yellow: moderate barrier Red: high barrier
Social and cultural barriers	The extent to which the intervention will be acceptable to relevant private stakeholders, citizens, communities, unions, or others	• Is the proposed intervention acceptable to the general public, community stakeholders, and other relevant groups? • Is the intervention aligned with the values of subpopulations in the community? • Will the intervention meet the real or perceived needs of the target group, the public, and other relevant groups?	Green: low barrier Yellow: moderate barrier Red: high barrier
Economic cost	Whether the intervention affects market supply and demand, employment, and potential business closure	• What are the effects on market supply and demand? • What are the effects on employment? • What are the costs to corporations and individuals?	Green: low cost Yellow: moderate cost Red: high cost
Social well-being	The extent to which the intervention causes isolation, domestic violence, stress, and anxiety	• How does the intervention affect the isolation, stresses, and anxiety levels of the affected population? • What are the effects on domestic dynamics, such as domestic violence?	Green: low impact Yellow: moderate impact Red: severe impact
When to start (trigger) and when to end (turn off)	Relative time for intervention to be implemented and to produce desired results	• How long will an intervention take to achieve predetermined milestones and eventually its ultimate goal? • When should the intervention be triggered? • When should the intervention be lifted?	N/A, qualitative coding is applied
Risk of unintended negative outcomes	Likelihood of intervention to have additional, unintended, and negative effects outside the stated goals	• Will the allocation of resources toward the proposed intervention limit the agency's ability to deliver standard services or limit its readiness to face other emergencies? • Will the implementation of the proposed intervention carry third-party risks (to other countries or communities)? • Will the intervention alter internal or external relationships or processes?	N/A, qualitative coding is applied

Figure 5.1 shows the section of the web tool where we assess each NPI on each criterion. The color-coded scorecard approach depicts the performance of an intervention in relation to each criterion. Our assessment of each NPI on each criterion is generated by a guided synthesis of the literature. The colors vary from red, which represents poor performance or severe negative trade-offs, to green, which represents performance close to expectations with the least-negative consequences. For comparison across interventions, the scorecard will align the performance judgments for each criterion and each intervention. This allows policymakers to systematically assess different interventions across all of the criteria and understand the trade-offs between them. For example, suppose a policymaker is comparing two interventions. The first one is not very costly to implement but hits low-income populations particularly hard and so does not score well on equity. The second intervention might cost a bit more, but the negative economic effects are likely more-equitably distributed across the population. In this hypothetical example, neither intervention is dominant (i.e., better on both criteria considered). Rather, there are trade-offs: One is better on cost, but the other is better on equity. The tool lays out these trade-offs for policymakers so that they can make informed decisions.

Figure 5.1. Color-Coded Intervention Assessment in the Tool

Detailed Description of Nonpharmaceutical Interventions

In this section, we provide detailed descriptions of and considerations for each NPI. The sources used to inform the descriptions and assessments of the NPIs are provided in Appendix B.

School Closures

School closing is one of the common NPIs used as an epidemic mitigating strategy for influenza pandemics. School systems represent an important element in flu pandemic preparedness for several reasons:

1. Children easily transmit infectious diseases to one another because of the high-contact context.

2. Because of the large number of students in one place, in close proximity, and with less-than-acceptable hygiene practices, the students, teachers, and staff would be highly susceptible to a novel virus.
3. Studies showed that interventions targeting school-age children against influenza reduced mortality of pneumonia in the general population.
4. The trigger for school closing could be when widespread community transmissions are evident, when children or their families report cases of acute respiratory illness, or when the novel virus has high infectiveness.

Evidence of the efficacy of school closures as NPIs in a pandemic mostly comes from qualitative reviews and modeling studies of the 1918 H1N1 and 2009 H1N1 influenza pandemics. Early implementation of school closures with a medium or long duration (four to eight weeks)—and when combined with bans on large crowds and the closure of businesses—can effectively reduce influenza transmissions and protect children, teachers, and their families and communities.

The following caveats related to school closures during a pandemic are worth considering:

- for COVID-19 specifically, children appear to be disproportionately less affected, and their transmission potential of COVID-19 versus influenza is still not well understood
- school closing usually is associated with at least half of the working adult population staying at home
- a parent at home might mean a shortage of health care workers
- a parent at home will disproportionally affect those who work in service and low-income jobs
- when school is closed, social mixing might happen more in the community than at school if no crowd ban is issued
- children might have more contact with older adults who are more susceptible to COVID-19
- homeless children and low-income children need school meals and other physical and mental health support
- children without access to laptops and high-speed internet will have difficulty keeping up with online teaching
- long-term school closing can cause major interruptions in students' learning and in assessments for qualification. Social isolation caused by school closing also can increase anxiety, depression, and other mental health problems among children and their families.

Travel Restrictions

Travel restrictions are immediate means by which to slow pandemic growth and reduce the number of imported cases. Travel restrictions can include temporary border closures, cancellations of flights, visa bans, and mandatory 14-day self-quarantines. Often, travel restrictions—especially at points of entry—have intuitive appeal to policymakers because they demonstrate that a tangible attempt is being made to prevent the ingress of a novel virus or onward spread. However, the relevant data that are available seem to indicate that restrictions on travel would have a limited impact on containment or even on the slowing of transmission, especially when community transmission is widespread and when travel restrictions are not combined with other NPIs, such as screening, testing, monitoring of self-quarantining.

The trigger for travel restrictions could be when imported cases dominate the disease transmission, either at the very beginning of the epidemic (a few cases or a few clusters) or when community transmission is well controlled and officials face challenges of a new wave of imported cases. Travel restrictions had no beneficial effect on attack rates if the level of strain transmissibility was moderate or high (i.e., when $R_0 > 2.5$). Travel restrictions will work best when the travel ban is extensive (e.g., 99 percent).

Travel restrictions usually require significant amounts of additional personnel and funding to support reinforcement, screening, testing, and monitoring. Some countries (e.g., Taiwan and Hong Kong) combine travel records with the health care data of their citizens and have achieved sufficient case tracing and traveler quarantine monitoring.

The unintended negative outcomes for travel bans are

- interrupting trade and international business
- interrupting the transportation of aid workers and health care supplies to crisis areas
- providing a false sense of security
- allowing political bias to influence the NPIs
- stranding migrant workers and international students without support.

Nonessential Business Closures

Nonessential business closures means temporarily ceasing all nonessential business activities. It is a major NPI that is used as an epidemic-mitigating strategy for influenza pandemics by different U.S. states. Closing businesses at such a scale is unprecedented in past policy responses to epidemics. Closing nonessential businesses is important for stopping epidemic transmission because it creates social distancing by decreasing contact time, duration, and density.

Given the unprecedented scale of nonessential business closing, our evidence for its efficacy is rather limited. Using the experience of China in combating COVID-19, a combination of a draconian lockdown of Wuhan City and Hubei Province, strict control of people's movement, and closing of businesses seem to be effective in flattening the curve and controlling the spread of COVID-19. Research on the 1918 pandemic suggests that cities in which multiple interventions were implemented at an early phase also showed a trend toward lower cumulative mortality.

The following caveats of the nonessential business closure approach are worth considering:

- Significant loss is likely to be incurred on business owners, who are most burdened by this policy. The interventions reduce revenue, making it difficult to keep employees on the payroll. Business owners also would incur loss in terms of the cost of purchased materials, lagged sale of manufactured goods, and rent and utilities costs.

- Continuing the closure of nonessential businesses would lead to rising unemployment in the informal sector. Prolonged business closure also will hurt the supply chain, disrupting future production.
- Small businesses account for nearly 50 percent of the U.S. economy (U.S. Small Business Administration, 2019). Macroeconomic performance will be severely affected by the close of nonessential businesses.
- China's National Bureau of Statistics predicted that gross domestic product would grow by 3.5 percent in the first quarter, and industrial output fell 13.5 percent through February. The services index fell 13 percent. According to the *Economist*, 2020, in the United States and Europe, gross domestic product could drop by 5 percent to 10 percent year-on-year, perhaps more.

Bar and Restaurant Closures

The need to socially distance has resulted in restaurant and bar closures. Across the United States, bars and restaurants have been told to shut their doors to the public to slow the spread of COVID-19. The intervention refers to the shut-down of bars, nightclubs, and wineries; and the closure of dine-in services, only allowing for online ordering and take-away services. This intervention has been adopted by more than 30 countries and regions around the world. It reduces transmission by reducing close contact in dining and drinking activities, thus achieving more-successful social distancing.

It is difficult to evaluate the effectiveness of specific measures to control disease spread in epidemiologic terms because of the complex relationships between individuals and groups and the individual biological differences in response to influenza. The results of a recent modeling study of cases of COVID-19 in the United Kingdom noted that "stopping mass gatherings is predicted to have relatively little impact . . . because the contact-time at such events is relatively small compared to the time spent at home, in schools or workplaces and in other community locations such as bars and restaurants" (Ferguson et al., 2020, p. 8).

The following caveats related to the closure of restaurants and bars are worth considering:

- According to research by the Urban Institute, in 2017, more than 7.5 million adults worked in food service and preparation occupations (Gangopadhyaya and Waxman, 2020).
- Few occupations have experienced the negative effects of containment more abruptly and dramatically than food service and preparation workers—from waiters and bartenders to dishwashers and cooks—who are already economically disadvantaged by their low earnings and lack of health insurance coverage. They risk falling into dire economic circumstances unless policies are implemented swiftly that allow families to meet their basic needs.
- Mandatory restaurant closures might have cascading effects because of reduced demand for linens, laundry services, equipment rentals, food, and workers. This could lead to widespread problems, such as inabilities to pay rent on property and equipment or inability to service corporate debt. The end result might be waves of business collapse across certain industries.

- States are burdened differently by the bar and restaurant closure intervention. Nationally, these workers represent 5.7 percent of the private-sector workforce over the age of 18, ranging from 4.3 percent in Nebraska to 11.8 percent in Hawaii. Besides Hawaii, states with higher percentages of workers in these categories include Nevada (10.8 percent), New Mexico (8.0 percent), Florida (6.9 percent), Wyoming (6.9 percent), Rhode Island (6.8 percent), and Louisiana (6.7 percent). Of these states, Hawaii, Nevada, and Louisiana have economies that depend heavily on tourism; this factor could make them more vulnerable to a severe economic downturn in the wake of the pandemic.

Large-Gathering Bans

Large events and mass gatherings can contribute to the spread of COVID-19 in the United States via travelers who attend these events and introduce the virus into new communities. Examples of large events and mass gatherings include conferences, festivals, parades, concerts, sporting events, and weddings. These events can be planned by organizations and communities or by individuals. In the United States, implementation of bans on large gatherings can be divided into the following categories: all gatherings prohibited; more than ten people gathering prohibited; 50 or more gathering are prohibited; other; and no action. This intervention has been adopted by more than 70 countries and regions. It has been applied in response to past global epidemics, including Severe Acute Respiratory Syndrome (SARS), H1N1, and Middle East Respiratory Syndrome (MERS).

Evidence suggests that mass gatherings shortly before an epidemic peak could increase the peak height by about 10 percent, and avoidance of mass gatherings might be beneficial. Bans on public gatherings in combination with other interventions can reduce death rates, as can bans on public gathering that are implemented for a longer duration.

The following caveats related to bans on large gatherings are worth considering:

- Decisionmakers need to consider the overall number of attendees, the number of people attending who are at greater risk of more-serious illness after contracting COVID-19 (such as older adults with preexisting conditions), and the density of attendees within a confined area (the spread from person to person happens most frequently among close contacts within six feet).
- Decisionmakers should consider the potential economic impact on participants, attendees, staff, and the larger community.
- The state bans on large gatherings will hit many local business owners hard in terms of the cost incurred from organizing large events and opportunity costs for investing the money to organize other activities. It will also hit the sponsors and volunteers for such events.
- Implementing such measures would have seriously disruptive consequences for a community if they are extended through the eight-week period of an epidemic in a municipal area.
- There is reported local resistance to large crowd bans. For example, hundreds of worshippers attended services at a Louisiana church on a Sunday in March, flouting a ban on large gatherings, angering neighbors, and seemingly turning a deaf ear to their

governor, who warned that hospitals could soon be overwhelmed with new cases of COVID-19 (Hennessy-Fiske, 2020).

Quarantine or Stay-at-Home Orders for All

The mandatory quarantine and stay-at-home orders aim to separate a person or group of people who have been exposed to a contagious disease but have not developed symptoms from those who have not been exposed to prevent the possible spread of the disease. *Quarantine* usually means limiting the movement of the healthy and it is different from the practice of *isolation*, which is a health care term that means keeping people who are infected with a contagious illness away from those who are not infected.

Scientific evidence shows high efficacy of quarantine as an NPI in pandemics. Quarantine helps case detection by raising awareness, mitigates the transmission of highly infectious diseases by reducing people's contacts, and decreases the opportunity that asymptomatic or mildly infected cases mix in a community.

The following caveats of mandatory quarantine and stay-at-home orders are worth considering:

- Quarantining in a densely populated environment or with potentially infected people (e.g., returned travelers, people with symptoms who cannot be isolated at clinics) can increase infection transmission chances.
- Quarantine compliance is crucial for the quarantine orders to be effective. Enforcement of compliance can be difficult.
- For the manufacturing sector, the labor supply will drop and the supply chain will be interrupted. The overall economy will be harmed because of lower productivity.
- There will be severe economic losses for businesses and people who work in service sectors, such as travel, hospitality, retail, and restaurants.
- Those who do not have internet service will suffer from loss in work and in education.
- The implementation burden to ensure compliance is almost entirely on local authorities and local police forces.
- Long periods of quarantine and social isolation might cause mental health issues. People also will experience logistical challenges, and there is an increased risk to those living in restricted zones.
- There are potential political barriers because public justification is hard to achieve during the early stages.

Quarantine for Vulnerable Populations

COVID-19 is a new disease, and there is limited information regarding risk factors for severe disease. According to currently available information and clinical expertise, older adults and people of any age who have serious underlying medical conditions might be at higher risk for severe illness from COVID-19. Some states, such as Oklahoma and Washington, issued mandatory quarantine orders for their vulnerable populations.

Although evidence for the efficacy of this NPI is limited, mandatory quarantine and stay-at-home orders for vulnerable populations should have similar efficacy to general quarantine orders.

The following caveats related to mandatory quarantine orders and stay-at-home orders for vulnerable populations are worth considering:

- Vulnerable populations require extra care and resources, which they might not be able to provide themselves.
- The government needs to provide extra resources to enable the vulnerable populations to be quarantined.
- Vulnerable populations might face more logistical challenges and experience higher mental stress under the quarantine order compared with the general population.

Testing and Isolation

Massive testing is essential in the COVID-19 containment and mitigation plans because it can help identify the infected; immune; and the rest, who are healthy but suspectable to the disease. With aggressive testing and patient isolation, government can achieve proportionality of response by applying quarantine interventions only to the infected (e.g., the source of disease transmission) and allowing the healthy to continue with economic and social activities. Without a sufficient and effective testing strategy, a broad quarantine will have to be applied to the whole population for an indefinite period of time and is likely to cause negative economic and social consequences. Testing also can facilitate regional disease surveillance for resource and logistic planning and link the infected to health care.

Testing for COVID-19 mainly includes polymerase chain reaction (PCR) tests and serological tests, which we describe further below:

- PCR tests identify the SARS-CoV-2 (severe acute respiratory syndrome coronavirus 2) RNA in patients' respiratory specimens. All of these tests are Real-Time Reverse Transcriptase (RT)-PCR Diagnostic Panels that can provide results in four to six hours. These tests should be used as evidence of active infection for those who are symptomatic, those with reasons to presume exposure (e.g., frontline workers), and for symptomatic and asymptomatic contacts of confirmed cases. Recently, innovative fast-response antigen molecular tests (e.g., Bosch, Germany, 2.5 hours) have the potential to help simplify the testing process and scale up the testing en-masse.
- Serological (antibody) tests identify people who have developed an immune response to the virus. Presence of the antibodies in blood can be detected one to two weeks after the start of the infection. The enzyme-linked immunoassay (ELIZA) blood test is lab-based (one to five hours), whereas the rapid diagnostic test (RDT) using lateral flow assay use finger prick can be used at point of care (results in ten to 30 minutes).

The following caveats related to testing are worth considering:

- Implementation of testing requires numerous factors, including sufficient production of the testing kits; laboratory capacities; sufficient swabs, testing tubes, and transportation equipment supplies; access to testing (e.g., testing at the clinic, community settings, home); availability of personnel conducting the test; and protection gear for people conducting the tests.

- A high rate of false negative results of the SARS-CoV-2 PCR tests could result in individuals believing that they are not infected, but they still could transmit the virus to others. Current estimates of the false negative rate of PCR tests are 15 percent to 30 percent.
- The presence of antibodies might not indicate full protection from reinfection, and the duration of the immunity is uncertain. Validity data on serological tests are unavailable now. Those who test negative might be in the early days of infections.
- People might get exposed to disease while trying to get tested for COVID-19. Health care providers also might have higher exposure to infected people.
- The lack of accessibility of testing for certain populations (e.g., people experiencing homelessness, people with no insurance coverage) brings issues of equality.

6. How to Use the COVID-19 Decision Support Tool

The web tool provides a simplified summary of the output of the economic and epidemiological models to allow users to estimate the effects of changing the NPI portfolio in effect for a selected U.S. state at a selected date. The tool also provides a snapshot of data about the current impact of the COVID-19 pandemic in the selected state.

Section 1: Current Impact of COVID-19 in Selected Location

Select a state from a drop-down menu to view the current impact data for that state.

Section 2: When to Stop and Start Interventions for COVID-19

Choose a new intervention level, or no intervention, and a start date for the selected change to review the projected epidemiological and economic effects. The user can choose an intervention level from the following escalating scale, with each level adding more-widespread restrictions:

- **Level 0:** No interventions, "new normal" activity levels.
- **Level 1:** Close schools.
- **Level 2:** Close schools, bars, and restaurants; and ban large events.
- **Level 3:** Close schools, bars, and restaurants; ban large events; and close nonessential businesses.
- **Level 4:** Close schools, bars, and restaurants; ban large events; close nonessential businesses; and shelter at home for the most vulnerable.
- **Level 5:** Close schools, bars, and restaurants; ban large events; close nonessential businesses; and shelter at home for everyone but essential workers.

Users can view a chart of the projected impact of the change in intervention level on health and economic indicators compared with the current intervention level in that state with no change.

Section 3: Qualitative Guidelines for COVID-19 Interventions

This section provides qualitative information about each NPI individually, including interventions not shown in the five modeled levels. The user can select one of the following interventions:

- close schools
- restrict travel

- close bars and restaurants
- close nonessential businesses
- ban large gatherings
- issue shelter-at-home orders for vulnerable population
- issue shelter-at-home orders for all
- increase clinical testing and self-quarantine the infected
- promote mask-wearing in public
- isolate patients in separate facilities.

For the selected intervention, information is shown on the efficacy of the measure, when to start and stop, and the main negative impacts to consider.

A comparison table provides a high-level view of other criteria that policymakers might need to consider for each intervention. Clicking on an intervention name provides more information for each of the following criteria, for each intervention:

- barriers to implementation
- cost of implementation
- economic cost
- impact on equity
- political barriers
- cultural and social barriers
- impact on social well-being.

7. Next Steps

The objective of this tool is to provide information to support decisionmaking during the COVID-19 pandemic. We have developed a tool based on sophisticated epidemiological and economic modeling and a comprehensive qualitative assessment of the literature on NPIs. We have used the best data available to inform these analyses. As the pandemic evolves, however, new information will become available, and we intend to continue refining the models, incorporating new parameter estimates, and building in new features. We also intend to build out the web tool, incorporating additional interactivity that will allow the user more choices in terms of NPIs, start and stop dates for NPIs, and values for the input parameters.

Appendix A. Case Fatality Rates and Percentage Income Losses

Figure A.1 shows case fatality rates, by countries other than the United States.

Figure A.1. Case Fatality Rate, by Country

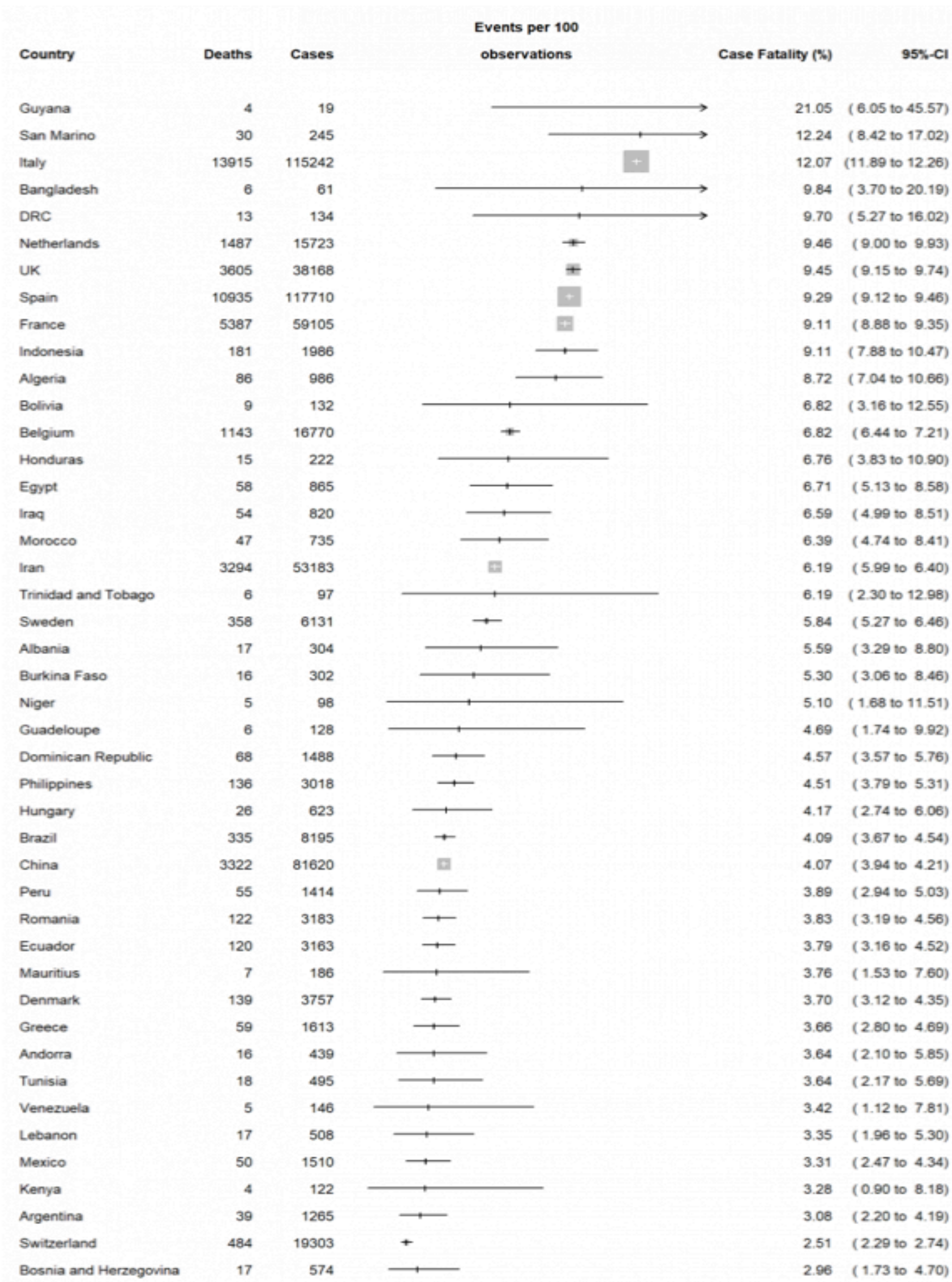


Table A.1 shows the percentage income losses under social-distancing portfolios, by U.S. state.

Table A.1. Percentage Losses in Income, by State Under Social-Distancing Portfolios

	1L	1B	1H	2L	2B	2H	3L	3B	3H	4L	4B	4H	5L	5B	5H
National	4.6	6.0	7.9	6.4	9.7	13.1	9.0	13.9	17.9	11.6	17.2	20.8	13.8	19.8	25.6
Alabama	4.2	4.4	4.9	4.5	5.3	6.7	4.9	6.4	9.6	5.5	8.4	11.2	6.7	11.1	22.2
Alaska	4.6	5.4	6.7	5.1	6.5	8.5	5.8	7.8	9.8	6.6	9.2	9.9	7.4	9.5	9.0
Arizona	4.6	4.9	5.4	5.0	5.8	6.9	5.5	6.6	9.8	6.1	8.6	11.9	6.6	10.2	16.4
Arkansas	4.1	4.3	4.6	4.4	5.1	6.5	4.8	6.2	10.1	5.4	8.8	16.6	6.5	12.8	29.1
California	6.4	7.0	7.8	6.9	8.1	9.8	7.5	9.5	12.8	8.4	12.1	15.5	9.4	13.9	21.3
Colorado	5.0	5.5	6.2	5.6	6.7	8.3	6.3	8.0	11.3	7.2	11.0	16.5	7.9	13.0	21.4
Connecticut	7.1	7.3	7.7	7.3	8.0	9.3	7.6	8.8	11.7	8.2	11.1	17.4	9.1	13.5	26.4
Delaware	5.1	5.4	5.8	5.5	6.3	7.7	5.9	7.4	10.8	6.6	10.5	19.2	7.7	12.6	23.7
Florida	4.5	4.9	5.4	5.2	6.5	8.1	6.3	8.7	13.0	7.5	12.7	16.9	8.5	14.2	20.8
Georgia	4.6	5.1	5.7	5.1	6.1	7.6	5.7	7.6	10.3	6.5	10.4	15.4	7.4	11.4	18.8
Hawaii	4.8	5.6	6.7	6.0	8.4	10.8	8.0	11.0	13.7	9.9	13.7	14.6	11.1	13.9	13.6
Idaho	4.3	4.5	4.8	4.6	5.2	6.4	4.9	6.0	9.2	5.4	8.1	15.2	6.3	11.8	29.4
Illinois	5.7	6.1	6.8	6.1	7.1	8.8	6.6	8.5	11.4	7.6	11.7	23.1	8.3	13.1	26.9
Indiana	4.1	4.5	5.1	4.6	5.5	7.3	5.2	7.4	12.3	6.0	10.6	23.5	7.6	15.3	45.1
Iowa	4.4	4.8	5.4	4.8	5.7	7.6	5.3	7.5	13.4	6.0	10.7	24.5	7.9	16.9	43.1
Kansas	4.7	5.0	5.4	5.1	5.9	7.6	5.5	7.2	12.3	6.1	10.4	20.0	7.8	15.2	36.9
Kentucky	4.6	4.8	5.2	4.9	5.7	7.0	5.4	7.0	9.9	6.0	8.7	11.5	7.1	11.0	21.5
Louisiana	3.5	4.0	4.7	3.9	5.0	6.7	4.6	7.0	11.0	5.4	9.4	13.2	6.9	12.5	24.7
Maine	4.7	5.0	5.4	5.1	5.8	7.2	5.4	6.9	11.1	6.0	10.1	18.8	7.3	13.5	28.8
Maryland	4.4	5.1	6.1	5.0	6.3	8.3	5.7	8.0	12.1	6.8	11.5	16.4	7.8	13.1	17.7
Massachusetts	7.4	7.9	8.7	7.8	8.9	10.7	8.4	10.3	13.9	9.3	13.8	22.7	10.3	15.8	28.8
Michigan	4.8	5.1	5.5	5.2	5.9	7.4	5.6	7.2	10.4	6.3	10.0	25.8	7.2	12.3	33.3
Minnesota	5.7	6.0	6.5	6.1	6.8	8.2	6.4	7.9	10.8	7.2	11.0	28.2	7.9	12.7	33.1
Mississippi	3.5	3.8	4.2	3.8	4.5	5.8	4.1	5.5	9.1	4.6	7.7	12.6	5.7	11.1	23.1
Missouri	4.4	4.8	5.3	4.8	5.7	7.4	5.3	7.3	11.3	6.2	10.2	19.8	7.5	13.8	33.3
Montana	3.7	4.1	4.7	4.2	5.1	6.7	4.8	6.9	12.1	5.6	11.2	21.5	6.8	14.4	28.7
Nebraska	4.3	4.7	5.4	4.8	5.9	8.1	5.4	7.8	14.4	6.3	11.5	22.2	8.5	18.1	38.7
Nevada	5.0	5.3	5.6	5.5	6.5	9.3	6.5	10.9	14.1	9.9	14.6	16.2	11.3	15.3	18.5
New Hampshire	6.3	6.5	6.8	6.6	7.3	8.6	7.1	8.7	11.9	7.8	11.4	19.6	8.9	14.0	29.0
New Jersey	6.0	6.4	7.0	6.3	7.2	8.6	6.7	8.3	11.1	7.5	10.6	17.2	8.1	12.0	20.7
New Mexico	3.5	4.0	4.7	3.9	4.9	6.5	4.4	6.3	9.0	5.2	8.1	11.0	6.1	9.5	12.2
New York	6.9	7.4	8.3	7.2	8.3	10.0	7.7	9.4	12.0	8.6	11.7	18.2	9.2	12.9	20.8
North Carolina	3.7	4.1	4.8	4.1	5.2	6.7	4.8	6.8	9.5	5.6	8.7	10.7	6.7	10.1	16.2
North Dakota	4.8	5.2	5.7	5.2	6.2	7.9	5.9	8.1	12.1	6.6	10.5	15.8	8.1	14.1	27.7
Ohio	4.8	5.1	5.6	5.2	6.0	7.6	5.6	7.4	11.4	6.4	10.4	22.9	7.6	13.8	36.6
Oklahoma	4.5	4.8	5.1	4.9	5.5	6.6	5.2	6.7	9.3	5.8	8.9	13.4	6.7	10.7	18.4
Oregon	4.4	4.9	5.5	4.9	5.8	7.4	5.4	7.2	10.1	6.2	9.5	22.5	7.1	11.3	27.8

	1L	1B	1H	2L	2B	2H	3L	3B	3H	4L	4B	4H	5L	5B	5H
Pennsylvania	5.3	5.8	6.4	5.8	6.8	8.5	6.3	8.2	11.7	7.2	11.1	20.4	8.2	13.4	28.3
Rhode Island	5.3	5.5	6.0	5.6	6.3	7.7	6.0	7.5	11.1	6.7	10.4	15.4	7.8	12.9	23.6
South Carolina	4.0	4.3	4.7	4.4	5.2	6.5	4.9	6.5	9.8	5.5	8.4	10.9	6.8	11.3	25.4
South Dakota	4.4	4.7	5.1	4.8	5.6	7.3	5.2	7.0	12.0	5.9	10.4	19.7	7.5	15.4	32.2
Tennessee	4.9	5.2	5.6	5.4	6.4	8.1	6.1	8.4	13.1	7.1	11.5	19.7	8.7	16.3	38.4
Texas	4.6	5.1	5.9	5.0	6.0	7.5	5.6	7.5	10.8	6.2	9.8	13.1	7.2	11.5	18.6
Utah	5.3	5.7	6.4	5.7	6.8	8.5	6.3	8.2	11.6	7.4	11.4	17.6	8.2	13.1	25.1
Vermont	5.5	5.8	6.2	5.9	6.6	8.2	6.3	8.3	13.3	6.9	11.7	30.6	8.5	16.2	39.0
Virginia	5.0	5.4	6.0	5.5	6.5	7.8	6.2	7.7	9.5	7.0	9.1	9.9	7.7	9.8	11.1
Washington	5.4	5.7	6.2	5.7	6.4	7.4	6.1	7.1	8.9	6.6	8.3	9.7	7.0	9.5	12.5
West Virginia	3.6	3.9	4.3	4.1	4.9	6.3	4.6	6.4	9.4	5.3	8.5	14.5	6.4	10.7	20.1
Wisconsin	5.1	5.3	5.7	5.4	6.2	7.8	5.8	7.6	12.7	6.5	11.1	27.5	8.0	16.2	44.9
Wyoming	4.3	4.7	5.3	4.6	5.5	6.9	5.1	6.6	9.2	5.7	8.2	16.4	6.5	10.6	20.6

Appendix B. Bibliography for Nonpharmaceutical Intervention Description and Assessment

School Closing

Carroll, Aaron E., "Is Closing the Schools a Good Idea?" *New York Times*, March 17, 2020. As of April 23, 2020: https://www.nytimes.com/2020/03/17/upshot/coronavirus-school-closings.html

Cowling, Benjamin J., Eric H. Y. Lau, Conrad L. H. Lam, Calvin K. Y. Cheng, Jana Kovar, Kwok Hung Chan, J. S. Malik Peiris, and Gabriel M. Leung, "Effects of School Closures, 2008 Winter Influenza Season, Hong Kong," *Emerging Infectious Diseases*, Vol. 14, No. 10, 2008, pp. 1660–1662.

Dickin McGinnis, Janice P., "The Impact of Epidemic Influenza, Canada, 1918–1919," *Historical Papers Communications Historiques*, Vol. 12, No. 1, 1977, pp. 120–140.

Inglesby, Thomas V., Jennifer B. Nuzzo, Tara O'Toole, and D. A. Henderson, "Disease Mitigation Measures in the Control of Pandemic Influenza," *Biosecurity and Bioterrorism: Biodefense Strategy, Practice, and Science*, Vol. 4, No. 4, 2006, pp. 366–375.

Neuzil, Kathleen M., Cynthia Hohlbein, and Yuwei Zhu, "Illness Among Schoolchildren During Influenza Season: Effect on School Absenteeism, Parental Absenteeism from Work, and Secondary Illness in Families," *Archives of Pediatrics and Adolescent Medicine*, Vol. 156, No. 10, 2002, pp. 986–991.

Patterson, K. David, "The Influenza Epidemic of 1918–1919 in the Gold Coast," *Journal of African History*, Vol. 24, No. 4, 1983, pp. 485–502.

Sparks, Sarah D., "Number of Homeless Students Hits All-Time High," *Education Week*, February 10, 2020. As of April 23, 2020: https://www.edweek.org/ew/articles/2020/02/12/number-of-homeless-students-hits-all-time-high.html

Vynnycky, E., and W. J. Edmunds, "Analyses of the 1957 (Asian) Influenza Pandemic in the United Kingdom and the Impact of School Closures," *Epidemiology and Infection*, Vol. 136, No. 2, 2008, pp. 166–179.

World Health Organization, *Expert Committee on Respiratory Virus Diseases: First Report*, Geneva, 1959. As of April 23, 2020: https://apps.who.int/iris/bitstream/handle/10665/40436/WHO_TRS_170.pdf?sequence=1&isAllowed=y

Wu, Joseph T., Benjamin J. Cowling, Eric H. Y. Lau, Dennis K. M. Ip, Lai-Ming Ho, Thomas Tsang, Shuk-Kwan Chuang, Pak-Yin Leung, Su-Vui Lo, Shao-Haei Liu, and Steven Riley, "School Closure and Mitigation of Pandemic (H1N1) 2009, Hong Kong," *Emerging Infectious Diseases*, Vol. 16, No. 3, 2010, pp. 538–541.

Bar and Restaurant Closing and Nonessential Business Closing

Arnold, Chris, "America Closed: Thousands of Stores, Resorts, Theaters Shut Down," NPR.org, March 16, 2020. As of April 16, 2020: https://www.npr.org/2020/03/16/816398498/america-closed-thousands-of-stores-resorts-theaters-shut-down

Keogh-Brown, Marcus Richard, Richard D. Smith, John W. Edmunds, and Philippe Beutels, "The Macroeconomic Impact of Pandemic Influenza: Estimates from Models of the United Kingdom, France, Belgium and The Netherlands," *European Journal of Health Economics*, Vol. 11, December 2010, pp. 543–554.

Smit, Sven, Martin Hirt, Kevin Buehler, Susan Lund, Ezra Greenberg, and Arvind Govindarajan, "Safeguarding Our Lives *and* Our Livelihoods: The Imperative of Our Time," *McKinsey & Company*, March 2020, As of April 16, 2020: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/safeguarding-our-lives-and-our-livelihoods-the-imperative-of-our-time

Thornton, William, "Alabama Non-Essential Business Closure Affects Non-Profits," *Advance Local Media LLC*, March 27, 2020. As of March 31, 2020: https://www.al.com/business/2020/03/alabama-non-essential-business-closure-affects-non-profits.html

World Health Organization Writing Group, "Nonpharmaceutical Interventions for Pandemic Influenza, National and Community Measures," *Emerging Infectious Diseases*, Vol. 12, No. 1, January 2006, pp. 88–94.

Quarantine (Shelter at Home)

Bass, Sarah Bauerle, Sheryl Burt Ruzek, Lawrence Ward, Thomas F. Gordon, Alexandra Hanlon, Alice J. Hausman, and Michael Hagan, "If You Ask Them, Will They Come? Predictors of Quarantine Compliance During a Hypothetical Avian Influenza Pandemic: Results From a Statewide Survey," *Disaster Medicine and Public Health Preparedness*, Vol. 4, No. 2, 2010, pp. 135–144.

Centers for Disease Control and Prevention, "People Who Are at Higher Risk for Severe Illness," webpage, April 15, 2020. As of April 17, 2020:

https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-at-higher-risk.html

Day, Troy, Andrew Park, Neal Madras, Abba Gumel, and Jianhong Wu, “When Is Quarantine a Useful Control Strategy for Emerging Infectious Diseases?” *American Journal of Epidemiology*, Vol. 163, No. 5, March 1, 2006, pp. 479–485.

Fraser, Christophe, Steven Riley, Roy M. Anderson, and Neil M. Ferguson, “Factors That Make an Infectious Disease Outbreak Controllable,” *Proceedings of the National Academy Sciences*, Vol. 101, No. 16, 2004, pp. 6146–6151.

Hien Lau, Veria Khosrawipour, Piotr Kocbach, Agata Mikolajczyk, Justyna Schubert, Jacek Bania, and Tanja Khosrawipour, “The Positive Impact of Lockdown in Wuhan on Containing the COVID-19 Outbreak in China,” *Journal of Travel Medicine*, 2020.

Kavanagh, Anne M., Rebecca J. Bentley, Kate E. Mason, Jodie McVernon, Sylvia Petrony, James Fielding, Anthony D. LaMontagne, and David M. Studdert, “Sources, Perceived Usefulness and Understanding of Information Disseminated to Families Who Entered Home Quarantine During the H1N1 Pandemic in Victoria, Australia: A Cross-Sectional Study,” *BMC Infectious Diseases*, Vol. 11, No. 2, 2011.

LaMotte, Sandee, “Coronavirus: What to Do If You or a Loved One Has Symptoms,” *CNN*, April 1, 2020. As of April 15, 2020: https://www.cnn.com/2020/03/25/health/how-to-prepare-for-coronavirus-quarantine-wellness/index.html

Lang, Marissa J., Justin William Moyer, and Nitasha Tiku, “Cities Struggle to Protect Vulnerable Homeless Populations as Coronavirus Spreads,” *Washington Post*, March 20, 2020. As of April 15, 2020: https://www.washingtonpost.com/local/cities-struggle-to-protect-vulnerable-homeless-populations-as-coronavirus-spreads/2020/03/20/1144249c-67be-11ea-b5f1-a5a804158597_story.html

Maragakis, Lisa Lockerd, “Coronavirus, Social and Physical Distancing and Self-Quarantine,” webpage, April 11, 2020. As of April 16, 2020: https://www.hopkinsmedicine.org/health/conditions-and-diseases/coronavirus/coronavirus-social-distancing-and-self-quarantine

Miyaki, Koichi, Hirofumi Sakurazawa, Hajime Mikurube, Mika Nishizaka, Hidehiko Ando, Yixuan Song, and Takuro Shimbo, “An Effective Quarantine Measure Reduced the Total Incidence of Influenza A H1N1 in the Workplace: Another Way to Control the H1N1 Flu Pandemic,” *Journal of Occupational Health*, Vol. 53, No. 4, 2011.

Mubayi, Anuj, Christopher Kribs Zaleta, Maia Martcheva, and Carlos Castillo-Cháves, “A Cost-Based Comparison of Quarantine Strategies for New Emerging Diseases,” *Mathematical Biosciences and Engineering*, Vol. 7, No. 3, 2010, pp. 687–717.

Ng, Yixiang, Zongbin Li, Yi Xian Chua, Wei Lang Chaw, Zheng Zhao, Benjamin Er, Rachael Pung, Calvin J. Chiew, David C. Lye, Derrick Heng, and Vernon J. Lee, “Evaluation of the Effectiveness of Surveillance and Containment Measures for the First 100 Patients with COVID-19 in Singapore—January 2–February 29, 2020,” *Morbidity and Mortality Weekly Report*, Vol. 69, No. 11, March 20, 2020, pp. 307–311.

Nishiura, Hiroshi, Nick Wilson, and Michael G. Baker, “Quarantine for Pandemic Influenza Control at the Borders of Small Island Nations,” *BMC Infectious Diseases*, Vol. 9, No. 27, 2009.

Parmet, Wendy E., and Michael S. Sinha, “Covid-19—The Law and Limits of Quarantine,” *New England Journal of Medicine*, Vol. 382, No. 15, April 9, 2020.

Reynolds, D. L., J. R. Garay, S. L. Deamond, M. K. Moran, W. Gold, and R. Styra, “Understanding, Compliance and Psychological Impact of the SARS Quarantine Experience,” *Epidemiology and Infection*, Vol. 136, No. 7, 2008, pp. 997–1007.

Rothstein, Mark, “From SARS to Ebola: Legal and Ethical Considerations for Modern Quarantine,” *Indiana Health Law Review*, Vol. 12, No. 1, 2015, pp. 227–280.

Rothstein, Mark A., and Christine N. Coughlin, “Ensuring Compliance with Quarantine by Undocumented Immigrants and Other Vulnerable Groups: Public Health Versus Politics,” *American Journal of Public Health*, Vol. 109, No. 9, 2019, pp. 1179–1183.

Smit, Sven, Martin Hirt, Kevin Buehler, Susan Lund, Ezra Greenberg, and Arvind Govindarajan, “Safeguarding Our Lives *and* Our Livelihoods: The Imperative of Our Time,” *McKinsey & Company*, March 2020, As of April 16, 2020: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/safeguarding-our-lives-and-our-livelihoods-the-imperative-of-our-time

Tavares Lima, Carlos Kennedy, Poliana Moreira de Medeiros Carvalho, Igor de Araújo Araruna Silva Lima, José Victor Alexandre de Oliveira Nunes, Jeferson Steves Saraiva, Ricardo Inácio de Souza, Claúdio Gleidiston Lima da Silva, Modesto Leite Rolim Neto, “The Emotional Impact of Coronavirus 2019-nCoV (New Coronavirus Disease),” *Psychiatry Research*, Vol. 287, May 2020, p. 112915.

van Gemert, Caroline, Margaret Hellard, Emma S. McBryde, James Fielding, Tim Spelman, Nasra Higgins, Rosemary Lester, Hassan Vally, and Isabel Bergeri, “Intrahousehold Transmission of Pandemic (H1N1) 2009 Virus, Victoria, Australia,” *Emerging Infectious Diseases*, Vol. 17, No. 9, 2011, pp. 1599–1607.

World Health Organization, “Considerations for Quarantine of Individuals in the Context of Containment for Coronavirus Disease (COVID-19),” Interim Guidance, March 19, 2020. As of April 15, 2020: https://www.who.int/publications-detail/considerations-for-quarantine-of-individuals-in-the-context-of-containment-for-coronavirus-disease-(covid-19)

Zhang, Daitao, Wenting Liu, Peng Yang, Yi Zhang, Xinyu Li, Kaylyn E. Germ, Song Tang, Wenjie Sun, and Quanyi Wang, “Factors Associated with Household Transmission of Pandemic (H1N1) 2009 Among Self-Quarantined Patients in Beijing, China,” *PLoS One,* Vol. 8, No. 10, 2013.

Zhang, Qingxia, and Dingcheng Wang, “Assessing the Role of Voluntary Self-Isolation in the Control of Pandemic Influenza Using a Household Epidemic Model,” *International Journal of Environmental Research Public and Health*, 2015.

Testing

Abbott, “Detect COVID-19 in as Little as 5 Minutes,” webpage, March 27, 2020. As of April 16, 2020: https://www.abbott.com/corpnewsroom/product-and-innovation/detect-covid-19-in-as-little-as-5-minutes.html

BD (Becton, Dickinson and Company), “BD, BioMedomics Announce Launch of Rapid Serology Test to Detect Exposure to COVID-19,” press release, March 31, 2020. As of April 16, 2020: https://investors.bd.com/news-releases/news-release-details/bd-biomedomics-announce-launch-rapid-serology-test-detect

Centers for Disease Control and Prevention, “Testing for COVID-19,” webpage, April 15, 2020. As of April 16, 2020: https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/testing.html

Cowling, Benjamin J., Lincoln L. H. Lau, Peng Wu, Helen W. C. Wong, Vicky J. Fang, Steven Riley, and Hiroshi Nishiura, “Entry Screening to Delay Local Transmission of 2009 Pandemic Influenza A (H1N1),” *BMC Infectious Diseases*, Vol. 10, No. 82, 2010.

Easom, Nicholas, Peter Moss, Gavin Barlow, Anda Samson, Thomas Taynton, Kate Adams, Monica Ivan, Phillipa Burns, Kavitha Gajee, Kirstine Eastick, and Patrick J. Lillie, “Sixty-Eight Consecutive Patients Assessed for COVID-19 Infection: Experience from a UK Regional Infectious Diseases Unit,” *Influenza and Other Respiratory Viruses*, March 29, 2020.

Epitope Diagnostics, Inc., “EDI™ Novel Coronavirus COVID-19 ELISA Kits,” webpage, undated. As of April 16, 2020: http://www.epitopediagnostics.com/covid-19-elisa

EWG Science Team, “Lessons from Coronavirus: Testing Is Essential to Save Lives and Protect Human Health,” webpage, March 17, 2020. As of April 16, 2020: https://www.ewg.org/news-and-analysis/2020/03/lessons-coronavirus-testing-essential-save-lives-and-protect-human-health

John, Tara, “Iceland Lab’s Testing Suggests 50% of Coronavirus Cases Have No Symptoms,” CNN.com, April 3, 2020. As of April 16, 2020: https://www.cnn.com/2020/04/01/europe/iceland-testing-coronavirus-intl/index.html

Krumholz, Harlan M., “If You Have Coronavirus Symptoms, Assume You Have the Illness, Even If You Test Negative,” *New York Times*, April 1, 2020. As of April 16, 2020: https://www.nytimes.com/2020/04/01/well/live/coronavirus-symptoms-tests-false-negative.html

Madrigal, Alexis C., and Robinson Meyer, “Private Labs Are Fueling a New Coronavirus Testing Crisis,” *Atlantic*, March 31, 2020. As of April 16, 2020: https://www.theatlantic.com/health/archive/2020/03/next-covid-19-testing-crisis/609193/

Medicare.gov, “Is My Test, Item, or Service Covered?” webpage, undated. As of April 16, 2020: https://www.medicare.gov/coverage/coronavirus-test

Rogers, Kaleigh, “Why We Still Need to Test Widely for Coronavirus,” *FiveThirtyEight*, March 18, 2020. As of April 16, 2020: https://fivethirtyeight.com/features/why-we-still-need-to-test-widely-for-coronavirus/

Shear, Michael D., Abby Goodnough, Sheila Kaplan, Sheri Fink, Katie Thomas, and Noah Weiland, “The Lost Month: How a Failure to Test Blinded the U.S. to Covid-19,” *New York Times*, March 28, 2020. As of April 16, 2020: https://www.nytimes.com/2020/03/28/us/testing-coronavirus-pandemic.html

Thomke, Stefan, “Why Is the U.S. Behind on Coronavirus Testing?” *Harvard Business Review*, March 30, 2020. As of April 16, 2020: https://hbr.org/2020/03/why-is-the-u-s-behind-on-coronavirus-testing

Tolia, Vaishal M., Theodore C. Chan, and Edward M. Castillo, “Preliminary Results of Initial Testing for Coronavirus (COVID-19) in the Emergency Department,” *Western Journal of Emergency Medicine*, March 27, 2020.

Disinfection

Kampf, G., D. Todt, S. Pfaender, and E. Steinmann, "Persistence of Coronaviruses on Inanimate Surfaces and Their Inactivation with Biocidal Agents," *Journal of Hospital Infection*, Vol. 104, No. 1, March 1, 2020, pp. 246–251.

Palmer, Marisa, Dylan Barth, and Mark Abadi, "People in China are Walking Through These Giant Disinfectant Machines to Ward Off the Coronavirus—But Experts Don't Think It Works," *Business Insider*, February 27, 2020. As of April 16, 2020: https://www.businessinsider.com/coronavirus-china-wuhan-spray-disinfectant-tunnel-bleach-2020-2

Rabenau, H. F., G. Kampf, J. Cinatl, and H. W. Doerr, "Efficacy of Various Disinfectants Against SARS Coronavirus," *Journal of Hospital Infection*, Vol. 61, No. 2, 2005, pp. 107–111.

Service, Robert F., "Does Disinfecting Surfaces Really Prevent the Spread of Coronavirus?" *Science*, March 12, 2020. As of April 2020: https://www.sciencemag.org/news/2020/03/does-disinfecting-surfaces-really-prevent-spread-coronavirus#

van Doremalen, Neeltje, Trenton Bushmaker, Dylan H. Morris, Myndi G. Holbrook, Amandine Gamble, Brandi N. Williamson, Azaibi Tamin, Jennifer L. Harcourt, Natalie J. Thornburg, Susan I. Gerber, James O. Lloyd-Smith, Emmie de Wit, and Vincent J. Munster, "Aerosol and Surface Stability of SARS-CoV-2 as Compared with SARS-CoV-1," *New England Journal of Medicine*, Vol. 382, No. 16, 2020, pp. 1564–1567.

Zhen-Dong Guo, Zhong-Yi Wang, Shou-Feng Zhang, Xiao Li, Lin Li, Chao Li, Yan Cui, Rui-Bin Fu, Yun-Zhu Dong, Xiang-Yang Chi, Meng-Yao Zhang, Kun Liu, Cheng Cao, Bin Liu, Ke Zhang, Yu-Wei Gao, Bing Lu, and Wei Chen, "Aerosol and Surface Distribution of Severe Acute Respiratory Syndrome Coronavirus 2 in Hospital Wards, Wuhan, China, 2020," *Emerging Infectious Diseases*, Vol. 26, No. 7, 2020.

Isolation Facilities

Aledort, Julia E., Nicole Lurie, Jeffrey Wasserman, and Samual A. Bozzette, "Non-Pharmaceutical Public Health Interventions for Pandemic Influenza: An Evaluation of the Evidence Base," *BMC Public Health*, Vol. 7, No. 208, 2007.

Gostin, Lawrence, "Public Health Strategies for Pandemic Influenza: Ethics and the Law," *JAMA*, Vol. 295, No. 14, 2006, pp. 1700–1704.

Hellewell, Joel, Sam Abbott, Amy Gimma, Nikos I. Bosse, Christopher I. Jarvis, and Timothy W. Russell, “Feasibility of Controlling COVID-19 Outbreaks by Isolation of Cases and Contacts,” *Lancet Global Health*, Vol. 8, No. 4, April 1, 2020, pp. E488–E496.

Institute of Medicine Forum on Microbial Threats, “Strategies for Disease Containment,” in Alison Mack, ed., *Ethical and Legal Considerations in Mitigating Pandemic Disease: Workshop Summary*, Washington, D.C.: National Academies Press, 2007.

Lam, Clarence, Richard Waldhorn, Eric Toner, Thomas V. Inglesby, and Tara O’Toole, “The Prospect of Using Alternative Medical Care Facilities in an Influenza Pandemic,” *Biosecurity and Bioterrorism: Biodefense Strategy, Practice and Science*, Vol. 4, No. 4, 2006, pp. 384–390.

Lee, Sunmi, Gerardo Chowell, and Carlos Castillo-Chávez, “Optimal Control for Pandemic Influenza: The Role of Limited Antiviral Treatment and Isolation,” *Journal of Theoretical Biology*, Vol. 265, No. 2, July 21, 2010, pp. 136–150.

Niu, Yan, and Fujie Xu, “Deciphering the Power of Isolation in Controlling COVID-19 Outbreaks,” *Lancet Global Health*, Vol. 8, No. 4, 2020.

Rewar, Suresh, Dashrath Mirdha, and Prahlad Rewar, “Treatment and Prevention of Pandemic H1N1 Influenza,” *Annals of Global Health*, Vol. 81, No. 5, September–October, 2015, pp. 645–653.

Subhash, Shobha S., Gio Baracco, Shelly L. Miller, Aaron Eagan, and Lewis J. Radonovich, “Estimation of Needed Isolation Capacity for an Airborne Influenza Pandemic,” *Health Security*, Vol. 14, No. 4, 2016, pp. 258–263.

Yeun, P. L., R. Yam, R. Yung, and K. L. Choy, “Fast-Track Ventilation Strategy to Cater for Pandemic Patient Isolation Surges,” *Journal of Hospital Infection*, Vol. 81, No. 4, 2012, pp. 246–250.

Travel Ban

Balcan, Duygu, Vittoria Colizza, Bruno Gonçalves, Hao Hu, José J. Ramasco, and Alessandro Vespignani, “Multiscale Mobility Networks and the Spatial Spreading of Infectious Diseases,” *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 106, No. 51, 2009, pp. 21484–21489.

Bettencourt, Luís M. A., and Ruy M. Ribeiro, “Real Time Bayesian Estimation of the Epidemic Potential of Emerging Infectious Diseases,” *PloS One*, Vol. 3, No. 5, 2008, p. e2185.

Bolton, K. J., J. M. McCaw, R. Moss, R. S. Morris, S. Wang, A. Burma, B. Darma, D. Narangerel, P. Nymadawa, and J. McVernon, “Likely Effectiveness of Pharmaceutical and

Non-Pharmaceutical Interventions for Mitigating Influenza Virus Transmission in Mongolia," *Bulletin of the World Health Organization*, Vol. 90, No. 4, 2012, pp. 264–271.

Brownstein, John S., Cecily J. Wolfe, and Kenneth D. Mandl, "Empirical Evidence for the Effect of Airline Travel on Inter-Regional Influenza Spread in the United States," *PLoS Medicine,* Vol. 3, No. 10, 2006, pp. 1826–1835.

Chong, Ka Chun, and Benny Chung Ying Zee, "Modeling the Impact of Air, Sea, and Land Travel Restrictions Supplemented by Other Interventions on the Emergence of a New Influenza Pandemic Virus," *BMC Infectious Diseases*, Vol. 12, No. 1, 2012.

Ciofi degli Atti, Marta Luisa, Stefano Merler, Caterina Rizzo, Marco Ajelli, Marco Massari, Piero Manfredi, Cesare Furlanello, Gianpaolo Scalia Tomba, and Mimmo Iannelli, "Mitigation Measures for Pandemic Influenza in Italy: An Individual Based Model Considering Different Scenarios," *PloS One*, Vol. 3, No. 3, 2008.

Colizza, Vittoria, Alain Barrat, Marc Barthelemy, Alain-Jacques Valleron, and Alessandro Vespignani, "Modeling the Worldwide Spread of Pandemic Influenza: Baseline Case and Containment Interventions," *PLoS Medicine*, Vol. 4, No. 1, 2007.

Cooper, Ben S., Richard J. Pitman, W. John Edmunds, and Nigel J. Gay, "Delaying the International Spread of Pandemic Influenza," *PLoS Medicine*, Vol. 3, No. 6, 2006.

Cowling, Benjamin J., Lincoln L. H. Lau, Peng Wu, Helen W. C. Wong, Vicky J. Fang, Steven Riley, and Hiroshi Nishiura, "Entry Screening to Delay Local Transmission of 2009 Pandemic Influenza A (H1N1)," *BMC Infectious Diseases*, Vol. 10, 2010.

Eichner, Martin, Markus Schwehm, Nick Wilson, and Michael G. Baker, "Small Islands and Pandemic Influenza: Potential Benefits and Limitations of Travel Volume Reduction as a Border Control Measure," *BMC Infectious Diseases*, Vol. 9, 2009.

Epstein, Joshua M., D. Michael Goedecke, Feng Yu, Robert J. Morris, Diane K. Wagener, and Georgiy V. Bobashev, "Controlling Pandemic Flu: The Value of International Air Travel Restrictions," *PloS One,* Vol. 2, No. 5, 2007.

Ferguson, Neil M., Derek A. T. Cummings, Christophe Fraser, James C. Cajka, Philip C. Cooley, and Donald S. Burke, "Strategies for Mitigating an Influenza Pandemic," *Nature,* Vol. 442, No. 7101, 2006, pp. 448-452.

Flahault, Antoine, Elisabeta Vergu, Laurent Coudeville, and Rebecca F. Grais, "Strategies for Containing a Global Influenza Pandemic," *Vaccine*, Vol. 24, No. 44-46, 2006, pp. 6751–6755.

Flahault, Antoine, Elisabeta Vergu, and Pierre-Yves Boelle, "Potential for a Global Dynamic of Influenza A (H1N1)," *BMC Infectious Diseases*, Vol. 9, No. 129, 2009.

Germann, Timothy C., Kai Kadau, Ira M. Longini, Jr., and Catherine A. Macken, "Mitigation Strategies for Pandemic Influenza in the United States," *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 103, No. 15, 2006, pp. 5935–5940.

Grais, Rebecca F., J. Hugh Ellis, and Gregory E. Glass, "Assessing the Impact of Airline Travel on the Geographic Spread of Pandemic Influenza," *European Journal of Epidemiology*, Vol. 18, No. 11, 2004, pp. 1065–1072.

Hollingsworth, T. Deirdre, Neil M. Ferguson, and Roy M. Anderson, "Will Travel Restrictions Control the International Spread of Pandemic Influenza?" *Nature Medicine*, Vol. 12, No. 5, 2006, pp. 497–499.

Hsieh, Ying-Hen, P. van den Driessche, and Lin Wang, "Impact of Travel Between Patches for Spatial Spread of Disease," *Bulletin of Mathematical Biology*, Vol. 69, No. 4, 2007, pp. 1355–1375.

Hufnagel, L., D. Brockmann, and T. Geisel, "Forecast and Control of Epidemics in a Globalized World," *Proceedings of the National Academy of Sciences of the United States of America*, Vol. 101, No. 42, 2004, pp. 15124–15129.

Johns Hopkins Center for Health Security, "U.S. Travel Screening," January 22, 2020. As of April 20, 2020: https://www.centerforhealthsecurity.org/resources/COVID-19/COVID-19-resources/200122-nCoV-UStravelScreening.pdf

Kernéis, Solen, Rebecca F. Grais, Pierre-Yves Boëlle, Antoine Flahault, and Elisabeta Vergu, "Does the Effectiveness of Control Measures Depend on the Influenza Pandemic Profile?" *PloS One*, Vol. 3, No. 1, 2008.

Lam, Elson H. Y., Benjamin J. Cowling, Alex R. Cook, Jessica Y. T. Wong, Max S. Y. Lau, and Hiroshi Nishiura, "The Feasibility of Age-Specific Travel Restrictions During Influenza Pandemics," *Theoretical Biology and Medical Modelling*, Vol. 8, No. 1, 44, 2011.

Lee, Jung Min, Donghoon Choi, Giphil Cho, and Yongkuk Kim, "The Effect of Public Health Interventions on the Spread of Influenza Among Cities," *Journal of Theoretical Biology*, Vol. 293, 2012, pp. 131–142.

Lee, Vernon J., David C. Lye, and Annelies Wilder-Smith, "Combination Strategies for Pandemic Influenza Response: A Systematic Review of Mathematical Modeling Studies," *BMC Medicine*, Vol. 7, No. 76, 2009.

Marcelino, Jose, and Marcus Kaiser, "Critical Paths in a Metapopulation Model of H1N1: Efficiently Delaying Influenza Spreading Through Flight Cancellation," *PLoS Currents*, Vol. 4, 2012.

Mateus, Ana L. P., Harmony E. Otete, Charles R. Beck, Gayle P. Dolan, and Jonathan S. Nguyen-Van-Tam, "Effectiveness of Travel Restrictions in the Rapid Containment of Human Influenza: A Systematic Review," *Bulletin of the World Health Organization*, Vol. 92, No. 12, 2014, pp. 868–880D.

Nicoll, A., A. Ammon, A. Amato, B. Ciancio, P. Zucs, I. Devaux, F. Plata, A. Mazick, K. Molbak, T. Asikainen, and P. Kramarz, "Experience and Lessons from Surveillance and Studies of the 2009 Pandemic in Europe," *Public Health*, Vol. 124, No. 1, 2010, pp. 14–23.

Pandemic Influenza Preparedness Team, *Scientific Summary of Pandemic Influenza and its Mitigation: Scientific Evidence Base Review*, London: Department of Health, March 22, 2011. As of April 22, 2020: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/215666/dh_125333.pdf

Pérez Velasco, Román, Naiyana Praditsitthikorn, Kamonthip Wichmann, Adun Mohara, Surachai Kotirum, Sripen Tantivess, Constanza Vallenas, Hande Harmanci, and Yot Teerawattananon, "Systematic Review of Economic Evaluations of Preparedness Strategies and Interventions Against Influenza Pandemics," *PloS One*, Vol. 7, No. 2, 2012.

Pitman, R. J., B. S. Cooper, C. L. Trotter, N. J. Gay, and W. J. Edmunds, "Entry Screening for Severe Acute Respiratory Syndrome (SARS) or Influenza: Policy Evaluation," *British Medical Journal*, Vol. 331, No. 7527, 2005, pp. 1242–1243.

Scalia Tomba, Gianpaolo, and Jacco Wallinga, "A Simple Explanation for the Low Impact of Border Control as a Countermeasure to the Spread of an Infectious Disease," *Mathematical Biosciences*, Vol. 214, No. 1-2, 2008, pp. 70–72.

Wood, James G., Nasim Zamani, C. Raina MacIntyre, and Niels G. Beckert, "Effects of Internal Border Control on Spread of Pandemic Influenza," *Emerging Infectious Diseases*, Vol. 13, No. 7, 2007, pp. 1038–1045.

World Health Organization, *WHO Global Influenza Preparedness Plan*, Geneva, 2005. As of April 23, 2020: https://www.who.int/csr/resources/publications/influenza/WHO_CDS_CSR_GIP_2005_5.pdf

World Health Organization, *WHO Interim Protocol: Rapid Operations to Contain the Initial Emergence of Pandemic Influenza*, Geneva, October 2007. As of April 23, 2020: https://www.who.int/influenza/resources/documents/RapidContProtOct15.pdf

World Health Organization, *Pandemic Influenza Preparedness and Response*, Geneva, 2009. As of April 23, 2020: https://apps.who.int/iris/bitstream/handle/10665/44123/9789241547680_eng.pdf;jsessionid=4170C2E062CCDD9023BB0B1BFCDBC551?sequence=1

World Health Organization, *International Health Regulations*, 3rd ed., Geneva, 2016. As of April 23, 2020: https://apps.who.int/iris/bitstream/handle/10665/246107/9789241580496-eng.pdf?sequence=1

References

Agency for Healthcare Research and Quality, "Medical Expenditure Panel Survey," webpage, undated. As of April 20, 2020:
https://www.meps.ahrq.gov/mepsweb/

AHA—*See* American Hospital Association.

AHLA—*See* American Hotel and Lodging Association.

Aledort, Julia E., Nicole Lurie, Jeffrey Wasserman, and Samuel A. Bozzette, "Non-Pharmaceutical Public Health Interventions for Pandemic Influenza: An Evaluation of the Evidence Base," *BMC Public Health*, Vol. 7, No. 208, 2007.

American Hospital Association, *COVID-19 Models: Forecasting the Pandemic's Spread*, Chicago, Ill., April 2020. As of April 20, 2020:
https://www.aha.org/system/files/media/file/2020/04/COVID-19-Modeling-Forecasting-the-Pandemics-Spread.pdf

American Hotel and Lodging Association, "COVID-19's Impact on the Hotel Industry," webpage, undated. As of April 17, 2020:
https://www.ahla.com/covid-19s-impact-hotel-industry

Arentz, Matt, Eric Yim, Lindy Klaff, Sharukh Lokhandwala, Francis X. Riedo, Maria Chong, and Melissa Lee, "Characteristics and Outcomes of 21 Critically Ill Patients with COVID-19 in Washington State," *JAMA*, March 19, 2020.

Backer, Jantien A., Don Klinkenberg, and Jacco Wallinga, "Incubation Period of 2019 Novel Coronavirus (2019-nCoV) Infections Among Travellers from Wuhan, China, 20–28 January 2020," *Eurosurveillance*, Vol. 25, No. 5, February 6, 2020.

Begley, Sharon, "Influential Covid-19 Model Uses Flawed Methods and Shouldn't Guide U.S. Policies, Critics Say," STAT News, April 17, 2020. As of April 24, 2020:
https://www.statnews.com/2020/04/17/influential-covid-19-model-uses-flawed-methods-shouldnt-guide-policies-critics-say/

Binlot, Ann, "Retailers Report 50 Percent Revenue Impact Due to Coronavirus in New Survey," *Forbes*, March 31, 2020. As of April 17, 2020:
https://www.forbes.com/sites/abinlot/2020/03/31/retailers-report-50-percent-revenue-impact-due-to-coronavirus-in-new-survey/#404a2d24c569

Biocomplexity Institute, "Estimation of COVID-19 Impact in Virginia," briefing, Charlottesville, Va.: University of Virginia, April 13, 2020. As of April 20, 2020:

https://covid19.biocomplexity.virginia.edu/sites/covid19.biocomplexity/files/COVID-19-UVA-MODEL-FINDINGS-Apr13-2020-FINAL%20PRESS.pdf

Blume, Lawrence, "Agent-Based Models for Policy Analysis," in R. Wallace, A. Geller, and V. A. Ogawa, eds, *Assessing the Use of Agent-Based Models for Tobacco Regulation*, Washington, D.C.: National Academies Press, 2015.

CDC—*See* Centers for Disease Control and Prevention.

Centers for Disease Control and Prevention, "Implementation of Mitigation Strategies for Communities with Local COVID-19 Transmission," fact sheet, 2020a. As of March 12, 2020:
https://www.cdc.gov/coronavirus/2019-ncov/downloads/community-mitigation-strategy.pdf

Centers for Disease Control and Prevention, "Interim Clinical Guidance for Management of Patients with Confirmed Coronavirus Disease (COVID-19)," webpage, 2020b. As of February 11, 2020:
https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical-guidance-management-patients.html

Chamberlin, Margaret, Shira Efron, and Melinda Moore, *A Simple Approach to Assessing Potential Health Emergency Interventions: A Proof of Concept and Illustrative Application to the 2014–2015 Ebola Crisis*, Santa Monica, Calif.: RAND Corporation, PE-148-RC, 2015. As of April 20, 2020:
https://www.rand.org/pubs/perspectives/PE148.html

China Centers for Disease Control and Prevention, "The Epidemiological Characteristics of an Outbreak of 2019 Novel Coronavirus Diseases (COVID-19)—China, 2020," *China CDC Weekly*, Vol. 2, February 1, 2020, pp. 1–10.

Cottrell, Wayne D., "Simplified Program Evaluation and Review Technique (PERT)," *Journal of Construction Engineering and Management*, Vol. 125, No. 1, 1999, pp. 16–22.

COVID Tracking Project, homepage, undated. As of April 20, 2020:
https://covidtracking.com/

COVID Tracking Project, "Most Recent Data," webpage, April 20, 2020. As of April 20, 2020:
https://covidtracking.com/data

Day, Michael, "Covid-19: Identifying and Isolating Asymptomatic People Helped Eliminate Virus in Italian Village," *BMJ*, Vol. 368, March 23, 2020.

The *Economist*, "The State in the Time of COVID-19," March 26, 2020. As of April 24, 2020:
https://www.economist.com/leaders/2020/03/26/the-state-in-the-time-of-covid-19

Edwards, Kathryn A., Grace Evans, and Daniel Schwam, "Parenting Through the Pandemic: Who's Working, Who's Caring for the Kids, and What Policies Might Help," *RAND Blog*, April 8, 2020. As of April 20, 2020: https://www.rand.org/blog/2020/04/parenting-through-the-pandemic-whos-working-whos-caring.html

Fedor, Lauren, and Christine Zhang, "Income of 73% in U.S. Hit by Coronavirus Outbreak: FT-Peterson Poll," *Financial Times*, April 7, 2020. As of April 9, 2020: https://www.ft.com/content/7a7233a3-160a-41be-8d63-40f64e041e57

Ferguson, Neil M., Daniel Laydon, Gemma Nedjati-Gilani, Natsuko Imai, Kylie Ainslie, Marc Baguelin, Sangeeta Bhatia, Adhiratha Boonyasiri, Zulma Cucunubá, Gina Cuomo-Dannenburg, Amy Dighe, Ilaria Dorigatti, Han Fu, Katy Gaythorpe, Will Green, Arran Hamlet, Wes Hinsley, Lucy C. Okell, Sabine van Elsland, Hayley Thompson, Robert Verity, Erik Volz, Haowei Wang, Yuanrong Wang, Patrick G. T. Walker, Caroline Walters, Peter Winskill, Charles Whittaker, Christl A. Donnelly, Steven Riley, and Azra C. Ghani, *Report 9: Impact of Non-Pharmaceutical Interventions (NPI) to Reduce COVID-19 Mortality and Healthcare Demand*, London: WHO Collaborating Centre for Infectious Disease Modelling, March 16, 2020. As of April 20, 2020: https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-NPI-modelling-16-03-2020.pdf

Flaxman, Seth, Swapnil Mishra, Axel Gandy, H. Juliette, T. Unwin, Helen Coupland, Thomas A. Mellan, Harrison Zhu, Tresnia Berah, Jeffrey W. Eaton, Pablo N. P. Guzman, Nora Schmit, Lucia Cilloni, Kylie E. C. Ainslie, Marc Baguelin, Isobel Blake, Adhiratha Boonyasiri, Olivia Boyd, Lorenzo Cattarino, Constanze Ciavarella, Laura Cooper, Zulma Cucunubá, Gina Cuomo-Dannenburg, Amy Dighe, Bimandra Djaafara, Ilaria Dorigatti, Sabine van Elsland, Rich FitzJohn, Han Fu, Katy Gaythorpe, Lily Geidelberg, Nicholas Grassly, Will Green, Timothy Hallett, Arran Hamlet, Wes Hinsley, Ben Jeffrey, David Jorgensen, Edward Knock, Daniel Laydon, Gemma Nedjati-Gilani, Pierre Nouvellet, Kris Parag, Igor Siveroni, Hayley Thompson, Robert Verity, Erik Volz, Caroline Walters, Haowei Wang, Yuanrong Wang, Oliver Watson, Peter Winskill, Xiaoyue Xi, Charles Whittaker, Patrick G. T. Walker, Azra Ghani, Christl A. Donnelly, Steven Riley, Lucy C. Okell, Michaela A. C. Vollmer, Neil M. Ferguson, and Samir Bhatt, *Estimating the Number of Infections and the Impact of Non-Pharmaceutical Interventions on COVID-19 in 11 European Countries*, Imperial College London, March 30, 2020.

Gangitano, Alex, "Restaurant Industry Estimates $225B in Losses from Coronavirus," *The Hill*, March 18, 2020. As of April 17, 2020: https://thehill.com/business-a-lobbying/business-a-lobbying/488223-restaurant-industry-estimates-225b-in-losses-from

Gangopadhyaya, Anuj, and Elaine Waxman, *Food Service and Preparation Workers and the COVID-19 Pandemic*, Washington, D.C.: Urban Institute, March 26, 2020. As of April 24, 2020: https://www.urban.org/research/publication/food-service-and-preparation-workers-and-covid-19-pandemic

Google, "COVID-19 Community Mobility Reports," webpage, undated. As of April 17, 2020: https://www.google.com/covid19/mobility/

Government of Iceland, "Large Scale Testing of General Population in Iceland Underway," press release, March 15, 2020. As of March 30, 2020: https://www.government.is/news/article/2020/03/15/Large-scale-testing-of-general-population-in-Iceland-underway/

Greenhalgh, Scott, and Carly Rozins, "Generalized Differential Equation Compartmental Models of Infectious Disease Transmission," *BioRxiv*, April 12, 2020.

Harvard Global Health Institute, "U.S. Hospital Capacity," webpage, March 17, 2020. As of April 20, 2020: https://globalepidemics.org/our-data/hospital-capacity/

He, Xi, Eric H. Y. Lau, Peng Wu, Xilong Deng, Jian Wang, Xinxin Hao, Yiu Chung Lau, Jessica Y. Wong, Yujuan Guan, Xinghua Tan, Xiaoneng Mo, Yanqing Chen, Baolin Liao, Weilie Chen, Fengyu Hu, Qing Zhang, Mingqui Zhong, Yanrong Wu, Lingzhai Zhao, Fuchun Zhang, Benjamin J. Cowling, Fang Li, and Gabriel M. Leung, "Temporal Dynamics in Viral Shedding and Transmissibility of COVID-19," *Nature Medicine*, 2020.

Heffernan, J. M., R. J. Smith, and L. M. Wahl, "Perspectives on the Basic Reproductive Ratio," *Journal of the Royal Society Interface*, Vol. 2, No. 4, 2005, pp. 281–293.

Helton, J. C., and R. L. Iman, "Sensitivity Analysis of a Model for the Environmental Movement of Radionuclides," *Health Physics*, Vol. 42, No. 5, May 1983, pp. 565–584.

Hennessy-Fiske, Molly, "Louisiana Church Defies COVID-19 Order, Holds Sunday Services," *Los Angeles Times*, March 29, 2020. As of April 24, 2020: https://www.latimes.com/world-nation/story/2020-03-29/louisiana-church-defies-covid-19-order-holds-sunday-services

Heron, Melonie, "Deaths: Leading Causes for 2017," *National Vital Statistics Reports*, Vol. 68, No. 6, June 24, 2019. As of April 20, 2020: https://www.cdc.gov/nchs/data/nvsr/nvsr68/nvsr68_06-508.pdf

Hindmarsh, Alan C., and Linda R. Petzold, "Algorithms and Software for Ordinary Differential Equations and Differential-Algebraic Equations, Part II: Higher-Order Methods and Software Packages," *Computers in Physics*, Vol. 9, No. 2, March 1, 1995, pp. 148–155.

Hoare, Alexander, David G. Regan, and David P. Wilson, "Sampling and Sensitivity Analyses Tools (SaSAT) for Computational Modelling," *Theoretical Biology and Medical Modelling*, Vol. 5, No. 4, 2008.

Institute of Medicine Forum on Microbial Threats, *Ethical and Legal Considerations in Mitigating Pandemic Disease: Workshop Summary*, Washington, D.C.: National Academies Press, 2007.

Kaiser Family Foundation, "State Data and Policy Actions to Address Coronavirus," webpage, April 17, 2020. As of April 17, 2020: https://www.kff.org/health-costs/issue-brief/state-data-and-policy-actions-to-address-coronavirus

Kelvin Kai-Wang To, Owen Tak-Yin Tsang, Wai-Shing Leung, Anthony Raymond Tam, Tak-Chiu Wu, David Christopher Lung, Cyril Chik-Yan Yip, Jian-Piao Cai, Jacky Man-Chun Chan, Thomas Shiu-Hong Chik, Daphne Pui-Ling Lau, Chris Yau-Chung Choi, Lin-Lei Chen, Wan-Mui Chan, Kwok-Hung Chan, Jonathan Daniel Ip, Anthony Chin-Ki Ng, Rosana Wing-Shan Poon, Cui-Ting Luo, Vincent Chi-Chung Cheng, Jasper Fuk-Woo Chan, Ivan Fan-Ngai Hung, Zhiwei Chen, Honglin Chen, and Kwok-Yung Yuen, "Temporal Profiles of Viral Load in Posterior Oropharyngeal Saliva Samples and Serum Antibody Responses During Infection by SARS-CoV-2: An Observational Cohort Study," *Lancet Infectious Diseases*, March 23, 2020.

Lachmann, Alexander, Kathleen M. Jagodnik, Federico Manuel Giorgi, and Forest Ray, "Correcting Under-Reported COVID-19 Case Numbers: Estimating the True Scale of the Pandemic," *MedRxiv*, January 1, 2020.

Li, Qun, Xuhua Guan, Peng Wu, Xiaoye Wang, Lei Zhou, Yeqing Tong, Ruiqi Ren, Kathy S. M. Leung, Eric H. Y. Lau, Jessica Y. Wong, Xuesen Xing, Nijuan Xiang, Yang Wu, Chao Li, Qi Chen, Dan Li, Tian Liu, Jing Zhao, Man Liu, Wenxiao Tu, Chuding Chen, Lianmei Jin, Rui Yang, Qi Wang, Suhua Zhou, Rui Wang, Hui Liu, Yinbo Luo, Yuan Liu, Ge Shao, Huan Li, Zhongfa Tao, Yang Yang, Zhiqiang Deng, Boxi Liu, Zhitao Ma, Yanping Zhang, Guoqing Shi, Tommy T. Y. Lam, Joseph T. Wu, George F. Gao, Benjamin J. Cowling, Bo Yang, Gabriel M. Leung, and Zijian Feng, "Early Transmission Dynamics in Wuhan, China, of Novel Coronavirus–Infected Pneumonia," *New England Journal of Medicine*, Vol. 382, No. 13, 2020, pp. 1199–1207.

Lofgren, E., N. H. Fefferman, Y. N. Naumov, J. Gorski, and E. N. Naumova, "Influenza Seasonality: Underlying Causes and Modeling Theories," *Journal of Virology*, Vol. 81, No. 11, June 1, 2007, pp. 5429–5436.

Manheim, David, Margaret Chamberlin, Osonde A. Osoba, Raffaele Vardavas, and Melinda Moore, *Improving Decision Support for Infectious Disease Prevention and Control: Aligning*

Models and Other Tools with Policymakers' Needs, Santa Monica, Calif.: RAND Corporation, RR-1576-OSD, 2016. As of April 20, 2020: https://www.rand.org/pubs/research_reports/RR1576.html

Marathe, M. V., *Synthetic Data Products for Societal Infrastructures and Proto-Populations: Data Set 2.0*, Blacksburg, Va.: Virginia Polytechnic Institute and State University, Network Dynamics and Simulation Science Laboratory, 2014.

Markel, Howard, Harvey B. Lipman, Alexander Navarro, Alexandra Sloan, Joseph R. Michalsen, Alexandra Minna Stern, and Martin S. Cetron, "Nonpharmaceutical Interventions Implemented by U.S. Cities During the 1918–1919 Influenza Pandemic," *JAMA*, Vol. 298, No. 6, 2007, pp. 644–654.

Moghadas, Seyed M., Affan Shoukat, Meagan C. Fitzpatrick, Chad R. Wells, Pratha Sah, Abhishek Pandey, Jeffrey D. Sachs, Zheng Wang, Lauren A. Meyers, Burton H. Singer, and Alison P. Galvani, "Projecting Hospital Utilization During the Covid-19 Outbreaks in the United States," *Proceedings of the National Academy of Sciences*, 2020.

Mossong, Joël, Niel Hens, Mark Jit, Philippe Beutels, Kari Auranen, Rafael Mikolajczyk, Marco Massari, Stefania Salmaso, Gianpaolo Scalia Tomba, Jacco Wallinga, Janneke Heijne, Malgorzata Sadkowska-Todys, Magdalena Rosinska, W. John Edmunds, "Social Contacts and Mixing Patterns Relevant to the Spread of Infectious Diseases," *PLOS Medicine*, Vol. 5, No. 3, March 25, 2008.

Nadreau, Timothy P., "WSU CGE Analysis of Carbon WA: Technical Documentation," Western Economics Forum, Vol. 14, No. 2, 2015, pp. 26–56.

New York Department of Health, "Deaths: Individual Nursing Homes," data tables, April 22, 2020. As of April 23, 2020: https://www.health.ny.gov/statistics/diseases/covid-19/fatalities_nursing_home_acf.pdf

Oguntunde, P. E., O. A. Odetunmibi, and A. O. Adejumo, "On the Sum of Exponentially Distributed Random Variables: A Convolution Approach," *European Journal of Statistics and Probability*, Vol. 2, No. 1, March 2014, pp. 1–8.

Pan, Feng, Tianhe Ye, Peng Sun, Shan Gui, Bo Liang, Lingli Li, Dandan Zheng, Jiazheng Wang, Richard L. Hesketh, Lian Yang, and Chuansheng Zheng, "Time Course of Lung Changes on Chest CT During Recovery from 2019 Novel Coronavirus (COVID-19) Pneumonia," *Radiology*, February 13, 2020.

Perroni, Carlo, and Thomas Rutherford, "Regular Flexibility of Nested CES Functions," *European Economic Review*, Vol. 39, No. 2, 1995, pp. 335–343.

Prem, Kiesha, Alex R. Cook, and Mark Jit, “Projecting Social Contact Matrices in 152 Countries Using Contact Surveys and Demographic Data,” *PLoS Computational Biology*, Vol. 13, No. 9, September 2017.

Press, William H., Brian P. Flannery, Saul A. Teukolsky, and William T. Vetterling, *Numerical Recipes in Fortran 77: The Art of Scientific Computing*, 2nd ed., New York: Press Syndicate of the University of Cambridge, September 25, 1992.

Raifman, J., K. Nocka, D. Jones, J. Bor, S. Lipson, J. Jay, and P. Chan “COVID-19 U.S. State Policy Database,” Google spreadsheet, 2020. As of April 28, 2020: www.tinyurl.com/statepolicies

Rausch, Sebastian, and Thomas F. Rutherford, *Tools for Building National Economic Models Using State-Level IMPLAN Social Accounts*, July 2008. As of January 15, 2019: http://www.mpsge.org/IMPLAN2006inGAMS/IMPLAN2006inGAMS.pdf

Rodrigue, Jean-Paul, *The Geography of Transport Systems*, 5th ed., New York: Routledge, 2020.

Romeo, Peter, “Restaurant Damage to Date: $25b in Sales, 3 Million Jobs,” Restaurant Business Online, March 30, 2020. As of April 17, 2020: https://www.restaurantbusinessonline.com/operations/restaurant-damage-date-25b-sales-3m-jobs

Russell, Timothy W., Joel Hellewell, Christopher I. Jarvis, Kevin van-Zandvoort, Sam Abbott, Ruwan Ratnayake, Stefan Flasche, Rosalind M. Eggo, Adam J. Kucharski, “Estimating the Infection and Case Fatality Ratio for COVID-19 Using Age-Adjusted Data from the Outbreak on the Diamond Princess Cruise Ship,” *MedRxiv*, March 9, 2020.

Rutherford, Thomas F., and Andrew Schreiber, “National Open Source Tools for General Equilibrium Analysis,” data set, undated. As of April 20, 2020: https://aae.wisc.edu/blueNOTE/

Smith, Richard D., Marcus R. Keogh-Brown, and Tony Barnett, “Estimating the Economic Impact of Pandemic Influenza: An Application of the Computable General Equilibrium Model to the UK,” *Social Science and Medicine*, Vol. 73, No. 2, 2011, pp. 235–244.

Soetaert, Karline, Thomas Petzoldt, and R. Woodrow Setzer, “Solving Differential Equations in R: Package DeSolve,” *Journal of Statistical Software*, Vol. 33, No. 9, February 23, 2010, pp. 1–25.

Sue Wing, Ian, *The Regional Impacts of U.S. Climate Change Policy: A General Equilibrium Analysis*, Boston, Mass.: Boston University, February 27, 2007. As of January 15, 2019: http://people.bu.edu/isw/papers/burgess_ecomod.pdf

Thomas, James, and Angela Harden, "Methods for the Thematic Synthesis of Qualitative Research in Systematic Reviews," *BMC Medical Research Methodology*, Vol. 8, No. 45, 2008.

U.S. Census Bureau, "State Population by Characteristics: 2010–2019," webpage, March 2, 2020. As of April 20, 2020:
https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-detail.html

U.S. Small Business Administration, "Small Businesses Generate 44 Percent of U.S. Economic Activity," press release, January 30, 2019. As of April 24, 2020;
https://advocacy.sba.gov/2019/01/30/small-businesses-generate-44-percent-of-u-s-economic-activity/

Wang, Dawei, Bo Hu, Chang Hu, Fangfang Zhu, Xing Liu, Jing Zhang, Binbin Wang, Hui Xiang, Zhenshun Cheng, Yong Xiong, Yan Zhao, Yirong Li, Xinghuan Wang, and Zhiyong Peng, "Clinical Characteristics of 138 Hospitalized Patients with 2019 Novel Coronavirus–Infected Pneumonia in Wuhan, China," *JAMA*, Vol. 323, No. 11, March 17, 2020, pp. 1061–1069.

Wang, Weier, Jianming Tang, and Fangqiang Wei, "Updated Understanding of the Outbreak of 2019 Novel Coronavirus (2019-NCoV) in Wuhan, China," *Journal of Medical Virology*, Vol. 92, No. 4, 2020, pp. 441–447.

Whitehead, Sam, and Carrie Feibel, "CDC Director on Models for the Months to Come: 'This Virus Is Going to Be with Us,'" NPR.org, March 31, 2020. As of April 1, 2020:
https://www.npr.org/sections/health-shots/2020/03/31/824155179/cdc-director-on-models-for-the-months-to-come-this-virus-is-going-to-be-with-us

Wu, Zunyou, and Jennifer M. McGoogan, "Characteristics of and Important Lessons from the Coronavirus Disease 2019 (COVID-19) Outbreak in China: Summary of a Report of 72314 Cases from the Chinese Center for Disease Control and Prevention," *JAMA*, Vol. 323, No. 13, 2020, pp. 1239–1242.

Yang, Xiaobo, Yuan Yu, Jiqian Xu, Huaqing Shu, Jia'an Xia, Hong Liu, Yongran Wu, Lu Zhang, Zhui Yu, Minghao Fang, Ting Yu, Yaxin Wang, Shangwen Pan, Xiaojing Zou, Shiying Yuan, and You Shang, "Clinical Course and Outcomes of Critically Ill Patients with SARS-CoV-2 Pneumonia in Wuhan, China: A Single-Centered, Retrospective, Observational Study," *The Lancet Respiratory Medicine*, February 24, 2020.

Zou, Lirong, Feng Ruan, Mingxing Huang, Lijun Liang, Huitao Huang, Zhongsi Hong, Jianxiang Yu, Jinyu Xia, Qianfang Guo, Hui-Leng Yen, and Jie Wu, "SARS-CoV-2 Viral Load in Upper Respiratory Specimens of Infected Patients," *New England Journal of Medicine*, Vol. 382, 2020, pp. 1177–1179.