Research Report

A Framework for Assessing Models of the COVID-19 Pandemic to Inform Policymaking in Virginia

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Preface

The study underlying this report was conducted during the coronavirus disease 2019 pandemic to provide context for the various models of the spread of the disease and present a framework for determining which models might be suitable for the Commonwealth of Virginia.

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As the coronavirus disease 2019 (COVID-19) pandemic has evolved, we have relied on models to predict the severity of the pandemic, when the pandemic might peak, and what might be done to avoid the worst-case scenario. Modelers have been rushing to respond, but not all models are suitable to inform policy. To make informed decisions, policymakers should have some notion of the variety of models available, the suitability of the model types, and areas of uncertainty for the models. This report describes a framework for assessing the suitability of models for addressing policy-relevant questions and applies the framework to the COVID-19 pandemic in Virginia.

This report builds on Gambhir et al., 2015, and Manheim et al., 2016, to develop a specific analytic framework for assessing the suitability of models for use in the COVID-19 pandemic in the state of Virginia. Although those studies considered generic infectious diseases, we are focused on COVID-19. We focus on two phases of the pandemic: the early stage and the late stage.

Early-stage models address questions about the period from the start of the outbreak until the point where it reaches its peak. To effectively support policy in the early stage, models should be able to address one or more of the following key questions:

- What will be the peak number of infections, hospitalizations, or deaths per day for an area?
- When will this peak occur?
- When will demand for key resources exceed capacity (i.e., intensive care beds or ventilators)?
- What would be the implication of a particular policy intervention on the peak infections, hospitalizations, or deaths?

Policymakers have begun to shift their focus to a "second phase" of forecasting COVID-19 following the initial peak of infections and deaths in many regions in the United States, and possible paths for reopening are being explored. Although it will still be important to model the rate and extent of COVID-19's spread, an additional layer of complexity is required to address policy and behavioral changes. Models of late-stage pandemics therefore should be able to address one or more of the following questions:

- What are the opportunity costs or trade-offs associated with the policy responses employed during the first phase?
- How can we maximize "normalcy" and economic activity while minimizing unnecessary deaths?
- What is the risk of a second peak?
- Are there risks of exhausting necessary equipment, personnel, or facilities?

- What is the delay between changing regulations and seeing the impact on infections and deaths?

Models can be classified as either *statistical* or *systems dynamics*. These two categories of models represent opposite ends of a spectrum, in terms of data requirements and assumptions; in practice, most models fall somewhere in between. *Statistical models* will typically make fewer assumptions about the pattern of spread and underlying disease characteristics but rely on having more data on the number of cases or deaths over time. *Systems dynamics models* begin with a set of assumptions about how the disease spreads (usually assuming exponential growth) and capture important epidemiological characteristics in a few key parameters. Ideally, these parameters are derived from the available data, but they can also be estimated using past epidemiological studies or calibrated to fit data on key observable outcomes. Put another way, systems dynamics models involve causal relationships, while statistical models capture trends and correlations.

In general, statistical models are best for forecasting trends, rather than comparing policies. Systems dynamics models are well suited for comparing policies, as long as the policy operates through a mechanism that is captured by the model. When distinguishing between models that are potentially suitable, we consider the following four factors:

- **Data:** Are the data used to train the model relevant to this case? If not entirely, are there adjustments made to the data (or statistical controls included) that make the data more relevant to this case? To the extent possible, models should rely on the most relevant data and, when that is not possible, adjustments or controls should be included to correct for known problems.
- **Design:** Is the model design appropriate for this case? The behavior of the model should fit the data and the system well (e.g., if the system will always be positive, the functional form should always be positive). The functional form will influence the range of outcomes that can feasibly be seen, and if that range is too restrictive, the model generally will not be suitable.
- **Performance:** How has the model performed? Although—as with financial instruments—past performance is not a guarantee of future outcomes, it is useful to examine how a model's predictions fared. If possible, it is useful to identify the cause for any large discrepancies between the forecast and the actual results, because this can be used to identify problems in the underlying assumptions of the model.
- **Transparency:** Are assumptions and data sources documented and available? Is a range or confidence interval provided with the key results? Ideally, the code will be publicly available. Without transparency, it is not possible to determine whether a model is suitable for assessing specific policy options.

As we move past the initial peak of the pandemic, models will also prove useful in evaluating various options for reopening the economy, balancing the trade-offs between economic and epidemiological concerns. In addition to the points outlined previously, models of reopening scenarios should account for the major components of available reopening plans, including gradual relaxation of physical distancing, widespread testing and contact tracing, and improved health care capacity. In particular, the extent and efficacy of such measures as widespread testing and contact tracing need to be considered because these measures will likely play a key role in successful reopening. Existing early-stage models can be extended to encompass these aspects, or other types of models could be developed—such as microsimulations or agent-based models—that better capture behavior and outcomes on an individual level.

We reiterate that models are being continually developed, updated, and improved, and the situation continues to evolve. As more is known about COVID-19, the behavioral response to the pandemic, and the efficacy of policies, the models should evolve. Some of the existing models will cease to be useful after the end of the first phase or after certain policy responses are phased out. New models will be needed to handle the introduction of new policy responses and, if and when a vaccine is developed, models should help inform the dissemination of the vaccine to minimize the risk of death. This report should serve as a framework for assessing models of COVID-19 and also provide some guidance for factors to consider when developing a model.

Acknowledgments

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Abbreviations

AEI	American Enterprise Institute
CAP	Center for American Progress
CDC	Centers for Disease Control and Prevention
CHIME	University of Pennsylvania COVID-19 Hospital Impact Model for Epidemics
COVID-19	coronavirus disease 2019
ICU	intensive care unit
IFR	infection fatality rate
IHME	Institute for Health Metrics and Evaluation
JHU	Johns Hopkins University
MIT	Massachusetts Institute of Technology
PPE	personal protective equipment
SEIR	susceptible-exposed-infected-recovered
UVA	University of Virginia

1. Background

As the coronavirus disease 2019 (COVID-19) pandemic has evolved, we have relied on models to predict the severity of the pandemic, when the pandemic might peak, and what might be done to avoid the worst-case scenario. Modelers have been rushing to respond, but not all models are suitable to inform policy. As its name suggests, very little is known about the novel coronavirus disease. This novelty means that the data about the virus and its characteristics are being collected, analyzed, and applied in models in real time. To make informed decisions, policymakers should have some notion of the variety of models available, the suitability of the model types, and areas of uncertainty for the models. This report describes a framework for assessing the suitability of models for addressing policy-relevant questions and applies the framework to the COVID-19 pandemic in Virginia.

This work builds on Gambhir et al., 2015, and Manheim et al., 2016, to develop a specific analytic framework for assessing the suitability of models for use in the COVID-19 pandemic in the state of Virginia. Although those studies considered generic infectious diseases, we are focused on COVID-19. We will first describe the recent history of the spread of COVID-19 in Virginia and the response to that spread. Next, we will describe the key questions for state-level policymakers at each phase, and introduce a rubric to evaluate the suitability of forecasting models to answer key questions. Then we will describe and evaluate some of the available forecasting models that are able to make estimates for Virginia. Finally, we will provide recommendations derived from this analysis.

We acknowledge that models are being continually updated and improved. The analysis for this report was conducted prior to May 4, 2020, and might not reflect the most-recent versions of all models.

COVID-19 in the Commonwealth of Virginia

Virginia first announced the presence of a COVID-19 case on March 7, 2020. As the virus spread during March 2020, the governor of Virginia, Ralph Northam, implemented several government-mandated physical-distancing measures to reduce the spread of COVID-19 (Northam, 2020). All kindergarten through grade 12 schools were closed on March 13, restrictions on mass gatherings were implemented on March 15, the number of patrons permitted in businesses was restricted on March 17, nonessential services were closed on March 24, all gatherings of ten or more people were prohibited on March 24, and a stay-at-home order was enacted on March 30. The first interventions were put in place with only a few dozen confirmed cases having been reported, and Virginia had just over 1,000 confirmed cases when the stay-at-home order was implemented (COVID Tracking Project, 2020). These restrictions were put in place because exponential growth seen in other places indicated that, without intervention, Virginia was on track to see its hospital capacity exceeded.

As of May 6, 2020, the Virginia Department of Health had reported 112,809 unique individuals tested, 20,257 cases,[1] 2,773 total hospitalizations,[2] and 713 deaths. The state has experienced 244 individual *outbreaks*, defined as at least two laboratory-confirmed cases from a single setting. These have been concentrated in long-term care facilities (143), as well as incongregate settings, health care settings, correctional facilities, and educational settings (Virginia Department of Health, undated).

Organization of This Report

Chapter 2 introduces the types of models discussed in this report and the types of factors that must be considered when assessing the models' suitability. In Chapter 3, we describe what constitutes a suitable model for policymaking and then explore the different classes of early-stage models. Chapter 4 provides similar information on late-stage models. Chapter 5 discusses a few additional considerations that are not explicitly represented in the models but must be accounted for, and Chapter 6 offers some concluding remarks.

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[1] The total number of cases includes both confirmed cases (19,357) and those who are *probable* cases (899), i.e., symptomatic and with known exposure.

[2] This value is the number of hospitalizations that the Virginia Department of Health has investigated and, therefore, is likely an underestimate.

2. Assessing the Suitability of Modeling

To assess the suitability of a model, it is important to determine what the model should be able to do. In addition to the types of questions a model seeks to answer, suitability will be determined by both the scope and accuracy of the model. A model might focus on one segment of the population, such as essential workers, or explicitly exclude a segment of the population, such as the incarcerated. Similarly, a model might need to be extremely accurate in some cases, while an order-of-magnitude estimate might be sufficient for other situations.

The suitability of models to address key questions might differ depending on the phase of the pandemic. Gambhir et al., 2015, divides the time period of a pandemic into pre-pandemic, early pandemic (before and up to the peak in infections), and late pandemic (this includes the time after the pandemic peak and also post-pandemic assessments). Pre-pandemic models assess preparedness activities, planning, and monitoring. Although pre-pandemic modeling is very important, it is irrelevant for the purposes of this analysis because Virginia already has community spread of COVID-19. Given where Virginia is in its pandemic, the early pandemic and late pandemic phases are particularly relevant. We will use the term "early stage" to describe those questions that focus on the early pandemic phase and "late stage" for those questions focused on the events following the peak. In practice, the peak will be known only in retrospect, and the pandemic might not follow a simple pattern of preemergent, crisis, and recovery phases. That said, the models for the early stage and late stage must address fundamentally different questions because the objectives of the different phases are not entirely the same.

Manheim et al., 2016, note a trade-off between relying heavily on theory and assumptions on the one hand and data on the other. Modeling approaches that rely on epidemiological theory or other assumptions need fewer data; those that do not rely on theory need more data. In the case of COVID-19, where there is little historical record on which to rely, theory-based approaches might be more appropriate.

Regardless of the underlying theory or data, it is critical to acknowledge asymmetric risks associated with policy. Specifically, the cost associated with a small error in one direction can be orders of magnitude higher than an equally small error in the other direction. Avoiding breaches of hospital capacity is a primary objective in managing the pandemic response because reaching or exceeding hospital capacity will limit access to care for COVID-19 and non-COVID-19 patients, strain health care staff, and potentially result in much higher death rates, as each additional case over capacity is less likely to receive the regular standard of care. Thus, there is an asymmetric risk associated with these pandemics: Having a few empty beds will cost several thousands of dollars per week, but having too few beds will cost lives because people will not be able to receive adequate treatment for the disease. Models should highlight these risks in the form of uncertainty estimates, but it is up to policymakers to factor the implications of these asymmetries into their decisions.

Early-Stage Models

Once COVID-19 has been openly spreading in a community, the immediate problem is avoiding the worst-case scenario. In practice, this can be boiled down to: Which resources and actions will be needed to prevent the health care system from being overwhelmed? This is an epidemiological question that requires either knowledge or assumptions about the rate of spread, the severity of the disease, and treatment response. Analysts working with a model will also need to account for existing resources, and the models should be used to inform acquisition priorities, labor assessments, and other emergency-response activities.

Late-Stage Models

Once the immediate risk to the health care system has subsided (either because the system was able to avoid being overwhelmed or because it has been overwhelmed and has started to recover), models can be used to inform the transition from the initial reaction to the pandemic to longer-term response and management. This transition needs to balance epidemiological concerns with economic concerns, if only because epidemiological models will nearly always indicate that relaxing a restriction has some minuscule negative effect on the mortality rate. Thus, an economic model that estimates the increased economic activity and improved economic outcomes associated with a less-strict environment will be needed to complement what an epidemiological model tells us about how the relaxation of policies designed to contain the pandemic translates into increased cases and deaths. Essentially, what is needed is an economic model to determine the costs associated with restrictions to balance the benefits in the form of lower mortality risk assessed by the epidemiological models. Just as the goal of the initial phase was to minimize deaths and avoid overwhelming the health care system, modeling is also needed to assess whether and when additional tightening is required as the environment becomes more relaxed. Thus, in addition to informing when it might be possible to begin relaxing restrictions, it is important that forecasts are able to inform whether and when an additional tightening phase is needed. Ultimately, it will be policymakers that will choose how to balance the economic and the epidemiological outcomes, but models should help inform those decisions.

3. Assessment Criteria for Early-Stage Models

Early-stage models address questions about the period from the start of outbreak until the point where it reaches its peak. To effectively support policy in the early stage, models should be able to address one or more of the following key questions:

- What will be the peak number of infections, hospitalizations, or deaths per day for an area?
- When will this peak occur?
- When will demand for key resources exceed capacity (i.e., intensive care beds or ventilators)?
- What would be the implication of a policy intervention on the peak infections, hospitalizations, or deaths?

For each of these questions, the model developers ideally should provide a range or confidence interval associated with the key results. The modelers should also be able to convey the key sources of uncertainty in these results and how those sources of uncertainty might change as more information is gained.

Types of Models

Most available models designed to answer early-stage questions can be categorized as statistical models or systems dynamics models (sometimes called theory-based or simulation models).[3] These two categories of models represent opposite ends of a spectrum, in terms of data requirements and assumptions, and, in practice, most models fall somewhere in between. Statistical models typically will make fewer assumptions about the pattern of spread and underlying disease characteristics, but they rely on having more data on the number of cases or deaths over time. Systems dynamics models begin with a set of assumptions about how the disease spreads (usually assuming exponential growth) and capture important epidemiological characteristics in a few key parameters. Ideally, these parameters are derived from the available data, but they can also be estimated using past epidemiological studies or calibrated to fit data on key observable outcomes. Put another way, systems dynamics models involve causal relationships, while statistical models capture trends and correlations.

Manheim et al., 2016, provided a useful summary of the applicability of different modeling approaches to various policy questions. In general, they argued that systems dynamics models are better suited to explore policy interventions and the overall rate and extent of spread than statistical models. However, statistical models might provide more information about the near-

[3] See, for example, Gambhir et al., 2015, or Manheim et al., 2016.

term disease progression and resource requirements. Table 3.1 provides a nonexhaustive list of COVID-19 models, indicating whether each is a statistical, systems dynamic, or hybrid model, and listing the questions that the model seeks to answer. This is a sampling of high-profile models that include state-level estimates. However, many more models have been developed, some of which are listed on the Centers for Disease Control and Prevention (CDC) website (CDC, 2020c).

Table 3.1. Sample of COVID-19 Models

Model	Model Class	Questions
University of Washington Institute for Health Metrics and Evaluation (IHME)	Statistical	• Confirmed infections • Deaths per day • Demand for hospital beds, ICU beds, ventilators
Los Alamos National Laboratory	Statistical	• Confirmed infections • Deaths per day • Peak timing
University of Virginia (UVA) Biocomplexity Center PatchSim model	Systems dynamic	• Demand for hospital beds, ICU beds, ventilators (by county)
Massachusetts Institute of Technology (MIT) Operations Research Center (DELPHI model)	Systems dynamic	• Confirmed infections • Deaths per day • Demand for hospital beds
RAND Corporation policy evaluation tool	Systems dynamic	• Confirmed infections • Deaths per day • Demand for hospital beds, ICU beds • Gross state income loss
University of Pennsylvania COVID-19 Hospital Impact Model for Epidemics (CHIME)	Systems dynamic	• Confirmed infections • Demand for hospital beds, ICU beds, ventilators
Youyang Gu model[b]	Hybrid	• Confirmed infections • Deaths per day

[a] COVID Analytics, 2020.
[b] Youyang Gu, 2020.
NOTE: ICU = intensive care unit.

Statistical Models

Statistical models, such as the University of Washington IHME and Los Alamos National Laboratory models (Los Alamos National Laboratory, 2020), provide projections using curves fitted to historical data. In the case of COVID-19, data from sites where COVID-19 spread earlier are used to help forecast the spread in other locations later.

Statistical models often include additional data about characteristics that might lead the behavior in one situation to differ from that in another (i.e., because of location, time period, political climate, or some combination thereof). These “control variables” attempt to account for differences between scenarios. For example, population density might be included as a control variable because it is relevant for the rate of spread. Statistical models can be overfit, which means that they can include certain controls or follow certain functional forms that reproduce the historical trends quite well but are less relevant to future spread. An overfit model will not perform as well when applied to new situations. Thus, great care is required when considering which controls to include. The performance of a statistical model should be judged not on its fit to the data used to train it, but on its predictions.

Although statistical models might not make strong assumptions about the characteristics of the disease, they are not devoid of assumptions or theory. In particular, a model's *functional form*—the nature of the relationship between the input and output variables—will rely on the modeler's understanding of the system being studied.[4] A misspecification of the functional form can lead the model's forecasts to significantly deviate from future trends because the chosen function does not match the behavior of the system outside the period where the initial data were collected.

Systems Dynamics Models

Systems dynamics models, such as the UVA Biocomplexity Center PatchSim model, MIT Operations Research Center's DELPHI model, the RAND Corporation policy evaluation tool, the University of Pennsylvania's CHIME model, and Youyang Gu's model, begin with a mathematical framing of the system and how its behavior evolves over time that is derived from the full history of pandemics. Often, these are compartmental models where the population shifts from one clinical state to another. For example, in a susceptible-exposed-infected-recovered (SEIR) model, the population is divided into susceptible (S),[5] exposed (E), infected (I), and recovered (R) states, in which the transitions between states represent the spread of disease through the population.[6]

Systems dynamics models generally assume exponential growth in the number of infected individuals and rely on estimates of key epidemiological parameters, such the basic reproduction number (R_0),[7] effective contact rate, rate of recovery or fatality, incubation period, and infectious period. The MIDAS network (MIDAS, undated) has compiled a repository of peer-reviewed and

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[4] For example, *linear regression* assumes the relationship between the input data and the outcome being modeled is a straight line. Other functional forms include logarithmic, sigmoidal, or Gaussian (used by IHME).

[5] The *susceptible* group includes individuals who are not infected and have not been exposed, but potentially could be exposed and become infected.

[6] SEIR models assume that once someone has been infected, they cannot be reinfected, but a small modification can allow the model to account for the possibility that recovered individuals could lose immunity over time. These models are called SEIRS models.

[7] The basic reproduction number, R_0, is the expected number of people an exposed person will infect during the initial phase of an epidemic. In other words, it is the number of additional infections that are expected to directly result from each infection.

non-peer-reviewed parameter estimates from the literature. Some provide regional estimates, while others provide global estimates.

In general, systems dynamics models have an advantage over statistical models in that they are better suited to capture the rate and extent of spread. Systems dynamics models are also flexible, as any number of parameters can be adjusted to represent changes in the disease dynamics, for example as a result of government intervention. However, the simplicity of population-level models can limit their accuracy, and they require major assumptions when translating policy responses into parameter values. Although traditional SEIR-style population models do not account for uncertainty, a variety of parameter values can be tested easily to show sensitivity to model assumptions.

In addition to population-level models, another class of systems dynamics models includes finer-grain simulations, such as microsimulations and agent-based simulations. These take longer to develop than aggregate population-level models because they track individuals or small groups rather than aggregating using infection status. However, these finer-grain simulations can have higher fidelity and can allow for the exploration of more-specific policies and behavioral considerations. Some of the systems dynamics models have microsimulation components, and we are aware of agent-based simulations that are under development, but at the time of this analysis, we are not aware of these models being used to produce reliable forecasts in this pandemic. Given the development time and data requirements, it is unlikely that microsimulation models or agent-based models will be deployed during the early phase of COVID-19 for Virginia.

Model Suitability for Policy

In evaluating the applicability of a model, it is important to understand the strengths of the underlying information available. Systems dynamics models benefit from a sophisticated understanding of disease characteristics and behavioral science. Parameters, such as the rate of infection, rate of spread, time for incubation, and time for recovery, must be specified; if these are not well known for the disease at hand, they must be estimated, and the sensitivity of model outputs to changes in parameter values should be evaluated.[8]

An advantage of systems dynamics models, in this respect, is that they are well suited to examining potential policy interventions by tweaking such variables as infection rate or effective contact rate. For example, a policy like physical distancing—which seeks to reduce the rate of spread and reduce the size of the susceptible population—can be captured by reducing the rate of spread parameter and by reducing the susceptible-population compartment for the duration of the distancing phase. It is not always clear how to quantify the effects of such policies, but in the absence of rigorous data about the efficacy of the direct effect of the policy (e.g., how many

[8] This type of analysis is often called a *sensitivity analysis*.

people are practicing strict physical distancing or to what extent distancing reduces the rate of spread), the model can test the sensitivity to a variety of possible effects. Furthermore, the model estimates can be refined as additional data become available regarding policy impacts.

Systems dynamics models are not well suited for exploring policies that are not parameterized in the model. For example, an SEIR model typically would not be able to assess policies targeted toward skilled nursing facilities or prisons, because those populations will have different dynamics than the general population. It is therefore important to assess the mechanism by which the policy is expected to operate and then determine whether the model has an appropriate parameter for that mechanism.

Statistical models, such as regression-based models, capture empirical trends and require a large amount of high-quality data to perform well. These models do not assume causality but provide forecasts using observed relationships between input and output variables.

In general, statistical models are not well suited to assess policy options during the early phase of a pandemic because data capturing the policy variation are typically unavailable or insufficient to estimate a reliable relationship between the policy lever and outcome variables of interest. Statistical models are built to fit a limited set of observed "training" data, which makes them relatively inflexible. Changes to the baseline scenario—demographic, geographic, or political, for example—might affect changes in the progression of the disease that are not captured by the model. However, after the pandemic is over and the outcomes are known for a wide variety of areas, statistical models can be used to retrospectively estimate the efficacy of policy responses by looking for variation in the outcomes that can reasonably be attributed to different policies when controlling for other factors.

Transparency is important for all types of modeling but particularly for systems dynamics models. Although many statistical models can be reproduced with knowledge of the data used and the details of the functional forms, that is less likely to be the case for a systems dynamics model. The model should be well documented so that policymakers and other researchers can understand the choices made regarding what behaviors to include, what behaviors to exclude, which data sources to use, and other critical design decisions. This is particularly important because the true parameter values are unknown and could change over time or in response to interventions. It is also helpful if the model code is shared via GitHub or another similar platform. This allows interested parties to understand the details of and identify potential flaws in the implementation approach. A systems dynamics model that performs well but whose structure is proprietary (i.e., a "black box") cannot be evaluated for theoretical soundness and should not form the basis for policy decisions.

Open Modeling Questions

There is significant uncertainty surrounding many epidemiological characteristics of COVID-19, with implications for model parameter estimates, the expected efficacy of policy interventions and guidelines, and the prognosis for various reopening scenarios. In this section, we discuss three particularly critical sources of uncertainty: the potential for reinfection after recovery from COVID-19, the asymptomatic rate of infection, and the duration of the infectious period.

It remains an open question whether individuals who have recovered from COVID-19 can be reinfected, which increases uncertainty in population-level (i.e., SEIR-type) models that assume full recovery. This has major implications for modeling the effects of lifting restrictions because it could cause models to overlook the possibility of a second wave of infections, particularly when compounded with the effects of seasonality. Modeling the possibility for recovered individuals to become susceptible again is not difficult, but there is a high level of uncertainty regarding the period of immunity. Some models have begun to explore this. For example, Malkov (2020) considered an SEIR-type model and compared results with an adjusted model allowing for reinfection, testing several values for the period of immunity. The results of the full immunity model and reinfection models are indistinguishable before the pandemic's peak, but following the peak, many more individuals are infected and die when reinfection is possible, as would be expected. The difference is dramatic for the shortest tested period of immunity Malkov considered (60 days).

At the time of this writing, however, the literature and data do not suggest that reinfection is a major issue. Rhesus monkeys who had recovered from COVID-19 did not contract the disease again after subsequent exposure 28 days after recovery (Bao et al., 2020). There have been reports of reinfection in multiple locations in Asia (Mandavilli, 2020; Leung, 2020). However, these could be the result of residual viral RNA, or of cases in which a lingering infection resulted in one or several false negatives before being detected again. Many of the individuals who appear to have been reinfected are asymptomatic, and it has been suggested that if reinfection is possible, it might present as a milder form of the disease. A study in Shenzhen, China, found that "re-detectable, positive" patients, in general, were younger and exhibited milder symptoms than the non-redetectable positive patients (An et al., 2020). However, even if recovering from COVID-19 does confer immunity, it is too soon to know how long this immunity could last. This issue will become more important at the end of summer, which brings cooler weather and higher rates of influenza-like illnesses.

The incidence of asymptomatic infection is also poorly understood. Some estimates of the *asymptomatic rate*—the proportion of cases that do not show symptoms—reach up to 86 percent (Li et al., 2020; Stock, 2020), but the true rate might vary depending on the age distribution of the population. An asymptomatic rate of over 50 percent was confirmed in at least one nursing facility (Aarons et al., 2020). To date, testing has been focused on those with symptoms, limiting the extent to which this value can be accurately estimated. Recent studies (e.g., Streeck et al., 2020) have aimed to improve our understanding of the asymptomatic rate by testing large proportions of certain subpopulations, such as towns or counties. However, these studies have faced criticisms. Given the evidence that asymptomatic (and presymptomatic) individuals can infect others (Furukawa et al., 2020), the asymptomatic rate will have major implications for the effectiveness of policy interventions. It is therefore essential that we continue to invest effort into improving our estimates of the asymptomatic rate through widespread collection of serial virologic and serologic data.

The CDC recommends that those infected or suspected to be infected isolate themselves for a period of ten days (CDC, 2020b), although the *infectious period*—the duration in which an infected individual can infect others—is not perfectly known for COVID-19. According to Zhou et al., 2020, viral RNA is detectable in COVID-19 survivors for a median of 20 days, and up to 37 days in some cases. Xiao et al., 2020, found comparable results, and also observed that individuals with comorbidities, such as diabetes, were more likely to exhibit prolonged viral shedding. However, the presence and shedding of viral RNA does not necessarily translate to infectiousness. A German study (Woelfel et al., 2020) was unable to isolate replication-competent virus after eight to ten days of infection, suggesting that infectiousness is unlikely to exceed this time period.

Uncertainty regarding these issues—reinfection, asymptomatic infection rate, and the duration of the infectious period—translates into uncertainty in model parameters. These issues also undermine the efficacy of official guidelines and policy interventions. For example, the CDC guideline that individuals with known exposure should self-isolate for 14 days does not account for asymptomatic spread. As more and better data become available, it is important that epidemiological parameters are continuously tuned and their effect on model results assessed.

Data

All of these models rely on data to some extent. The key piece of data for understanding the disease's dynamics is the number of people who have been infected at any given point in time. Although reliable testing is a prerequisite for having good data, testing was scarce for much of the early stage of the pandemic. This can have several different effects on the results. Initially, a lack of testing could lead to an underestimate of the scale of the problem and produce an artificially low rate of spread. As the testing rate increases, the number of cases detected should increase faster than the actual rate of spread and, unless corrections are made for the increased testing rate, resulting in an artificially high estimate of the rate of spread. Changes to the testing criteria can also alter the estimates of the rate of spread, though that will depend on the nature of the criteria change. For these and other reasons, many models, such as IHME, have opted to fit curves to and extract growth rates from mortality data rather than incidence data. However, mortality data have their own issues.

Mortality rate is another piece of data that is critical to understanding and modeling disease dynamics. Rather than telling us how many people might become infected with a disease, mortality rate offers insight into what happens to the infected population. The COVID-19 mortality rate appears to vary over time and by region. According to the Johns Hopkins

Coronavirus Resource Center, the case-fatality rate (or number of deaths per 100 confirmed cases) is approximately 5.9 percent in the United States. That is on par with the estimate of 5 to 6 percent for China, but far lower than the estimated 13.8 percent in Italy and 11.7 percent in Spain. Of the ten countries most affected by COVID-19, observed case-fatality rates vary from 15.9 percent in Belgium to 4.2 percent in Germany (Johns Hopkins Coronavirus Resource Center, undated). Differences in case-fatality rates can reflect many factors, including different testing rates, demographics, and the capacity of the health care system. Fatalities are also reported differently in different countries. For example, policies on what constitutes a "death due to COVID-19" could include or exclude indirect deaths, and patients who suffered from more than one chronic condition might be recorded as "death *with* COVID-19" rather than "death *by* COVID-19." Case-fatality rates might also be inflated because in many areas, testing is reserved for the most-severe cases. Furthermore, because of the dearth of testing, postmortem testing has also been depressed, and many deaths caused by COVID-19 could be missed.

The true infection fatality rate (IFR) is unknown because the true number of infections is unknown. However, small-scale antibody surveys suggest it might be low: approximately 0.36 percent, according to a German survey (Streeck et al., 2020). Although these and other serology studies have faced criticism of their sampling, testing, and statistical methods, there is consensus that the true infection rate is much higher than observed, and therefore the IFR likely is much lower than the case fatality rate would suggest (Offord, 2020; Vogel, 2020).

However, the evaluation of excess deaths in the United States and other countries in 2020, relative to seasonal averages, suggests significant underreporting of COVID-19–related deaths (Brown et al., 2020; Burn-Murdoch, Romei, and Giles, 2020; Katz and Sanger-Katz, 2020). This analysis also reveals that, in some regions, increases in deaths because of pneumonia and influenza preceded widespread testing protocols by several weeks (Weinberger et al., 2020). This raises questions about whether data from early COVID-19 outbreaks can reliably be used to predict the current and future spread of the disease. Future modeling efforts or improvements to existing models could consider excess deaths as a way to correct for this underreporting and compare across countries. However, it should be noted that the excess death rate also includes additional deaths from other causes and reduced deaths because of fewer traffic accidents, for example.

Statistical and system dynamics models can also provide alternative approaches to identifying the true number of deaths attributable to COVID-19. In cases in which the data deviate from the models, it might be the case that the data are deficient. Thus, the models can be used to iteratively improve the data. Specifically, the models can be used to fill gaps in data, smooth the data, or adjust the data in cases in which there is a known source of bias in the data source.

Virginia Context

It is important to understand how Virginia compares with the regions that experienced the earliest outbreaks of COVID-19, because data from these early-outbreak sites are incorporated into many models and used to estimate epidemiological parameters. In particular, certain characteristics, such as age distribution, presence of comorbidities, and air quality, would affect the severity of the disease, but others, such as population density, would affect the rate of spread.

Virginia's population is older than that of New York City and younger than that of Italy, overall, but comparable with that of Washington state (Central Intelligence Agency [CIA], 2020b; CIA, 2020d). Virginia has a larger proportion of individuals age 65 and over than do Wuhan and Hubei Province (CIA, 2020a; CIA, 2020c). Virginia's proportion of smokers is higher than that of New York and Washington state, but less than that of Italy and China (WHO, undated). The prevalence of diabetes and ischemic heart disease is also high in Virginia relative to the other regions considered (IHME, undated a; IHME, undated b; IHME, undated c; IHME, undated d; World Bank, undated). Air quality in Virginia is generally better than in Italy and much better than in Wuhan and Hubei Province (IQair, 2020a; IQar, 2020b; IQAir, 2020c). Overall, these comparisons indicate that we might expect to see somewhat lower severity of COVID-19 in Virginia than in Italy, Wuhan, and Hubei Province, but somewhat greater severity than in some domestic regions, such as New York City and Washington state. Virginia's population density is rather low, comparable with that of Washington state and Hubei Province, but less than that of Italy and far less than that of New York City and Wuhan (World Bank, 2020). Therefore, we would expect the rate of spread to be more comparable with Washington state and Hubei Province, except in higher-population cities and regions, such as the Washington, D.C., metro area, Arlington, and Richmond.

Recommendations for the Early Stage

The primary policy questions for the early stage revolve around avoiding worst-case scenarios, which requires the peak in cases to stay below a level that overwhelms the health care system. Because the risks associated with exponential growth are not generally intuitive, models are useful for helping to predict the severity of the pandemic and to understand what policies might help avoid the worst-case scenarios. Statistical models lean heavily on data regarding the spread of a pandemic. They are well suited for understanding the progression of pandemics, though less well suited for comparing policy options. System dynamics models posit a general behavior for the pandemic using a few key parameters. Such models can provide reasonable estimates for the pandemic's progression and are particularly well suited for comparing policy options, as long as those options can be represented as influencing one or more of the key parameters. For the purposes of informing Virginia's leadership on policy options, we recommend focusing on systems dynamics models and monitoring both statistical and systems dynamics models for situational awareness about the progression and likely trends of the pandemic.

4. Assessment Criteria for Late-Stage Models

Policymakers have begun to shift their focus to a “second phase” of forecasting COVID-19, now that the initial peak of infections and deaths has passed in many regions and possible paths for reopening are being explored. Although it will remain important to model the rate and extent of spread, an additional layer of complexity is required to address policy and behavioral changes in forecasting. Models of late-stage pandemics therefore should be able to address one or more of the following questions:

- What are the opportunity costs or trade-offs associated with the policy responses employed during the first phase?
- How can we maximize “normalcy” and economic activity while minimizing unnecessary deaths?
- What is the risk of a second peak?
- Are there risks of exhausting necessary equipment, personnel, or facilities?
- What is the delay between changing regulations and seeing the impact on infections and deaths?

For each of these questions, the developers ideally should provide a range or confidence interval associated with the key results. The modelers also should be able to convey the key sources of uncertainty in these results and how they might change as more information becomes available.

To assess the suitability of a model for the late stage, it is first necessary to define the desired end-state for the pandemic. There are at least three possible end-states:

- A cure or vaccine can be developed, eliminating the pandemic. In this case, the goal of the late-stage model would be to buy time for the development and dissemination of the treatment. Because this could take more than a year, policymakers might want to use models to determine the likely number of deaths and hospitalizations for a given level of economic activity.
- An alternative goal would be to reach herd immunity, where enough people have recovered from COVID-19 to make it impossible for the disease to spread widely. In this instance, a model would be used to identify what proportion of the population would need to be infected for herd immunity to be effective, and what the associated number of deaths would be. A model would also be necessary to determine how to avoid overwhelming the capacity of key resources.
- In a new normal, disease outbreaks might reappear with some degree of regularity, similar to seasonal influenza. This might be the long-term situation if the virus mutates and the population does not retain immunity. In this case, models similar to those designed for the early stage would be useful to assess capacity requirements and necessary policy interventions.

These three end-states are not equally desirable. Reaching herd immunity will require a substantial portion of the population to be infected and, although younger people have a lower mortality rate with COVID-19, the mortality rate is not zero. Furthermore, there will be some ambient level of COVID-19 infections even after herd immunity is reached. This therefore would result in millions of deaths in the United States and tens of thousands of deaths in Virginia. Similarly, a new normal that involves periodic coronavirus season, similar to flu season, would result in seasonal deaths that would be an order of magnitude worse than flu season. Furthermore, although the cure or a vaccine is likely the most desirable outcome, it is by no means guaranteed that such a cure would be available in the next few years. Leaders, therefore, should prepare for and make plans in case either herd immunity or a new normal is the ultimate end-state.

Once the objective or strategy is defined, the existing plans to relax physical-distancing measures and replace them with other interventions can provide a scope for the models. In Table 4.1, we list the key components of plans from Governor Northam (Forward Virginia), the American Enterprise Institute (AEI), the Center for American Progress (CAP), Johns Hopkins University (JHU), the Rockefeller Foundation, and President Trump.

Table 4.1. Plans to Relax Physical Distancing, by Strategy

Plan	Physical Distancing	Test and Trace	Data Platform	Health Care System
Forward Virginia: Phase 1[a]	• Maintain general physical-distancing precautions • Lift stay-at-home policy	• Improve testing and tracing volumes		• Increase supply of personal protective equipment (PPE) • Increase capacity of health care system
AEI[b]	• Maintain general physical-distancing precautions	• Isolate infected individuals, quarantine close contacts for 14 days • Test to identify immune individuals • 750,000 tests per week • Widespread serological testing		• Accelerate development of therapeutics that reduce risk of death • Increase supply of PPE • Increase capacity of health care system
CAP[c]	• Maintain stay-at-home policy for 45 days after April 5 • Restrict mass transit	• 2.6 million tests per day • Instantaneous digitized contact tracing • Widespread serological testing	• Necessary to enable instantaneous contact tracing • Hosted by a trusted nonprofit	• Increase supply of PPE
JHU[d]		• Test all symptomatic or exposed individuals • Widespread serological testing • Trace all contacts of reported cases	• Suggest mobile contact tracing platform synced with health records	• Hire 100,000 health care workers to carry out testing and tracing • Appropriate $3.6 billion in emergency funding to state health departments
Rockefeller Foundation[e]		• Three million tests per week within eight weeks • 30 million tests per week within six months	• Integrated platform to optimize resource allocation, trace infections, store medical history	• Hire 100,000–300,000 workers to carry out testing and tracing
President Trump[f]	• Gradually lift as criteria are reached	• Test all symptomatic or exposed individuals • Trace all contacts of reported cases • Screen for asymptomatic cases		• Ability to surge ICU capacity

[a] Commonwealth of Virginia, undated.
[b] Gottlieb et al., 2020.
[c] Emanuel et al., 2020.
[d] Rivers et al., 2020.
[e] Allen, Krein, et al., 2020.
[f] White House and CDC, 2020.

Each of these plans seeks to control the pandemic through different mechanisms, and a suitable model will need to capture the extent and effectiveness of these mechanisms. The remainder of this section will describe these mechanisms and how they can be modeled, and will mention any relevant literature for COVID-19.

Additional Models

For the early stage of COVID-19, the mortality risk associated with uncontrolled spread was so high that estimates of the economic costs for interventions, such as blanket stay-at-home orders and shutting down nonessential businesses, were irrelevant to policymaking. Some of the epidemiological models will continue to be relevant after the initial peak has passed and the immediate catastrophic risk has been reduced, but economic and other costs will also be relevant. Additional modeling will be needed to understand the relevant economic, social, and other costs.

When performing a cost estimate for these types of policies, it is important to specify which costs to include and who is bearing those costs. There will be direct costs that are associated with these policies, such as the cost to install barriers between cashiers and customers. There will also be opportunity costs, such as the lost business because of mandatory stay-at-home orders. Some of this economic activity will shift to complementary goods and services, such as the shift from eating at a restaurant to getting delivery or ordering from an online retailer instead of from a local retailer. Other economic activity will shift to later in time. It might also be useful to include noneconomic costs.

A study of the two-week federal government shutdown in 2013 found that the temporary loss of income for federal employees was largely shifted in time, though the lowest-income individuals took on high-cost debt (Gelman et al., 2019). Because that was from a two-week disruption of income, the adverse effects are likely to reach higher up on the pre–COVID-19 income distribution. Income data from the recovery from the 2008 financial crisis show that the top of the income distribution returned to pre-recession incomes within two years, while the bottom of the income distribution took seven or more years to recover to previous levels (Gould, 2019). Given the depth of the drop in employment and the general economic disruption, it might take much longer to recover from this economic crisis.

A suitable cost model should capture as many of the direct, indirect, and opportunity costs as possible. Additionally, it should identify who bears these costs. As with other models, it is important to understand the assumptions. Economists frequently will use computable general-equilibrium models to study the implications of policy changes. However, these models make some strong assumptions that will make them less suitable for studying a disease like COVID-19. Specifically, these models assume that the economy is in an equilibrium and that this equilibrium is reached in a path-independent manner. However, the economy is necessarily *out* of equilibrium during the pandemic and, as described earlier, for low-income individuals, there will be an accumulation of high-interest debt that was entirely path dependent.[9] As an alternative, microsimulation or agent-based models can include disequilibrium and path dependence.

[9] By *path-dependent*, we mean that the state at the outcome is dependent on the route taken to get there. For example, in Gelman et al., 2019, federal employees received their lost wages and salary for the period that the government was shut down. Thus, although the total income was the same, many of those in the study were materially worse off because they needed to resort to high-interest loans before receiving lost income.

Late-Stage Policies

Physical Distancing

For policies assessing the appropriate level of physical distancing, the systems dynamics models from the early stage will prove useful because this mechanism largely acts by reducing the rate of spread, which is one of the key parameters in most systems dynamics models. Thus, a relaxing of physical distancing can be modeled by increasing the rate of spread and expanding the susceptible population as people return to their normal activities. The discussion in the early-stage section regarding systems dynamics models is relevant for the late stage.

Testing and Tracing

Perhaps the most critical piece of many reopening plans is the assumption of high levels of testing for COVID-19 and robust contact tracing to identify individuals who might be exposed or infected.[10] These are serious assumptions, especially considering that levels of testing and contact tracing have been well below the levels recommended by public health experts thus far.

The plans identified in Table 4.1 vary in terms of the level of testing and timeline required. Of those that specify a weekly quota, figures are from 750,000 tests per week (Gottlieb et al., 2020) to 30 million tests per week (Allen, Krein, et al., 2020). At the far end of the spectrum, a plan for pandemic resilience developed at the Edmond J. Safra Center for Ethics at Harvard University focused on testing and tracing as its cornerstone, and called for 5 million tests per day by early June, gradually increasing to 20 million per day (Allen, Block, et al., 2020). Allen, Block, et al., 2020, estimated the economic cost of such measures at around $15 billion per month or $50–300 billion over the next two years, and $100–350 billion per month to maintain current shelter-in-place and stay-at-home policies.

The level of testing and isolation required will depend on the efficacy of tracing. This is partly determined by the definition of a *close contact*. For example, if a close contact is defined as someone with whom the individual has had more than four hours of contact or exposure, fewer tests will be required, but testing and tracing is unlikely to be effective in controlling spread (Keeling, Hollingsworth, and Read, 2020). However, Keeling and colleagues' results indicated that the United Kingdom's definition (contact duration of 15 minutes or longer while being within two meters during the two weeks before detection) could be effective, assuming that tracing is rapid enough to trace contacts within the incubation period. That said, the burden will be large: The Keeling, Hollingsworth, and Read, 2020, model required an average of 36 individuals to be traced per infected individual.

Kretzschmar, Rozhnova, and van Boven, 2020, found that contact tracing, accompanied by physical-distancing measures and isolation of confirmed and suspected cases, is essential to

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[10] *Contact tracing* refers to tracking down individuals with whom a confirmed case has come in contact within the likely infectious period so that those individuals can be isolated and monitored.

stopping the spread of COVID-19. Again, the rate of asymptomatic infection is critical: As this rate rises, the potential to control the model outbreak with contact tracing and isolation fades quickly. For example, Kretzschmar and colleagues (2020) found that with $R_0 = 2.5$ and an asymptomatic rate of 40 percent, the model suggests that control is not possible with contact tracing and isolation alone, and increased physical distancing is necessary.

Testing and tracing might be incorporated into a model by reducing the transmission rate, reflecting the reduction in the number of secondary infections. Testing and tracing will break the chain of transmission by isolating people who have been exposed to someone with a positive test; this functionally reduces the rate of spread. However, unlike with physical distancing, a systems dynamics model that is designed for the early phase will need to be modified to appropriately study testing and tracing. Specifically, the reduction in the rate of spread will be a function of the number of tests available, the criteria for selecting individuals to be tested, and the aggressiveness of contact tracing. Thus, a microsimulation or agent-based model will be better suited than a standard SEIR-type model in addressing these concerns.

Data Platforms

Traditionally, contact tracing is done manually, with a team of investigators attempting to identify and locate everyone who has come in contact with a confirmed COVID-19 case; the process is slow and often imprecise. Apple and Google are collaborating on a promising "privacy-first," automatic contact-tracing system (Apple, Inc., and Google, Inc., 2020; Goodin, 2020; Google, Inc., 2020). The Bluetooth-based platform will begin as an app and later will be integrated into the operating systems of Android and iOS devices. The system will be opt-in and includes special considerations intended to protect users' privacy. The model results of Ferretti et al., 2020, suggested that the tracing speed of such a platform will be necessary to ensure effectiveness of contact tracing.

Improvements to the Health Care System

Many plans for reopening assume improvements to the health care system and increases in its capacity. Additional PPE should reduce the transmission rate, while additional health care workers and surge ICU capacity, along with improved therapeutics, should improve health care outcomes and reduce the fatality rate.

Lessons from the Literature

The timeline along which such reopening plans are implemented will be critical. If the levels of infection have not dropped low enough or for long enough before reopening, the potential for a severe second wave of the pandemic is high. Feng, Damon-Feng, and Zhao, 2020, explored reopening scenarios and their impact on the severity of a potential second wave using an SEIR model. The authors examined different simplified combinations of lockdown timing, severity, and duration. Their results indicate that the duration of initial physical-distancing policies might be more important than the extent of relaxation in determining the severity of the second peak.

Uncertainty in the asymptomatic rate, discussed previously, also has major implications for reopening. Feng, Damon-Feng, and Zhao, 2020, found that, counterintuitively, maximally severe physical-distancing policies could lead to worse outcomes once they are lifted or relaxed because they leave more of the population in the “susceptible” category. However, if the asymptomatic rate is high and post-infection immunity can be assumed, this no longer holds true. Economic models, such as Toda, 2020, rely heavily on the asymptomatic rate when weighing the costs and benefits of reopening. A robust estimate of the asymptomatic rate therefore will be critical to accurately predict economic effects and optimize policy response because this estimate informs the IFR and the point at which herd immunity can be assumed.

Greenstone and Nigam, 2020, found that physical distancing for three to four months could save 1.7 million lives, the equivalent of about $8 trillion using the value of a statistical life (between $10 million and $11 million). Even in a lower-bound scenario predicting fewer deaths (and thus fewer lives saved by physical distancing), the savings of such policy measures amount to about $3 trillion. Such analysis supported the severe physical-distancing measures implemented in many regions in the early phases of the COVID-19 pandemic. A comparable analysis should be conducted for each of the suggested mechanisms of the proposed reopening plans to maximize health outcomes while minimizing economic loss.

Recommendations for the Late Stage

The exact goal for the late stage is a question of relative values that will need to be set by policy, but it must balance both the epidemiological concern of reducing the number of deaths from the pandemic and also the economic concerns of preserving standards of living. To that end, systems dynamics models used for the early stage can be useful for studying some of the approaches, but other models or modifications to these models will be needed to explore other factors. Additionally, economic models will be needed to explore the costs associated with the different policy options.

5. Additional Considerations

Evidence has emerged showing the disproportionate burden of COVID-19-related illness and death among racial and ethnic minority groups across the country, particularly African Americans and Hispanics (CDC, 2020a; Garg et al., 2020; Dwyer, 2020; New York City Department of Health, 2020a; New York City Department of Health, 2020b). Black residents in Cook County, Illinois, make up 23 percent of the population but 58 percent of COVID-19 deaths (Ramos and Zamudio, 2020). In Milwaukee, the numbers are 26 percent and 70 percent, respectively (Golden, 2020). Virginia also shows imbalance, though not as drastic—a reported 30 percent of cases relative to 20 percent of residents (Augenstein, 2020). There are likely several factors at play here: Minority groups experience higher incidence of underlying health conditions and chronic disease, and they are less likely to have health insurance. They are also more likely to live in higher-density areas; have longer commutes to grocery stores and workplaces; and are overrepresented in jails, prisons, and detention centers, which have higher rates of outbreak. Furthermore, they are more likely to be deemed critical personnel, to work in service or agriculture industries, and to lack the levels of sick leave and work-from-home flexibility enjoyed by nonminority individuals. (CDC, 2020a; Golden, 2020) Anecdotal data suggests that minority individuals likely are not referred for testing as often as nonminority individuals (Golden, 2020). Moving forward in light of this evidence, it will be important to implement targeted messaging and testing in an effort to correct these imbalances.

Insurance and access to care is another relevant factor. In 2018, 49 percent of the U.S. population received insurance coverage from their employer (Kaiser Family Foundation, undated). However, the unemployment rate in April 2020 reached 14.7 percent (U.S. Bureau of Labor Statistics, undated). This will result in a loss of access to affordable health care for a significant share of the population, in particular within those states that have not expanded Medicaid.[11] The fear of cost could lead a significant share of the population to avoid testing and treatment for COVID-19, which could extend the duration of the spread and mitigate the ability to contain the spread.

[11] Virginia has expanded Medicaid, which should mitigate this effect, but there will still be a discontinuity in insurance sources for a large segment of the population.

6. Conclusions

Models can help policymakers explore options and understand the variety of likely outcomes. However, modelers must clearly describe and present the areas of uncertainty and the factors that might change. When describing these limitations, modelers should clearly indicate for which questions their approach is suitable and for which they are not. Similarly, when covering model results, members of the media should not focus on the most-extreme results, but instead should look toward areas of consensus between the models and identify areas where the different models diverge.

In general, statistical models are best at forecasting trends rather than comparing policies. Systems dynamics models are well suited for comparing policies, as long as the policies in question operate through mechanisms that are captured by the model. When distinguishing between models that are potentially suitable, the following four factors are important to consider:

- **Data:** Are the data used to train the model relevant to this case? If not entirely, are there adjustments made to the data or statistical controls included that make the data more relevant to this case? To the extent possible, models should rely on the most-relevant data and, when that is not possible, adjustments or controls should be included to correct for known problems.
- **Design:** Is the model design appropriate for this case? The behavior of the model should fit the data and the system well (e.g., if the system will always be positive, the functional form should always be positive). The functional form will influence the range of outcomes that can feasibly be seen, and if that range is too restrictive, the model generally will not be suitable.
- **Performance:** How has the model performed? Although past performance is not a guarantee of future outcomes (as with financial instruments), it is useful to examine how a model's predictions fared. If possible, it is useful to identify the cause for any large discrepancies between the forecast and the actual results because this information can be used to identify problems in the underlying assumptions of the model.
- **Transparency:** Are assumptions and data sources documented and available? Is a range or confidence interval provided with the key results? Ideally, the code will be publicly available. Without transparency, it is not possible to determine whether a model is suitable for assessing specific policy options.

As we move past the initial peak of the pandemic, models will also prove useful in evaluating various options for reopening the economy, balancing the trade-offs between economic and epidemiological concerns. In addition to the points outlined previously, models of reopening scenarios should account for the major components of available reopening plans, including gradual relaxation of physical distancing, widespread testing and tracing, and improved health care capacity. In particular, the extent and efficacy of such measures as widespread testing and contact tracing need to be considered because these measures will likely play a key role in a successful reopening. Existing early-stage models could be extended to encompass these aspects, or other types of models could be developed, such as microsimulations or agent-based models that better capture behavior and outcomes on an individual level.

We reiterate that models are being developed, updated, and improved continually, and the situation continues to evolve. As we learn more about COVID-19, the behavioral response to the pandemic, and the efficacy of policies relating to it, the models should evolve. Some of the existing models will cease to be useful after the end of the first phase or after certain policy responses are phased out. New models will be needed to handle the introduction of new policy responses and, if and when a vaccine is developed, models should help inform the dissemination of the vaccine to minimize the risk of death. This report should serve as a framework for assessing models of COVID-19 and also provide some guidance for factors to consider when developing a model.

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