Macroeconomic Consequences of the COVID-19 Pandemic

Terrie Walmsley, Adam Rose, Richard John, Dan Wei, Jakub Hlavka, Juan Machado, and Katie Byrd*

Center for Risk and Economic Analysis of Threats and Emergencies
University of Southern California

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* The authors are, respectively, Research Fellow, Center for Risk and Economic Analysis of Threats and Emergencies (CREATE), and Adjunct Assistant Professor of the Practice of Economics, Dornsife College of Letters, Arts and Sciences, University of Southern California (USC); Senior Research Fellow, CREATE, Senior Research Fellow, Schaeffer Center for Health Policy and Economics, and Research Professor, Sol Price School of Public Policy, USC; Senior Research Fellow, CREATE, and Professor, Department of Psychology, USC; Research Fellow, CREATE, and Research Associate Professor, Price School, USC; Research Fellow, CREATE, and Research Assistant Professor, Price School, and Research Fellow, Schaeffer Center, USC; Research Associate, CREATE; and PhD student, Department of Psychology, USC.The authors are grateful to the DHS Center for Accelerating Operational Efficiency (CAOE) for its financial support. We thank Tony Cheesebrough and other members of the research project stakeholder team for their helpful comments on earlier presentations of our work. We acknowledge the input from audiences at professional presentations of the research at meetings of various academic associations over the past year. We also acknowledge Andrew Kinoshita, Bari Noor, Konstantinos Papaefthymiou, and Adam Einbinder for their research assistance and the experts who have provided input to the team on epidemiological and health outcomes modeling. This research was supported by the United States Department of Homeland Security (DHS) through the Center for Accelerating Operational Efficiency (CAOE) at Arizona State University. However, any opinions, findings, conclusions or recommendations in this document are those of the authors and do not necessarily reflect views of DHS or the University of Southern California.

Abstract

We estimate the GDP impacts of COVID-19 in the U.S. using a disaster economic consequence analysis framework. This facilitates identification of the relative influence of several causal factors, including mandatory business closures, disease spread trajectories, behavioral responses, resilience, pent-up demand, and government stimulus packages. The analysis is undertaken with a dynamic computable general equilibrium model grounded in primary data on avoidance behavior and healthcare parameters. The decomposition of the influence of various causal factors will help policymakers make adjustments to offset the negative influences and reinforce the positive ones during the remainder of this pandemic and in future ones.

Keywords: COVID-19, Disaster Economics, Avoidance Behavior, Resilience, CGE Modeling

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1. Introduction and Overview

1.1 Background

COVID-19 has had major economic consequences for the economy of the United States. Several studies have estimated its total impacts on GDP above a few trillion dollars, even before the Delta and Omicron variants run their course (del Rio-Chanona et al., 2020; Dixon et al., 2020; Ludvigson et al., 2020; Thunström et al., 2020; Walmsley et al., 2021b;). The pandemic's total economic impacts are estimated to be twice as great as those of the Great Recession, 20 times greater than the 2001 World Trade Center attacks, and 40 times greater than any natural disaster that befell the country in this century (Rose, 2021). The more than 700,000 deaths in the U.S. thus far are more than 200 times those associated with 9/11, the largest disaster in terms of fatalities this century.

Initial studies of the economics of COVID-19 have primarily used macroeconomic and financial models, likely because the most recent great disaster to hit the U.S. was a financial meltdown. Moreover, given the nature of these models in dealing with aggregates and the lack of data at the early stages, the modeling approaches have primarily been top-down. Thus, they were only able to include a limited number of causal factors unique to the pandemic and its impact on the overall economy.[1]

An alternative is a bottom-up approach that focuses on individual causal factors prevalent in disasters, including economy-wide impacts, though not including all financial considerations (likely to be minor in comparison). A major example is the CREATE[2] Economic Consequence Analysis (ECA) Framework (Rose,

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*The authors are, respectively, Research Fellow, Center for Risk and Economic Analysis of Threats and Emergencies (CREATE), and Adjunct Assistant Professor of the Practice of Economics, Dornsife College of Letters, Arts and Sciences, University of Southern California (USC); Senior Research Fellow, CREATE, Senior Research Fellow, Schaeffer Center for Health Policy and Economics, and Research Professor, Sol Price School of Public Policy, USC; Senior Research Fellow, CREATE, and Professor, Department of Psychology, USC; Research Fellow, CREATE, and Research Associate Professor, Price School, USC; Research Fellow, CREATE, and Research Assistant Professor, Price School,, and Research Fellow, Schaeffer Center, USC; Research Associate, CREATE; and PhD student, Department of Psychology, USC.The authors are grateful to the DHS Center for Accelerating Operational Efficiency (CAOE) for its financial support. We thank Tony Cheesebrough and other members of the research project stakeholder team for their helpful comments on earlier presentations of our work. We acknowledge the input from audiences at professional presentations of the research at meetings of various academic associations over the past year. We also acknowledge Andrew Kinoshita, Bari Noor, Konstantinos Papaefthymiou, and Adam Einbinder for their research assistance and the experts who have provided input to the team on epidemiological and health outcomes modeling. This research was supported by the United States Department of Homeland Security (DHS) through the Center for Accelerating Operational Efficiency (CAOE) at Arizona State University. However, any opinions, findings, conclusions or recommendations in this document are those of the authors and do not necessarily reflect views of DHS or the University of Southern California.

[1] In fact, BEA (2021) qualifies its recent economic forecasts by stating: "The full economic effects of the COVID-19 pandemic cannot be quantified in the GDP estimate... because the impacts are generally embedded in source data and cannot be separately identified."

[2] CREATE stands for the National Center for Risk and Economic Analysis of Threats and Emergencies.

2009; 2015; Rose et al, 2017), which has been applied to numerous actual and simulated disasters (see, e.g., Rose et al., 2009; Sue Wing et al., 2016; Chen et al., 2017), including a moderate-sized pandemic (Prager et al., 2017). It represents an advance over conventional economic impact analysis that has been applied for decades to more ordinary situations such as the closing of an automobile plant. It begins with the specification of direct economic impacts and then typically applies a state-of-the-art economy-wide model, such as a computable general equilibrium (CGE) model, to estimate total economic impacts. However, its major contribution is the inclusion of two additional considerations unique to disasters. The first is *resilience*, which pertains to various actions taken by producers, consumers, and governments to recover from the shock and mute the negative impacts on economic activity. It also includes behavioral responses, which are typically motivated by fear and exacerbate the losses. For example, Rose et al. (2009) estimated that the rapid relocation of tenants of the World Trade Center following the 9/11 attacks reduced the potential GDP impacts by 72%, but that more than 80% of the remaining impacts were due to the almost two-year reduction in airline travel and related tourism. Several other studies have found resilience to be a powerful strategy to reduce business interruption (BI) losses from disasters based on surveys and simulation analyses (see, e.g., Kajitani and Tatano, 2009; Dormady et al., 2019; Wei et al., 2020). Other studies have found that behavioral responses to disasters can increase BI losses by one or two orders of magnitude (see, e.g., Giesecke et al., 2012; Rose et al., 2017; Gertz et al., 2019).

1.2 Purpose

The purpose of this paper is to estimate the total economic impacts of COVID-19 in the U.S. We apply the CREATE ECA framework in the process, which enables us to identify the relative influence of several causal factors. We utilize a state-of-the-art dynamic, multi-country CGE model to estimate the time path of the impacts of these factors. CGE analysis essentially models the economy as a set of interconnected supply chains, which enables us to calculate indirect effects as well. Moreover, our analysis is based on the most up-to-date historical data on key causal factors and primary data relating to avoidance behavior and health outcomes and the effects of alternative intervention scenarios. Avoidance is the main behavioral response, and in this case pertains to people engaging in 10 types of activities like retail shopping, going to work, sending children to school, using public transportation, and going to entertainment venues. Moreover, we base our estimates of health outcomes on interviews with medical professionals. We decompose our analysis by performing a set of sequential dynamic simulations beginning with mandatory closures, gradual reopenings, avoidance behavior, and shifts in level and composition of healthcare. We include aspects of resilience, such as the increase in telework and the injection of pent-up demand at later stages of the recovery. Finally, we include the impact of various stimulus packages. All of these effects are disaggregated according to the 65 sectors of the dynamic CGE model to improve the accuracy of the estimation since general equilibrium(supply-chain) effects differ by sector. Given the many uncertainties around several causal factors and the trajectory of infection/hospitalization/deaths due to COVID, we consider alternative scenarios embodying combinations of key assumptions, and including several sensitivity tests.

This study builds on prior work of the research team on the economic consequences of COVID-19. Walmsley et al. (2021a) estimated the consequences of mandatory closures not only in the U.S. but around the globe. Walmsley et al. (2021b) used more up-to-date data to examine the effect of reopenings through the summer of 2020. Rose et al. (2021) analyzed the transmission of these consequences through international trade between the U.S., China, and the rest of the world. All of these studies included major causal factors analyzed in the current study, though they omitted the effects of fiscal stimulus packages. Moreover, all of the studies were based on secondary data and used a static CGE model, while the current study utilizes the primary data and performs the analysis with a dynamic CGE model.

The decomposition of the influence of various causal factors is important for several reasons. First, it improves analytical insight into their workings and interrelationships. Second, it enables policymakers to identify the most prominent causal factors, which is the first step toward making adjustments to offset the negative influences and reinforce the positive ones. For example, our analysis indicates that the mandatory closures by far had the largest negative effect on the results and that the slow reopenings, due to such factors as supply-chain bottlenecks and mixed messages and political debate about COVID contagion, continued some of that influence. Avoidance effects and telework were also prominent influences. In the case of the former, improved risk communication, a relatively inexpensive way to quell fear, has great potential to reduce economic losses. The same is true of public and private decision-makers placing a greater emphasis on providing remote work options.

1.3 Causal Factors Affecting the Economic Consequences of COVID-19

The CREATE ECA Framework distinguishes several different categories of factors affecting the consequences of disasters. These factors can be summarized in general terms as:

- Ordinary direct impacts relating to property damage, economic activity, and health
- Remediation, repair, and reconstruction
- Resilience
- Behavioral responses
- Indirect economic impacts stemming from the above four categories.

In this paper we populate these categories with specific causal factors pertaining to COVID-19:

1. Mandatory closures [Behavioral Linkage]
2. Reopenings [Behavioral Linkage]
3. Workforce declines due to health issues [Direct Effects]
4. Telework [Resilience]
5. Consumption and workforce declines due to avoidance [Behavioral Linkage]
6. Changes in net demand for health care services [Direct Effects of Pandemic and Behavioral Linkage in part]
7. Pent-up demand [Resilience]
8. Stimulus packages [Resilience at the macroeconomic level]
9. Indirect effects of all of the above

Nearly every one of these factors involves some aspects of resilience and behavioral linkages. This helps illustrate that conventional top-down macroeconomic analysis is likely to miss important considerations in estimating the impacts of the pandemic. This modeling approach serves as a valuable organizing framework for the various factors and is especially adept at estimating indirect effects (see Dixon et al., 2020; Walmsley et al., 2021a, 2021b). Moreover, the dynamic CGE formulation enables us to model the time-path of the impacts of the various factors, including lags in their effects.

1.4 Overview

This paper is divided into 10 sections. Section 2 provides the basis of the survey of avoidance behavior and its results. Section 3 presents the modeling results of health outcomes under alternative pandemic scenarios in terms of the efficacy of interventions informed by healthcare interviews. Section 4 presents the analysis of data on mandatory closures, reopening, telework, and pent-up demand, as well as the refinement of the avoidance and healthcare data for inclusion in the CGE model. Section 5 presents an assessment of the six federal stimulus packages that have been enacted to date and how they are translated for use in the CGE model. Section 6 presents the workings of the CGE model and Section 7 presents the details of individual causal factors. Section 8 provides a presentation and the interpretation of the aggregate impacts, as well as a decomposition of the results. Section 9 provides a comparison of the results with other recent findings and discusses the limitations of our analysis. Section 10 provides a summary and suggestions for future research.[3]

2. Avoidance Behavior Survey

2.1 Overview

Avoidance behavior has the potential to significantly affect the bottom-line economic impacts of COVID-19. The present study advances prior methods developed for survey research by the authors on the public's response to flu pandemics (Rosoff et al., 2012) and urban biological terror attacks (Rosoff et al., 2013). The survey estimates changes in behavior due to the COVID-19 pandemic in 10 different domains:

1) Staying home from work
2) Keeping children home from school
3) Canceling or postponing medical and dental appointments
4) Canceling or postponing professional grooming and spa treatments

[3]We also provide several data appendices for this paper, some of them quite extensive. Appendix A presents sample distribution of participants in terms of sex and age, race/ethnicity, income, education level, and state of residency. Appendix B presents the modeling of the various intervention scenarios Estimates on the number of infected international travelers, vaccination projections, and transmission reductions in each intervention scenario are also provided in this appendix. In Appendix C, direct output impacts by sector for mandatory closures and the reopening process are estimated and presented for six-month periods. This Appendix also presents the results of health-related impacts, including labor force workday losses and COVID-related health expenditures by health outcome category and by time period for individual scenarios, as well as the data for estimating pent-up demand. In Appendix D, detailed stimulus bill provisions, their mapping to CGE model sectors, and methods adopted to implement the simulations are presented. Appendix E presents the impacts on sectoral production in the first semi-annual period of 2020 due to the pandemic, decomposed by causal effect. In addition, we also provide a complete copy of the avoidance behavior survey as a separate supplementary file to this paper.

5) Canceling or postponing domestic and international air travel
6) Avoiding public transportation, e.g., taking the bus, rideshare
7) Avoiding local leisure activities, e.g., dining out, bars
8) Avoiding shopping, e.g., grocery, miscellaneous shopping
9) Avoiding recreational activities, e.g., golf, tennis, swimming
10) Avoiding large crowds, e.g., sports events, concerts, shows

For each domain, a representative sample of U.S. adult participants was asked to consider their behavior over the six months from November 2020 to April 2021 compared to their behavior before the pandemic (pre-March 2020). Participants indicated whether specific activities had increased, decreased, or stayed the same in the previous six months compared to the same activities before the pandemic. Participants who reported a change in the activity were asked to indicate the amount of increase or decrease and the reason for the change.

2.2 Survey Content

A series of specific activities were identified within each of the 10 domains, and participants were asked to reflect on their engagement in each activity during the two distinct periods. Participants who indicated a change in engagement were also asked to estimate absolute frequencies or percentages of increase or decrease (depending on the activity). To estimate changes due specifically to pandemic avoidance, participants were also asked to indicate whether the change was due primarily to one of three reasons: 1) Unavailability of the activity due to COVID, 2) Avoidance of the activity by the respondent due to COVID, or 3) Other.[4] A complete copy of the entire survey can be found in Rose et al., 2021 (Appendix A).

2.3 Participants and Sampling Weights

Data were collected in two separate waves – April 23, 2021, and May 3, 2021. All data were collected using the crowdsourcing platform, Prolific, a widely accepted source of online participants for behavioral research (Palan and Schitter, 2018; Peer et al., 2017). A sample of U.S. adults of just over 660 adult respondents was obtained in each wave, for a total sample of N=1328. Frequencies and percentages of participants are reported in Appendix A for sex and age, race/ethnicity, income, education level, and state of residency.

2.4 Estimating Decrease in Activities due to COVID-19 Avoidance

[4] For example, for medical appointments, participants were asked whether they had avoided: a) routine medical exams, b) medical exams for non-life-threatening acute problems, and c) recommended medical procedures during the previous six months. Participants were also asked if they had substituted telemedicine for in-person appointments. Participants who reported avoiding an exam or procedure were asked how many they had avoided over the last six months and were asked to select the primary reason for avoidance: appointments have been unavailable due to COVID-19 and appointments have been available but were avoided due to the risk of COVID infection.

The sample of respondents who participated in paid work reported a mean decrease of 1.25 days/week working outside the home during the pandemic due to all reasons, including avoiding exposure to COVID-19. The same sample of working respondents also reported a mean increase of 0.86 days/week worked at home during the pandemic due to all reasons. The sample of respondents with school-age children reported a mean decrease of 2.02 days/week of in-person school attendance during the pandemic due to all reasons, including parents' decision to avoid children's exposure to COVID-19.

We estimated the impact of COVID-19 avoidance behavior on health/medical and professional grooming visits in terms of the average number of canceled or postponed appointments from November 2020 through April 2021. We isolated the effects of behavioral avoidance of COVID-19 from other effects, such as mandated closures. Respondents indicated whether they had canceled or postponed three separate types of medical-care visits and whether they had substituted telemedicine visits for in-person visits during the pandemic. Respondents also indicated the approximate number of medical visits avoided (or substituted) and the primary reason for avoiding (or substituting) during this period. We focus on medical visits avoided due to behavioral avoidance of COVID, as opposed to other reasons, such as no insurance due to loss of job or unavailability of in-person medical visits for whatever reason.

The mean number of each type of visit avoided over the six-month period for the entire population that can be attributed to COVID avoidance was estimated using the following equation:

*Mean # of Visits Avoided Due to COVID = (Conditional Mean # Visits Avoided | Avoiding COVID Exposure) * (% Avoiding COVID Exposure | Medical Visits Decreased) * (% Medical Visits Decreased | Health Care Utilized)*

Avoidance of COVID-19 exposure during the pandemic (November 2020 through April 2021) was responsible for 0.73 fewer routine medical visits, 0.26 fewer medical visits for non-life-threatening acute problems, and 0.10 fewer visits for medical (diagnostic and treatment) procedures. Respondents' desire to avoid exposure to COVID-19 accounted for about 0.39 additional telemedicine visits substituted for in-person visits over six months of the pandemic.

The impacts of COVID-19 avoidance behavior across the six remaining activity categories were isolated and estimated in terms of percentage decrease during the pandemic using the same approach as described for medical/health appointments. Estimates are based on respondents who are engaged in each activity and are summarized in Figure 1, which plots the percentage of decreased activity. These percentages isolate the effects of behavioral avoidance of COVID-19 from other effects, such as mandatory business closures and stay-at-home mandates. The bars represent the percentage decrease in activity during six months of the pandemic (November 2020 through April 2021) compared to pre-pandemic (before March 2020). Pure behavioral avoidance effects, over and above business closures and other government mandates, resulted in a 40% to 70% reduction in activities during the pandemic (November 2020 through April 2021) compared to pre-pandemic activities. The only exceptions to this were two activities that did not require sustained presence in an indoor facility, namely to-go/delivery dining and outdoor recreational activities.

Increases in shopping and dining substitution activities attributable to COVID avoidance, over and above convenience considerations, or mandated business closures, were also isolated and estimated in terms of percentage increases in substitution activities. These substitution effects are substantial, ranging from 23% to 30% for shopping activities to over 36% for the use of to-go and food delivery dining alternatives, making up for some of the shopping and dining activity reductions attributable to behavioral avoidance of COVID-19 during the pandemic.

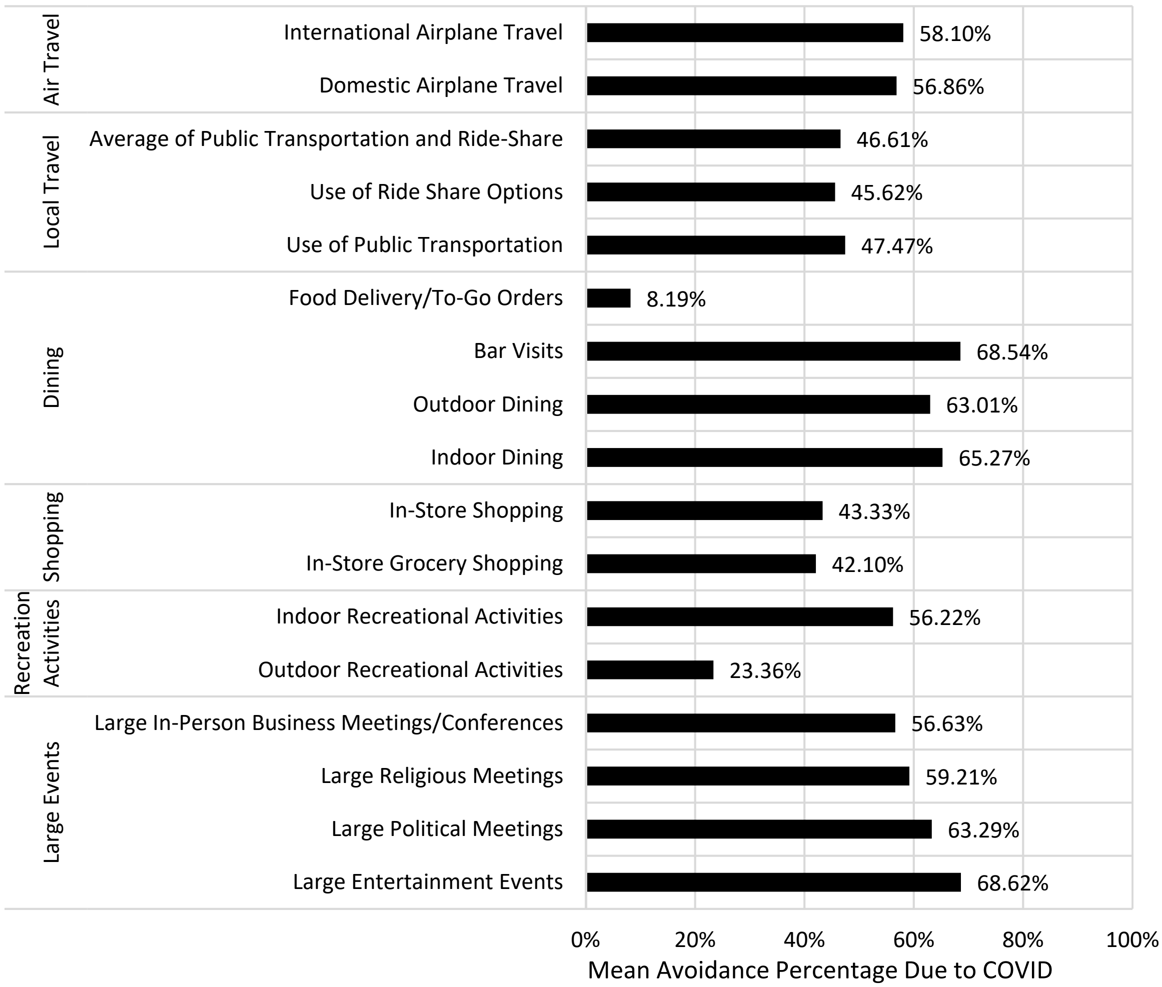

Figure 1. Summary of Percentage Decreases in Activities Across Six Domains during the Pandemic Compared to Pre-pandemic Attributable to Behavioral Avoidance of COVID.

3. Trajectory of the Pandemic under Select Intervention Scenarios

The U.S. started to screen for COVID-19 at select airports on January 20, 2020 and confirmed the first domestic case of the infection on January 21, 2020. A public health emergency was declared February 3, 2020, followed by a declaration by the WHO on March 11, 2020, of a pandemic (AJMC Staff, 2021).

3.1. Methods

We develop four COVID-19 pandemic scenarios in the U.S. between January 2020 and June 2022, with a benchmark scenario calibrated using reported COVID-19 deaths, and three scenarios with alternative assumptions on the efficacy of interventions. Our estimates of SARS-CoV-2 transmission use a traditional Susceptible-Exposed-Infectious-Recovered (SEIR) compartmental model. We draw on estimates of disease characteristics and mathematical models estimating the effectiveness of select interventions and virus seasonality, referenced below. Where empirical estimates were not available, we leveraged expert interviews to develop the most likely and realistic epidemiological scenarios for planning purposes, also described below.

3.1.1. Model Scenarios

Scenario 1: Real-world scenario

In approximating real-world estimates, our model draws on data published by the CDC until July 2021 (we calibrate itl to approximate mortality reported for the age bracket under-65-years and the age bracket 65-years and older in the U.S.) (CDC, 2021e). The model makes projections thru June 2022. Our calibration was conducted at weekly increments in 2020 and monthly increments thereafter. We assume that the reduction in the effective reproductive value attributed to behavioral interventions in July 2021 remains consistent through June 2022, but we do not explicitly model new viral strains that may increase compliance or decrease the effectiveness of behavioral interventions including mask-wearing and social distancing, as well as pharmaceutical interventions such as vaccination.[5]

Scenario 2: High-efficacy scenario

We model a hypothetical high-efficacy scenario to indicate a combination of successful policies that would reduce the adjusted reproduction number to under 1.0, which indicates suppression of transmission over time. We consider effective disease management policies that other countries achieved through measures such as mask mandates, remote work, closure of non-essential businesses, contact tracing, and quarantines (Brauner et al., 2021; Flaxman et al., 2020).

Scenario 3a: Very low-efficacy scenario

The very low-efficacy scenario assumes limited willingness of policy-makers to adopt public health interventions affecting social contact, such as business closures. As a result, compliant behavioral response leads to a maximum behavior-attributed reduction in transmission of 32% (based on Sharma et al., 2020). Behavioral fatigue is also taken into account and over time, effectiveness is expected to decrease (although as we show, most of the cases and deaths would occur within a short period, making long-term mitigation strategies less critical) (see Figure B-3c in Appendix B).

Scenario 3b: Low-efficacy scenario

[5] Our calibration was conducted after seasonality trends (discussed below) were taken into account, and was specific to the two age groups. Calibration results, with cumulative intervention effectiveness estimates for each period in the two population cohorts, can be found in Appendix Figure B-3a/b/c/d.

In this scenario, we use the estimated effectiveness of mask use from Sharma et al. in conjunction with the restriction of gatherings. Scenario 3b uses 50% as the maximum reduction (in the initial months of intervention) before declining due to behavioral fatigue (see Appendix Figure B-3d). Vaccination was incorporated into both the real-world scenario and the high efficacy scenarios. Data for vaccination was drawn from the CDC (CDC, 2021f). In our modeling, 90% of individuals who were vaccinated were removed from the susceptible population permanently and moved to the vaccinated population (see Section B3 of Appendix B).

3.1.2. Expert Interviews

We conducted 12 interviews with experts from variable backgrounds, including scientists in the field of public health and epidemiology from the United States, Canada, and the United Kingdom, state- and federal-level government institutions in the United States, and clinicians in the United States. IRB approval was obtained, and honoraria were offered. These interviews covered multiple areas of interest to the research team, including specification of interventions (social distancing, mask-wearing, and others), uncertainty in key parameters of interest (notably IFR, seasonality, hospitalization rates, vaccination effectiveness, and others), and effects of pandemic outcomes on the behavioral response. Further details about expert input are provided in Section B1 of Appendix B.

3.1.3. Data and Model Inputs

Drawing on published literature as well as expert input, our parameters and assumptions for SEIR and health outcome modeling are listed in Table 1.[6]

Table 1. Modeling Parameters and Assumptions

Parameter	Value	Source(s)
Basic reproductive number (R_0)	3.32	Alimohamadi et al. (2020)
Initial susceptible population	274,165,495 (<65) 54,074,028 (65+)	U.S. Census Bureau (2019)
Initial infections on 1/1/2020	0	Assumed
Daily infected international arrivals, January and February 2020	30 (January 2020) 45 (February 2020)	Calibrated on the basis of real-world data
Daily infected international arrivals, March 2020 through June 2022	0 - 947	Calculated based on I-94 Visitor Arrival Program; Bureau of Transportation Statistics 2019-2020 (Bureau of Transportation Statistics, 2021)
Latent period (pre-infectious)	2.5 days	Vardavas et al. (2021); Rhee et al. (2021)
Infectious period (asymptomatic, pre-symptomatic and	7.5 days	CDC (2021b); Rhee et al. (2021)

[6] The CDC estimates an undercount of actual cases as a multiple of reported cases to be approximately 4.6x; hence, our model does not reference confirmed infections to calibrate real-world outcomes (CDC, 2021c). For this reason, we use reported deaths as a source of calibration in Scenario 1. Where multiple parameter sources were identified, we discussed our choice with the experts consulted and chose estimates with the greatest degree of support (or least disagreement) among the experts.

symptomatic)		
Hospitalization rate (h)	2.90% (<65) 21.21% (65+)	CDC (2021c)
Age-specific infection fatality rate (IFR)	0.0969% (<65) 3.3049% (65+)	O'Driscoll et al. (2021)
Vaccine effectiveness (VE)	90%	CDC (2021a)
Proportion of population willing to vaccinate	73.54% (<65) 84.96% (65+)	Kapteyn and Gutsche (2021) weighted by American Community Survey (U.S. Census Bureau, 2019)
IFR Multiplier during peak hospitalization periods	Under 75,000 hospitalizations: 1.00 Over 75,000 hospitalizations[a]: 120% Over 125,000 hospitalizations[b]: 130%	Based on Rossman et al. (2021)
Seasonality adjustment	0.75 – 1.27	Based on Gavenčiak et al. (2021), see Appendix 5.A.6

[a] Based on the onset of highest hospitalization counts in Fall 2020 and Summer 2021, which resulted in local shortages of intensive care beds and personnel.
[b] Based on the reported peak of hospitalizations, when many states were running out of intensive care beds and personnel to provide the highest-quality care.

3.2. Results

We present the number of cases of COVID-19 by age, period and scenario in Table 2. Other outcomes of interest are reported in Section B6 of Appendix B.

Table 2. Age-Stratified COVID-19 Cases in Each 6-month Period (in thousands)

	Cases Age under65				**Cases Age 65 or Over**			
Scenario:	1	2	3a	3b	1	2	3a	3b
H1/2020	30,531	6,564	209,178	134,521	3,430	617	36,930	18,575
H2/2020	53,606	2,143	15,611	47,298	6,896	237	6,571	17,200
H1/2021	43,923	3,900	354	1,505	4,178	298	40	622
H2/2021	4,433	1,699	266	376	1,834	92	27	36
H1/2022	3,347	5,455	91	198	7,228	139	10	18
Total	135,840	19,761	225,500	183,897	23,565	1,383	43,578	36,451

Sums of semi-annual periods may not equal total due to rounding.

Scenario 1: Real-world scenario

In our real-world scenario, we estimate 142.6 million cases of COVID-19 by June 2021. Over the full 30-month period, 159.4 million infections are expected (23.6 million among 65+, 135.8 million among <65). These cumulative infection numbers represent 43.5% and 49.5%, respectively, of the initial susceptible populations in each age group. These infections result in 910,000 deaths between January 2020 and June 2022 (see Appendix B for more detail).

Notably, even with a relatively high number of cases and deaths, and vaccination willingness at 73.54% for the <65 population and 84.96% for the 65+ population, our model predicts another wave of COVID-19 deaths in Fall 2021/Spring 2022 if behavioral non-pharmaceutical interventions continue unchanged from July 2021 onwards, further accelerated by possibly new variants that challenge vaccine effectiveness.

Scenario 2: High-Efficacy Scenario

For this scenario, we estimate 21.1 million cases of COVID-19 by June 2022. These cumulative infection numbers represent 2.6% and 7.2%, respectively, of the initial susceptible populations in each age group. These infections result in 65,000 deaths between January 2020 and June 2022.

Scenario 3a: Very low-efficacy scenario

Here we estimate 269.1 million cases of COVID-19 by June 2022. These cumulative infection numbers represent 80.6% and 82.2%, respectively, of the initial susceptible populations in each age group. These infections result in 1,993,000 deaths between January 2020 and June 2022.

Scenario 3b: Low-efficacy scenario

Here we estimate 220.3 million cases of COVID-19 by June 2022. These cumulative infection numbers represent 67.4% and 67.1%, respectively, of the initial susceptible populations in each age group. These infections result in 1,504,000 deaths between January 2020 and June 2022.

These results indicate a broad range of possible health outcomes, ranging from well-controlled to devastating – with COVID-19 cases ranging from 21.1 million under the most effective response to 269 million in the most ineffective response. As a result, mortality projections vary significantly as well – from less than 65,000 to nearly 2 million deaths.

Achieving the most optimistic outcomes would require a coordinated national response from early on in the pandemic (in our model, we assumed most interventions would be in place by April 2020, consisting of measures such as broad testing, quarantines, isolation, social distancing, and remote work) so that any further fluctuations in incidence would not result in exponential growth, which was observed in the real-world. Given insights from the pandemic responses of other countries better management of the pandemic could have saved hundreds of thousands of lives in the U.S., particularly among the elderly (Brauner et al., 2021; Sharma et al., 2021).

Our analysis has several limitations. Notably, SEIR modeling assumes homogenous mixing of the population (Tolles and Luong, 2020). We aim to address the different dynamics for younger lower-risk individuals, and older higher-risk individuals by utilizing two different susceptible population pools. Moreover, we adjust for temporal variability by introducing a seasonality coefficient, but the seasonal estimates we draw on are not specific to the United States. We also do not model other health outcomes – it is yet to be determined what the short- and long-term consequences of deferred health care will be. Another limitation includes the dependence on fixed parameters in the initial model design. We conducted expert interviews to collect independent input to key model design choices. Finally, we draw on external estimates, including the expected effectiveness of social distancing, which also contain uncertainty and variability over time, and we finalize our disease modeling inputs in June 2021, before data about the more infectious delta (B.1.617.2) and omicron (B.1.1.529) variant were documented. As a result, our results should be interpreted as approximations of possible disease dynamics rather than accurate estimates for each scenario we study.

4. Data on Major Drivers of Economic Consequences

We collected data for some of the basic drivers of the economic consequences of the COVID-19 pandemic from various sources. These include federal and state government agency websites on the status of mandatory closures/reopenings, CDC reports and other health publications, U.S. Bureau of Labor Statistics (BLS) survey results on telework, and foot traffic and credit card spending data for pent-up demand estimation. In this section, we summarize the collection of these data and their refinement and translation into CGE model inputs.

4.1. Mandatory Shutdown and Reopening Process

During the initial outbreak of the coronavirus disease in the U.S. in 2020, 45 states plus D.C. implemented “stay-at-home” orders that also required the shut-down of non-essential businesses. In most states, the orders were issued in March and lifted by the end of May or early June, with an average length of 45 days (Wu et al., 2020; New York Times, 2021).

To determine the impacts of the mandatory closures on various economic sectors, we defined three categories of sectors based on the DHS Cybersecurity and Infrastructure Security Agency list of Essential Critical Infrastructure Sectors during COVID-19 (CISA, 2020): Category 1 includes sectors that fall entirely under the non-essential category and thus were shut down under the mandatory closures (such as Recreation & Entertainment); Category 2 includes sectors within which only some of their subsectors are non-essential (such as Retail Trade and Business Services); Category 3 includes sectors that are essential and were, therefore, able to maintain operation to the extent possible.

To estimate the reopening process by sector between June and September 2020, detailed reopening stages and timelines data were collected from the reopening plans issued in five major states: California, Texas, New York, Illinois, and Florida (Ting and Duree, 2020; Cowan and Arora, 2021; Florida Department of Health, 2021; Office of the Texas Governor, 2021; State of California, 2021; State of Illinois, 2021; State of New York, 2021). We also collected data of reopening status for each state at three additional points: September and December 2020, and March 2021.[7] as states gradually lessened the capacity limits on these venues.

[7]By mid-September 2020, 23 states had reopened, seven states kept with their original reopening schedules, 11 states paused the reopening process, and the remaining 10 states reversed their reopening plans, especially for bars, restaurants, and indoor entertainment activities. As the winter outbreak began in November 2020, more

Telework has been one of the most important resilience tactics during the mandatory closures and the phased-in reopening process. The weighted average telework potential across economic sectors was over 40% at the beginning of the pandemic and reduced to about 30% as the economy gradually reopened. Telework potentials ranged from about 8% for Leisure and Hospitality sectors to over 70% for the Financial and Education sectors during mandatory closures (BLS, 2021). Appendix Table C-1 presents the estimated direct percentage reduction in U.S. annual GDP by sector due to mandatory closures and the phased-in reopening process by 6-month period.[8]

4.2. COVID-19 Health Expenditures and Workday Losses

The health outcomes of COVID-19 in terms of the number of outpatients, hospitalizations, and deaths are translated into total COVID health expenditures by using the average per-patient cost by health outcome category and by age group (see Appendix Table C-2) (Bartsch et al., 2020; Fusco et al., 2021). For the base case scenario, the total estimated COVID-related health expenditures are estimated to be $214 billion over the entire study period or about 8.35% of the total annual gross output of the Health Care and Social Service sector. The impact is 0.78%, 14.23%, and 11.70% for Scenarios 2, 3a, and 3b, respectively. The detailed results are presented in the Appendix Table C-3.

We also estimate lost workdays due to COVID illness and deaths and caring for sick family members. For hospitalized patients, this is calculated by adding the average length of hospital stay for hospitalized COVID patients by age group, average length from illness onset to hospitalization, and the average number of days for the patients to fully recover before they can return to work/school after hospital discharge (Fusco et al., 2021; Chen et al., 2020; Zhou et al., 2020; Walmsley et al., 2021). For outpatients, productivity losses are assumed to be 1.5, 1.9, and 5.3 days, respectively, for the three age groups (Prager et al., 2017). However, the CDC guidelines suggest 10 days of isolation after the onset of symptoms. Therefore, we assume patients of all age groups will spend 10 days "sick at home." For the 20-64 age group, we adjust for telework potential (23.7% economy-wide) to estimate workday losses. Appendix Table C-4 summarizes per patient loss of productivity measured in days by age and health outcome category.

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states reversed the reopening of the economy by suspending or restricting indoor dining and recreation and entertainment venues. These winter reversals generally lasted 15 to 60 days across the states. By mid-March 2021, many states were still implementing capacity limitations for indoor dining and indoor/outdoor activities in entertainment venues (Bunis and Rough, 2021; Schoening and Wilcox, 2021). Therefore, for the first semester of 2021, disruptions to production activities were only calculated for the Food Services and Recreation sectors. The percentage restrictions data for these sectors collected in March were assumed for the first three months in 2021, and half of those levels were assumed for the following three months

[8] These estimates have factored in telecommuting potential for each non-essential sector based on the BLS data. For the rest of the world, data were collected on the timings of mandatory closures in each country (Wikipedia, 2020). Where closures were considered partial (e.g., city- or region-wide only), we applied a 50% closure rate. The same essential/non-essential categorization of sectors used in the U.S. was applied to China and the rest of the world. Each country's production data were then used to determine the overall share of the sector closed in the rest of the world, assuming the same essential sector shares as in the U.S. case. The phased-in schedule of U.S. reopenings was also used to determine the timing of reopenings for the rest of the world, adjusted for differences in the mandatory closure periods between each country and the U.S.

Lost productivity due to caring for sick family members includes caring for sick children in the 0–18 age group, a sick spouse in the 18–64 age group, and sick elderly family members in the 65+ age group. We made similar assumptions as in Prager et al. (2017) and Dixon et al. (2010) in calculating the productivity day losses for this category. For the Base Case scenario, the total estimated workday losses are over 600 million days. Appendix Table C-5 presents total lost productivity for each scenario.

For other countries, workday losses were assumed to occur at the same rate as in the U.S. Similarly, for health care expenditures, an adjustment was made to the cost of health care based on differences in per capita health care expenditure in each country.

4.3. Avoidance Behaviors

Our survey results on various types of avoidance behavior are translated into direct production impacts in the relevant GTAP sectors. In most cases, we multiply the percentage net decrease of a specific type of activity because of avoidance behavior by the percentage that the activity represents of the total output in the relevant GTAP sector. For a few categories of avoidance behavior (such as staying home from work, keeping children from school, and avoiding medical professionals), we conducted additional calculations to translate the survey results into the inputs for the CGE model. Table 3 first presents the linkage that is used to analyze the impacts of various types of avoidance behavior in the CGE model and then summarizes the direct impact inputs to the corresponding GTAP sectors.

Table 3. Magnitude of Avoidance Behaviors and CGE Modeling Method

Avoidance Behavior	GTAP CGE Modeling Linkage	Impacts on the GTAP Sector(s)
Staying home from work	Labor force productivity impact	-4.58%
Keeping children from school (impact on education sector)	Reduced demand in Education sector	-1.59%
Reduction of in-person school attendance (caregiver impact)	Labor force impact	-2.71%
Avoiding medical professionals	Demand reduction in Human Health and Social Work sector	-29.16%
Reducing shopping	Demand reduction in Wholesale and Retail Trade sector	-5.85%
Avoiding local leisure activities	Demand reduction in Recreation & Other Services sector	-21.17%
Avoiding dining out	Demand reduction in Accommodation, Food and Service Activities sector	-26.50%
Avoiding public transportation	Demand reduction in Land Transport and Transport via Pipelines sector	-4.21%
Canceling air travel	Demand reduction in Air Transport sector	-57.48%
	Demand reduction in Accommodation, Food and Service Activities sector	-9.67%

4.4. Pent-up Demand

Pent-up demand represents another important source of economic resilience that helps reduce the negative impacts from shutdowns and individual avoidance behaviors during the pandemic. To estimate the changes in consumer demand for key types of goods and services over time resulting from COVID-19 related lockdowns and reopenings in the U.S, we first estimate the “Lowest Point” level in consumption since the onset of COVID-19. For most consumption categories, this “Lowest Point” took place in early or mid-April 2020. Next, the percentage increase from the “Lowest Point” level in consumption for each category is estimated at five points in time with three-month intervals after the beginning of the reopening. The estimates are presented in Appendix Table C-6, calculated based on micro-level data from three distinct sources that track consumer credit card-spending information or foot traffic data at retail locations across different industries (Opportunity Insights, 2021; Unacast, 2021; SafeGraph, 2021). Similar rates of consumption changes were assumed in the rest of the world and China.

Factors influencing consumer expenditures during the pandemic include, but are not limited to, closures and reopenings of businesses, government stimulus paychecks and other household assistance programs, consumer avoidance behavior, and pent-up demand. It is difficult to collect data to separate the effects of these individual factors on consumer expenditure changes. Therefore, we compare the actual consumption changes with the model results in which several other key factors are incorporated (including closures/reopenings, avoidance, and fiscal policy), and attribute any positive differences to the effects of pent-up demand.

5. U.S. Federal Government Fiscal Stimulus Legislation

5.1 Individual Stimulus Bills

The U.S. federal government enacted six stimulus bills related to COVID-19 as of December 2021. Altogether, these six bills amount to an estimated \$5.13 trillion in assistance, forgivable and subsidized loans, funding support for state and local government, tax credits, and government expenditures (CBO, 2021a). We summarize the main provisions of each of these six bills in Table 4.

The first bill was signed into law in early March 2020 and focused on enhancing the government’s preparedness and public health response by providing funds to the Department of Health and Human Services (HHS) and state and local health agencies. Less than two weeks later, the U.S. Congress passed the Families First Coronavirus Response Act (CBO, 2020a). Like the first bill, this Act aimed to improve the public health response to the crisis, but it also sought to address the economic impact of the pandemic by enhancing safety net provisions. A paid sick leave provision, which required certain employers to pay the full or partial salary of employees unable to work due to COVID-19, was estimated to cost \$105 billion (more than half the total cost of the bill) in tax credits.

Table 4. Summary of COVID-19 Stimulus Bills Enacted by the U.S. Federal Government

Stimulus Bill	Date Enacted	Main Provisions	Estimated Spending (billions, USD)[a]
Coronavirus Preparedness and Response Supplemental Appropriations Act, 2020	3/6/2020	Funding for federal, state, and local health agencies, and the purchase of vaccines and treatments	8
Families First Coronavirus Response Act	3/18/2020	Tax credits for paid medical leave, increased funding for nutritional assistance, and unemployment benefits	192
Coronavirus Aid, Relief, and Economic Security (CARES) Act	3/27/2020	Cash payments for individuals, extra unemployment benefits, forgivable loans for small businesses, loans for medium and large businesses, and corporate tax relief	1,902
Paycheck Protection Program and Health Care Enhancement Act	4/24/2020	Extension of forgivable loan program for small businesses, reimbursements for health care providers, and funding for testing	342
Coronavirus Response and Relief Supplemental Appropriations Act, 2021 and Additional Coronavirus Response and Relief Act	12/27/2020	Cash payments for individuals, extra unemployment benefits, and extension of the forgivable loan program for small businesses	864
American Rescue Plan Act of 2021	3/11/2021	Cash payments for individuals, extra unemployment benefits, support for state and local governments	1,825

[a]Estimated spending is based on preliminary projections by the Congressional Budget Office (CBO, 2021a) and includes increases in direct spending as well as declines in tax and fee revenue.

As COVID-19 cases rose in mid-March, Congress enacted the Coronavirus Aid, Relief, and Economic Security (CARES) Act, enacted in late March, which amounted to more than $1.9 trillion in spending and tax credits (CBO, 2020b). The bill included $100 billion for hospitals and $50 billion for other public health provisions. Airline companies received $50 billion for not laying off employees. The legislation also provided $340 billion for state and local governments, mostly directed to COVID-19 response efforts. Three other provisions amounted to approximately half of the bill's total cost: payments for individuals and dependents, enhanced unemployment insurance, and the Paycheck Protection Program (PPP), a forgivable loan scheme for small businesses. The cash payments provided up to $1,200 per person making less than $99,000 a year, with an additional $500 per child. Unemployed individuals received supplemental weekly payments of $600 for 13 weeks. The PPP loans are fully forgivable if businesses use the funds to cover payroll or other eligible expenses and meet certain conditions such as not laying off workers -- we assume that they will not be paid back in our simulations.

After the $350 billion allocated by the CARES Act to PPP ran out, Congress funded an extension in April 2020 (Duehren and Omeokwe, 2021). The Paycheck Protection Program and Health Care Enhancement Act appropriated another $310 billion for PPP loans. It also included another $75 billion for hospitals and $25 billion for testing. In our model, we group these initial four bills because they went into effect during a relatively short period, from March to April 2020.

Eight months later, after a second wave of COVID-19 infections in the Fall of 2020, the U.S. Congress approved another comprehensive stimulus bill of nearly $900 billion as part of the Appropriations Act of 2021 (WSJ, 2020). Many of its provisions were scaled-back extensions of CARES Act provisions: cash payments of up to $600 for individuals earning up to $87,000 a year and additional $600 per dependent; weekly unemployment supplement payments of $300 for 11 weeks; and a third extension of the PPP program.

In March 2021, following a surge of COVID-19 cases and deaths, Congress approved another major stimulus bill. Some of the major provisions extended support provided to households and unemployed individuals under the December 2020 package. These provisions included additional one-time cash payments of up to $1,400 per adult and child for eligible households and an extension of boosted unemployment payments through September, additional funding for vaccines and testing, schools and universities, $350 billion to state and local governments, and an increase to the child tax credit (CBO, 2021b).

Across the six bills, the largest categories of stimulus were increased government spending, which represented 35% of total stimulus, followed by assistance to businesses (20%), direct payments to individuals (17%), unemployment payments (12%), and other forms of assistance to individuals (11%). See Appendix Table D-1 for a breakdown of stimulus measures by round and category over time.

5.2. Stimulus Implementation and Impact

Several issues with the implementation of the CARES Act delayed relief. These issues include confusion among borrowers and lenders about the PPP program and its eligibility criteria, and difficulties in delivering cash payments to nine million, hard-to-reach individuals (GAO, 2020). State governments were also overwhelmed and slow to process enhanced unemployment payments (Iacuri, 2021). Finally, the emergency programs administered by the Federal Reserve only provided $41.1 billion in assistance, a fraction of the announced size of those programs of $4 trillion (CRS, 2021). In the analysis below, we do not model the Federal Reserve loans directly because we assume they will be repaid and because the low uptake suggests the lending terms did not represent a subsidy relative to commercial credit.

Some economists have criticized the cash payments to individuals as not sufficiently targeted to those most in need, arguing that further increasing unemployment benefits or extending their duration would be a more efficient use of resources (Schwartz and Friedman, 2020). Coibion et al. (2020) find that those who received cash payments under the CARES Act on average planned to spend only 40% of their stimulus checks. Baker et al. (2020) similarly estimate that during the first weeks, payment recipients spent 25-40% of the stimulus, but that share was higher for households with lower or declining incomes, highlighting the importance of targeting. In our model, we assumed 7.8% of unemployment benefits and

36% of cash payments and other household payments were saved based on household surveys (Armantier et al., 2020; Coibion et al., 2020; Leer, 2021).

Another criticism of the stimulus provisions is that they had a limited capacity to restore economic activity for the most impacted sectors such as hospitality and entertainment, where consumer spending was constrained by mandatory shutdowns and avoidance (Chetty et al., 2020). We assumed that the stimulus provisions could raise production in sectors constrained by mandatory closures.

Furthermore, the PPP loans appear to have had a limited effect on preserving and creating jobs, the program's main goal. The short- and medium-term employment effects of the Program were small, with many firms using the loans to make non-payroll payments and build up savings (Granja et al., 2020). Chetty et al. (2020) estimate that the initial round of PPP loans increased employment at small businesses by only 2%, at $377,000 per job saved. For sectors constrained by mandatory closures, we assumed that a portion of the loans—equivalent to the portion of the sector subject to mandatory closures—went directly to the owners or employees as income, allowing us to capture some of this effect (option 1, discussed in Appendix D).

The aforementioned studies suggest that stimulus provisions are not equally cost-effective, and that policy design is critical to meeting the specific objectives of policymakers. Targeting and timing are important considerations. Provisions that provide aid to the most affected individuals (e.g., enhanced unemployment benefits), and sectors (e.g., forgivable loans to airlines) may be more effective than other measures. The methodology for refining the data on the six stimulus bills for modeling the impacts on the U.S. economy is presented in more detail in Appendix.

6. The Model and Data

We use a dynamic global supply-chain computable general equilibrium model developed by ImpactECON to examine the impact of COVID-19 on the U.S., China, and the rest of the world. The model is based on the Dynamic GTAP model (Ianchovichina and Walmsley, 2012) and the ImpactECON supply chain (IESC) model and database (Walmsley and Minor, 2016a, 2016b), which are both adaptations of the widely used GTAP model (Hertel and Tsigas, 1997; Corong et al., 2017).[9]

In the model, each region collects income from the supply of factors of production to firms and tax revenues. This income is then allocated to private and government consumption, and to savings which fund investment, using a Cobb-Douglas demand function, which in turn is allocated across commodities and domestic and foreign sources using a series of Armington Constant Elasticity of Substitution (CES) functions that characterize imports as imperfect substitutes for domestic goods. Given the demand for their goods by domestic and foreign agents, firms then produce these goods by combining intermediate inputs according to a Leontief (fixed proportion) relationship and elements of value-added and the value-added aggregate and intermediate good aggregate using CES production relationships. Taxes are

[9] The model is implemented in GEMPACK (Horridge et al., 2018).

levied on almost every transaction. Value-added and tax revenues (through transfers) then link back into the income of the regional household.

The underlying database contains input-output tables and trading relations for 65 commodities and 141 countries from the GTAP database (Aguiar et al., 2019), as well as additional detail on the source of final and intermediate goods based on HS6 trade data. We aggregate the 141 countries/regions (GTAP, 2021a) into three regions – the U.S., China, and the ROW – as we are primarily interested in the impact on the U.S. economy but also recognize the need to model the impact of the pandemic on trade with the rest of the world and hence supply chains. This feature improves our ability to examine how the delay or disruption of these imported intermediate inputs impact a U.S. firm's ability to produce and export commodities. For instance, to the extent that intermediate inputs come from China, rather than from the rest of the world, the supply-chain effects of COVID would be reduced because China's mandatory closures were relatively less severe. These supply chain disruptions are significant in some cases.[10]

The model is also dynamic, allowing us to examine the impact of COVID over eight semi-annual periods (2020_1, 2020_2, …, 2023_2). The dynamic model incorporates investment behavior through adaptive expectations that allow for the gradual equalization of global rates of return over time, and additional accounting relations to keep track of foreign ownership of capital based on the GDyn model (Ianchovichina and Walmsley, 2012).

More importantly, we incorporate short-run dynamics that take account of the impact of mandatory business closures and the other negative effects of the pandemic on unemployment. As businesses close and consumers avoid certain purchases, production falls and unemployment rises. Over time, as businesses reopen and demand returns, wages rise and unemployed workers gradually return to work.

We also allow for the unemployment/under-utilization of other resources, such as capital and land. As production falls, capital and land lay idle until businesses reopen and these resources are re-deployed.

The model includes eight factors of production: five labor types by occupation (officials, managers, and professionals; technicians and associate professionals; clerks; service/shop workers; and agricultural and unskilled workers), as well as capital, land, and natural resources. We also capture the supply of labor by education, which we link to our five occupations using information on the education levels of each occupation by country. This model has been used in several studies, including Minor, Walmsley, and Strutt (2017) and Walmsley, Strutt, and Minor (2021). Moreover, the dynamic supply chain model has been used in Walmsley and Minor (2018) and Walmsley and Minor (2020a).

Since the model is dynamic, a baseline scenario of how the world economy was expected to change without the pandemic must be established. To build this baseline scenario, we use historical and pre-COVID forecasts from the Bureau of Economic Analysis for the U.S. and the International Monetary

[10] Current and earlier versions of the ImpactECON supply chain model and database have been used in numerous studies (Hertel et al., 2014; Walmsley et al., 2014; Walmsley and Minor, 2021, 2020a, 2020b, 2018; Walmsley et al., 2021a, 2021b; Rose and Wei, 2021a, 2021b; Rose et al., 2021), and by other institutions, including the U.S. Trade Administration and the European Commission.

Fund's World Economic Outlook (IMF, 2019) for real gross domestic product (GDP), investment, and labor; United Nations (UN, 2017) data on population growth to update the 2014 GTAP data to the beginning of 2020 and create a baseline for 2020_1 to 2023_2 (in semi-annual periods). The baseline scenario between 2020_1 and 2023_2 reflects what the global economy would have looked like if the pandemic had not occurred.

7. Modeling Causal Factors

To model the impact of COVID, we sequentially add each of the following contributing factors:

Mandatory closures

To capture the impact of the mandatory business closures, we reduce the production of the affected sectors using an expedient device known as a "phantom tax" to raise prices and lower production through a reduction in final demand.[11] This must be done in several iterations to take account of the indirect effects of closing some sectors on other sectors. For instance, if restaurants are forced to close, demand for fruit and vegetables or beverages and tobacco used in producing restaurant meals also declines. In some cases (beverages and tobacco for instance), these indirect effects from the mandatory closures (of restaurants, for instance) are larger than the share of that sector subject to the mandatory closure, and, hence, we allow these indirect effects to dominate and sectoral production to decline by more than the share of the sector subject to the mandatory closure. As a result, we only need to impose a decline in production in those sectors where the direct impacts of the mandatory closure are greater than the indirect effects from the mandatory closures of other sectors.

As sectors reopen or are closed for shorter periods in the second and later semi-annual periods, these phantom taxes are removed gradually according to the rate of reopening. Again, this is undertaken as an iterative process as we need to ensure that the sector does not expand beyond the share of the sector forced to close during that period. We take account of any potential expansion in production over this share; however, it is captured under pent-up demand, rather than under mandatory closures.

We also take into account the ability to telework within an industry. This causal factor is incorporated into the mandatory closures "driver" of the model.

In addition to the business closures, we assume that government spending was fixed and that any income from foregone consumption due to the mandatory closures was saved; savings rates therefore rise. We also assume that consumption of essentials remains constant, thereby ensuring that the decline in demand resulting from lower household income falls more heavily on non-essential items, as we might expect with unemployment and the mandatory closure of non-essential businesses.

[11] The reduction in output reflecting the business closures is fixed, and the implied tax required to achieve that level of production is determined (endogenously) by the model (Dixon and Rimmer (2002)). The term "phantom" is simply a modeling device because the "taxes" are implicitly returned to the businesses as revenue increases associated with the higher price; essentially, the customers (both other businesses and consumers) cover this revenue by their expenditures at the higher price, and there is no effect on government revenues.

Decline in the workforce due to deaths and illness

The decline in the workforce due to deaths and illness is implemented as a decline in the supply of labor. We assume all labor types, regardless of education level, are impacted by the same proportion. Thus, we assume that the pandemic does not discriminate, even though evidence may suggest that lower-skilled workers in customer-facing occupations may have been affected more than other workers. Given the impact of these deaths and illnesses on the workforce and the overall economy is very small relative to the other causal factors, this assumption is unlikely to impact our results significantly.

Avoidance

Avoidance behavior impacted both the supply of labor and the demand for certain goods and services. These were implemented directly as changes in labor supply and changes in private consumers' preferences for goods and services, and, in the case of health care, government preferences. We assumed that government spending was fixed and that any income from foregone consumption due to avoidance was saved. As avoidance dissipated, preferences and savings return to normal.

Increased demand for health care

Increased demand for health care due to COVID was also implemented as an increase in demand (preferences) for health care by private and government consumers. It was assumed that any health care expenses were paid for out of savings, resulting in a reduction in the savings rate. Again, these preferences are reversed as the demand for health care returns to normal.

Pent-up demand

Pent-up demand was simulated as an increase in demand for goods and services that final consumers had been unable to purchase due to mandatory closures or avoidance. Pent-up demand was found by comparing actual changes in demand by final consumers to model estimates. Where demand was found to be stronger than the model predicted, an increase in demand was simulated. Any increased private consumption was assumed to be funded from savings. Again, the rise in preferences and savings are reversed as pent-up demand subsides. Since we were only able to obtain estimates of pent-up demand for 2020 and the first half of 2021, further pent-up demand in late 2021 and 2022 could possibly lead to further increases in real GDP.

Fiscal policy

The various rounds of fiscal stimulus were decomposed according to both round and mechanism for the U.S. Unlike the other causal effects where we also created estimates for China and the rest of the world, we did not implement any fiscal policy changes in China and the rest of world. In terms of rounds, the impacts of the fiscal stimulus were separated into three parts: 1) Rounds 1-4, implemented in early 2020, 2) Round 5, implemented in late 2020 and early 2021, and 3) Round 6, implemented in early 2021.

When we prepare the input data for the CGE modeling, detailed provisions in each of these rounds were categorized by the type of fiscal stimulus implemented. Not all rounds used all these categories. The fiscal stimulus was paid for by increased borrowing (i.e., using savings). We also assumed that a portion of the unemployment benefits and cash payments were saved and hence had no impact on the results. The portion saved depended on the type of payment and was based on the data collected on savings rates discussed in Section 5. Using these data as a guide, we assumed that the share of the cash payment saved (36%) was higher than the share saved from unemployment benefits (7.8%), reflecting the fact that unemployed households were found to have lower savings rates during the pandemic than households in general.[12]

8. Results

The model described in Section 6 estimates the macroeconomic impacts of the COVID-19 pandemic on the U.S. economy based on the "bottom-up" economic consequence analysis framework presented in Section 1. This enables us to isolate the effect of individual causal factors ("drivers") of these consequences.

Figure 2 presents the time-path of the estimated U.S. GDP over the eight semi-annual periods between 2020 and 2023 (i.e., cumulative GDP growth in six-month periods) in the baseline and with the pandemic.[13] The corresponding changes in billions of dollars of GDP in the baseline, during the pandemic, and the cumulative difference between the baseline and pandemic are given in Table 5. In the first six months of the pandemic, mandatory closures, avoidance, and deaths and illness caused a significant decline in the semi-annual real GDP of approximately 37%. With the introduction of the first four rounds of fiscal stimulus and increased (pent-up demand) spending as businesses were allowed to re-open, this decline was reduced to 27%. Growth rose in late 2020 as businesses continued to reopen, but dipped again slightly in early 2021 with the re-introduction of some mandatory business closures and further avoidance in response to another wave. Over time, the reopening of businesses, the decline of avoidance behaviors, and pent-up demand have resulted in a gradual crawl back toward baseline growth. The second dip in the first half of 2022 corresponds to the later stages of Round 6 of the fiscal

[12] An issue was the extent to which sectors subject to mandatory closures could respond to the loans and other fiscal stimulus. While we assumed that all sectors could respond to the fiscal stimulus, we adjusted the amount of the loans by assuming that the portion of the loans provided to closed businesses went directly to the business owners and workers of those businesses, rather than through the businesses themselves. This limited the extent to which closed businesses responded to the fiscal stimulus, at least partially addressing some of the issues raised by Chetty et al. (2020) discussed in Section 5. We also ran an alternative set of simulations to capture the impact of fiscal policy, assuming that those sectors subject to mandatory closures could not respond to the fiscal stimulus. We found that limiting the extent to which closed businesses could respond reduced the overall gains from the fiscal stimulus, particularly in the earlier rounds when more businesses were closed. Since each round of fiscal stimulus is temporary, the unemployment benefits, cash payments, loans, etc., are reversed in the following period/s, often to be re-introduced in the next round of fiscal stimulus.

[13] We refer to the time-path as cumulative change because we are cumulating growth over time. For instance, in the baseline, growth is just under 2% per year. The time-path therefore shows how this 2% cumulates over time, such that in year 1, the economy has grown by 2%; in year 2, the economy has grown by 4% (or $[1.02]^2$-1); in year 3, cumulative growth is around 6% ($[1.02]^3$-1), and so forth. Figure 8-1 therefore shows the cumulation of the annual growth rates under the two scenarios: baseline and COVID pandemic. In the rest of this section we show the results in terms of the difference or gap between those two cumulative time-paths; this gap is referred to as the cumulative difference from baseline.

stimulus, which is found to crowd out investment and exports, leading to a decline in growth. But in the second half of 2022, the gap starts to diminish again, and by the end of 2023, the semi-annual gap between economic growth under the pandemic and baseline growth is just under $800 billion.

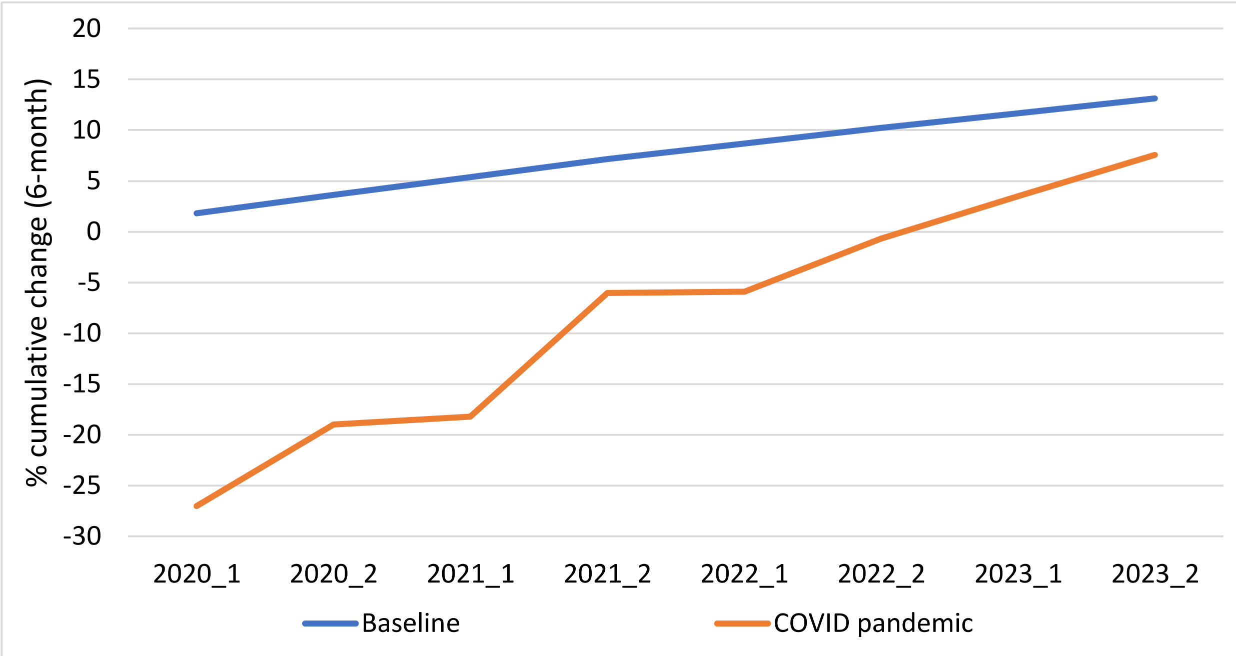

Figure 2: Percent Changes in Semi-annual GDP by Causal Factor
(cumulative percent change over time)

Table 5. Changes in Semi-annual U.S. GDP
(billions of dollars, unless otherwise specified)

	2020_1	2020_2	2021_1	2021_2	2022_1	2022_2	2023_1	2023_2
Difference (% change)	-27.6	-21.6	-22.3	-12.4	-13.7	-10.8	-8.8	-6.5
Baseline	10,909	11,104	11,292	11,480	11,645	11,810	11,965	12,120
Policy	7,898	8,705	8,774	10,057	10,050	10,534	10,912	11,332
Difference in Semi-annual GDP	-3,011	-2,398	-2,518	-1,424	-1,595	-1,275	-1,053	-788

Table 6 further decomposes the gap between the pandemic outcome and the baseline into the various contributing factors. The largest contributing factor is mandatory business closures, followed by avoidance. The mandatory business closures were most prevalent in the first half of 2020, with restrictions partly lifted in the second half. Additional closures in the first half of 2021 caused a further slowing of the recovery. In addition to mandatory closures, the avoidance of in-person shopping for goods and services and of the workplace also contributed significantly to the decline in GDP. The decline in labor due to illness and deaths of workers was relatively small due to the low percentage of workers impacted and the availability of other workers due to the high levels of unemployment. The small decline in real GDP here is due to the decline in population and demand rather than the decline in the labor force, as workers directly impacted by COVID are replaced by the unemployed.

The remaining factors tended to alleviate the losses in economic growth. Increased demand on the health care sector to treat COVID patients had positive implications for other sectors, albeit small. Pent-up demand was found to be an important factor in the recovery, raising real GDP in the first half of 2020 by 3% and by a further 2% in the first half of 2021, which then continued to boost growth due to a rise in investment. Pent-up demand in the second half of 2020 was found to be relatively small but increased again in early 2021. It is worth noting that we only capture pent-up demand in 2020 and the first part of 2021, although it is likely that there is further pent-up demand in the latter part of 2021 and perhaps even into 2022. Hence, this is likely to be an underestimate of the longer-run impact of all pent-up demand.

The fiscal stimulus was also found to positively impact the economy, particularly when first implemented. Rounds 1-4 had the greatest impact, alleviating the decline in growth at its most severe stages. Round 5 provided further relief in 2021, while round 6 was found not to be beneficial for economic growth, in large part because it was becoming harder to fund the fiscal stimulus using domestic savings.

Table 6. Percent Changes in Semi-annual U.S. GDP by Causal Effect (cumulative percent differences from baseline)

	2020_1	2020_2	2021_1	2021_2	2022_1	2022_2	2023_1	2023_2
Mandatory Closures	-26.3	-22.9	-21.7	-15.9	-12.3	-10.3	-8.9	-7.8
Avoidance	-12.2	-11.3	-10.2	-5.4	-4.6	-4.1	-3.8	-3.6
Labor	0.0	-0.1	-0.3	-0.5	-0.6	-0.7	-0.8	-0.8
Health Care	0.8	0.9	0.8	0.7	0.6	0.5	0.5	0.4
Pent-up Demand	3.0	2.9	5.0	5.4	6.1	5.8	6.2	6.9
Fiscal Policy								
Rounds 1-4	7.1	8.9	2.1	1.9	1.2	1.4	1.4	1.6
Round 5	0.0	0.0	1.7	1.4	0.2	0.2	0.1	0.1
Round 6	0.0	0.0	0.3	0.0	-4.3	-3.6	-3.5	-3.3

With the decline in production due to mandatory business closures and avoidance, employment of all factors declined, with the largest declines due to the mandatory closure of businesses. The decline in labor is particularly large, with unemployment rising slightly more than GDP in percentage terms. This is because non-essential businesses, and services, in particular, tend to be more labor-intensive and hence have a greater impact on labor than other factors of production, such as capital.

With deaths and illness, ethe supply of labor declines. Those left unemployed as a result of the mandatory closures and avoidance fill these vacant positions, causing unemployment to fall slightly. Similarly, with avoidance, there is also a decline in labor supply as some employees avoid going to work for fear of unsafe working conditions, or the need to stay home to take care of children or household members in need of care. Overall, however, unemployment still rises with avoidance as the decline in production and demand for labor resulting from the avoidance of non-essential goods and services is greater than the fall in supply of labor due to avoidance of work. The fall in labor supply due to deaths, illnesses and avoidance of work also leads to a shift towards capital that has implications for investment, discussed below. Increased health care expenditures, pent-up demand, and Rounds 1-5 of the fiscal stimulus also raise the demand for labor.

The impact on investment is generally consistent with the impacts on real GDP. There are a few notable exceptions: avoidance and fiscal stimulus. Avoidance by workers raises investment because the decrease in the supply of labor raises the use of capital (e.g., increased automation). Increased demand for capital increases returns to capital and hence investment. Investment then adds to capital stocks over time, and so increases in investment increase growth in real GDP in the following period. Similarly, declines in investment result in a decline in growth in real GDP in the following period.

The different impacts of the various rounds of the fiscal stimulus on investment explain some of the paradoxical results in real GDP from the various fiscal stimulus rounds. Rounds 1-4 cause investment to increase, while in Round 6 investment decreases, resulting in declining growth in real GDP in 2022 and beyond. This decrease in investment in Round 6 is caused by government spending crowding out investment. This crowding out is exacerbated in Round 6 because much of its spending is implemented in late 2021, just as savings rates are returning to normal. In 2020, as Rounds 1-4 of the fiscal stimulus are implemented, savings rates rise as people could not spend their money due to business closures and avoidance. This rise in savings provided the government with sufficient funds to stimulate the economy without significant crowding out of exports and investment. By late 2021, however, businesses are projected to be open, and savings rates have fallen; savings are therefore scarcer, and foreign savings must be used to fund Round 6 of the fiscal stimulus, which has implications for the trade balance and trade (see Walmsley et al. (2021c)

Appendix Figure E-1 shows the impact of the various causal factors on sectoral production in the first half of 2020. As expected, mandatory closure of businesses causes most of the declines in production, followed by avoidance. These declines are most significant for the non-essential sectors, although there are clear indirect implications for essential sectors too, as incomes fall and non-essential businesses reduce their demand for intermediate inputs (e.g., pharmaceuticals used in health care). The impact of avoidance behavior in accommodation and food services, recreational services, transportation, and health care on production is also clear. We also see a reflection of some pent-up demand in the first half of 2020, as people eager to enjoy restaurants increase demand when businesses resume operation. Rounds 1-4 of the fiscal stimulus (Rounds 5 and 6 are not implemented until 2021) have a clear, positive impact on most sectors.

9. Discussion

9.1 Impact of Alternative Scenarios

In Table 7, we show how changes in our assumptions about the number of deaths and illnesses, and the resulting impact on the health sector, impact the economy. These are compared with Scenario 1. The results show that increased efficacy of interventions (Scenario 2) reduces the impact of the deaths and illnesses and health care expenses on the economy. In Scenarios 3a and 3b, lower efficacy means that the impacts are larger in absolute terms, with deaths and illnesses causing further declines in real GDP for Scenarios 1 and 2 and the increase in health care expenditures raising real GDP sizably. The extent of the changes depends on the level of social distancing assumed in Scenarios 3a and 3b – with more social distancing in the latter resulting in fewer cases and hence a smaller absolute economic impact.[14]

Table 7. Percent Changes in Semi-annual Real GDP Due to Deaths and Illnesses and Health Care Expenses under the Alternative Scenarios (cumulative percent differences from baseline)

Scenario	2020_1	2020_2	2021_1	2021_2	2022_1	2022_2	2023_1	2023_2
Scenario 1								
Deaths and Illnesses	0.0	-0.1	-0.3	-0.5	-0.6	-0.7	-0.8	-0.8
Health care expenses	0.8	0.9	0.8	0.7	0.6	0.5	0.5	0.4
Scenario 2								
Deaths and Illnesses	0.0	0.0	-0.1	-0.1	-0.2	-0.2	-0.2	-0.2
Health care expenses	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2
Scenario 3a								
Deaths and Illnesses	0.0	-0.3	-0.8	-1.0	-1.2	-1.4	-1.5	-1.6
Health care expenses	7.4	5.3	2.9	2.1	1.9	1.9	2.0	2.0
Scenario 3b								
Deaths and Illnesses	0.0	-0.2	-0.7	-0.9	-1.0	-1.1	-1.2	-1.3
Health care expenses	5.8	4.9	3.1	2.5	2.2	2.0	2.0	1.9

9.2 Comparison with Results of Other Studies

Few studies have performed a decomposition of the economy-wide impacts of COVID-19 according to several causal factors, such as those provided in this report. One of the reasons is that many of the estimates utilize macro-econometric or time-series models, which are typically “top-down” approaches and hence less amenable to decomposition in comparison to “bottom-up” models such as ours. However, there are a few studies that lend themselves to comparison. The first set of studies, including

[14] We explicitly assume only changes in social distancing. Hence there are no changes in the other causal factors considered above. For instance, less social distancing is assumed not to cause less avoidance, and low-efficacy does not impact business closures or avoidance. This avoids the potential for having to model further interactions between the causal factors and cases/death. As illustrated above, these other causal factors can have serious implications for economic growth (see Walmsley et al., 2020a).

one by the authors of this chapter, have focused on mandatory closures and generally found the impacts on GDP to be in the range of 20 to 25% for closure scenarios similar to those that took place (see del Rio-Chanona et al., 2020; Mandel and Veetil, 2020; OECD, 2020; Walmsley et al. 2021a). Dixon et al. (2020), using a quarterly dynamic CGE model, explored the macroeconomic impacts of COVID-19 concerning several drivers over a two-year time horizon. They estimated a 19% reduction in GDP at the trough of the economic downturn at the end of the first quarter of 2020 and a 12% decline by the end of the second quarter. They incorporated our estimates of telework and also included government expenditures on health care and some countervailing fiscal policies, such as unemployment compensation and tax relief, all of which dampen the negative impacts. CBO (2020) estimates that real GDP would decline by 11% in the second quarter of 2020, resulting in the number of people employed being almost 26 million lower than the number in the fourth quarter of 2019. If this rate were to continue, the decline in U.S. real GDP for the year was projected to be up to 38% on an annual basis; however, given the reopenings, the overall annual decline was projected to drop to 5.4%.

9.3. Limitations

This is a short-run study of the impact of the pandemic over the period 2020 to 2023 using data collected or estimated for that period. While we partially examine the impact of higher and lower efficacy of intervention scenarios on the labor force and health care, we do not consider the potential ramifications of these or other alternative scenarios on mandatory closures and avoidance. In addition, we do not take into account the impact of a long-term decline in labor due to longer-term illness, or "long COVID," or the potential for behavior changes, such as teleworking and avoidance of certain activities, to become more permanent. Nor do we include a measure of the total value of lives lost.

Our results should be considered upper-bound estimates for several reasons. First, we have assumed that reductions in business output are accompanied by reductions in wages and salaries paid as people become unemployed, though some businesses continued paying their employees. Second, we have omitted some sources of business resilience, such as the use of inventories, relocation (e.g., haircuts in parking lots), and the internet (e.g., education) to continue to help produce goods and services (Rose, 2017; Dormady et al., 2019). We also do not consider the increase in demand for communications due to the increased use of the internet and remote working. Finally, we only include avoidance and pent-up demand in 2020 and 2021. The extent to which avoidance may continue is uncertain, but further increases in pent-up demand spending that are likely to occur in the latter part of 2021 and into 2022 are not considered.

We also acknowledge the limitations of our model and its application, as well as of our assessment on how they bear on the results. As is the case in most GTAP-based analyses, we assume that, except for factor markets, all other markets clear and firms are perfectly competitive. In addition to unemployment, factors of production are also assumed to be immobile across sectors within six months, consistent with this paper focusing on very short-run impacts of the pandemic. Our results also rely on the estimated elasticities taken from the literature and used in the GTAP database. Although we calculated the expected changes in government savings (deficit) and private household savings separately for our decomposition, for modelling purposes these changes had to be aggregated into a single change in domestic savings, as the model does not separately identify government savings (deficit) and private household savings.

10. Conclusion

We applied a dynamic CGE model to estimate the economic consequences of COVID-19 over eight semi-annual periods from 2020-2023. A baseline scenario in which the COVID pandemic is assumed not to occurwas first established based on pre-pandemic growth forecasts. The COVID pandemic was then incorporated into the model and compared to baseline growth. The various causal factors of the pandemic were added sequentially to decompose their contributions to the overall impact of COVID on the U.S. economy. These causal factors include the mandatory closure of businesses and gradual reopenings, the avoidance of workplace and various activities (such as restaurant dining), the impact of deaths and illness on the labor force, the increase in hospitalizations and health care expenses, the fiscal stimulus implemented in 2020 and 2021, and the increase in pent-up demand once businesses were allowed to reopen. Sensitivity analysis was performed on disease spread in relation to various interventions relating to vaccine availability, efficacy, and take-up. The decomposition of the influence of various causal factors will help policymakers make adjustments to offset the negative influences and reinforce the positive ones during the remainder of this pandemic and in anticipation of future ones.

The major results of this decomposition are:

- The largest losses from COVID were associated with the mandatory closure of businesses and the slow reopening process, followed by the avoidance of workplace and other activities by households.
- While deaths and illnesses resulted in a minimal decline in real GDP, primarily due to the decline in demand caused by the declining population, the increase in demand for health care led to a rise in real GDP.
- Pent-up demand is a significant factor in the recovery process, raising growth ever closer to the original baseline growth.
- Early rounds (1-4) of fiscal policy were very helpful in alleviating some of the losses in economic growth due to mandatory business closures, avoidance, and other causal factors. The benefits of the last round of fiscal policy are considerably lower, and even negative, compared to earlier rounds due to crowding out of private investment and need for businesses to repay loans.

Several areas future research present themselves. Prime example would be developing future scenarios involving new variants, more effective vaccines, and more effective anti-viral treatments. Another would be conducting surveys to ascertain the long-term impact of avoidance and changes in the way people work. Survey research can also be extended to improve the accuracy of estimates of pent-up demand by major consumption categories. An additional topic area would be to examine the macroeconomic consequences of supply-chain bottlenecks caused by the pandemic.

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Appendix A. Appendix to Section 2

Population estimates from the U.S. Census Bureau (2019, July) were used to determine the benchmark demographic composition of U.S. adults, by sex and age, race/ethnicity, income, education level, and state of residency. Joint distribution of sex by age is presented since sex and age are not independent, i.e., population ratio of males to females varies by age.

Observed distributions of sample demographics are similar to U.S. Census estimates of the adult population but do not match exactly. To obtain a weighted sample more representative of the U.S. population, we calculated sampling weights from the observed sample percentages and the population benchmark percentages.

We used the sampling weights reported in Tables A-1 through A-5 to construct a weighted sample that assigns a weight to each of the N=1328 cases determined as the product of the sampling weights (SW) of the six matching variables: sex by age, race/ethnicity, income, education, and state of residency.

$$SW = SW_{sex\ X\ age} * SW_{race/ethnicity} * SW_{income} * SW_{education} * SW_{state\ of\ residency}$$

The computed sampling weights allow us to construct a sample to adjust the observed sample to match exactly the marginal distributions of the U.S. adult population. Overall, the majority of sampling weights reported in all five tables are close to 1.0, indicating that the sample recruited through Prolific was representative of the U.S. adult population for sex, age, race/ethnicity, income, education, and state of residency. For those groups over-sampled or under-sampled, the weighted sample constructed from the sampling weights results in a representative sample that matches the U.S. adult population.[15]

Table A-1. Sample Joint Distribution by Sex and Age, Benchmark Percentages, and Sampling Weights

	Sample Distribution										Sampling Weights	
	Frequency				Observed Percentage			Benchmark Percentage				
Age	M	F	U	Total	M	F	Total	M	F	Total	M	F
18-29	128	124	6	258	9.7%	9.4%	19.4%	10.7%	10.3%	21.0%	1.10	1.09

[15] Examples where sampling weights corrected discrepancies between the observed sample and the benchmark population include the following:

1. Older adults (70+), and particularly females 70 and over, were under-sampled.
2. Hispanic adults were under-sampled.
3. Low income (under $10K) and high income (over $150K) adults were under-sampled.
4. Adults with a high school diploma (or less) were under-sampled, and adults with a four-year college degree (or more) were over-sampled.
5. Various over- and under-sampling by state of residency

30-39	139	117	4	260	10.6%	8.9%	19.6%	8.7%	8.6%	17.3%	0.82	0.96
40-49	105	106	1	212	8.0%	8.1%	16.0%	7.9%	8.0%	15.9%	0.99	0.99
50-59	111	113	3	227	8.5%	8.6%	17.1%	8.0%	8.4%	16.4%	0.95	0.98
60-69	115	162	0	277	8.8%	12.3%	20.9%	7.2%	7.9%	15.1%	0.82	0.64
70+	52	42	0	94	4.0%	3.2%	7.1%	6.2%	8.2%	14.4%	1.57	2.55
Total	650	664	14	1328	49.5%	50.5%	100.0%	48.7%	51.3%	100.0%		

Sampling weights are the ratio of benchmark population % to observed sample %. (M=Male, F=Female, U=Unknown/Other). Participants with unknown sex were assigned sampling weights of 1.00.

Table A-2. Sample Distribution by Race/Ethnicity, Benchmark Percentages, and Sampling Weights

	Sample Distribution			
Race/Ethnicity	**Frequency**	**Observed Percentage**	**Benchmark Percentage**	**Sampling Weights**
White, Non-Hispanic	944	71.19%	59.95%	0.84
Black or African American	161	12.14%	12.37%	1.02
American Indian or Alaska Native	5	0.38%	0.68%	1.81
Asian	93	7.01%	5.61%	0.80
Pacific Islander or Native Hawaiian	1	0.08%	0.17%	2.28
Hispanic	81	6.11%	17.77%	2.91
Multi-Racial	41	3.09%	3.45%	1.11
Unknown	2	NA	NA	1.00
Total	1328	100.00%	100.00%	

Note. Sampling weights are the ratio of benchmark population % to observed sample %. Participants with unknown race/ethnicity were assigned sampling weights of 1.00.

Table A-3. Sample Distribution by Income, Benchmark Percentages, and Sampling Weights

	Sample Distribution			
Income	**Frequency**	**Observed Percentage**	**Benchmark Percentage**	**Sampling Weights**
< $10k	41	3.14%	5.80%	1.84
$10k - $49,999k	446	34.20%	32.60%	0.95
$50k - $99,999k	495	37.96%	30.20%	0.80

$100k - $149,999k	195	14.95%	15.70%	1.05
> $150k	127	9.74%	15.70%	1.61
Unknown	24	NA	NA	1.00
Total	1328	100.00%	100.00%	

Note. Sampling weights are the ratio of benchmark population % to observed sample %. Participants with unknown income were assigned sampling weights of 1.00.

Table A-4. Sample Distribution by Education, Benchmark Percentages, and Sampling Weights

	Sample Distribution			
Education	**Frequency**	**Observed Percentage**	**Benchmark Percentage**	**Sampling Weights**
No high school diploma	13	0.98%	11.39%	11.64
High school graduate (includes equivalency)	113	8.51%	26.89%	3.16
Some college, no degree	267	20.11%	19.97%	0.99
Associate's degree	134	10.09%	8.62%	0.85
Bachelor's degree	500	37.65%	20.33%	0.54
Graduate or professional degree	301	22.67%	12.79%	0.56
Total	1328	100.00%	100.00%	

Note. Sampling weights are the ratio of benchmark population % to observed sample %.

Table A-5. Sample Distribution by State of Residency, Benchmark Percentages, and Sampling Weights

	Sample Distribution			
State	**Frequency**	**Observed Percentage**	**Benchmark Percentage**	**Sampling Weights**
Alabama	13	0.98%	1.49%	1.53
Alaska	1	0.08%	0.22%	2.87
Arizona	26	1.96%	2.21%	1.13
Arkansas	17	1.28%	0.91%	0.71
California	138	10.39%	11.99%	1.15
Colorado	26	1.96%	1.76%	0.90
Connecticut	11	0.83%	1.11%	1.34

DC	2	0.15%	0.23%	1.50
Delaware	2	0.15%	0.30%	2.00
Florida	120	9.04%	6.76%	0.75
Georgia	47	3.54%	3.18%	0.90
Hawaii	3	0.23%	0.44%	1.94
Idaho	10	0.75%	0.52%	0.70
Illinois	49	3.69%	3.86%	1.05
Indiana	23	1.73%	2.02%	1.17
Iowa	12	0.90%	0.95%	1.05
Kansas	4	0.30%	0.87%	2.88
Kentucky	17	1.28%	1.36%	1.06
Louisiana	13	0.98%	1.40%	1.43
Maine	8	0.60%	0.43%	0.71
Maryland	27	2.03%	1.85%	0.91
Massachusetts	34	2.56%	2.19%	0.86
Michigan	38	2.86%	3.07%	1.07
Minnesota	15	1.13%	1.70%	1.50
Mississippi	6	0.45%	0.89%	1.97
Missouri	24	1.81%	1.87%	1.03
Montana	5	0.38%	0.33%	0.87
Nebraska	7	0.53%	0.57%	1.08
Nevada	18	1.36%	0.94%	0.69
New Hampshire	6	0.45%	0.43%	0.96
New Jersey	36	2.71%	2.72%	1.00
New Mexico	5	0.38%	0.64%	1.69
New York	106	7.98%	6.04%	0.76
North Carolina	43	3.24%	3.21%	0.99
North Dakota	2	0.15%	0.23%	1.51
Ohio	58	4.37%	3.57%	0.82
Oklahoma	14	1.05%	1.18%	1.12
Oregon	19	1.43%	1.31%	0.92
Pennsylvania	62	4.67%	3.98%	0.85
Rhode Island	3	0.23%	0.33%	1.48
South Carolina	21	1.58%	1.58%	1.00
South Dakota	1	0.08%	0.26%	3.47
Tennessee	20	1.51%	2.09%	1.38
Texas	103	7.76%	8.46%	1.09
Utah	4	0.30%	0.89%	2.96
Vermont	2	0.15%	0.20%	1.33
Virginia	33	2.48%	2.61%	1.05
Washington	44	3.31%	2.33%	0.70
West Virginia	4	0.30%	0.56%	1.86
Wisconsin	26	1.96%	1.78%	0.91
Wyoming	0	0.00%	0.17%	NA
Total	1328	100.00%	100.00%	

Note. Sampling weights are the ratio of benchmark population % to observed sample %.

Appendix B. Appendix to Section 3

B1. Summary of Expert Interviews

We conducted 12 interviews with experts from variable backgrounds including scientists in the field of public health and epidemiology from the United States, Canada, and the United Kingdom; health officials from state- and federal-level government institutions in the United States; and clinicians in the United States. The convenience sample was assembled from experts who work in academic, public, and clinical settings, and who have published work on COVID-19. Interviews focused on specific issues of interest where literature (at the time of modeling) was limited, including the effectiveness of social distancing, the likely behavioral response of the public, and the ability of the health care system to handle excessive numbers of COVID-19 patients during pandemic peaks.

Due to the evolving nature of the COVID-19 pandemic and the limited availability of strong data regarding intervention effectiveness, experts were consulted on both the parameters used in our model and on possible additions that should be accounted for. Two parameter changes we made on expert advice are of note.

Multiple interviewees suggested that we account for the effects of seasonality on the effective reproductive number. To account for this variable, we implemented monthly adjustments to the reproductive number based on Gavenčiak et al. (2021).

Multiple interviewees also recommended that we distinguish between younger and older individuals due to the large differences in mortality and hospitalization risks as well as the differences in behavioral responses to the pandemic. It was noted that some interventions, including stay-at-home orders, experienced differing compliance between age groups (CDC, 2020a). While more granular modeling is possible, the dichotomous distinction between the population under 65 and the population 65 and older has been sufficient for the outcome of interest in the employed model. Parameters including hospitalization rate, infection fatality rate, and vaccine hesitancy were age-stratified.

B2. Estimating the Number of Infected International Travelers

COVID-19 was initially introduced to the U.S. through international travel (CDC, 2020c). Our model estimates the number of international travelers entering the United States on any given day from 6 regions – the Americas, Africa, Europe, Middle East, Western Pacific, and South and Southeast Asia. Our model utilizes historical estimates for the percentage of travelers from each region and predicts each traveler’s likelihood of carrying COVID-19 to determine the likely number of COVID-19 cases entering the country.

International travel trends for the 2.5 years included in the model are adjusted based on domestic travel reduction trends in 2019 and 2020 (Bureau of Transportation Statistics, 2021; International Trade Administration, 2021), referred to as the coefficient reduction due to travel avoidance (we abstract from international travel restrictions, which affected the numbers of international travelers unevenly. The incoming travelers are then split into two age groups: travelers under 65 and travelers over 65 based on historical estimates of traveler demographics (it is, however, possible that older travelers reduced international travel to a higher degree than younger ones).

We draw on I-94 statistics (International Trade Administration, 2021) and develop a model of infection risk as well as an adjustment for lower travel volumes due to avoidance behavior. We utilize domestic traveler data from 2019 and 2020 from the Bureau of Transportation Statistics to determine how many fewer international travelers would have come to the United States, had there not been travel restrictions in other countries (their effects were not modeled explicitly due to their time-varying nature and limited effect given the magnitude of domestic infection counts). Using these data, we determine a coefficient reduction (as a faction of 2020 travel relative to 2019 volumes). For 2021 and 2022, we estimate a stepwise growth in international travel based on estimates by the U.S. Travel Association (2021). The calculation of coefficient reductions for each month between January 2020-June 2022 is shown in Table B-1.

Table B-1. Estimating International Traveler Volumes due to the COVID-19 Pandemic

Month	2019 International Travelers (total)	2019 Domestic Travelers (total)	2020 Domestic Travelers (total)	Coefficient Reduction (19 vs 20)	Coefficient Reduction (21 vs 19)	Coefficient Reduction (22 vs 19)
Jan	5,836,439	58,033,637	61,610,519	106.2%	46.5%	55.5%
Feb	5,091,485	55,679,100	59,849,890	107.5%	47.0%	56.0%
Mar	6,258,503	70,234,011	34,410,743	49.0%	47.5%	56.6%
Apr	7,044,707	66,938,177	2,877,134	4.3%	48.0%	57.2%
May	6,703,974	71,365,029	8,238,474	11.5%	48.5%	57.8%
Jun	6,326,970	72,789,897	16,207,341	22.3%	48.9%	58.4%
Jul	7,702,922	75,281,255	22,878,828	30.4%	49.4%	
Aug	8,114,715	72,715,907	23,910,297	32.9%	49.9%	
Sep	6,703,451	63,979,337	23,854,435	37.3%	50.4%	
Oct	6,687,063	69,922,300	28,026,462	40.1%	50.9%	
Nov	6,095,118	64,816,897	26,293,043	40.6%	51.4%	
Dec	6,876,248	69,718,719	27,263,496	39.1%	51.9%	
Total	79,441,595	811,474,266	335,420,662	41.3%	49.2%	56.9%

Next, we divide countries of travel origin based on the WHO (2021) and U.N. World Tourism Organization's classification: Americas, Africa, East Asia and Pacific, Europe, Middle East, and South and Southeast Asia. Using data from the (WHO, 2021), the percentage of individuals infected with COVID-19 within each region per month was estimated, which allowed us to calculate the likelihood of a traveler from that region being infectious upon entry to the U.S.

As Figure B-1. shows, Europe had the largest risk of infection among travelers to the United States for most of 2020 while Africa had the least. For periods when data were not yet available (starting in April

2021 at the time of modeling, shaded in the figure), we estimated 10% monthly decrements of a moving average from the previous 6-month period, resulting in near-complete elimination of the risk of infection by June 2022 (0.03% for a traveler from the Americas, 0.02% from South (East) Asia, and 0.01% or less for travelers from the Middle East, Europe, and East Asia/Pacific.

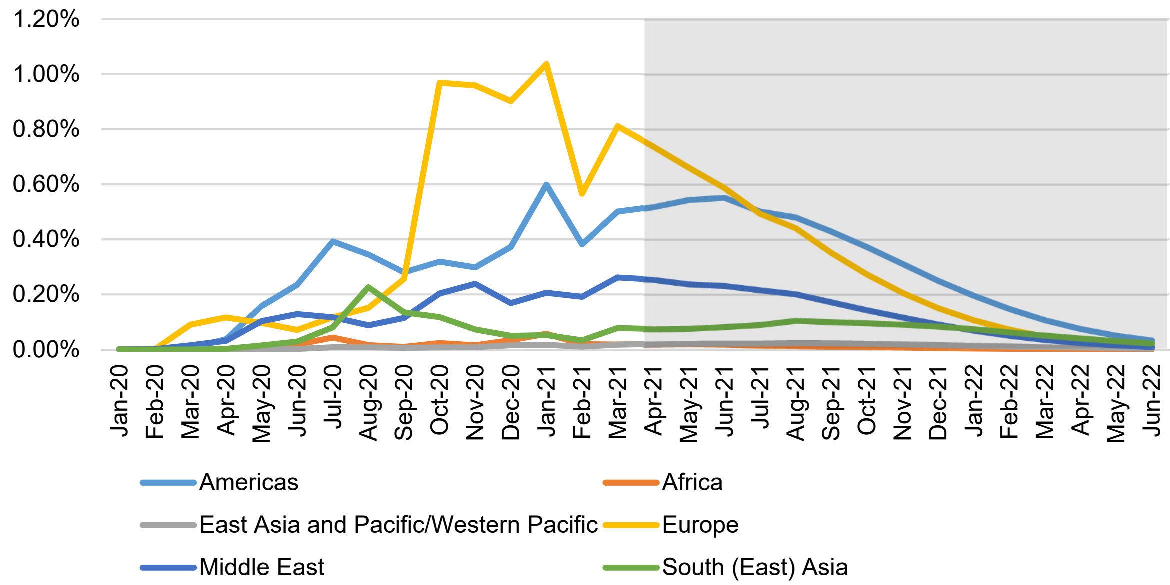


Figure B-1. Probability of Infection by Region, by Month

Following this, we combine these estimates to determine the likely number of infected travelers by region entering the United States on any given day. Initially, the most infected travelers came from Europe, similar to conclusions by Gonzalez-Reiche et al. (2020), who suggest that most index cases of the March 2020 New York State outbreak originated in Europe. Figure B-2. shows the estimated numbers of daily infectious travelers entering the United States by region of origin.

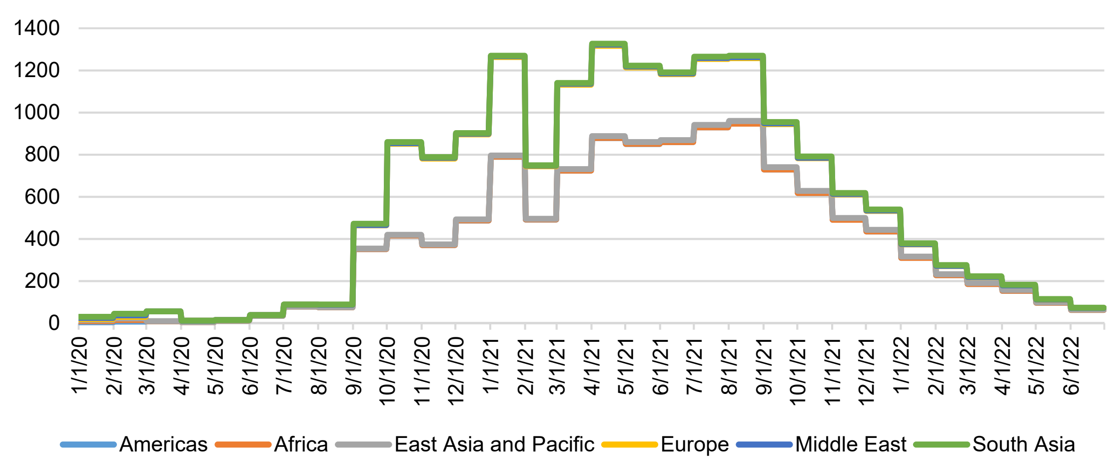


Figure B-2. Estimates of Infected International Travelers Entering the U.S. (Daily Average by Month)

B3. Vaccination projections

Vaccination projections for the period starting at the beginning of the model (January 1, 2020) and ending on August 12, 2021, of the model were drawn from CDC vaccination data and based on a delay period after vaccination, vaccine effectiveness, and an assumption on the number of vaccinated individuals who had already been conferred immunity through previous infection.

Vaccine effectiveness (VE) was assumed as 90% based on a CDC real-world analysis of the Pfizer and Moderna mRNA vaccines (CDC, 2021d); the effectiveness of the Johnson & Johnson vaccine was not incorporated due to a lack of data on the exact breakdown of administered vaccines by day and the assumption that the vaccine was not prevalently used (Follow et al., 2021). We accounted for individuals being vaccinated who were already conferred immunity from a previous infection by weighting the number of vaccinations (v) given by the proportion of the population susceptible to disease (S) out of all initially susceptible (S_0), as shown in the equation below.

$$S \rightarrow Effectively\ vaccinated = v * VE * \frac{S}{S_0}$$

From August 13, 2021 of the model until the end of the model (July 31, 2022), we halted data scraping from the CDC and stipulated that the number of individuals transitioning from susceptible to vaccinated on a given day was equal to the average of model days August 6, 2021 through August 12, 2021 (a 7-day average) until the population that had undergone vaccination (including those determined to have had an "ineffective" vaccination regimen) was equal to the population expected to be vaccinated (Kapteyn & Gutsche, 2021).

B4. Reduction in R0 in each scenario

In *Figures B-3a/b/c/d*, we show the percentage reduction in R0 for each week of 2020 and months of 2021/2022 modeled in the four scenarios.

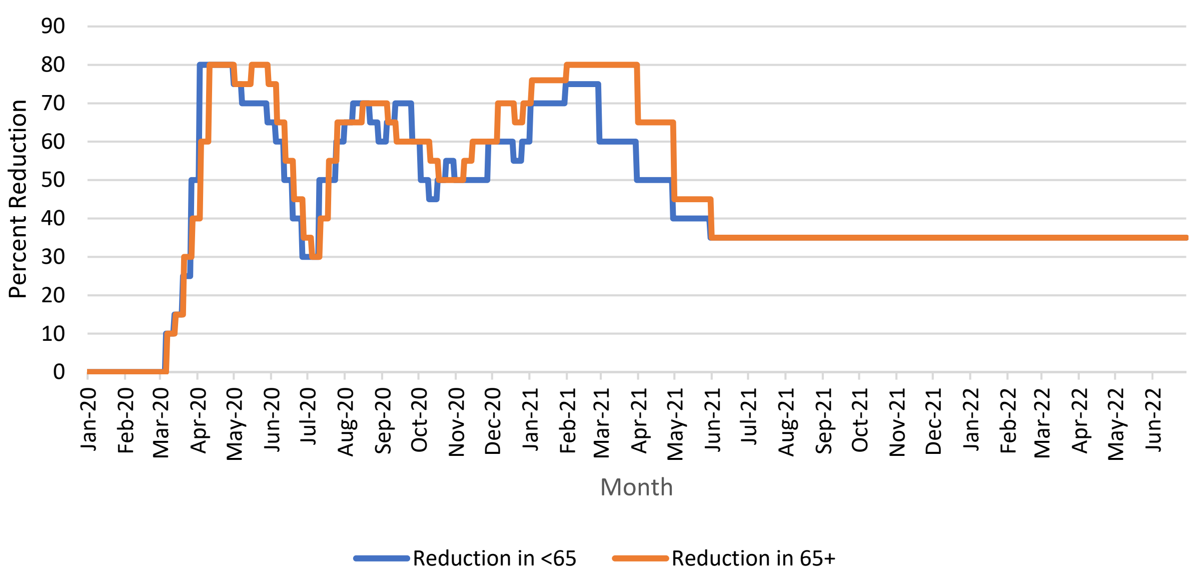


Figure B-3a: Scenario 1 - Percent Reductions in R_0 for 2020-22

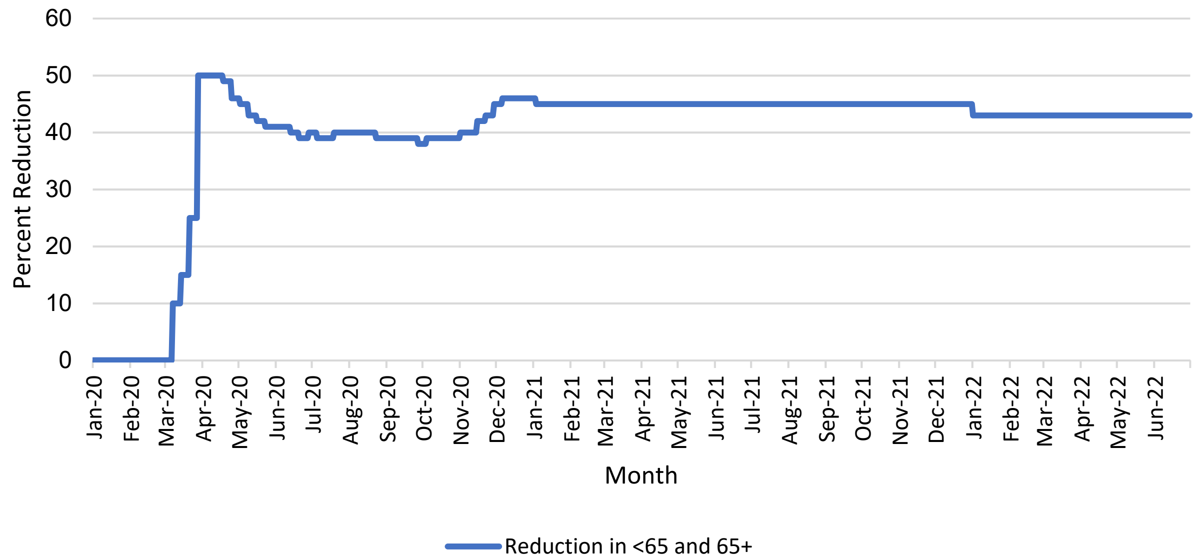


Figure B-3b: Scenario 2 - Percent Reductions in R_0 for 2020-22

Percentage reduction estimates in scenario 2 were calibrated to approximate deaths due to influenza deaths in the United States over a comparable period. We use CDC data (CDC, 2020b) to calculate the mean number of influenza deaths over 2.5 years:

Table B-2. Deaths Caused by Influenza from 2015 to 2020

Year	Deaths <65	Deaths 65+	Total
2015-2016	5,248	17,458	22,706
2016-2017	5,396	32,833	38,229
2017-2018	10,197	50,903	61,100
2018-2019	8,603	25,555	34,158
2019-2020	8,236	13,673	21,909
Means (per year)	7,536	28,084	35,620
Mean estimate over 2.5 years	18,840	70,211	89,051

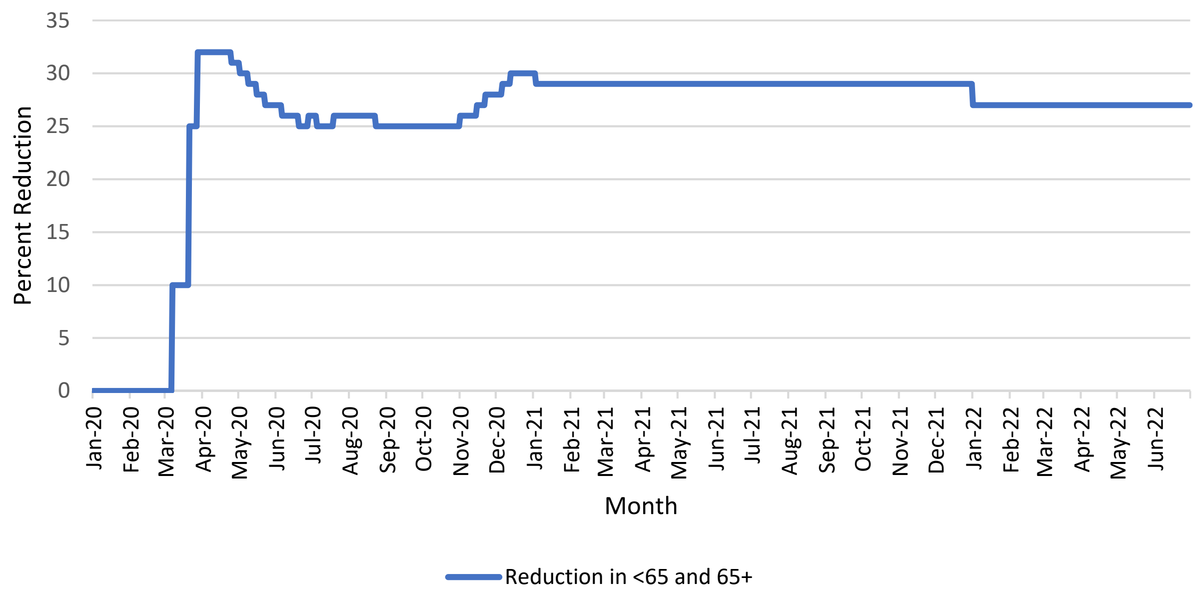


Figure B-3c: Scenario 3a - Percent Reductions in R_0 for 2020-22

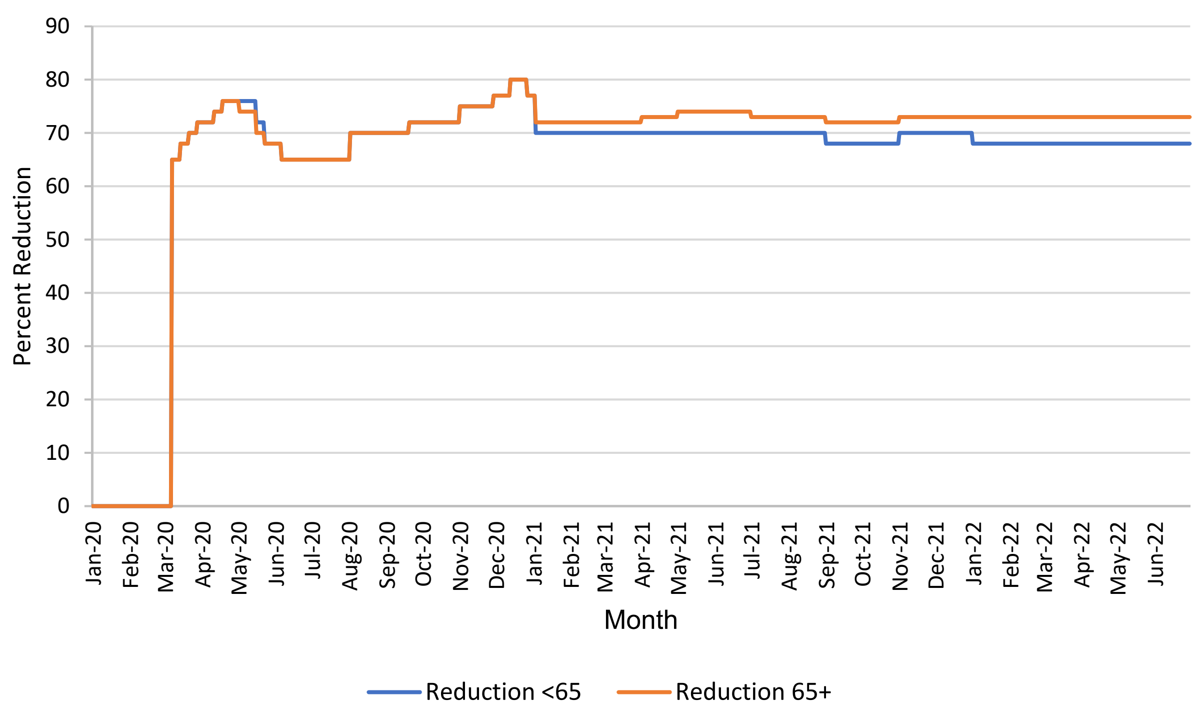


Figure B-3d: Scenario 3b - Percent Reductions in R_0 for 2020-22

B5. Viral Seasonality

Liu et al. (2021) showed that the transmission rate of COVID-19 was time-dependent and cyclical, with reductions during the warm season in the Northern Hemisphere of 46.38 ± 29.10% (Liu et al., 2021). We draw on seasonality adjustments estimated by Gavenčiak et al. (2021), calculated for 143 European regions, and assume the reductions apply similarly in the United States.

B6. Estimates of Hospitalizations and Deaths by Scenario, Period, and Age

Table B-3: Age-stratified Estimated Hospitalizations due to COVID-19 in each 6 Months (in millions)

	Hospitalizations <65				Hospitalizations 65+			
Scenario:	1	2	3a	3b	1	2	3a	3b
H1/2020	863.8	187.9	5,963.7	3,746.8	714.0	128.9	7,546.6	3,671.5
H2/2020	1,493.3	64.0	561.6	1,528.8	1,399.3	51.5	1,679.9	3,906.4
H1/2021	1,352.7	112.5	10.3	45.9	958.6	63.2	8.6	141.7
H2/2021	133.9	49.2	7.8	11.0	364.9	19.5	5.7	7.7
H2/2022	99.1	158.3	2.8	6.0	1,559.3	29.9	2.2	3.9
Total	3,942.8	571.9	6,546.1	5,338.5	4,996.1	293.1	9,243.0	7,731.2

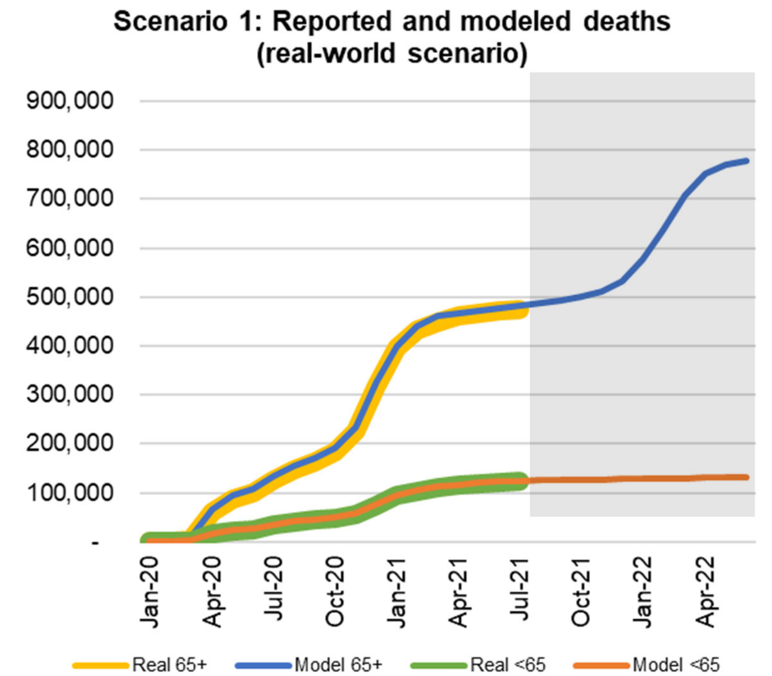
Note: Sums of semi-annual periods may not equal total due to rounding. These are model estimates.

Table B-4: Age-stratified Estimated Deaths from COVID-19 in each 6 Months (In millions)

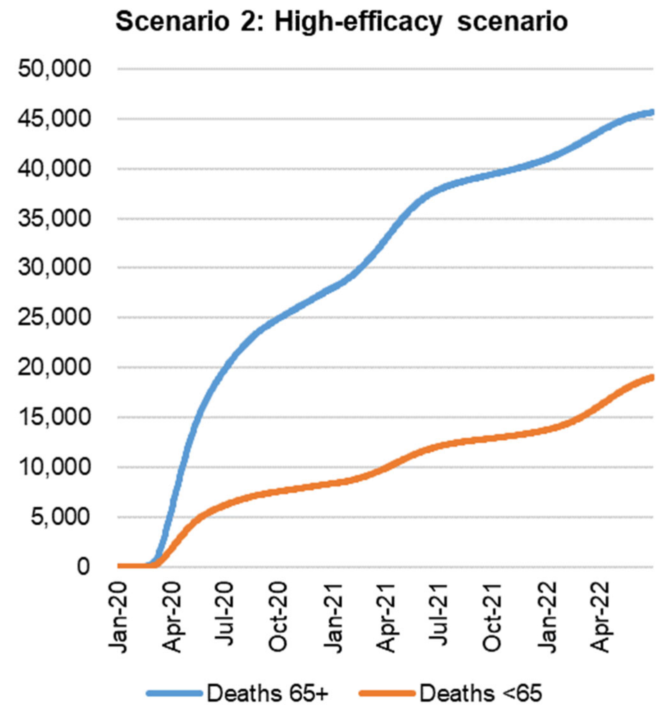
	Deaths <65				Deaths 65+			
Scenario:	1	2	3a	3b	1	2	3a	3b
H1/2020	28.3	6.2	228.4	128.3	109.7	19.8	1,397.8	599.4
H2/2020	48.2	2.2	24.1	56.4	209.8	8.2	339.5	692.6
H1/2021	47.0	3.7	.3	1.6	158.5	9.9	1.4	23.7
H2/2021	4.7	1.7	.3	.4	54.4	3.1	.9	1.2
H1/2022	3.4	5.3	1	.204	245.6	4.7	.4	.6
Total	131.6	19.1	253.2	186.8	778.0	45.6	1,739.9	1,317.5

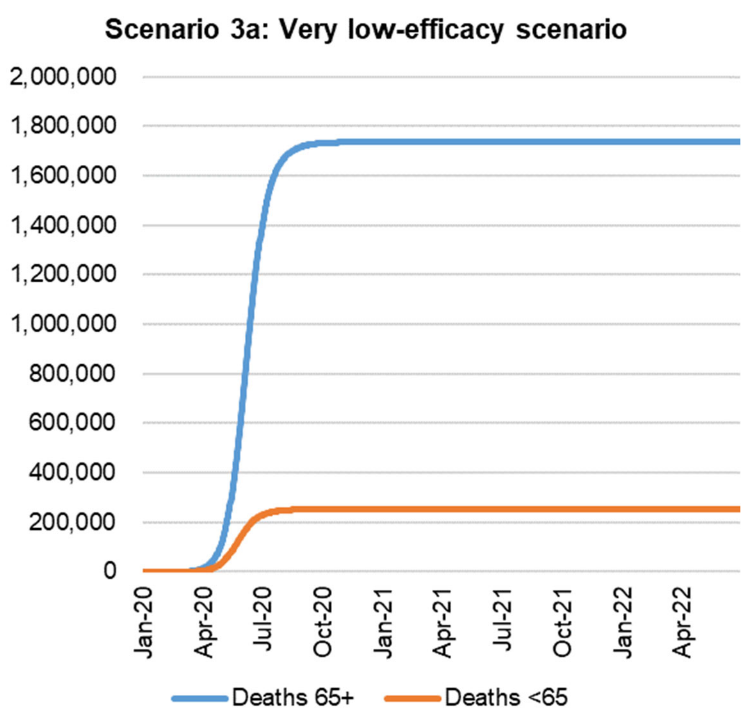
Note: Sums of semi-annual periods may not equal total due to rounding.

We indicate how cumulative deaths differ by scenario and between the age-stratified groups in Figure B-4.



Note: We assume a constant 35% reduction in the effective R-value due to behavioral interventions starting in July 2021 (shaded area).





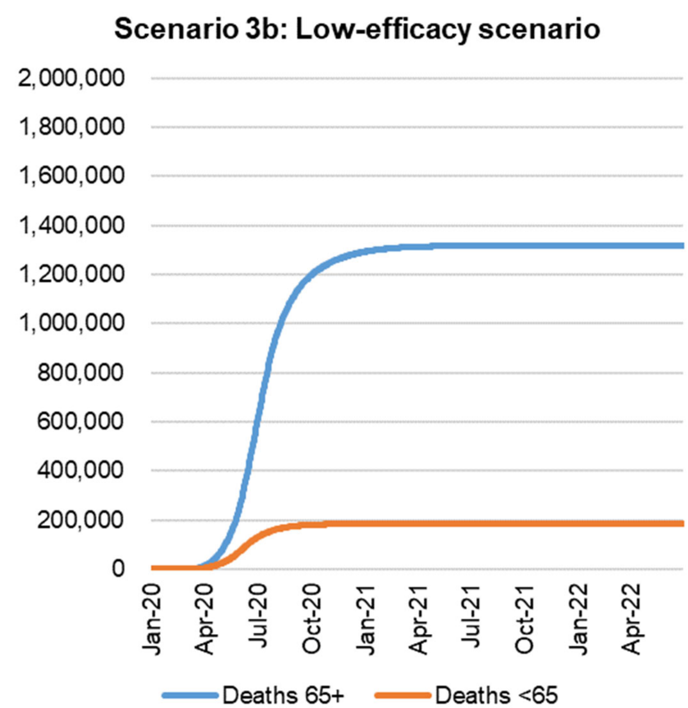


Figure B-4. Graphs of Cumulative Predicted Deaths for the 4 Scenarios

Appendix C. Appendix to Section 4

Table C-1. Percentage Reduction of Output by Sector due to Mandatory Closure and Reopening Process (with Telecommuting)

#	Sector	Mandatory Closure Category[a]	% Reduction in U.S. annual GDP by sector due to mandatory closures after factoring in telework		% Reduction in U.S. annual GDP by sector due to phased-in reopening after factoring in telework		
			2020_1	2020_2	2020_1	2020_2	2021_1
1-25	Agriculture, Fishing, and Forestry; Mining; Food Processing	3	0.00%	0.00%	0.00%	0.00%	0.00%
26	Beverages and Tobacco products	2	2.90%	0.00%	1.30%	0.00%	0.00%
27	Manufacture of textiles	1	10.60%	0.00%	5.70%	0.01%	0.00%
28	Manufacture of wearing apparel	1	14.10%	0.00%	5.60%	0.02%	0.00%
29	Manufacture of leather and related products	1	14.10%	0.00%	5.60%	0.02%	0.00%
30	Lumber	3	0.00%	0.00%	0.00%	0.00%	0.00%
31-34	Paper and Paper Products; Petroleum and Coke Products; Manufacture of chemicals and products; Manufacture of pharmaceuticals, medicinal chemical, and botanical products	3	0.00%	0.00%	0.00%	0.00%	0.00%
35	Manufacture of rubber and plastic products	1	11.50%	0.02%	5.50%	0.02%	0.00%
36	Manufacture of other non-metallic mineral products	1	12.00%	0.01%	5.50%	0.02%	0.00%
37	Iron & Steel: basic production and casting	3	0.00%	0.00%	0.00%	0.00%	0.00%
38, 39	Non-Ferrous Metals; Manufacture of fabricated metal products	3	0.00%	0.00%	0.00%	0.00%	0.00%
40	Manufacture of computer, electronic and optical products	1	13.80%	0.01%	5.70%	0.01%	0.00%
41-44	Manufacture of electrical equipment, machinery and equipment, and transport equipment	3	0.00%	0.00%	0.00%	0.00%	0.00%
45-47	Other Manufacturing: includes furniture	1	12.70%	0.01%	5.50%	0.03%	0.00%
46-48	Electricity; Gas manufacture, distribution; Water supply; sewerage, waste management and remediation activities	3	0.00%	0.00%	0.00%	0.00%	0.00%
49	Construction	2	2.90%	0.00%	1.70%	0.01%	0.00%
50	Wholesale and retail trade; repair of motor vehicles and motorcycles	2	5.40%	0.01%	2.50%	0.01%	0.00%
51	Accommodation, Food and service activities	2	9.30%	0.02%	5.10%	7.44%	4.52%
52	Land transport and transport via pipelines	2	2.20%	0.00%	1.00%	0.15%	0.00%
53	Water transport	2	4.70%	0.00%	2.60%	0.28%	0.00%
54	Air transport	2	8.30%	0.01%	4.50%	0.51%	0.00%

55	Warehousing and support activities	3	0.00%	0.00%	0.00%	0.00%	0.00%
56	Information and communication	2	0.50%	0.00%	0.50%	0.00%	0.00%
57	Other Financial Intermediation: auxiliary activities but not insurance and pensions	2	1.40%	0.00%	1.40%	0.00%	0.00%
58	Insurance	3	0.00%	0.00%	0.00%	0.00%	0.00%
59	Real estate activities	1	7.50%	0.01%	7.70%	0.59%	0.00%
60	Other Business Services not elsewhere classified	2	5.10%	0.01%	5.10%	0.40%	0.00%
61	Recreation & Other Services	1	10.30%	0.01%	14.80%	23.32%	15.00%
62	Other Services (Government)	2	3.60%	0.01%	1.90%	0.13%	0.00%
63	Education	1	4.10%	0.01%	8.10%	10.06%	6.02%
64	Human health and social work	3	0.00%	0.00%	0.00%	0.00%	0.00%
65	Dwellings: imputed rents of owner-occupied dwellings	3	0.00%	0.00%	0.00%	0.00%	0.00%

[a] Mandatory Closure Categories:
1. Sector is entirely non-essential and thus is completely shut down.
2. Sector for which only some subsectors are non-essential (see notes in the last column).
3. Sector that is essential and thus still able to operate in its usual manner to the extent possible.

Table C-2. COVID per Patient Health Expenses by Treatment Category and by Age Group

Age Group	Hospital Cost		Outpatients (with mild symptoms)
	Non-ICU	ICU	
0-19	$15,620	$55,542	$91
20-64	$15,430	$54,866	$57
65+	$16,758	$59,587	$96
Weighted Average	$16,131	$56,677	$67

Source: calculated based on Bartsch et al. (2020) and Fusco et al. (2021)

Table C-3. COVID Total Health Expenditures (in millions of 2020 dollars)

Scenario	Outpatient	Hospitalizations - Non-ICU	Hospitalizations - ICU	COVID Health Expenses	% of Total Annual Output of GTAP Health Sector
Scenario 1	6,211	125,952	82,265	214,427	8.35%
Scenario 2	789	11,312	7,903	20,004	0.78%
Scenario 3a	10,559	212,972	142,086	365,617	14.23%
Scenario 3b	8,662	176,103	115,678	300,443	11.70%

Table C-4. COVID per Patient Lost Productivity (in days)

Age Group	Hospital LOS		Productivity Days Loss		Outpatient	
	Non-ICU	ICU	Non-ICU	ICU	Productivity Days Loss	Additional Days in Isolation
0-19	4.0	9.4	11.5	18.9	1.5	8.5
20-64	6.0	14.1	13.5	23.6	1.9	8.1
65+	7.0	16.6	14.5	26.1	5.3	4.7

Sources: Calculations based on Prager et al. (2017), Chen et al. (2020), Zhou et al. (2020), Fusco et al. (2021), and Walmsley et al. (2021).

Table C-5. Lost Productivity Due to Own COVID Illness and Caring for Sick Family Members from COVID (in thousands of days)

Scenario	Outpatient Medical Treatment	Hospitalizations Non-ICU	Hospitalizations ICU	Fatalities	Total
Scenario 1	392,153	78,665	25,350	113,700	609,868
Scenario 2	48,507	7,384	2,514	8,083	66,488
Scenario 3a	669,611	138,956	45,412	249,136	1,103,115
Scenario 3b	549,885	115,291	37,348	188,049	890,572

Table C-6. Percentage Consumption Changes Compared to the "Lowest Level" after COVID by Commodity/Service Type and Mapping to CGE Sectors

Good/Service	2020.6	2020.9	2020.12	2021.3	2021.6	GTAP Sector	Share of GTAP Sector
Automobiles	79%	65%	20%	200%	200%	50 Wholesale and retail trade; repair of motor vehicles	5.5%
Real Estate	50%	60%	55%	50%		59 Real estate activities	100%
Air Travel	32%	37%	25%	72%	56%	54 Air transport	94.1%
Restaurant Dining	56%	55%	43%	119%	120%	51 Accommodation, Food and service activities	71.7%
Live Experiences (sporting events, concerts, etc.)	39%	35%	30%	65%	85%	61 Recreation & Other Services	16.5%
Apparel	72%	56%	66%	143%	148%	50 Wholesale and Retail Trade; Repair of Motor Vehicles	4.1%
General Merchandise	67%	22%	19%	158%	142%	50 Wholesale and Retail Trade; Repair of Motor Vehicles	6.8%
Hotels and other Hospitality	45%	49%	54%	79%	81%	51 Accommodation, Food and Service Activities	16.8%
Wellness and Fitness	54%	38%	12%	106%	96%	61 Recreation and Other Services	3.0%

Appendix D. Appendix to Section 5

Each bill was broken down into several provisions. The cost of each provision was determined based on the text of the bill or projections by the Congressional Budget Office (CBO). Cash payments to individuals and enhanced unemployment insurance benefits were assumed to benefit households. Other provisions were matched to the most appropriate GTAP sector.

For most stimulus provisions, we assume the federal government spends the stimulus funds over time rather than at once. The CBO provides estimates of the direct cost of each provision, measured as an increase in spending or decline in revenue, yearly for the next 10 years. In the dynamic CGE model, the effects of the stimulus are estimated every six months. Annual CBO cost estimates are converted to semiannual figures for each provision by assuming an even distribution over a given year after accounting for the date that the related stimulus bill was passed. Some of the CBO cost estimates are implemented after 2023 and hence do not enter our simulations, but 98% of the fiscal stimulus spending is estimated to take place before then. Table D-1 shows how the funds were implemented into the model over time.

Funding for the PPP was assigned to various GTAP sectors based on loan disbursement breakdowns published by the Small Business Administration (SBA, 2020a). The initial $342 billion provided by the CARES Act for PPP was apportioned to corresponding GTAP sectors based on loan approvals through April 16, 2020, when the initial PPP funds had run out, but before the U.S. Congress had approved additional funds.[16]

The following assumptions are adopted when simulating the impacts of loans to businesses. The method used in the CGE simulations depends on the assumption of whether the sector/firm receiving the forgivable loans is open or closed for business. The distribution of loans is assumed to take place through the following two mechanisms:

- Option 1: As a direct payment to households when the intention is to give money directly to the workers or owners to survive a period when their business or place of work is closed. This is simulated as increased payments to households in the CGE modeling.

  Option 2: As a subsidy to businesses when the intention is to help the business stay open and keep producing, despite issues with sick workers and transition to telework. This is simulated as subsidies split between capital and labor using value-added shares for each sector in the CGE

[16] The allocation of PPP funds made available by the Paycheck Protection Program and Health Care Enhancement Act, which extended funding for the program, was based on the breakdown of approvals from April 16 to August 8, 2020, the last such report published by the SBA (2020b) that year. The distribution of the PPP loans from the third round of funding, provided in late December 2020, is based on the cumulative loan approvals for 2021 after subtracting funds earmarked for live entertainment venues ($15 billion). In the model, we assume all PPP loans are fully forgiven as Congress has greatly simplified the application process and relaxed the criteria for forgiveness.

modeling or where information on who the loans were intended for is available (e.g., workers or owners), this information was used to allocate the subsidy.[17]

Table D-1 depicts how the amounts for each provision over time for each of the 6 rounds were incorporated into the model as three rounds (1-4, 5, and 6) and for five major categories (Unemployment assistance; Assistance to households (direct payments and assistance); Government spending (Federal, State and Local); Assistance to businesses (e.g., loans) and Corporate tax relief). Not all rounds included all categories and increases in foreign aid and unallocated funds were not modeled.

Table D-1. Total Spending Amount by Round and Aggregate Category Modelled over Time

Round	Details	2020	2021	2022	2023	Post-2023 (or not captured)	Total
1-4	Unemployment Assistance	222.0	49.9	0.0	0.0	0.0	272.0
1-4	Direct Payments to Individuals	270.0	23.0	0.0	0.0	0.0	293.0
1-4	Assistance to individuals	216.1	110.1	-3.5	-2.2	-6.5	314.0
1-4	Government spending (Federal, State and Local)	348.4	234.7	82.9	23.1	9.0	698.2
1-4	Assistance to Businesses (e.g., Loans)	630.6	10.0	1.9	1.4	0.0	643.9
1-4	Corporate tax Relief	348.5	258.5	-174.0	-173.0	-56.0	204.0
1-4	Foreign aid					1.2	1.2
5	Unemployment Assistance	0.0	117.0	0.3	0.7	1.2	119.2
5	Direct Payments to Individuals	0.0	169.2	0.1	-0.1	-0.3	168.9
5	Assistance to individuals	0.0	36.8	0.3	0.1	0.2	37.4
5	Government spending (Federal, State and Local)	0.0	96.8	66.1	30.5	23.4	216.7
5	Assistance to Businesses (e.g., Loans)	0.0	315.7	6.8	0.2	-0.5	322.1
6	Unemployment Assistance	0.0	221.3	10.4	0.0	-0.1	231.6
6	Direct Payments to Individuals	0.0	393.7	16.9	0.0	0.0	410.6
6	Assistance to individuals	0.0	68.3	126.9	11.1	-3.8	202.5
6	Government spending (Federal, State and Local)	0.0	398.5	266.2	94.9	107.0	866.7
6	Assistance to Businesses (e.g., Loans)	0.0	72.8	3.3	0.6	-2.6	74.1
6	Corporate tax Relief	0.0	2.7	5.7	-3.1	-26.3	-21.0
6	Foreign aid					10.3	10.3
6	Unallocated					50.3	50.3
	Totals	**2,035.7**	**2,579.1**	**410.3**	**-16.0**	**106.5**	**5,115.6**

Note: The negative numbers for some of the provisions in later years represent the impacts of tax deferral or removal of some tax exemptions.

[17] There can also be cases in which the loans help the sectors in both ways as illustrated in the above two options. In such cases, we split the loan amounts between Option 1 and Option 2 depending on the extent to which the sector was subject to mandatory closures.

Appendix E: Appendix to Section 8

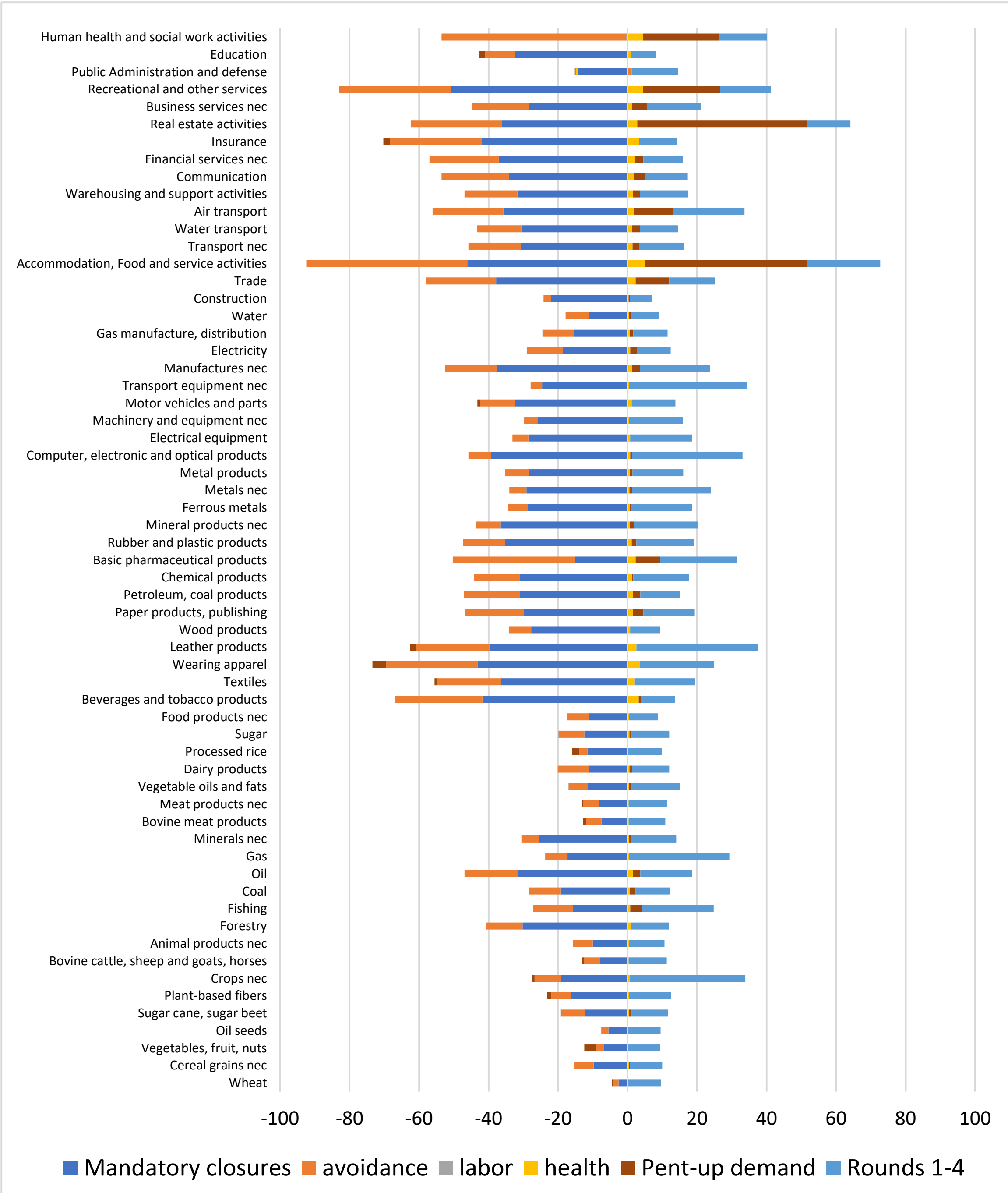


Figure E-1. Percent Changes in Sectoral Production in First Semi-annual Period of 2020 Due to Pandemic, Decomposed by Causal Effect (cumulative percent differences from baseline)