Stockholm Environment Institute Epidemic-Macroeconomic Model: Introduction and Documentation

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Abstract

This working paper presents a new software tool, the Stockholm Environment Institute Epidemic-Macroeconomic Model. It is desktop software designed to help national and regional authorities generate planning scenarios that include the economic ramifications of the pandemic and the measures undertaken to contain its spread. The integrated Epidemic-Macroeconomic Model simulates the spread of Covid-19 and the resulting economic impacts – both of which depend on the types of public health measures adopted. The measures represented in the model include establishing lockdowns, urging social distancing, isolating those who have symptoms and/or those are especially vulnerable to the disease; implementing testing and tracing programmes: imposing international travel restrictions, and rolling out vaccinations. The software can be used on its own, or in combination with tools such as SEI's Low Emissions Analysis Platform (LEAP) and the Water Evaluation and Planning system (WEAP), or with other non-SEI models that require economic projections. Generally, it is intended to be used to create economic projections that consider Covid-19 impacts, and to explore the impacts of different types of public health measures on the **economy**, rather than to model the pandemic itself.

Introduction

As of this writing, Covid-19 is estimated to have infected more than 250 million people, and to have led to the death of more than 5 million people worldwide (WHO, 2021). These grim figures continue to rise, as do the incalculable economic ramifications, both from the pandemic itself and from the efforts to contain it. The emergence of new variants (such as, most recently, Omicron) amidst a vaccination roll-out that lacks global reach has left developing countries especially vulnerable to the disease. Governments' attempts to reduce the spread of the disease have relied largely on public health measures intended to reduce face-to-face interactions – restrictions that have further upended economies worldwide. The overall result was "a global recession whose depth was surpassed only by the two World Wars and the Great Depression over the past century and a half", and an ensuing, highly uneven global recovery with the threat of inflation now looming in some countries (World Bank 2021a, 2021b). By the end of 2022, only one-third of emerging and developing countries are expected to regain their pre-pandemic per capita income levels, whereas 90% of advanced economies will likely do so (Worldometer, 2021).

In developing countries, the pandemic has thrust millions into joblessness, poverty and despair. Travel and tourism, important sources of foreign exchange for many developing countries, have plummeted. A contracting global economy, with uncertain near-term prospects and supply chains in disarray, has hurt the export-oriented manufacturing on which many developing countries depend. Though the impacts are being felt everywhere – even in countries where the virus appears to be under some degree of control, and where vaccination programmes have reached a significant portion of the population – developing economies face additional socioeconomic burdens. Health care systems in developing countries were under enormous strain well before the pandemic began, and social safety nets were very frayed or absent. Pressure for such services now grows even as private and public budgets shrink. National and regional authorities seeking to plan for a sustainable economic future must take all this into account to plan amid tremendous uncertainty, with the pandemic continuing, and vaccination roll-outs continuing to be highly uneven.

As a contribution to aid sustainability planning by policy analysts in developing countries, this working paper thus presents a new tool: a combined Epidemic-Macroeconomic Model. It is software that generates Covid-19-adjusted baselines for sector output, value added, and GDP. The model reports estimates of "susceptible", "exposed", "infected", and "recovered" populations, as well as mortality due to Covid-19. The key aim is to generate economic trajectories for scenario models, such as SEI's Low Emissions Analysis Platform (LEAP) and Water Evaluation And Planning system (WEAP). The scenario approach implemented by the LEAP and WEAP tools allows an analyst to assess the implications of a wide range of possible futures. Given the focus on energy and water resources, those scenarios typically assume reasonably smooth economic growth, at most differentiating among "low", "medium", or "high" trajectories. They do not assume events such as a global pandemic. The model described in this paper calculates departures from a smooth economic trajectory arising from Covid-19-related public health interventions. The model presently focuses specifically on Covid-19, but it can be applied to any epidemic disease whose dynamics are well described by a susceptible-exposed-infected-recovered (SEIR) dynamic, widely used in the literature. The SEI Epidemic-Macroeconomic Model is a short-run model for exploring potential deviations from an existing trajectory; it does not replace long-run demographic or economic models.

To accurately reproduce observed disease dynamics, the software includes the ability to model reinfections, post-vaccination breakthrough infections, waning immunity, and multiple variants that may be spreading concurrently or consecutively in the population. In its present form the model includes two variants of Covid-19 whose epidemiologic characteristics resemble those of the Alpha and Delta variants, but the model can be easily adapted to include emerging variants and as well as public health measures put in place to control their spread.

This working paper explains the use and structure of the model. It outlines the logic of the model and provides an extended example loosely based on disease spread and associated public health interventions present in the United States since early 2021. In an effort to replicate data limitations that may be present in many national contexts and to increase model robustness to such data-poor environments, the evaluation of the model focuses on reproducing temporal trends in population mortality rates, which are commonly the most reliable indicator for disease spread. Detailed information on the epidemic and macroeconomic model components is provided in the technical appendix.

Key assumptions and model structure

Covid-19 initially impacted upper-middle- and high-income countries; during the first year of the pandemic. Factors that may have contributed to the comparatively low incidence initially reported in developing countries include inaccurate reporting (Hanaei & Rezaei, 2020), and a comparatively young population (Alon et al., 2020). A further potential factor is limited mobility, particularly between rural and urban areas. At the time of this writing, the situation is changing, with low- and middle-income countries representing six of the ten countries with the greatest number of reported Covid-19-related deaths.

Governments have taken various, aggressive actions to limit the spread of the disease. They have imposed lockdowns, required social distancing, closed certain businesses, and limited travel – in some cases prohibiting arrival of anyone from certain countries, or all other countries. These measures have devastated tourism, entertainment, hotel, transport, and restaurant sectors, and non-essential retail businesses. Multiplier effects have spread the negative impacts throughout wider economies. Domestically driven loss of revenue from these and similar interventions occurred at the same time that demand for exports (whether in volume, in value, or both) declined, as the global economy itself contracted; this caused additional, severe strains on developing-country economies (Djankov & Panizza, 2020; Swinnen & McDermott, 2020, Chapter 4).

The pandemic situation reveals the need to help country authorities plan for their futures in the face of tremendous uncertainty and upheaval. The context powerfully illustrates the need to combine epidemiological and macroeconomic models that can be used to help plan for sustainable economic development and recovery. These circumstances motivated the creation of the SEI model and software as tools for country planners. Figure 1 shows the overall structure of the SEI “Epi-Macro” Model, which allows users to adapt parameters and data for the individual epidemic and macroeconomic models it contains. The tool allows users to adapt the models according to national circumstances, and to create alternative scenarios for global trends, including infection rates and GDP, and public health measures, such as social distancing, testing and tracing, and vaccination. One can specify parameters to generate diverse projections for the progress of the disease and economic trends.

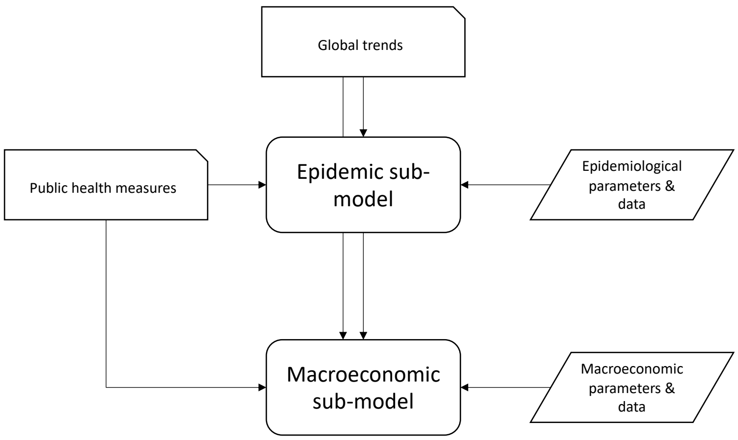


Figure 1: SEI Epidemic-Macroeconomic Model structure overview

(Details of the epidemic and macroeconomic sub-models are provided in the appendices.) The next sections outline the motivations for underlying assumptions of the models.

Epidemic sub-model

The epidemic sub-model is a modified version of a conventional "compartment" model (Kermack & McKendrick, 1927; Wearing et al., 2005). More specifically, it is an "SEIR-type" model (Krylova & Earn, 2013), with compartments consisting of susceptible (S), exposed (E), infected (I), recovered (R), and deceased populations. In the model, the probability of moving from the susceptible to the exposed category depends crucially on public health measures. The standard SEIR model has been applied extensively to Covid-19 (e.g., Gupta et al., 2020; Hou et al., 2020; Lopez & Rodo, 2020; Picchiotti et al., 2020; Zhang et al., 2020), but does not accurately capture the duration any individual spends in a given compartment and hence cannot reproduce the transient, non-steady state dynamics of epidemics (Wearing et al., 2005). Following Grant (2020), we expand the standard model by incorporating discrete time sub-compartments with a daily timestep; this allows the model to better reflect the likelihood of progressing from one compartment to the next given the time spent within the compartment (temporal heterogeneity). To represent the risk of reinfections following recovery or vaccination, the conventional model is further expanded by a second SEIR model added "in series" as shown in Figure 2. The recovered pool is the relevant susceptible pool for reinfections; the risk of reinfection is specific to each variant and can be time variant (i.e. waning immunity). Several such models can be defined in parallel to represent the concurrent or consecutive presence of multiple variants and their associated differing epidemiological characteristics and transmission dynamics. A single recovered pool across variants captures the possibility of being infected with any variant following an initial infection or vaccination. To capture spatial heterogeneity, the model expands on an approach introduced by Kemp-Benedict (2020).

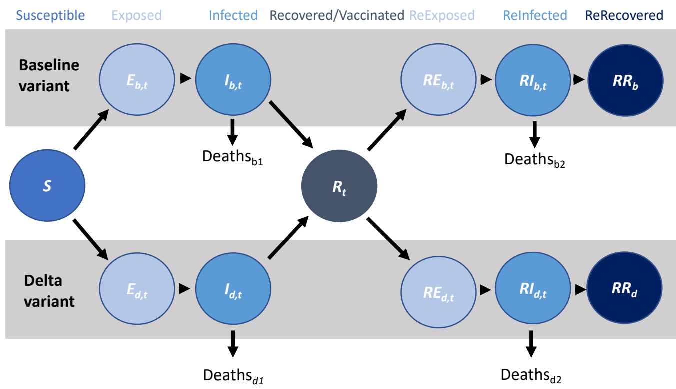


Figure 2*: Model structure of epidemic sub-model.*

Spatial structure is captured in a two-tier hierarchy. At one level, at coarser resolution, are "regions", such as provinces, states, collections of provinces or states, or large categories such as urban and rural. The definition of regions should be informed by what is known about the spread of the disease in the country (conditional on data availability), and need not match administrative boundaries. Characteristics for regions are specified explicitly by the model user. One critical difference between regions is the number of international arrivals. For example, a "rural" region might have no international arrivals, unlike an "urban" region. Where the frequency of visits between rural and urban areas is low, rural regions may be partially isolated from cases introduced by international travelers.

At the next level, at finer resolution, are "localities", which might be districts or counties, that are presumed to be nested within the top-level regions. These are not specified in detail, and very few model parameters are required to characterize localities (for example, the number of localities per region). The model takes this limited information and uses it to estimate the rate of community spread across regions and localities. This approach respects the limited data available for many developing countries, while taking into account the highly heterogeneous spread of the disease within those countries.

Public health measures in the model include international travel restrictions, social distancing, isolating symptomatic cases, isolating the high-risk population, testing and tracing, and vaccination roll-out. The model assumes that mortality rates are higher when hospital bed capacity is exceeded, in line with observation (Moghadas et al., 2020).

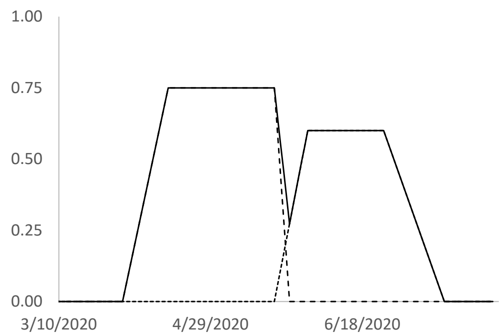


Figure 3: Two "windows" and their combination

Aside from vaccination, which is specified as a time series of the maximum number of doses per day, public health measures are set by the model user in a configuration file as "windows". Each window is characterized by a level of effectiveness, a start date, a ramp-up time, an end date, and a ramp-down time. The "ramp-up" and "ramp-down" reflect partial implementation, e.g., for only part of the population or at a lower level of intensity or efficacy. Overlapping windows will be added together to give the full effect, as illustrated in Figure 3. An example of specifying windows in the configuration file is shown in Figure 4.

```
social distance:
    # An official lockdown -- adds to a baseline level (below)
    -   apply: true
        effectiveness: 0.40 # + 0.05 = 0.45
        start date: {year: 2020, month: 3, day: 12}
        ramp up for: 15 # days
        end date: {year: 2020, month: 5, day: 31}
        ramp down for: 5 # days
    # This is ongoing, baseline, social distancing
    -   apply: true
        effectiveness: 0.05
        start date: {year: 2020, month: 3, day: 12}
        ramp up for: 15 # days
        end date: {year: 2021, month: 12, day: 31}
        ramp down for: 15 # days
```

Figure 4: Example of specifying "windows" in the configuration file

The overall model logic means that the epidemic model can be run independently from the macroeconomic model. As shown in Figure 2, it is entirely upstream of the macroeconomic model.

Macroeconomic sub-model

The macroeconomic model simulates a short-run (three- to five-year) trajectory. It simulates a departure from a trajectory of "balanced growth" due to demand disruptions[1] arising from Covid-19. On the

[1] That is, the model seeks to capture the effect of "demand shocks", whether for exports or for domestic and tourist demand for Covid-19-sensitive sector outputs. Price responses are not simulated, but if they were, they would tend to worsen the situation. For example, a fall in demand for exports will normally be accompanied by a fall in the export price levels, and, therefore, a fall in revenue per unit sold. If export firms' unit costs do not change, that will depress profits and investment. If firms pass on the lower price to workers through lower wages, then it will depress domestic demand.

balanced-growth path, the global economy grows at a steady rate, as do all sectors in the national economy. The growth rates of the global and national balanced-growth paths are set by the model user in a configuration file. Along this path, all prices move in tandem, at a common (but unspecified) rate of inflation. Wages grow in line with (unspecified) labour productivity.

The Covid-19 pandemic induces changes in demand for the country's goods and services. The changes will often be contractionary, with falling demand for goods and services, aside from those services related to health care. (The model allows for an expansionary impact, if one is either observed or anticipated.) As a result, firms curtail investment. Nevertheless, firms are assumed to be run by optimistic managers, in that their investment plans always assume at least partial recovery towards the balanced-growth path. For this reason, the model tends to produce "V-shaped" recoveries (a sharp rebound) in the absence of any persistent outside influence. However, the simulated trajectory may be "U-shaped" (a slow rebound) or "L-shaped" (a very long recovery), depending on external factors, such as a slow recovery by the global economy, or extended lockdowns due to the lack of access to vaccines.

Because the economy tends to return towards a particular growth rate, the level of output might be below the pre-Covid-19 trend. This is an example of "hysteresis", in which the effects of specific events, such as an economic crisis, persist long into the future (Lavoie, 2018). Many economic models assume no hysteresis; instead, GDP eventually returns to a long-run trend. Yet, hysteresis is observed in reality. For example, in the wake of the Great Recession that followed the 2007-2008 financial crisis, Ball (2014) found evidence of hysteresis in the majority of countries that belong to the Organisation for Economic Co-operation and Development (OECD). The model does not take into account the possibility for public investment, which can raise the growth rate of the economy and the level of output (Lavoie, 2018, p. 10). However, it does allow for a recovery boom that raises utilization above normal levels.

To propagate demand shocks between sectors, the model takes into account the structure of the economy in the form of input-output relationships. The relationships can be between any number of sectors. Aggregate sectors are defined by the model user via configuration files, while the aggregation is carried out within the model. Input-output tables are available at different levels of detail. The "Epi-Macro" Model requires only the least-detailed version: a symmetric input-output matrix. The symmetric matrix can be constructed from more detailed tables, such as a set of supply-use tables (SUTs) or a social accounting matrix (SAM). Symmetric I-O tables, SUTs, and SAMs are available for a large number of countries.

Example of model application

The model is implemented in Python, and is open source. It is also available as a stand-alone programme for a 64-bit Windows system.[2] The model runs on the command line, takes text files as inputs, and produces text files as outputs. It has a single command-line option, which allows the model user to run only the epidemic model. This section demonstrates the model using representative sample data. The explanation in this section assumes that the model is being run using the Windows executable.

[2] The programme, with source code and sample files, can be downloaded from the GitHub repository: https://github.com/sei-international/epi-macro-model/releases/tag/v1.0.0

Name	Date modified	Type	Size
cemm.exe	3/4/2021 11:17 AM	Application	247,529 KB
common_params.yaml	3/4/2021 11:17 AM	YAML File	5 KB
input_output_data.csv	3/4/2021 11:17 AM	Microsoft Excel C...	5 KB
io_config.yaml	3/4/2021 11:17 AM	YAML File	4 KB
regions.yaml	3/4/2021 11:17 AM	YAML File	2 KB
seir_params.yaml	3/4/2021 11:17 AM	YAML File	2 KB

Figure 5: Files required to run the model (with 64-bit Windows executable)

Configuration files

A sample of the needed files is shown in Figure 5. The configuration files all have a ".yaml" extension and must have the names shown in the figure. They are formatted following the YAML specification, which is recognized by a large number of programming languages and syntax-highlighting editors.[3]

regions.yaml

Regions are defined in the `regions.yaml` file. A sample file is shown in Figure 6. It provides some basic statistics, including the definition of each region and the number of localities within it. In the sample file, there are two "regions" in the model. Guided by the dynamics of the disease, these are large regions composed of multiple provinces. The first, "Ports of entry", is composed of the provinces containing the major ports of entry to the country. The "localities" are defined as the districts within the provinces that compose the regions. The other model region consists of the remaining provinces. These two regions were chosen because the ports of entry are the primary locations where the disease enters the country.[4] Initial values are provided for the population and hospital beds. A further parameter, **population with community spread**, is set, for example, to the population of the metropolitan centre where the first case appears as a fraction of the population in the "Ports of entry" region. The population with community spread is the population in those localities in which the disease is spreading.

The remaining parameters specify mobility. First, the **between-locality mobility rate** determines how rapidly the disease spreads within the model region. Second, the **between-region mobility rate** determines how quickly the disease spreads from one model region (e.g., "Ports of entry") to the others (in this case, "Other provinces"). Finally, an **international travel** entry specifies the number of daily arrivals and the typical duration of stay. In the sample file, the "Other provinces" model region is assumed to have no (or negligible) international visitors.[5]

[3] The official documentation is available at: https://yaml.org/start.html. The syntax highlighting used in this document was generated using Notepad++.
[4] The choice of regions should be guided by what is known about the spread of COVID-19 within the country. However, note that the choice of regional disaggregation can affect the results. If time permits, a sensitivity analysis can be carried out with different regional specifications.
[5] The number of international visitors is "negligible" if most of them arrive elsewhere. Infection rates are density dependent, when the number of exposed or infected individuals is low, this strongly dampens the probability of the spread of disease.

```
################################################################
#
# Regions
#
################################################################
- name: Ports of entry
  number of localities: 34
  initial:
    population: 1000000
    beds per 1000: 2.4
    population with community spread: 0.06 # As a fraction of total population
  # Probability of an individual moving from one locality to another per day
  between locality mobility rate: 0.00657
  between region mobility rate: 0.001
  international travel:
      daily arrivals: 217000
      duration of stay: 7 # Assume 1 week/visitor
- name: Other provinces
  number of localities: 401
  initial:
    population: 12500000
    beds per 1000: 2.4 # Assume same in both regions
    population with community spread: 0.06 # As a fraction of total population
  # Probability of an individual moving from one locality to another per day
  between locality mobility rate: 0.0001
  between region mobility rate: 0.0001
```

Figure 6: Sample `regions.yaml` *file*

common_params.yaml

The main configuration file is `common_params.yaml`. The first block in this file sets the time bounds for the model, as shown in Figure 7. The **start date** is when the economic model begins running. It should correspond to the year for which the economic data are available. The **Covid-19 start** date is when the epidemic model starts running[6]. It should correspond to the first introduction of Covid-19 into the country that results in the spread of the disease. The **end date** is the same for both the macroeconomic and epidemic models.

```
################################################################
#
# Start/end time in days
#
################################################################
time:
    start date: {year: 2015, month: 12, day: 31}
    COVID start: {year: 2020, month: 1, day: 1}
    end date: {year: 2023, month: 12, day: 31}
```

Figure 7: First block in `common_params.yaml`*: setting time time bounds*

The second block in `common_params.yaml` says whether elective operations are avoided when social-distancing protocols are in place. In that case, hospital bed occupancy for non-Covid-19 cases lies below

[6] The start dates of individual variants can be specified in seir_params.yaml and should correspond to the first introduction of the variants to the country

the normal level, using the parameters specified in the configuration file. Using the parameters in Figure 8, in normal times, 86% of hospital beds are occupied on average. When social-distancing protocols are in place, occupancy is reduced, depending on the extent of social distancing. For example, if social distancing is 70% effective, then the reduction is 70% × 33% = 23%. Occupancy is then 86% × (100% − 23%) = 66%.

```yaml
###############################################################
#
# Beds & hospitals
#
###############################################################
avoid elective operations: true
bed occupancy:
    normal: 0.64
    max reduction: 0.33
```

Figure 8: Second block in `common_params.yaml`*: setting bed occupancy rates*

The next block in `common_params.yaml` specifies global trends for two parameters: the global infection rate per 1,000 population across all variants and the global GDP growth rate. The global infection rate is used, together with other parameters, to calculate the probability that an international traveler will introduce the virus. The global GDP growth rate is used to estimate demand for exports, with the final value (here, 0.03 = 3% / year) acting as a reference value for the export demand calculation. Both of these are key scenario assumptions, as they must extend beyond the historically observable period in order to run the model. The global trends shown in Figure 9 assume that the recent sharp downturn in the global infection rate continues, while the global GDP trajectory follows an “L-shaped” pattern.

```
################################################################
#
# Global trends
#
################################################################

global infection rate: # per 1000 across variants
    - [{year: 2020, month: 1, day: 1}, 0.0000]
    - [{year: 2020, month: 4, day: 8}, 0.0960]
    - [{year: 2020, month: 7, day: 29}, 0.0332]
    - [{year: 2021, month: 1, day: 11}, 0.0960]
    - [{year: 2021, month: 2, day: 21}, 0.0471]
    - [{year: 2021, month: 4, day: 26}, 0.1064]
    - [{year: 2021, month: 6, day: 20}, 0.0465]
    - [{year: 2021, month: 8, day: 23}, 0.0849]
    - [{year: 2021, month: 10, day: 15}, 0.0520]
    - [{year: 2021, month: 12, day: 5}, 0.0802]

# For global GDP trajectory:
#  - Specify growth on an annualized basis
#  - The final value will be taken as a long-run trend that is
#    compatible with balanced growth at the target growth rate
#    specified in the IO model configuration file.
global-GDP-trajectory: # Growth on an annualized basis
    - [{year: 2020, month: 3, day: 17}, 0.03]
    - [{year: 2020, month: 5, day: 1}, -0.10]
    - [{year: 2020, month: 10, day: 1}, 0.0]
    - [{year: 2021, month: 2, day: 1}, 0.03]
```

Figure 9: Third block in `common_params.yaml`*: global trends (the "…" indicates where lines are omitted)*

The fourth block in `common_params.yaml`, shown in Figure 10, contains public health measures specified as "windows" (see Figure 3). Windows covering historical periods can be used to calibrate against observed data. While the calibration will never precisely match the data, both because of limitations in the model and because the course of the disease is never fully predictable, the model should be able to represent key patterns. Windows covering future periods distinguish different scenarios. To simplify the creation of alternative scenarios and the testing of different assumptions against historical data, windows can be turned on and off by setting **apply** to `true` or `false`. Note that the **social-distance** window encompasses lockdowns as well. The difference is in the degree of effectiveness. That is, 100% effective is a full lockdown with full compliance. A 90% effective lockdown would have an effectiveness of 0.9.

The **international travel restrictions section** has an option not available for the other sections. This option is "**ban**", which distinguishes travel bans, which exclude tourist arrivals, from testing and quarantine requirements, which can be consistent with tourism. Thus, a ban means no arrivals of people from abroad, infected or not; hence, a fall in tourism revenues occurs. Travel restrictions without a ban could include tests (before and after arrival); quarantines; and vaccination certifications. Such measures can dramatically reduce the likelihood of introduction of the disease. They may also slow tourism, but are unlikely to eliminate it.

The "public health measures" block provides a crucial link between the epidemic and macroeconomic models. As discussed further in the section on the configuration file io_config.yaml, social distancing and limits on international arrivals are assumed to impact upon economic activity.

```
################################################################
#
# Public health measures
#
################################################################
isolate symptomatic cases:
    -   apply: true
        fraction of cases isolated: 0.5
        start date: {year: 2020, month: 3, day: 17}
        ramp up for: 31
        end date: {year: 2022, month: 12, day: 31}
        ramp down for: 31
isolate at risk:
    -   apply: false
        fraction of population isolated: 0.70
        start date: {year: 2020, month: 3, day: 12}
        ramp up for: 31
        end date: {year: 2022, month: 12, day: 31}
        ramp down for: 31
test and trace: # until testing capabilities are ramped up
    -   apply: true
        fraction of infectious cases isolated: 0.3
        start date: {year: 2020, month: 3, day: 17}
        ramp up for: 90 # 3 month
        end date: {year: 2022, month: 12, day: 30}
        ramp down for: 31
social distance:
    # An official lockdown
    -   apply: true
        effectiveness: 0.6
        start date: {year: 2020, month: 3, day: 17}
        ramp up for: 31 # days
        end date: {year: 2020, month: 7, day: 30}
        ramp down for: 90 # days
    ...
international travel restrictions:
    # Airport closure
    -   apply: true
        ban: true
        effectiveness: 1.00
        start date: {year: 2020, month: 3, day: 22}
        ramp up for: 1 # days
        end date: {year: 2020, month: 9, day: 1}
        ramp down for: 1 # days
```

Figure 10: Fourth block in `common_params.yaml`*: non-vaccine public health measures ("…" indicates omitted lines)*

The final block in `common_params.yaml` specifies a vaccination scenario. As shown in Figure 11 the schedule is specified through a **time to efficacy** in weeks and a schedule of **maximum doses available per day**. The "time to efficacy" parameter is used to generate a lag between administering the vaccine and the time the person moves from the "susceptible" to "recovered" category. The "**vaccinate at risk first**" parameter, which may be omitted, specifies whether the population at highest risk category should be moved from the "susceptible" to the "recovered" category before the rest of the population.

```yaml
##############################################################
#
# Vaccination
#
##############################################################

vaccination:
    time to efficacy: 6 # weeks  - 4 weeks between doses +2 weeks to efficacy
    vaccinate at risk first: true
    maximum doses per day:
        - [{year: 2021, month: 2, day: 1}, 0]
        - [{year: 2021, month: 2, day: 15}, 33000]
        - [{year: 2021, month: 4, day: 14}, 56000]
        - [{year: 2021, month: 7, day: 11}, 11000]
        - [{year: 2021, month: 9, day: 2}, 18000]
        - [{year: 2021, month: 12, day: 1}, 1000]
        - [{year: 2022, month: 1, day: 1}, 10000]
```

Figure 11: Fifth block in `common_params.yaml`*: vaccination schedule*

seir_params.yaml

The parameters for the epidemic model for included variants are specified in a single file, shown in Figure 12. For each variant, epidemiological characteristics such as R_0, hospitalization rate, and case fatality rate are defined for an initial infection as well as reinfection. It should not normally be necessary to modify this file except when a providing additional data on the prevalence of a specific variant or adding additional variants to the model. Adding a new variant can be accomplished by adding another block to the file and detailing the epidemiologic characteristics specific to the new variant. Together the variants must account for all global infections in the model and sum to 1. Moreover, the section **transitioning rates** must be chosen so that all of the population is accounted for. It is possible to for the model to simulate a spurious increase or decrease in population if those values are not chosen well. Nevertheless, there may be good reasons to change the values in this file. First, knowledge of Covid-19 continues to evolve. Second, some key parameters, such as R_0, k, and case fatality rates, and vaccine efficacy through time are uncertain or variable. The impact of varying the values of those parameters can be easily ascertained by changing the values in this file and re-running the model.

Reinfection is modeled by running two SEIR models in series with the population that has been vaccinated or recovered from an initial infection being at risk of reinfection with any of the modeled variant. Waning immunity is treated as a decline in protective efficacy of previous infection/full vaccination with time that can be specified by the model user by providing a time series of protective efficacy values measured since time of infection or full inoculation.

The treatment of at-risk populations is quite basic. The model allows for only one type of at-risk population, thus lumping together the elderly and those with comorbidities. The “at-risk” parameters are optional, and may be omitted. The at-risk fraction defaults to 0.0, the case fatality and cases requiring hospitalization to the average, and the relative recovery rate to 1.0.

```yaml
################################################################
#
# These are parameters for a discrete time model implementation of
# a susceptible-exposed-infective-recovered (SEIR)
# epidemiological model. These parameters are for variants of
# COVID-19.
#
################################################################
- name: Baseline variant

  start date: {year: 2020, month: 1, day: 1}
  R0:
    1st infection: 2.25
    Reinfection: 1.9
  k factor: 0.1
  unobserved fraction of cases:
        first infection: 0.47
        reinfection: 0.47
  population at risk fraction: 0.05 # As a fraction of total population
  case fatality rate among 1st infections:
      average: 0.011
      at risk: 0.073
      overflow hospitalized mortality rate factor: 2
  fraction of observed cases among 1st infections requiring hospitalization:
      average: 0.031
      at risk: 0.108
  case fatality rate among reinfections:
      average: 0.008
      at risk: 0.033
  fraction of observed reinfection cases requiring hospitalization:
      average: 0.021
      at risk: 0.060
  transitioning rates:
      prob infected given exposed: [0,0.025,0.1,0.2,0.3,0.4,0.4,0.4,0.4,0.4,0.4,0.4]
      prob recover or death given infected: [0,0,0,0,0.05,0.05,0.06,0.06,0.06,0.07,0.07,
                                             0.08,0.08,0.09,0.08,0.09,0.1,0.11,
                                             0.12,0.13,0.15,0.18,0.22,0.29,0.06,
                                             0.07,0.07,0.08,0.08,0.09,0.1,0.11]
      prob reinfected given reexposed: [0,0.11,0.22,0.29,0.34,0.38,0.41,0.45,0.51,0.61]
      prob immunity or death given reinfected: [0.00,0.00,0.13,0.13,0.19,0.19,0.16,0.16,
                                                0.16,0.16,0.16,0.19,0.19,0.19,0.19,0.19,
                                                0.30,0.30,0.30,0.30,0.30]
      recovery rate for at risk as fraction of not at risk: 0.75
      recovery rate for at risk as fraction of not at risk among reinfected: 1.0
  protective efficacy of previous infection or inocculation: # points of interpolation given
                                                              # by month since infection/inocculation
                                                            - [{month: 0}, 0.9]
                                                            - [{month: 4}, 0.9] #
  statistical-model:
      coeff of variation of infected where spreading: 0.6
  initial:
    infected fraction:
      Ports of entry: 0.0001 # As a fraction of total population
      Other provinces: 0.00005
  proportion of global infection rate:
      - [{year: 2020, month: 1, day: 1}, 1]
      - [{year: 2020, month: 3, day: 20}, 1]
      - [{year: 2020, month: 4, day: 7}, 1]
      - [{year: 2020, month: 5, day: 19}, 1]
      - [{year: 2020, month: 7, day: 30}, 1]
```

Figure 12: Section in seir_params.yaml for specifying the epidemic (SEIR) model for one variant named "Baseline variant"

io_config.yaml

The input-output matrix is specified in a text file, as described below. The `io_config.yaml` configuration file points to the data file and specifies how to read it. This configuration file also specifies how public health measures impact upon economic activity.

The first block in the `io_config.yaml` file is shown in Figure 13. It specifies the time step in days, which may be given as a fractional number (e.g., 7 days for a week, 30.42 days for a month, 91.26 days for a quarter). It further specifies a target growth rate for the country. In the absence of impacts from Covid-19, the model economy will exhibit balanced growth at the target growth rate. The **input-file** section identifies the data file with the input-output data, along with a delimiter and quote character. For example, a standard comma-separated variable (CSV) file will have a comma as a delimiter and a double-quote mark as a quote character (these are the values entered in Figure 13).

The **monetary-units** section is reasonably self-explanatory. In the sample input-output data file, values are in millions of a (fictitious) Local Currency, so the scale is entered as `1.0e+6` (it could also have been `1000000`), while the currency is `Local Currency`. An alternative would be to set the scale equal to `1.0` and have the currency unit be `Million Local Currency`.

The next two entries in this block, for **final-demand** and **wages**, specify the name for these sectors in the input-output file. The final entry, **govt-expend-autonomous-frac**, is the fraction of total government expenditure that reliably grows at the target growth rate.[7] This captures expenditure that has been committed several years in advance. The remainder grows on the basis of a smoothed GDP growth rate with a one-year smoothing period.

---

[7] This is a conservative assumption. Planned government expenditures could either rise or fall. This is intended as a simple assumption that is consistent with the goal of constructing "COVID-19-adjusted baselines".

```yaml
##############################################################
#
# Input-output configuration file
#
##############################################################
days-per-time-step: 7 # week: 7; month: 30.42; quarter: 91.26

target-growth-rate: 0.035 # Annual target growth rate

input-file:
    name: input_output_data.csv
    delimiter: ',' # Use "\t" for a tab-separated file
    quote-character: '"'

monetary-units:
    scale: 1.0e+6 # Note that both the ".0" and "+" sign are required
    currency: Local Currency

final-demand:
    # Note that imports should be negative
    household: Personal consumption expenditures
    government: Government consumption expenditures and gross investment
    investment: Private fixed investment
    exports: Exports of goods and services
    imports: Imports of goods and services

wages: Compensation of employees

# The fraction of government expenditure that grows at target growth rate
govt-expend-autonomous-fraction: 0.9
```

Figure 13: First block in the `io_config.yaml` *file*

The next block in the `io_config.yaml` file specifies the sectors in the model and connects them to the sectors in the input-output data file. The matching might be one to one. However, it is likely that some aggregation will be called for.[8] In the sample file shown in Figure, 15 sectors are aggregated into 6 sectors, with 3 each in the **non-tradeables** and **tradeables** sections. For effectively non-traded goods, there will often be some small amount of trade recorded. The model assumes that the value of trade be very small compared to total use. The model will set trade precisely to zero, leading to small deviations from the official statistics. The choice of sectors should be guided by the likely impact of public health measures to counter Covid-19.

[8] Any disaggregation must be done offline, prior to reading the data into the model. The aggregation feature is for convenience, and to allow for readily adjusting the aggregation if that becomes necessary.

```yaml
sectors:
    count: 15
    non-tradeables:
        construction:
            - Construction
        public_facing:
            - Retail trade
            - Arts, entertainment, recreation, accommodation, and food services
        social_support:
            - Educational services, health care, and social assistance
            - Government
    tradeables:
        necessities:
            - Agriculture, forestry, fishing, and hunting
            - Utilities
        industry:
            - Mining
            - Manufacturing
        other:
            - Wholesale trade
            - Transportation and warehousing
            - Information
            - Finance, insurance, real estate, rental, and leasing
            - Professional and business services
            - Other services, except government
```

Figure 14: Start of second block in the `io_config.yaml` *file: Definition of sector aggregation*

The following lines within the **sectors** block provides parameters for specific sectors. First, as shown in Figure 15, the user can specify whether there is a minimum domestic sourcing for the household consumption of some tradeable goods. In this case, only the "necessities" sector has a value entered for it. This parameter captures domestic supply for basic or minimum consumption levels. This entry is not required, and can be omitted. If it is used, the values should be set well below the reported domestic share.

```yaml
    min-hh-dom-share:
        necessities: 0.20
```

Figure 15: Additional entries in the **sector** *block: minimum household domestic share*

The next two sections, shown in Figure 16, contain a parameter that is required for all sectors, **typical-lifetime**, which determines depreciation rates. (The depreciation rate is set to one divided by the typical lifetime.)

```yaml
    typical-lifetime: # In years
        construction: 20
        public_facing: 15
        social_support: 20
        necessities: 20
        industry: 30
        other: 20
```

Figure 16: Parameter required for all sectors

The next section, which is optional, sets initial and maximum utilization levels (see Figure 17). The **initial-utilization** can normally be set to `1.0`. In that case, it can be omitted in the configuration file, as is done in the example. As a reminder that it can be added in future, it has been commented out rather than deleted. It might be needed if, for example, the country was experiencing a recession at the time the input-output data were collected. In that case, these values could be set to a lower value to improve the calibration. The format for initial utilization is the same as for the maximum utilization parameter. Note that, in the model, utilization can exceed a value of one – for example, by reducing maintenance cycles or adding shifts. The actual, fully constraining, maximum is set using the **max-utilization** parameter.

```yaml
    # initial-utilization: # This defaults to 1.00, and may be omitted
    max-utilization: # This defaults to 1.00, and may be omitted
        construction: 1.02
        public_facing: 1.02
        social_support: 1.05 # Allow overflow in hospitals
        necessities: 1.02
        industry: 1.02
        other: 1.02
```

Figure 17: Optional parameters for all sectors: initial and maximum utilization

The next section is required for sectors producing tradeable goods: **global-GDP-elasticity-of-exports**. The model assumes that export growth normally proceeds at the **target-growth-rate** (see Figure 13). However, if the global GDP growth rate departs from its initial rate as specified in the `common_params.yaml` file (see Figure 9) then the deviation is multiplied by the elasticities specified in this section and added to the target growth rate. This captures the impact of falling demand for the country's exports given the global Covid-19-induced recession.

```yaml
    global-GDP-elasticity-of-exports:
        necessities: 1.0
        industry: 1.2
        other: 1.2
```

Figure 18: Parameters required for all tradeable sectors

The next block contains a single parameter, **threshold-util**, which must be adjusted to achieve reasonable trajectories. Plausible values for this parameter depend on the time step, with shorter time steps requiring higher values of this parameter. Values will typically lie between 0.60 and 0.80. For a weekly (7-day) timestep, a value of 0.70 is a reasonable starting assumption.

```yaml
# Calibration parameters
calib:
    # A utilization level below which firms replace capital equipment but do not otherwise invest
    threshold-util: 0.7
```

Figure 19: Parameters required for calibration

The final block specifies the link between the public health measures and macroeconomic impacts. As shown in Figure 20, sectors can be identified that are particularly sensitive to social distancing and travel bans. The section **hospitalization-sensitivity** connects hospital bed occupancy to economic activity in related health-care sectors.

```yaml
#------------------------------------------
# COVID-related parameters
#------------------------------------------
# The sectors under "public-health-response" should differ from "hospitalization-sensitivity"
public-health-response:
# Fractional reduction in final demand when social distancing fully effective
    social-distance-sensitivity:
        public_facing: 0.10
        other: 0.05
    # Fractional reduction in final demand when travel bans are in place
    travel-ban-sensitivity:
        public_facing: 0.05
# Fractional increase/reduction in final demand due to excess/deficit hospital visits
hospitalization-sensitivity:
    social_support: 0.1
```

Figure 20: Covid-19-related parameters in the `io_config.yaml` file

Input-output file

The input-output matrix must be a delimited text file (e.g., CSV or tab-separated) with a particular structure. As shown in Table 1, the model expects an industry-by-industry, symmetric input-output matrix. Such a matrix can be constructed from supply-use tables (see Eurostat, 2008) or a social accounting matrix (SAM). The I-O table used by the model is particularly simple, consisting of: the matrix of technical coefficients **A**; household and government demand as column vectors **H** and **G, respectively**; demand for investment goods **J**; exports **X**; and imports, entered as negative values −**M**. The sum across the rows is total domestic supply.[9] For factor payments, there is a row vector **W** with payments for labour. Profits and taxes are left unspecified.

Table 1: Schematic layout for the input-output matrix

	industries	households	government	investment	exports	imports
industries	**A**	**H**	**G**	**J**	**X**	−**M**
wages	**W**					

Running the model

The model can be run using Python or (on a 64-bit Windows system) from the command line. This section assumes the model is run from the command line.

As shown in Figure 21, all of the files should be in a single folder. The files include the programme itself, `epi_macro_model.exe`, as well the `.yaml` configuration files, and the I-O datafile in CSV format. The sample input files can be downloaded separately as a .zip file.

[9] If direct and indirect taxes are excluded, then the row sum is output at basic prices. For output at purchasers' prices, taxes must be allocated to entries within the table. Similarly, any margins must be allocated – for example, as demand for transport.

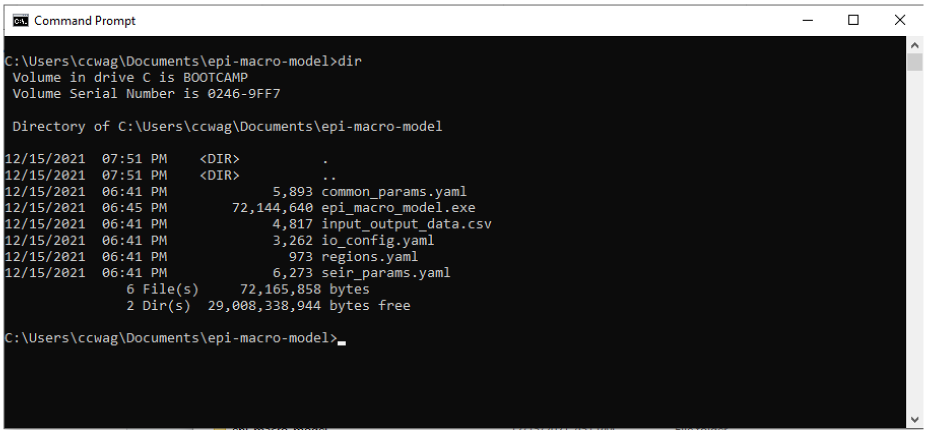


Figure 21: List of files in the model folder

The model can be run by typing the programme name. To run only the epidemic model, without running the macroeconomic model, either `-m epi` or `--model epi` can be added after the programme name. This is illustrated in Figure 22, which shows both the command and the response from the programme. Note that the model takes a while to load, and may appear to "hang" for some time before responding.

A useful strategy when developing a model is to first calibrate the epidemic model, and then run the macroeconomic model. For this purpose, the end date can initially be set within a historical period in the `common_params.yaml` file, to more easily compare model outputs to observed Covid-19 statistics.

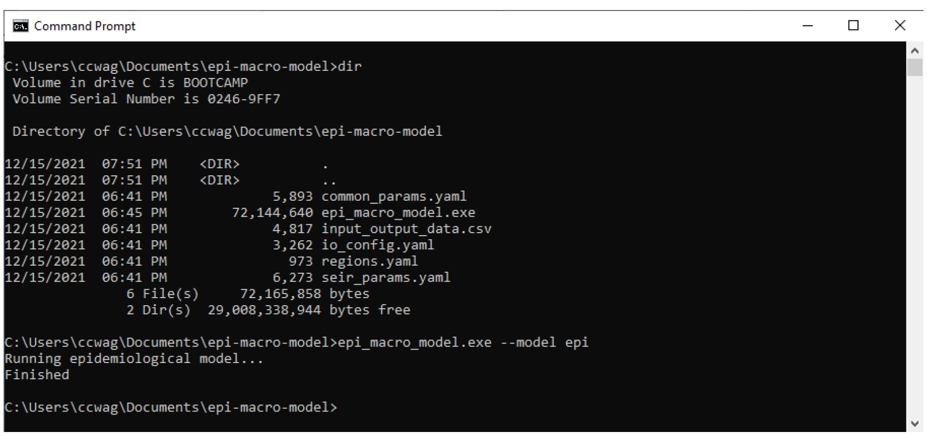


Figure 22: Running the epidemic model

The model produces output files, one per model region and variant, with a filename of the form `output_populations_<region>_<variantname>_variant.csv`, where `<region>` is replaced with the region name and `<variantname>` is replaced with the name of the variant. This is shown in Figure 23, while a sample of the output is shown in Figure 24.

```
Command Prompt
Finished

C:\Users\ccwag\Documents\epi-macro-model>dir
 Volume in drive C is BOOTCAMP
 Volume Serial Number is 0246-9FF7

 Directory of C:\Users\ccwag\Documents\epi-macro-model

12/15/2021  07:52 PM    <DIR>          .
12/15/2021  07:52 PM    <DIR>          ..
12/15/2021  06:41 PM             5,893 common_params.yaml
12/15/2021  06:45 PM        72,144,640 epi_macro_model.exe
12/15/2021  06:41 PM             4,817 input_output_data.csv
12/15/2021  06:41 PM             3,262 io_config.yaml
12/15/2021  07:52 PM           241,590 output_populations_Other_provinces_Baseline_variant.csv
12/15/2021  07:52 PM           191,286 output_populations_Other_provinces_Delta_variant.csv
12/15/2021  07:52 PM           234,366 output_populations_Ports_of_entry_Baseline_variant.csv
12/15/2021  07:52 PM           183,246 output_populations_Ports_of_entry_Delta_variant.csv
12/15/2021  06:41 PM               973 regions.yaml
12/15/2021  06:41 PM             6,273 seir_params.yaml
              10 File(s)     73,016,346 bytes
               2 Dir(s)  29,004,517,376 bytes free

C:\Users\ccwag\Documents\epi-macro-model>
```

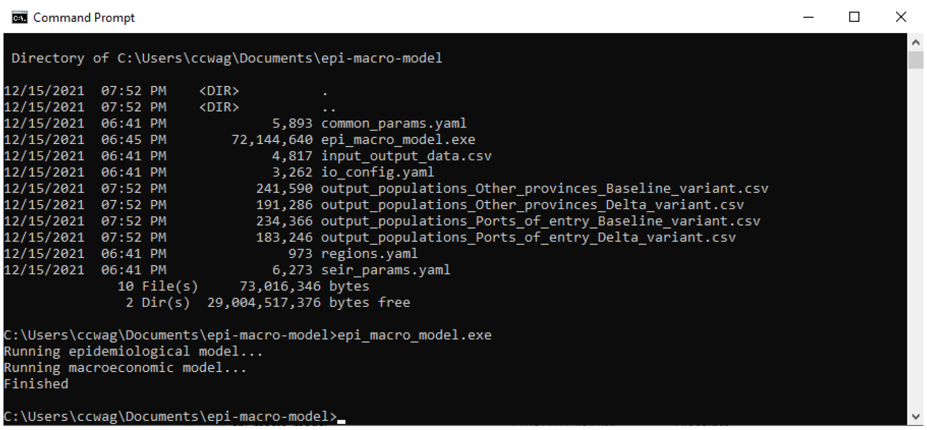
Figure 23: Directory listing showing the epidemic model output files

	A	B	C	D	E	F	G	H	I	J	K	L
1	date	susceptible	exposed	infected	recovered	died during 1	reexposed	reinfected	rerecovered	died during reinfection		
2	1/1/20	999784.711	15.2893669	100	0	0	0	0	0	0		
3	1/2/20	999769.42	30.1979868	100.382234	0	0	0	0	0	0		
4	1/3/20	999754.091	43.653963	102.255219	0	0	0	0	0	0		
5	1/4/20	999738.475	54.7125681	102.271242	4.51874479	0.02259857	0	0	0	0		
6	1/5/20	999722.854	62.5452958	105.724983	8.83187395	0.04417913	7.06E-06	0	0	0		
7	1/6/20	999706.704	67.8661518	111.571469	13.7894092	0.06899579	2.01E-05	7.77E-07	0	0		
8	1/7/20	999689.66	72.2057034	119.480305	18.5610784	0.09289541	3.95E-05	3.68E-06	0	0		
9	1/8/20	999671.407	76.5295903	128.664674	23.2822601	0.11655393	6.45E-05	1.02E-05	9.07E-08	2.50E-10		
10	1/9/20	999651.75	81.3361466	137.958379	28.8114614	0.14427368	9.52E-05	2.15E-05	5.09E-07	1.41E-09		
11	1/10/20	999630.671	86.7155182	147.913756	34.5263975	0.17293606	0.00013336	3.89E-05	1.68E-06	4.64E-09		
12	1/11/20	999608.071	92.6838624	157.89273	41.146292	0.2061504	0.00017922	6.33E-05	4.21E-06	1.16E-08		
13	1/12/20	999583.944	99.1086221	168.648904	48.0570521	0.24083578	0.00023502	9.59E-05	8.84E-06	2.45E-08		
14	1/13/20	999558.173	105.847229	179.846814	55.8522566	0.27997605	0.00030127	0.00013803	1.65E-05	4.56E-08		
15	1/14/20	999530.69	113.032485	192.448459	63.5099082	0.31843077	0.00038048	0.00019116	2.81E-05	7.79E-08		
16	1/15/20	999501.281	120.76734	205.479456	72.110103	0.36163392	0.00047232	0.0002571	4.49E-05	1.25E-07		
17	1/16/20	999469.879	129.016945	219.080238	81.6133354	0.4093911	0.00058053	0.00033765	6.83E-05	1.90E-07		
18	1/17/20	999436.398	137.77228	233.37803	91.9885703	0.46154957	0.00070812	0.00043492	9.98E-05	2.77E-07		
19	1/18/20	999400.732	147.027402	248.521972	103.19922	0.51792801	0.00085819	0.00055146	0.00014119	3.93E-07		
20	1/19/20	999362.751	156.800532	264.644255	115.224162	0.57842185	0.00103396	0.00069037	0.00019466	5.42E-07		
21	1/20/20	999322.305	167.130708	281.595197	128.322081	0.64434433	0.00123891	0.00085525	0.00026258	7.31E-07		

output_populations_Ports_of_ent

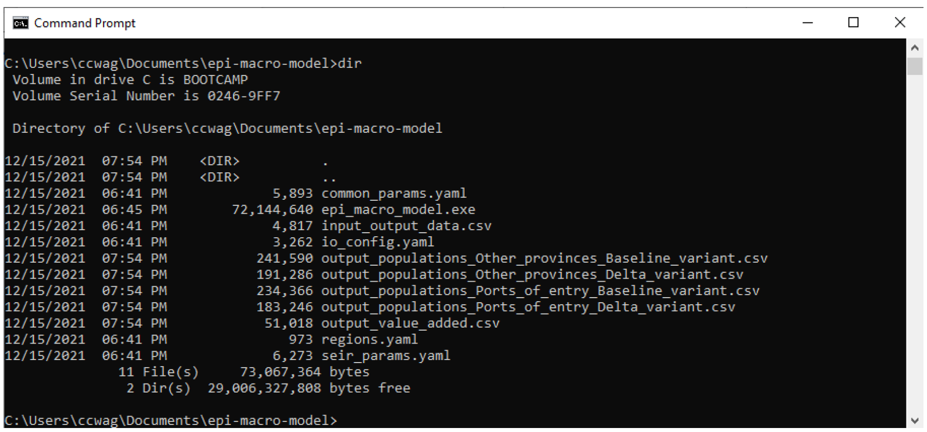
Figure 24: Sample output from the epidemic model

By leaving off the `--model epi` condition, both the epidemic and macroeconomic models are run in sequence. This is shown in Figure 25. A directory listing (see Figure 26) then shows an additional file, `output_value_added.csv`.



```
Command Prompt

 Directory of C:\Users\ccwag\Documents\epi-macro-model

12/15/2021  07:52 PM    <DIR>          .
12/15/2021  07:52 PM    <DIR>          ..
12/15/2021  06:41 PM             5,893 common_params.yaml
12/15/2021  06:45 PM        72,144,640 epi_macro_model.exe
12/15/2021  06:41 PM             4,817 input_output_data.csv
12/15/2021  06:41 PM             3,262 io_config.yaml
12/15/2021  07:52 PM           241,590 output_populations_Other_provinces_Baseline_variant.csv
12/15/2021  07:52 PM           191,286 output_populations_Other_provinces_Delta_variant.csv
12/15/2021  07:52 PM           234,366 output_populations_Ports_of_entry_Baseline_variant.csv
12/15/2021  07:52 PM           183,246 output_populations_Ports_of_entry_Delta_variant.csv
12/15/2021  06:41 PM               973 regions.yaml
12/15/2021  06:41 PM             6,273 seir_params.yaml
              10 File(s)     73,016,346 bytes
               2 Dir(s)  29,004,517,376 bytes free

C:\Users\ccwag\Documents\epi-macro-model>epi_macro_model.exe
Running epidemiological model...
Running macroeconomic model...
Finished

C:\Users\ccwag\Documents\epi-macro-model>
```

Figure 25: Running both the epidemic and macroeconomic models



```
Command Prompt

C:\Users\ccwag\Documents\epi-macro-model>dir
 Volume in drive C is BOOTCAMP
 Volume Serial Number is 0246-9FF7

 Directory of C:\Users\ccwag\Documents\epi-macro-model

12/15/2021  07:54 PM    <DIR>          .
12/15/2021  07:54 PM    <DIR>          ..
12/15/2021  06:41 PM             5,893 common_params.yaml
12/15/2021  06:45 PM        72,144,640 epi_macro_model.exe
12/15/2021  06:41 PM             4,817 input_output_data.csv
12/15/2021  06:41 PM             3,262 io_config.yaml
12/15/2021  07:54 PM           241,590 output_populations_Other_provinces_Baseline_variant.csv
12/15/2021  07:54 PM           191,286 output_populations_Other_provinces_Delta_variant.csv
12/15/2021  07:54 PM           234,366 output_populations_Ports_of_entry_Baseline_variant.csv
12/15/2021  07:54 PM           183,246 output_populations_Ports_of_entry_Delta_variant.csv
12/15/2021  07:54 PM            51,018 output_value_added.csv
12/15/2021  06:41 PM               973 regions.yaml
12/15/2021  06:41 PM             6,273 seir_params.yaml
              11 File(s)     73,067,364 bytes
               2 Dir(s)  29,006,327,808 bytes free

C:\Users\ccwag\Documents\epi-macro-model>
```

Figure 26: Directory listing, with output files produced by the combined models

Results

Selected results from the epidemic model are shown in Figure 27. Based on the assumptions entered in the configuration files, there is a rise in deaths as an initial lockdown is relaxed. That is partially corrected by later and less-effective social distancing measures. Deaths rise again as these are lifted and cold-weather makes social distancing measures less effective. Eventually another lock-down becomes effective and vaccinations begin to roll out, decreasing mortality rates substantially. However, as the delta variant emerges in the spring of 2021 at the same time as social distancing measures are lifted, mortality rates increase again and are only controlled by renewed social distancing measures. Cold-weather and waning vaccine induced immunity in the fall of 2021 lead to another rapid increase that requires renewed social distancing measures and vaccination efforts. The total number of deaths is around 5,300 by the end of

2022. Note that this is just one scenario. Once the model has been constructed, it is straightforward to explore alternative scenarios.

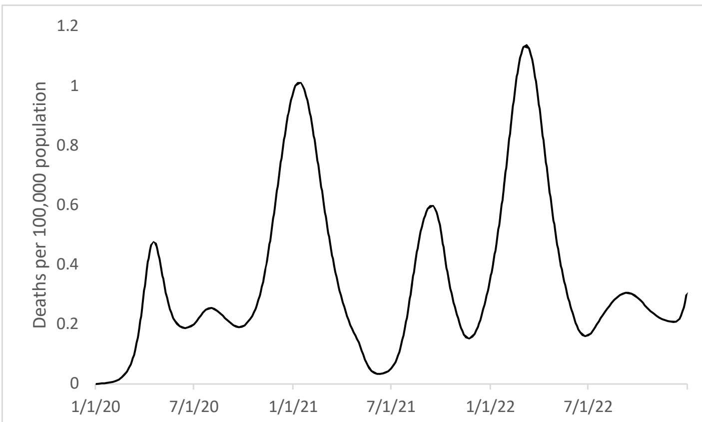


Figure 27: Mortality rate in the sample model run

Figure 28 shows annual totals for GDP; the week-by-week variation is more pronounced. As shown in the figure, the simulated economy experiences a recession, recovering by the end of 2024. At that point growth slightly exceeds the long-run target rate. Due to lower levels of investment during the pandemic, the level of GDP does not rise to the level that would have been achieved under the balanced-growth path. However, the gap partly closes due to a recovery boom that drives capacity utilization above normal levels.

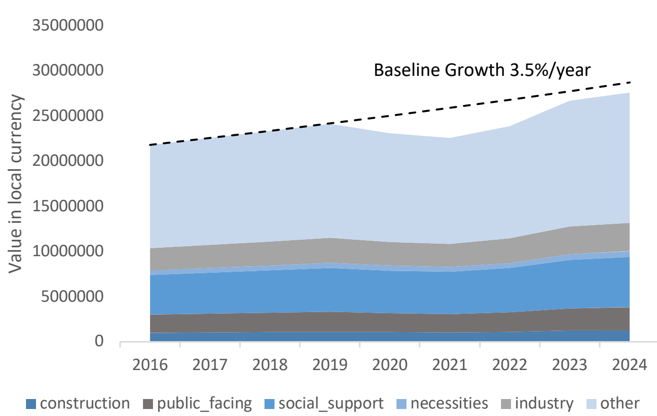


Figure 28: Total GDP and sector value added

Discussion and conclusion

The model described in this working paper is designed for rapid scenario exploration of alternative Covid-19 baselines, taking into account the structure of the economy, the global economic environment, and domestic public health measures. Because the impacts of Covid-19 have no close parallel in recent decades, several parameters are highly uncertain. Moreover, the model simplifies many aspects of reality in order to be tractable and reasonably robust. For this reason, outputs should be taken with caution. The purpose is to generate plausible demographic and economic scenarios for use in planning models such as SEI's LEAP and WEAP.

The tool allows for flexibility for authorities as they attempt to make plans amid uncertainty, and with situations that might vary to a great degree in different settings. To that end, sectors can be aggregated in a variety of ways to capture different possible channels between public health measures and economic output. Moreover, a variety of health measures can be specified: testing and tracing regimes, the isolating of particular populations; establishing social distancing rules; imposing international travel restrictions; and rolling out vaccinations. The model takes heterogeneity of the population into account while seeking to accommodate data limitations. This is a time of great uncertainty, and this model has its limitations. At the same time, it represents a serious effort to provide planners in developing countries with a tool that can help them proceed in ways that reflect some of the realities emerging in the pandemic.

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